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DEVELOPING AN EFFECTIVE APPROACH TO ASSESS PAVEMENT CONDITION FOR HIGH FRICTION SURFACE TREATMENT (HFST) INSTALLATION

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Abstract. For more than two decades, High Friction Surfacing Treatments (HFST) have been used worldwide to improve road safety at critical locations, such as sharp curves and intersections. However, the costs associated with HFST installation and the rapid deterioration observed on pavements with poor structural conditions cannot be overlooked. To address these concerns, this research study sought a reliable and accurate method for assessing the suitability of applying HFST to pavements. The main focus was on using machine learning techniques and incorporating International Roughness Index (IRI) and Pavement Condition Index (PCI) data to predict and provide informed recommendations for HFST application. To achieve this, ensemble models were employed, of which the decision tree and extreme gradient boosting showed robust performance, achieving an impressive R-squared value of 0.90, indicating a high level of accuracy in predicting PCI. These models were further assessed for HFST application using the LTPP dataset, with sections classified as suitable and categorised them as good, fair, or poor. The suggestions from these models were particularly reliable in determining the appropriate area for HFST application. The research results clearly demonstrated the efficacy of the ensemble models in accurately predicting PCI and providing informed recommendations for HFST application.

Keywords: High friction surface treatment (HFST), ensemble machine learning models, pavement condition index (PCI), international roughness index (IRI).

1. Introduction

High Friction Surface Treatment (HFST) consists of a thin layer of high-quality, polish-resistant aggregate bonded to the pavement surface with a polymer resin binder. Over the past twenty years, HFST has been used worldwide, significantly reducing accidents on locations with high friction demand. HFST offers a level of friction that conventional paving materials cannot achieve and maintains this high level of friction over time. It is primarily used as a spot treatment to address specific locations with high friction requirements, such as horizontal curves, steep grades, intersection approaches, and other critical areas, rather than being applied to longer sections of pavement. This system is designed to markedly improve the friction properties of both asphalt and concrete pavements. However, it is important to note that HFST installation can be costly, and there have been instances where the treatment experienced a rapid deterioration [1].

HFST is a safety treatment that aims to enhance the skid resistance of pavement surfaces. It is important to note that HFST should only be installed on pavements that are structurally sound, in good condition, and functionally adequate. Pavements that are scheduled for preventive maintenance, resurfacing, rehabilitation, or reconstruction should not be selected for HFST installation without proper coordination to optimise funding allocation. It is crucial to understand that HFST does not address underlying structural deficiencies or pavement maintenance issues. To ensure the effectiveness of HFST, the pavement should be in a good structural condition before applying the treatment. The structural integrity of HFST is considered acceptable when the HFST-pavement system can perform its intended function for a specified duration of use. An appropriately installed HFST on a stable pavement surface is expected to remain functional for a minimum of 7 to 10 years, or possibly longer, depending on the amount of traffic level [2]. However, premature distresses, such as aggregate loss, cracking, debonding, and delamination can cause the HFST to lose its efficiency earlier than expected. Several factors contribute to early distresses in HFST, with the epoxy resin binder and existing pavement condition being significant factors. Only pavements that meet specific criteria should be considered for HFST. These criteria include being structurally sound, having a smooth surface, having good surface condition (or functional sufficiency), and having minimal to no surface distress. In addition, if the site is to be repaved within 1 to 2 years of HFST installation, it is advised that the treatment be delayed until after the repaving.

Applying HFST to pavements that are in poor structural condition can result in early failure of the treatment and may pose safety risks. HFST is not intended as a maintenance or rehabilitation solution, it is essential to carry out a comprehensive evaluation of the pavement condition to detect any underlying problems like cracks, potholes, or drainage issues that could impact the effectiveness of the HFST treatment. The current condition of the pavement may require addressing minor distresses, performing minor rehabilitation, or complete repaving before HFST installation. Thus, the condition of the pavement before the HFST installation plays a vital role in ensuring the long-term efficiency and safety of the treatment. A thorough assessment of the pavement condition and appropriate preparation of the pavement surface are essential steps to ensure the success of the HFST treatment [3].

