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Machine Learning Models for Pavement Structural Condition Prediction: A Comparative Study of Random Forest (RF) and eXtreme Gradient Boosting (XGBoost)

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Abstract

Effective pavement maintenance and rehabilitation decisions rely on both pavement functional and structural condition data. Traditionally, state transportation agencies prioritize pavement segments based on functional conditions, often neglecting structural assessments due to the time, cost, and labor involved with methods like the Falling Weight Deflectometer (FWD). The objective of this paper to develop machine learning models—Random Forest (RF) and eXtreme Gradient Boosting (XGBoost)—to predict pavement Surface Curvature Index (SCI), a key indicator of pavement structural condition, as a cost-effective alternative to frequent FWD testing. Using 3016 samples from the Long-Term Pavement Performance (LTPP) program, the models were trained and tested with variables such as surface layer condition at year 0, thickness, pavement age, environmental, and traffic data. XGBoost outperformed RF, achieving R^2, RMSE, and MAE values of 0.90, 0.64, and 0.41, respectively, compared to RF's 0.80, 0.90, and 0.51. The study highlights the importance of machine learning applications in predicting pavement structural conditions, offering precise models that can help transportation agencies optimize maintenance planning and resource allocation.

Keywords

Pavement Condition Assessment, Pavement Performance Modeling, Pavement Structural Condition, Falling Weight Deflectometer, Machine Learning

1. Introduction

Transportation asset management systems, such as Pavement Management Systems

(PMS), are crucial tools for state agencies to efficiently maintain their pavement assets despite limited funding. In simpler terms, a pavement management system is the practice of managing the pavement infrastructure cost-effectively. It enables systematic and logical decision-making, which assists state agencies in effectively distributing maintenance and rehabilitation activities across road networks. Thus, this optimizes the utilization of available resources while planning for the pavement asset's investment decisions for the State Highway Agencies [1] [2].

The pavement condition is a key element in the decision-making process of Pavement Management Systems (PMS). Pavement data is categorized into various metrics such as Ride Quality, Distresses, and Structural Integrity, which comprehensively assess pavement condition. Specifically, Ride Quality refers to the smoothness of the pavement surface as experienced by road users. Rutting and Cracking, significant indicators of pavement distress, quantify the extent of deformation along wheel paths and the occurrence of cracks in the pavement surface, respectively [3]. Pavement functional condition refers to the surface characteristics of the pavement and how they impact the usability and safety of vehicles. It includes aspects like smoothness, skid resistance, and the presence of ruts or potholes. Essentially, the functional condition assesses how well the pavement serves its intended purpose from a user's perspective. On the other hand, pavement structural condition pertains to the pavement's ability to support traffic loading without deteriorating. It involves evaluating the strength and integrity of the pavement structure, including the surface, base, subbase, and subgrade layers. The structural condition is crucial for determining the pavement's need for major rehabilitation or reconstruction.

Successful implementation of pavement maintenance and rehabilitation decisions relies on both pavement functional and structural condition data. Without considering pavement structural condition data can result in the inappropriate selection of pavement maintenance techniques and inefficient budget allocation. Incorporating structural information into pavement maintenance decisions that do not require it causes Type 1 errors. On the other hand, without considering the structural condition causes Type II errors in the pavement maintenance decision-making process. Therefore, it is important to incorporate pavement structural conditions into treatment selection and fund allocation [2]. Significant researchers have recommended the consideration of both pavement functional and structural conditions for finalizing pavement maintenance decisions [4]-[9]. Baus *et al.* [10] concluded that the "addition of a separate deflection-based structural assessment would be valuable for identifying structurally weak sections, developing rehabilitation strategies based on structurally homogeneous sections, and, once a database has been established, for evaluating the structural performance of pavements." Enhancing pavement management practices by integrating machine learning-based predictions of structural conditions will enable more informed and strategic decision-making. These machine learning models will assist transportation agencies in prioritizing pavement maintenance tasks and optimizing budget allocation within the constraints of limited resources. The objectives of this paper are outlined below:

- Develop and evaluate two ensemble machine learning models, Random Forest (RF) and eXtreme Gradient Boosting (XGBoost), to predict the Surface Curvature Index (SCI), a key indicator of pavement structural condition, using various influencing factors such as surface layer condition at year 0, thickness, traffic data, and environmental conditions.
- Compare the performance of the RF and XGBoost models using metrics such as R^2, Root Mean Square Error (RMSE), and Marginal Average Error (MAE) to determine which model provides more accurate predictions of pavement structural conditions.
- Identify the most critical factors in predicting pavement surface layer condition, such as surface layer condition at year 0, pavement age, surface thickness, base thickness, precipitation, and freeze thaw cycle.

2. Literature Review

2.1. Deflection Basin Parameters

Deflection Basin Parameters can be calculated from the FWD collected deflection values, which are shown in Figure 1. Several researchers showed that the deflection basin parameters are effective tools to identify the possible distressed layer of the asphalt pavement. Chang *et al.* [11] and Horak *et al.* [12] developed threshold values for categorizing each pavement layer condition. Table 1 and Table 2 show the threshold values of the FWD Deflection basin parameter. For example, the asphalt layer is in very good condition if the SCI values are <4 mils. On the other hand, the range of values 4 - 6 mils, 6 - 8 mils, 8 - 10 mils, and greater than 10 mils indicate good, fair, poor, and very poor asphalt layer condition, respectively [11]. Similarly, the base layer is in very good condition if the BCI values are <2 mils. On the other hand, the range of values 2 - 3 mils, 3 - 4 mils, 4 - 5 mils, and greater than 5 mils indicate good, fair, poor, and very poor base layer condition, respectively [12].

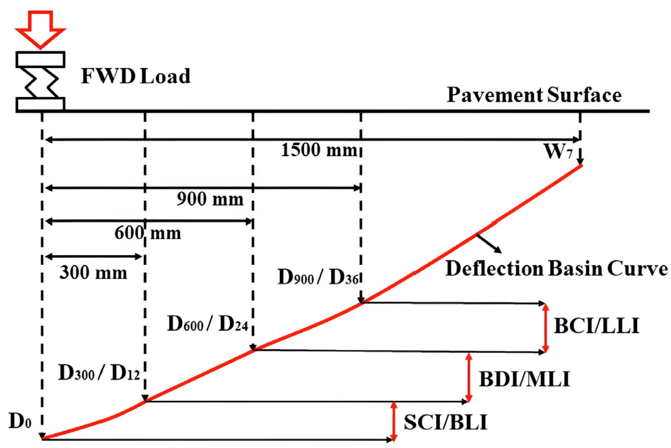

Figure 1. Schematic of FWD testing device [19].

Table 1. FWD deflection basin parameter threshold development [11].

Performance Indicator	Pavement Layers	Threshold ranges (mils)	Layer Condition Assessment
Surface Curvature Index (SCI)	Asphalt Layer	<4	Very Good Asphalt Layer
		4 - 6	Good Asphalt Layer
		6 - 8	Fair Asphalt Layer
		8 - 10	Poor Asphalt Layer
		>10	Very Poor Asphalt Layer
Base Curvature Index (BCI)	Base Layer	<2	Very Good Base Layer
		3 - 4	Fair Base Layer
		4 - 5	Poor Base Layer
		>5	Very Poor Base Layer
Deflection of the sensor at 60 inch offset (W60)	Subgrade Layer	<1	Very Good Subgrade Layer
		1 - 1.4	Good Subgrade Layer
		1.4 - 1.8	Fair Subgrade Layer
		1.8 - 2.2	Poor Subgrade Layer
		>2.2	Very Poor Subgrade Layer

Table 2. FWD Deflection basin parameter threshold development [12].

Performance Indicator	Pavement Layers	Threshold ranges (μm)	Layer Condition Assessment
Maximum Deflection (D_0)	Entire Pavement Structure	<625	Sound
		625 - 925	Warning
		>925	Severe
Base Layer Index (BLI)	Base Layer	<250	Sound
		250 - 475	Warning
		>475	Severe
Middle Layer Index (MLI)	Subbase/Subgrade Layer	<115	Sound
		115 - 225	Warning
		>225	Severe
Lower Layer Index (LLI)	Subbase/Subgrade Layer	<65	Sound
		65 - 120	Warning
		>120	Severe

2.2. Previous Studies Regarding Pavement Structural Condition Prediction Models

Significant research works developed statistical and machine learning models for the predicting the pavement surface condition while few research works focused on the pavement structural condition prediction model. Table 3 shows the list of papers which developed pavement structural condition prediction models utilizing

Falling Weight Deflectometer (FWD) data. After conducting the literature review, only six relevant research papers were found in terms of predicting pavement structural condition.

Table 3. Pavement structural condition prediction models using FWD data.