The Federal Highway Administration (FHWA) recommends that agencies establish specific criteria for pavement distress that need to be resolved before applying HFST, based on their experience and expertise. While agencies often carry out annual pavement condition surveys for major roads, which can assist with the initial assessment of the pavement condition, access to up-to-date pavement condition data is not always be possible, particularly for minor and local roads [4]. Some agencies acknowledge facing the complexity of evaluating pavement conditions for HFST application. Crucial factors, such as distress, skid resistance, and age, guide informed decisions. For example, the New Jersey Department of Transportation (NJDOT) emphasises the importance of a thorough assessment prior to HFST application to optimise effectiveness and cost. Suitable candidates include structurally sound, smooth pavements with minimal distress, paved within two years prior to the HFST application [5].

Various approaches exist for assessing pavement conditions, such as visual inspection, manual surveys, and automated data collection methods, for example, ARAN video. These methods can be used individually or in combination to offer a comprehensive evaluation of the pavement's condition. Several pavement condition indicators are often used, such as the PCI, Present Serviceability Rating (PSR), Pavement Quality Index (PQI), and IRI. These indicators play an essential role in Pavement Management Systems. It is essential to choose an impartial and consistent survey method, preferably one that is straightforward to comprehend and relatively easy to execute in the field. The widely used PCI procedure, created by the United States Army Corps of Engineers in the 1970s, is commonly used for the evaluation of flexible pavements. This procedure follows the Micro Paver distress guide methodology [6, 7]. The calculation of PCI incorporates different distinct distress types, taking into consideration their extent and severity. This approach is widely acknowledged as a standard ASTM Test Method, specifically known as ASTM D6433-11 “Standard Practice for Roads and Parking Lots Pavement Condition Index Surveys”. PCI values range from 0 to 100, with a score of zero indicating inadequate or failed pavements, and a score of 100 representing outstanding performance with no visible distresses. The use of a composite index provides an assessment of both surface condition and ride quality. The IRI provides valuable information about the surface roughness experienced by vehicles travelling on the road. Originally developed by the World Bank in 1986, the IRI is determined by dividing the cumulative vibrations or vertical movements by the profile length. It is measured using a laser profiler and reported as a non-dimensional index, typically expressed as $\mathrm{m\,km^{-1}}$ or $\mathrm{in\,mi^{-1}}$ [8]. Previous research has showed that different approaches were taken by researchers when selecting the pavement condition variable or pavement performance measure. Some researchers chose to adopt the IRI for this purpose. Conversely, other researchers used the PCI technique as their preferred pavement performance measure [9, 10]. In a separate research endeavour, a study was carried out to investigate the relationship between the IRI and pavement damage on a selected highway section in Saudi Arabia. The results of the research showed a significant correlation between the IRI values and cracking and IRI values and raveling, at the 95 % confidence level. However, the study did not find a significant relationship between the IRI values and rutting [11].

Multiple studies have demonstrated the influence of the IRI on PCI. While the IRI is measured using profiling equipment to record surface roughness, the PCI calculation relies on a subjective assessment of various pavement distresses. The existing literature suggests a correlation between these two pavement indices, which has led to the development of predictive models aimed at estimating one index based on the other. For example, a research study aimed to establish parametric models between the PCI and the IRI using a database encompassing nine states in the North Atlantic region. They proposed an empirical model, which is presented as Equation (1), to describe the relationship between PCI and IRI. The model achieved an accuracy with an R-squared value of 0.55, indicating a moderate level of predictive capability [12].

$$\log \mathrm{PCI} = 2 - 0.436(\log \mathrm{IRI}). \tag{1}$$

In another study, the objective was to develop regression models that could predict PCI from IRI using data obtained from the District of Columbia (DC) Department of Transportation (DOT) over three years. The model developed specifically for asphalt concrete (AC) pavements, using the ordinary least squares method, is described in Equation (2). Due to the low accuracy of the model, the authors extended the relationship between PCI and IRI based on highway classifications or pavement types, and they developed a new model for AC pavements, which is shown in Equation (3). The first analysis yielded a poor level of accuracy, with an R-squared value of 0.013. However, the developed model outperformed the regression model, demonstrating improved accuracy with an R-squared value of 0.82 [13, 14].