Authors	Response Variable	Input Variables	Method	Data
[13]	SCI, BCI	Asphalt Layer Thickness, Base Layer Thickness, Total Pavement Thickness, IRI, Atmospheric Temperature, Asphalt Pavement Temperature at the time of Testing, Subgrade Soil Strength	ANN	India (collected using FWD device)
[14]	D0, BLI, MLI, LLI	IRI, Pavement Age, Traffic, Precipitation, Atmospheric Temperature, Pavement Temperature	DNN	LTPP (collected using FWD device)
[15]	SNeff	Asphalt Layer Thickness, Base Layer Thickness, Total Pavement Thickness, IRI at year 0, IRI at a specific year, ESAL, Average Temperature, Standardized Temperature	ANN	LTPP (collected using FWD device)
[16]	BLI, MLI, LLI	IRI	ANN, Regression models	Iran
[17]	Structural Condition Index	ADT, ESAL, M&R Treatment year, IRI, distress data	Decision Tree, Data Mining Strategies	Texas
[18]	BDI, BCI	Time elapsed after various types of pavement preservation applied	ARIMA	Alabama based on field test

Note: ANN = Artificial Neural Network, ARIMA = Autoregressive integrated moving average time-series analysis, ADT = Annual Daily Traffic, BDI = Base Damage Index, BCI = Base Curvature Index, BLI = Base Layer Index, DNN = Deep Neural Network, D0 = Maximum Deflection, FWD = Falling Weight Deflectometer, MLI = Middle Layer Index, LTPP = Long Term Pavement Performance, LLI = Lower Layer Index, IRI = International Roughness Index, ESAL = Equivalent Single Axle Load, SNeff = Effective Structural Number.

From the above literature review, it was found that only 2 research papers used Long Term Pavement Performance (LTPP) data for pavement structural condition prediction. Haridas *et al.* [14] developed Deep Neural Network (DNN) to predict Maximum Deflection (D_0), Base Layer Index (BLI), Middle Layer Index (MLI), and Lower Layer Index (LLI). This research used IRI, Pavement Age, Traffic, Precipitation, Atmospheric Temperature, Pavement Temperature as the predictor variables. Sollazzo *et al.* [15] predicted Effective Structural Number (SN_{eff}) using Artificial Neural Network (ANN). This research used Asphalt Layer Thickness, Base Layer Thickness, Total Pavement Thickness, IRI at year 0, IRI at a specific year, ESAL, Average Temperature, and Standardized Temperature as the predictor variables. In addition, both research works used Artificial Neural Network (ANN), which is subject to overfitting problem. In this case, the prediction performance cannot be reliable even if it provides high accuracy. To improve the existing research in the field of pavement structural condition prediction, more novel methodologies are required to be applied, which are theoretically superior.

3. Methodology

3.1. Structural Condition Data Collection Using Falling Weight Deflectometer (FWD)

There are several methods for pavement structural condition data collection. Out of these, the three most popular devices for structural data collection are the Falling Weight Deflectometer (FWD), Traffic Speed Deflectometer (TSD), and Rolling Weight Deflectometer (RWD). Non-destructive tests (NDTs) are essential for evaluating the pavement structural condition evaluation. The advantages of non-destructive testing (NDT) compared to destructive testing methods include quicker test completion times, simpler operation, lower costs of operation, a smaller required workforce, less disruptive procedures, and the ability to conduct tests at a greater number of locations. The technology used in this field has progressed from older devices such as the Benkelman Beam, Dynaflect, and Road Rater to the modern impulse loading system known as the Falling Weight Deflectometer (FWD). The Falling Weight Deflectometer (FWD) is the most popular and commonly used non-destructive testing (NDT) device. The FWD applies dynamic loads to a pavement surface, simulating the magnitude and duration of a single heavy-moving wheel load. The FWD loading system delivers a transient impulse load to the pavement surface. The pavement response (vertical deformation or deflection) at various distances from the loading plate is measured by a series of geophone sensors (usually seven). The geophones/sensors are located at 0, 8, 12, 18, 24, 36, 48, 60, and 72-in. spacing from the center of the load plate to measure the deflections. The geophones are capable of measuring with an accuracy of up to ±0.01 mils, while the minimum resolution for measuring deflection is ±0.04 mils. Many State Departments of Transportation (DOTs) integrated the assessment obtained from the FWD device into the broader network-level maintenance activities. The advantage of using the FWD in pavement assessment lies in its precision and the depth of information it provides. By accurately simulating real-world loading conditions and measuring the pavement's response, it offers an accurate estimation of the pavement's structural condition. This allows for more targeted and effective maintenance strategies [11]. **Figure 1** shows the diagram of the FWD testing device. After obtaining the deflection measurements from the FWD device, structural condition indicator parameters can be calculated using these measurement values. Table 4 shows the equation of the FWD deflection parameters. Here, D0 is the maximum deflection value, which the sensor collects at the point of load application. D300/D12 is the deflection value collected by the sensor located at 300 mm/12-inch inches from the load application point. The unit of deflections is expressed in mils.

Table 4. FWD Parameters and Full Meaning.

Abbr.	Full Meaning	Equation
D_0	Maximum Deflection	
SCI/BLI	Surface Curvature Index/Base Layer Index	D_0 - D_{300}/D_{12}
BDI/MLI	Base Damage Index/Middel Layer Index	D_{300}/D_{12} - D_{600}/D_{24}
BCI/LLI	Base Curvature Index/Lower Layer Index	D_{600}/D_{24} - D_{900}/D_{36}

Huynh *et al.* [4] surveyed the transportation agencies of the USA regarding the integration of pavement structural condition into the pavement management system decision making process. Twenty-five agencies responded to this survey. Out of the 25 responses, it was found that 15 agencies depend on the Falling Weight Deflectometer (FWD) device for pavement structural condition evaluation. Five agencies use both FWD and Traffic Speed Deflectometer (TSD) to collect pavement structural condition data. Another question was asked to the agencies whether they are interested in incorporating the pavement structural condition into the pavement management system decision making process. Among the responses, 13% of the agencies out of 25 responses agreed to incorporate pavement structural conditions into their pavement management system decisions. On the other hand, approximately 48% of the agencies out of 25 respondents are interested in integrating pavement structural conditions into the pavement management system decision-making.

3.2. Data Preparation

The data preparation process for this study followed a rigorous and systematic approach to ensure both the quality and relevance of the data used in the machine learning models. The primary data source was the Long-Term Pavement Performance (LTPP) dataset, which is a highly comprehensive collection of pavement performance data gathered from across the United States, covering a time span from 1989 to 2018. This extensive dataset provided a rich source of information for pavement condition analysis and predictive modeling. Figure 2 shows a detailed framework for the Pavement Structural Condition Prediction Model Development. Each step in the flow chart is contained within a rectangular box, and the steps are connected with arrows indicating the sequential flow of the process. The essential steps of the framework are FWD Data collection, LTPP FWD Data Processing, Important Variables Selection, Data Preparation, Model Development, and Evaluation, respectively. Data Collection is the initial step to gather data for the model. LTPP FWD Data Processing step involves taking the FWD deflection values and preparing them for further model development use. After processing the data, important variables that will be included in the model are selected from the literature review. The data preparation step includes integrating the FWD data with the pavement rehabilitation, traffic, climate, and structural information data based on the LTPP segment number and FWD data collection year for each state. A Python script was developed to automate the data preparation task. With the data prepared, the next phase was to develop the model, which involved selecting an appropriate modeling technique, training the model on the data, and tuning the model parameters. After the model was developed, it was evaluated to determine its performance, which will involve assessing how well the model predicts or fits new data and making any necessary adjustments. After evaluation, the model will be finalized, which will consider any refinements needed from the evaluation phase.

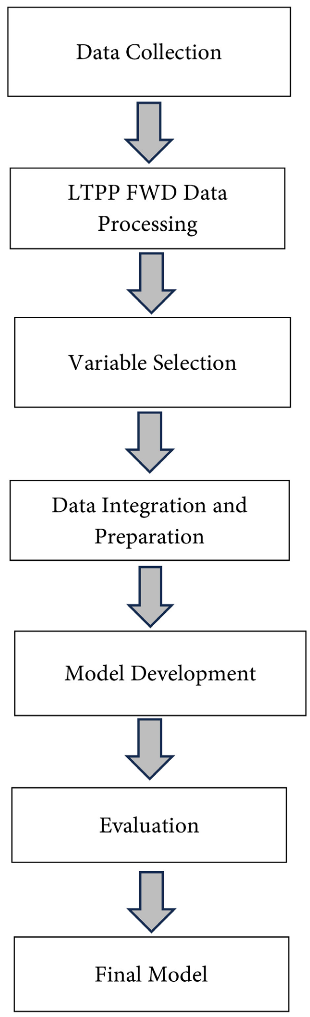

Figure 2. Framework for the development of pavement structural condition prediction model.

The target variable selected for prediction in this study was the Surface Curvature Index (SCI). The SCI is calculated by subtracting the deflection value recorded by the sensor located at a 12-inch distance from the load application point from the maximum deflection value. Previous research [1] [5] has demonstrated that the Surface Curvature Index (SCI) serves as a highly effective parameter for assessing pavement structural conditions. Motivated by this finding, this research adopted SCI as the target variable for predicting pavement structural condition, building on the foundation of earlier studies that recognized its significance in pavement structural performance evaluation. To predict the target variable (SCI), several predictor variables were chosen. These variables represent a balanced combination of traffic loading, structural properties, and climatic factors. Specifically, the predictors included the surface curvature index at year 0, pavement age, surface thickness, base thickness, KESAL (equivalent single axle loads in thousands), annual precipitation, and freeze index. Each of these variables plays a crucial role in influencing pavement behavior and deterioration. The data for these variables were meticulously extracted from multiple tables within the LTPP database, ensuring consistency and precision in the data collection process. To enable effective model development and validation, the dataset was strategically split into training (80%) and testing (20%) sets. This division allowed for robust model training and unbiased performance evaluation. As part of the data preparation, comprehensive descriptive statistics were computed for each variable.