$$\log \mathrm{PCI} = -0.115(\log \mathrm{IRI}) + 2.131, \tag{2}$$

$$\mathrm{PCI} = -0.224\mathrm{IRI} + 120.02. \tag{3}$$

In another research, regression and Artificial Neural Networks (ANNs) models were proposed to predict IRI using a comprehensive Long-Term Pavement Performance (LTPP) database [15]. The regression analysis yielded a moderate level of accuracy, with an R-squared value of 0.57. However, the ANNs model outperformed the regression model, demonstrating improved accuracy with an R-squared value of 0.75. These findings indicate that the ANNs model provided more reliable predictions of IRI based on the specified distress parameters, offering potential improvements in assessing pavement conditions.

In another research paper, a Gene Expression Programming (GEP) model was developed to predict PCI values based on IRI values specifically for asphalt concrete (AC) pavements. The results revealed that the GEP model achieved a maximum R-squared value of 0.82 for the complete dataset [16].

As stated, the assessment of pavement condition presents a complex task, which often relies on varying levels of expertise to determine the suitability of a pavement for HFST application. It is crucial to consider several factors, such as pavement distress, skid resistance, and roughness, in order to make informed decisions about HFST application. To address this challenge, machine learning techniques were employed to predict the PCI for evaluating the suitability of pavements for HFST application in this research. By using previous IRI and PCI data, the evaluation process was streamlined, eliminating the need for extensive assessment of distress extent and severity. This approach not only saves costs and man-hours but also allows a number of factors to be taken into account when determining whether a pavement is suitable for HFST application. Previous research attempted to predict the PCI using simple models that rely on IRI. However, these models yielded low accuracy. Additionally, there is a lack of research on evaluating the suitability of HFST application based on available data and predicting pavement condition using IRI and previous PCI [17]. These limitations were addressed in this study by using powerful machine learning ensemble models to predict PCI with a high level of accuracy. By incorporating IRI into the prediction process and considering various recommendations, the suitability of a pavement for HFST application could be suggested. In line with this prevailing approach, the research capitalised on the potential of ensemble models to achieve accurate PCI predictions, with a particular focus on incorporating IRI as a critical parameter. PCI evaluation relies on several factors, such as crack type and severity. By integrating IRI and historical PCI data, a machine learning model was built to assess the updated PCI using the latest IRI value for a specific pavement section. Subsequently, the model was used to evaluate both the PCI and the suitability of installing HFST on selected case study sections. Comparing the conditions of these sections with the predicted PCI values provided insight into the accuracy of the ML models and the recommendations for HFST installation.

2. Materials and methods

Pavement condition data typically include metrics such as the PCI, IRI, and skid resistance. The PCI assesses different types of distress or combines them to provide an overall assessment of pavement condition. It begins with a score of 100, indicating a pavement in perfect condition, with deductions made from this initial value based on the observed quantities of distress. The IRI is a key indicator of ride quality, with values ranging from 0 to 95 in mi^{-1} (1.50 $\mathrm{m\,km}^{-1}$) for good condition, 95 to 170 in mi^{-1} (1.51 to 2.68 $\mathrm{m\,km}^{-1}$) for fair condition, and above 170 in mi^{-1} (2.68 $\mathrm{m\,km}^{-1}$) for poor pavement condition.

The use of machine learning (ML) techniques in civil engineering proved advantageous by delivering rapid and precise outcomes, thereby minimising error rates to negligible levels. The diverse range of ML methods empowers civil engineering researchers to improve efficiency and accuracy in their analyses and decision-making processes. Following this trend, this research used ensemble models to achieve precise predictions of the PCI, incorporating IRI as a crucial factor. Embracing these advanced ML techniques significantly improved the evaluation process and enabled more reliable recommendations regarding the suitability of HFST application on pavements. Using the ensemble models played a pivotal role in improving the accuracy and effectiveness of the analysis, leading to valuable contributions to informed decision-making in the field of pavement engineering [18].