Table 5 presents descriptive statistics for the variables used in machine learning model development, highlighting key features such as the Surface Curvature Index (SCI), Pavement Age, Annual ESAL, and environmental factors like Precipitation and Freeze Index. These statistics provide insights into the distribution of the variables, with minimum, 25th percentile, median, mean, 75th percentile, and maximum values reported. The data suggest significant variability across the variables, which are critical for developing predictive models for pavement performance.

Table 5. Descriptive statistics of the variables used for the machine learning model development.

Variables Name	Min	25th Percentile	Median	Mean	75th Percentile	Max
Surface Curvature Index (SCI) (mils)	0.1	0.83	1.62	2.30	3.16	14.39
Surface Curvature Index at year 0 (mils)	0.08	0.83	1.60	2.23	2.85	12.92
Pavement Age (Years)	0	4	9	10.87	16	12.92
Annual ESAL	0	4.28e+04	1.17e+05	2.04e+05	3.02e+05	2.66e+06
Precipitation (mm)	34.73	579.32	969.71	926.44	1283.87	2027.13
Surface Layer Thickness (in)	0.9	4	5.25	5.98	7.3	23.2
Freeze Index	0	3	102	248.48	307	2243
Base Layer Thickness (in)	0	7.9	12	14	18.8	61

Figure 3 shows the relationships between various factors related to pavement conditions. Key observations include a strong positive correlation between Surface Curvature Index and Surface Curvature Index at year 0 (0.80), indicating that initial structural conditions highly influence current conditions. Surface layer thickness has a moderate negative correlation with Surface Curvature Index (−0.39) suggesting thicker surface layers may be associated with reduced structural condition scores.

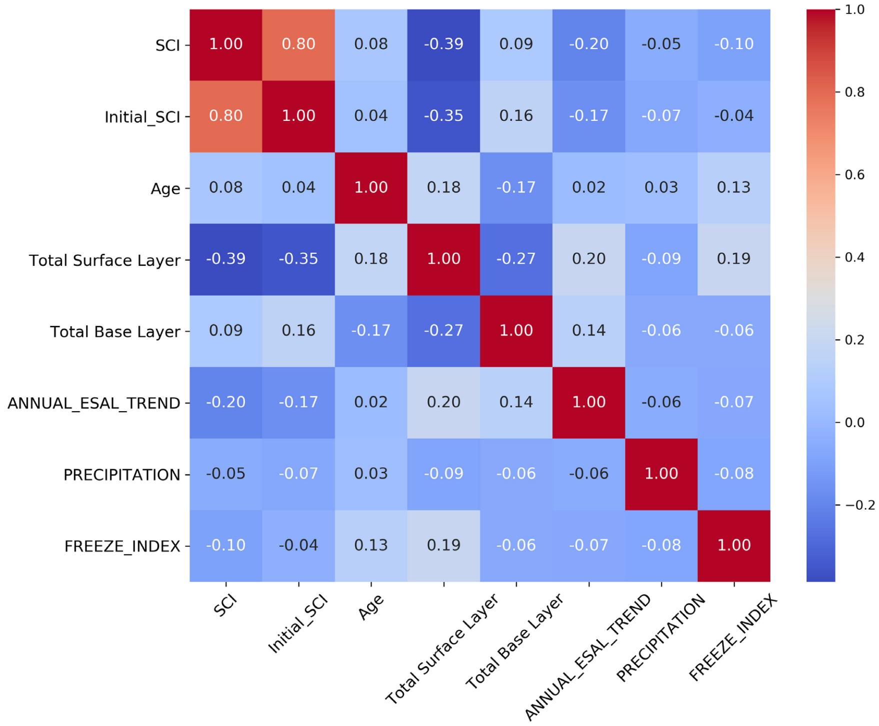

Figure 3. Correlation Matrix among the variables.