2.1. Ensemble learning methods

There are three distinct categories of ensemble learning methods,: bagging, boosting, and stacking. In this study, as shown in Figure 1, bagging and boosting techniques were used based on data visualisation and observed relationships between IRI and PCI. These ensemble learning methods were chosen to improve the accuracy and robustness of the predictive models. By integrating these powerful ensemble methods, the goal was to improve the prediction of PCI and allow for more dependable evaluations of HFST suitability on pavements.

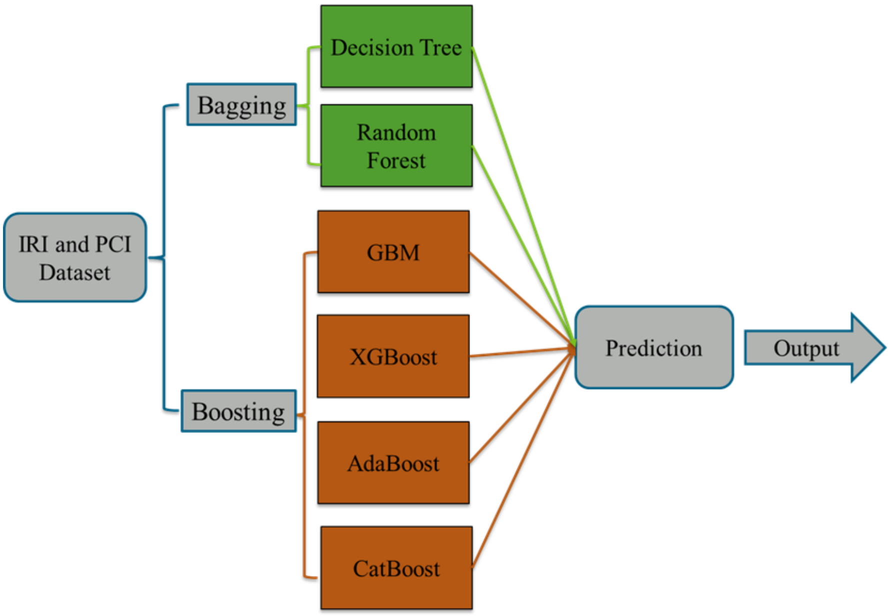

Figure 1. Flowchart of ensemble methods.

2.1.1. Decision tree

Decision trees build regression or classification models in the form of tree structures. The data set is broken down into smaller and smaller subsets as the associated decision tree grows. The result is a tree with decision nodes and leaf nodes. One of the machine learning methods that simulates the brain's inductive learning process is the decision tree method. This method compares well to other methods. Soft computing is considered to be a newer approach [19].

2.1.2. Random forest

Random forest regression is a supervised learning algorithm that uses set learning for regression. Compound learning is a technique that combines predictions from multiple machine learning algorithms to make predictions that are more accurate than a single model. Random Forest Regression (RFR) is a bagging-based ensemble learning method used for both regression and classification tasks. In RFR, multiple individual binary decision trees are constructed, each incorporating an element of randomness. This randomness encourages the trees to provide independent estimates, even though they are built using a deterministic algorithm and a calibration dataset [20].

2.1.3. Gradient boosting machine (GBM)

The Gradient Boosting Machine (GBM) was introduced by Friedman. It adopts a stage-wise approach to building and updating models to minimise loss functions. By using the gradient descent approach, GBM constructs models based on the negative partial derivatives of the loss function. The initial model is modified to fit the original data and then adjusted to account for the residuals to address the limitations of the previous model. This iterative process continues until a convergence criterion is satisfied [21].

2.1.4. Extreme gradient boosting (XGBoost)

XGBoost is a prominent boosting method that serves as an extension to GBM. Its key concept involves sequentially building regression trees, where each subsequent tree is trained using the residuals of the previous tree. This approach prevents overfitting and optimises the use of computational resources. XGBoost adopts a level-wise learning strategy, selecting splits that result in the greatest reduction in loss at each leaf [22].