3.3. Random Forest

Random Forest algorithm is a powerful ensemble machine learning technique renowned for its prediction accuracy and ability to handle complex datasets. It operates by constructing multiple decision trees, each constructed from a random subset of the training data. This subset is chosen using a method known as bootstrapping, which allows for the same data point to be used in multiple trees, leading to a reduction in variance and an increase in the model's robustness [5]. These predictions are then combined to form the final output of the Random Forest model. Random Forest (RF) can be used for both classification and regression problem. For a classification problem, the result is achieved through majority voting, where the prediction that most trees agree on is chosen as the final decision. For regression tasks, the model averages the numerical predictions from each tree to determine the final model result. Following this approach, Random Forest (RF) model enhances the predictive accuracy by mitigating the errors of individual trees but also helps in preventing overfitting, which is a common problem of the machine learning model particularly Artificial Neural Network (ANN). In brief, the Random Forest algorithm provides a robust predictive performance [20].

3.4. eXtreme Gradient Boosting (XGBoost)

XGBoost is an ensemble technique based on decision trees. It combines multiple weak tree models into a strong learner by sequential training, optimizing an objective function at each step. The XGBoost model develops a prediction model by combining multiple weak learners. Each model learns from the previous model and builds a strong model by adjusting weights in a sequential manner. XGBoost has the capability to automatically handle missing data, which can be useful for infrastructure condition monitoring when there are significant missing values [21]. XGBoost is more robust to outliers and easier to tune hyperparameters than Artificial Neural Networks (ANNs) or Support Vector Machine (SVMs). XGBoost can be used for both regression and classification problems. The eXtreme Gradient Boosting (XGBoost) method is an improvement of the Gradient Boosting algorithm. The theoretical foundation of XGBoost can be expressed mathematically as follows [5]:

$$\hat{y}_i = \sum_{k=1}^{t} f_k\left(x_i\right) \tag{1}$$

where t is the set of regression trees, and f_k is a regression tree in the set. The main idea of the XGBoost algorithm is that each update is based on the prediction results of the previous model. By adding a new tree f_k to fit the residual error between the predicted value of the previous tree and the actual value, a new model is formed, and the new model is used as the basis for the next model learning. Mathematically, this process can be stated as follows:

$$\hat{y}_i = \hat{y}_i^{(t-1)} + f_t\left(x_i\right) \tag{2}$$

where $\hat{y}_i^{(t-1)}$ is the predicted value at time $t-1$, and $f_t\left(x_i\right)$ is the residual fitting value by the newly added regression tree, with x_i being the input data. To obtain a prediction as close as possible to the true value of y_i, the following objective function is minimized by the XGBoost algorithm:

$$obj^{(t)} = l\left(y_i, \hat{y}_t^{(t)}\right) + \Upsilon^{\mathrm{T}} + \frac{1}{2}\lambda\sum_{j=1}^{T} w_j^2 \tag{3}$$

4. Machine Learning Hyperparameter Tuning

Hyperparameter tuning was conducted for the Machine Learning model development. A grid search technique was applied to fine-tune the model, testing various combinations of the number of trees (n_estimators: 50, 100, 200, 300, 400, 500), the maximum depth of the trees (max_depth: 10, 20, 30, 40, 50), and the minimum number of samples required to split a node (min_samples_split: 2, 3, 4, 5, 6). After evaluating all combinations, the best-performing model was identified with 500 trees, a maximum depth of 20, and minimum samples split of 2. This configuration provided the most accurate predictions, effectively capturing the relationships in the dataset for reliable pavement structural condition prediction. For the XGBoost model, a hyperparameter tuning process was conducted to enhance the model's predictive performance by using a grid search approach. The grid search was applied to explore various combinations of parameters including the number of estimators (n_estimators: 100, 200, 300, 400, 500), the maximum tree depth (max_depth: 2, 3, 4, 5), and the learning rate (learning_rate: 0.05, 0.1, 0.2, 0.3). Additionally, the minimum child weight (min_child_weight: 2, 3), subsample ratio (subsample: 0.8, 0.9, 1.0), and column sample by tree (colsample_bytree: 0.8, 0.9, 1.0) were also adjusted. After evaluating the different hyperparameter combinations, the best XGBoost model was found with 500 estimators, a maximum depth of 5, a learning rate of 0.1, a minimum child weight of 2, a subsample ratio of 0.8, and a colsample_bytree value of 1. This configuration provided the optimal balance between model complexity and prediction accuracy, making it the most suitable for predicting pavement performance. Table 6 shows the hyperparameter tuning parameters and their optimal value for the RF and XGBoost model.

Table 6. Machine learning model hyperparameter tuning.

Model	Parameters	Optimal Value
RF	max_depth	20
	min_samples_spli	2
	n_estimators	500
XGBoost	colsample_bytree	1
	max_depth	5
	learning_rate	0.1
	min_child_weight	2
	subsample	0.8
	n_estimators	500

5. Result and Discussion

To evaluate the performance of the XGBoost and Random Forest model, three commonly used metrics were used: R-squared (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). These metrics were utilized by a significant number of researchers for the performance assessment of the machine learning models. Equations (4)-(6) show the equations of R^2, RMSE, and MAE, respectively. Table 7 presents the results of the Pavement Structural Condition Models developed using RF and XGBoost model.