2.1.5. Adaptive boosting (AdaBoost)

AdaBoost, introduced by Freund and Schapire, is one of the pioneering boosting methods. It uses multiple decision tree regressors as weak learners, which learn from various attributes of the dataset. The essence of AdaBoost lies in the sequential update of parameters associated with a specific family of functions. By iteratively incorporating new trees, the learning process gradually constructs a strong learner with enhanced predictive capabilities [23].

2.1.6. Categorical gradient boosting (CatBoost)

CatBoost, introduced by Dorogush et al., is a novel gradient boosting method designed to address overfitting and optimise model efficiency. It employs a balanced level-wise tree growth approach, which leads to faster training times and improved performance. CatBoost uses the entire dataset for training and employs random permutations for each example. It introduces a new schema for calculating leaf values during the tree structure selection, effectively overcoming biased gradient issues typically encountered in traditional boosting algorithms [24].

3. Data collection and processing

The specific focus of this research was on the application of ensemble methods to predict the PCI based on IRI and to evaluate the suitability of the pavement for HFST. A total of 202 data samples were used to construct the initial database and the statistical analysis of the dataset is shown in Tables 1 and 2. These data samples were obtained from various literature sources, specifically chosen for training and evaluating machine learning models. The violin and joint grid graphs of the data points are shown in Figure 2 and 3.

Data visualisation can be a valuable tool for understanding qualitative data. This tool can be used to extract information from datasets and to identify patterns, corrupted data, and other anomalies. The violin plots revealed interesting patterns in the data distribution of the IRI and PCI variables. For the IRI, the plot showcased a multimodal distribution, suggesting the presence of different road conditions within the dataset. Additionally, the violin plot for the PCI demonstrated a relatively normal distribution, indicating a more consistent range of pavement conditions. These findings highlighted the inherent variability in road roughness and pavement condition across the studied locations. The joint grid plot provided valuable insights into the relationship between IRI and PCI. The scatterplot in the joint grid plot displayed the individual data points, illustrating the varying combinations of road roughness and pavement condition. Interestingly, a visible trend emerged, indicating a moderate positive correlation between the IRI and PCI variables. There is a dense cluster of points towards the lower end of the IRI values (around 1 to 3) and higher PCI values (around 80 to 100). As the IRI values increase beyond 3, the PCI values decrease and the data points become sparser. This finding suggested that higher road roughness tends to be associated with lower pavement condition scores. Such information can aid decision-makers in prioritising maintenance and rehabilitation efforts for road networks.

Data splitting strategies were adopted to build and evaluate ML models. The dataset was divided into two parts: the training sample, which comprised 80 % of the data, and the test sample, which comprised the remaining 20 %. Various ensemble methods were used during this phase, leveraging the training data to learn the underlying patterns and relationships between the input feature IRI and the PCI. Once the model was built, the performance was evaluated using the test sample, which was kept separate during the training phase. The test sample was subjected to the application of the trained model to assess its ability to accurately predict PCI based on the input data provided. To further validate the practical application of the developed models, a case study was conducted. The models were employed to predict the PCI of a specific section, using the corresponding input data. Predefined thresholds for IRI and PCI, as mentioned in the literature, were used for comparing the predicted PCI values. This comparison allowed to ascertain the suitability of the section for the application of HFST.

ID	IRI	PCI	Ref
1	2.17	61	Park et al. [12]
2	1.2	89	Park et al. [12]
3	1.43	61	Park et al. [12]
4	2.38	71.87	Hasibuan [25]
5	5.45	75.29	Hasibuan [25]
6	1.07	92	L. Girardi Omar [26]
7	1.05	93	L. Girardi Omar [26]
8	5.45	75.29	Arhin and Noel [13]
9	3.6	60.86	Arhin and Noel [13]
10	3.36	32	Ali et al. [27]
11	4.35	34.5	Ali et al. [27]
12	0.89	76.82	Dewan and Smith [28]

Table 1. Selected dataset.

	IRI	PCI
Count	202	202
Mean	1.77	77.56
Std	1.20	14.24
Min	0.72	31
25 %	1	69
50 %	1.29	76.01
75 %	2.03	88.53
Max	5.86	100

Table 2. Statistical properties of dataset.