Table 7. Pavement structural condition prediction models using RF and XGBoost.

Metrics	Random Forest (RF)	eXtreme Gradient Boosting (XGBoost)
R^2	0.80	0.90
RMSE	0.90	0.64
MAE	0.59	0.41

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y}_i)^2} \tag{4}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{5}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{6}$$

The performance comparison between Random Forest and eXtreme Gradient Boosting (XGBoost) models for predicting the Surface Curvature Index (SCI) reveals that XGBoost outperformed Random Forest across all evaluation metrics. Specifically, the R^2 score for XGBoost was 0.90, indicating a higher proportion of variance explained by the model, compared to 0.80 for Random Forest. Additionally, the Root Mean Squared Error (RMSE) for XGBoost was 0.64, which is lower than the RMSE of 0.90 for Random Forest, suggesting that XGBoost made more accurate predictions than the RF. Furthermore, the Mean Absolute Error (MAE) for XGBoost was 0.41, better than Random Forest's MAE of 0.59, demonstrating that XGBoost yielded predictions closer to the actual values overall. These results suggest that XGBoost is the more effective model, offering greater predictive accuracy and lower error rates compared to Random Forest. The superior performance of XGBoost over RF in predicting pavement structural conditions can be attributed to XGBoost's advanced gradient boosting technique. Unlike RF, which aggregates predictions from individual decision trees with equal weights, XGBoost enhances each subsequent tree by focusing on errors from prior predictions. This sequential learning method allows XGBoost to better capture complex non-linear relationships within the data, especially in datasets with significant variability in predictors, such as pavement age, layer thickness, and climate conditions. Additionally, XGBoost's flexibility in handling missing values and outliers contributes to its robustness, making it more adept at generalizing patterns within pavement condition datasets. By leveraging these attributes, XGBoost achieved a higher R^2 and lower RMSE and MAE than RF, suggesting that its predictions align more closely with the observed values. This insight enhances the practical value of the study, as it underscores the importance of using an algorithm like XGBoost for accurate and reliable pavement structural performance predictions. **Figure 4** and **Figure 5** show the feature importance score of the eXtreme Gradient Boosting (XGBoost) and Random Forest (RF) models, respectively. From both model result, it can be obtained that Surface Curvature Index at the year 0 and Age are two most important variables for predicting the pavement structural condition. This can be attributed to the fact that Initial Structural Condition reflects the pavement's inherent strength, while Age accounts for the natural wear and degradation over time, making them essential indicators for assessing the pavement's current and future performance. **Figure 6** and **Figure 7** illustrate the relationship between the actual and predicted values for the XGBoost model and RF model, respectively.

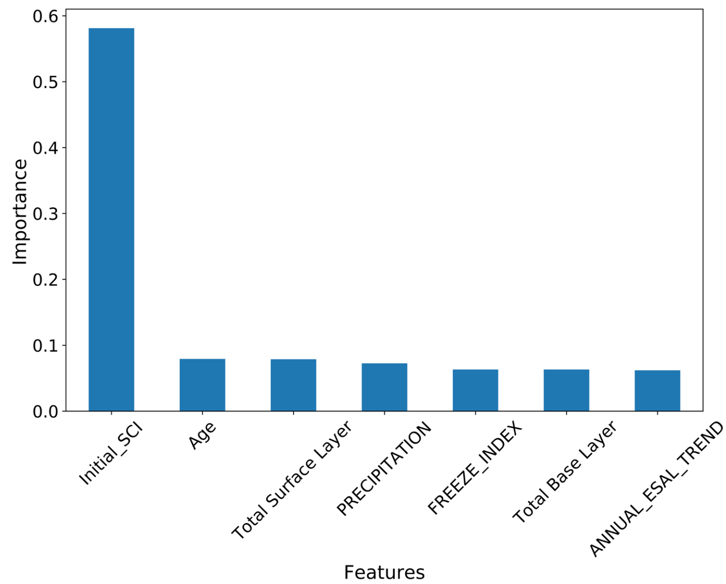

Figure 4. Feature importance score (XGBoost).

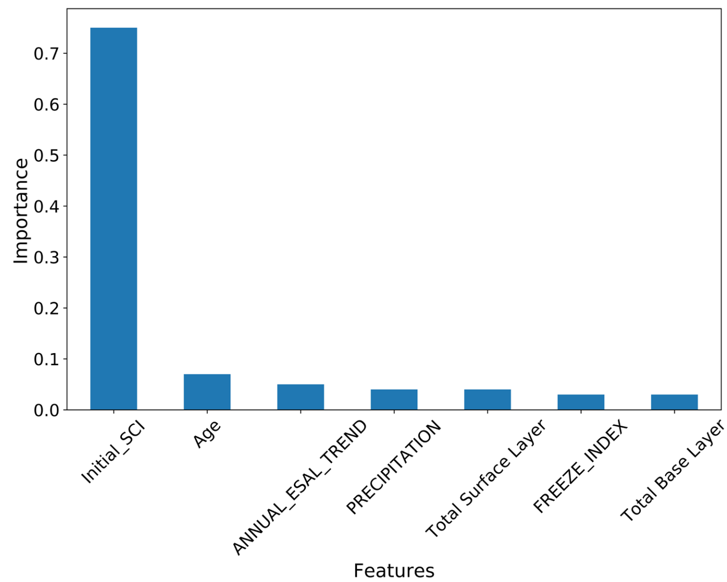

Figure 5. Feature importance score (Random Forest).

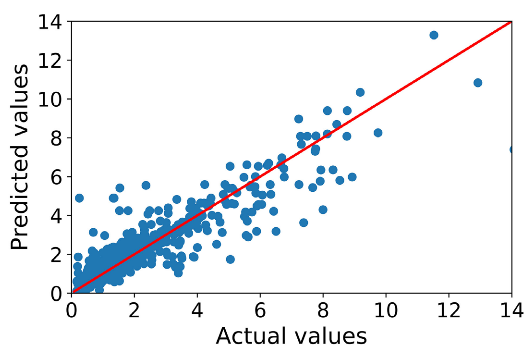

Figure 6. Scatter plot of actual vs predicted value for the XGBoost model.

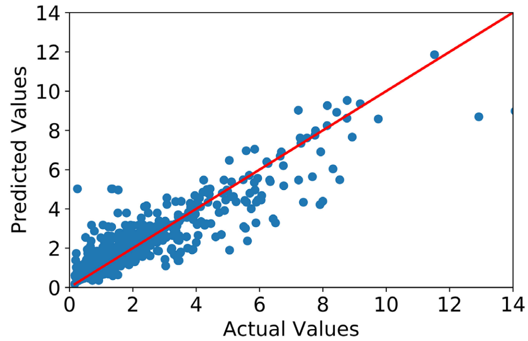

Figure 7. Scatter plot of actual vs predicted value for the RF model.

6. Conclusion

This research demonstrates the effectiveness of machine learning models, particularly Random Forest (RF) and eXtreme Gradient Boosting (XGBoost), in predicting pavement structural conditions. Using data from the Long-Term Pavement Performance (LTPP) program, the models successfully predicted the Surface Curvature Index (SCI), a key indicator of pavement structural health. Among the models, XGBoost outperformed RF, achieving higher predictive accuracy and lower error rates across various metrics. Traditional pavement deterioration models often rely on predefined relationships between pavement functional and structural parameters. However, these models lack adaptability to the unique complexities of pavement conditions and may not capture nonlinear interactions effectively, potentially leading to limitations in accuracy. Our findings show that the XGBoost model demonstrates substantial predictive accuracy improvements over Random Forest with an R^2 of 0.90 and lower RMSE and MAE values. This enhanced performance highlights XGBoost's capability to handle complex datasets with heterogeneous variables involving climate factors, traffic loads, and varying pavement conditions. Additionally, XGBoost's robustness against missing data and outliers offers practical advantages over empirical equations, which typically require a completer and more homogenous dataset for reliable predictions. Machine learning models' enhanced accuracy and adaptability suggest they could improve decision-making by providing more reliable forecasts of pavement structural conditions. The results highlight the potential for transportation agencies to adopt these models as cost-effective tools for optimizing pavement maintenance decisions. By integrating structural condition predictions into pavement management systems, agencies can prioritize pavement maintenance decisions more effectively, extending pavement life and improving resource allocation. Future research should focus on further refining these models and incorporating additional variables to enhance their predictive capabilities and applicability across different pavement types and conditions. This research developed machine learning models using LTPP data; however, applying these models to state-level datasets with diverse pavement structures and climatic conditions is recommended. Such an approach would help validate the models' adaptability, enhancing their practical application across different regional contexts and ultimately strengthening their generalizability for broader use by transportation agencies. Based on recommendations from previous studies, this research selected the Surface Curvature Index (SCI) as the primary predictor variable for pavement structural condition. However, future research could also consider incorporating the Base Damage Index (BDI) and Base Curvature Index (BCI) as additional variables for pavement structural condition prediction.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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