4. Results and discussion

Accurate prediction models were trained using a dataset of continuous input and labelled output data. The focus was on supervised machine learning algorithms, with specific attention given to ensemble models. Six ensemble models, namely the decision tree, random forest, GBM, XGBoost, AdaBoost and CatBoost, were used. The implementation of these models was achieved using the scikit-learn library in Python [29]. The PCI was predicted based on the IRI. The labelled dataset served as the basis for training each model, allowing them to understand the intricate relationships between input features and their corresponding PCI values.

The accuracy and effectiveness of these ML models were assessed using three commonly employed metrics: the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE), and the R-squared. These metrics provided insights into the models' performance in accurately predicting the PCI values and capturing the underlying patterns within the data.

MAE is the mean error in predictions, derived from the absolute difference between the actual and predicted values. RMSE gauges the prediction devia-

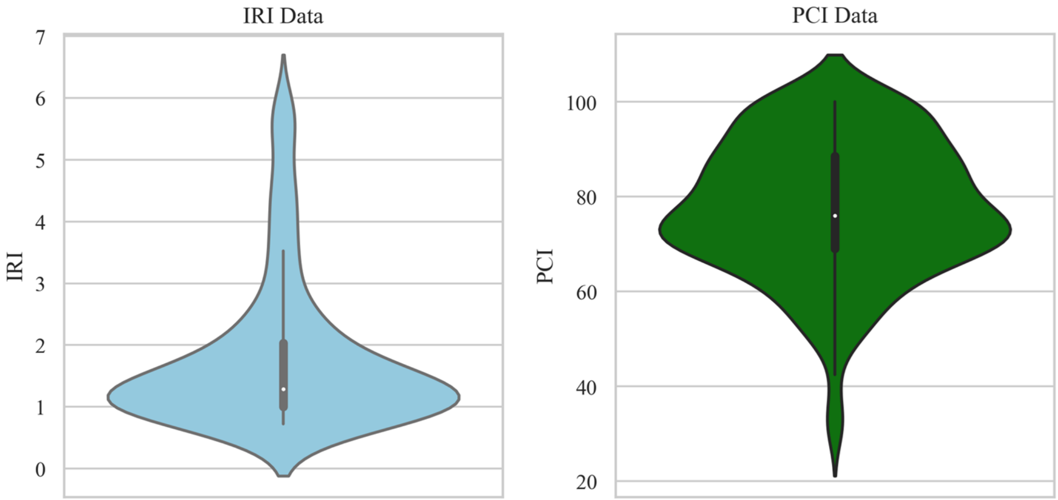

Figure 2. Violin plot of dataset.

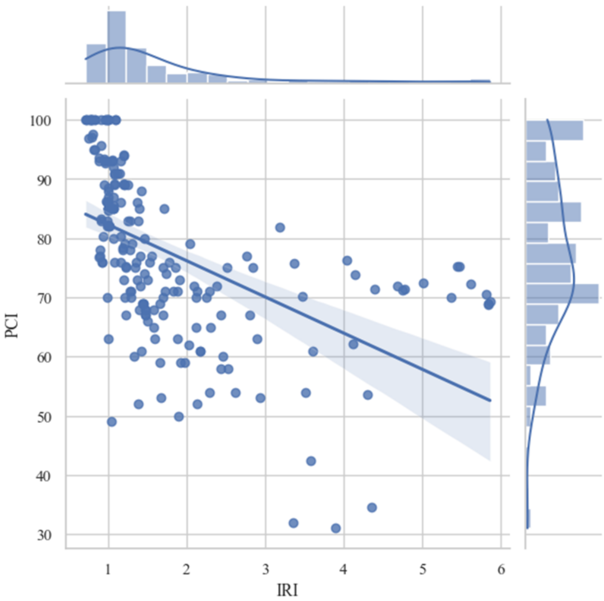

Figure 3. Joingrid graph of dataset.

Model	MAE	RMSE	R-squared
Decision Tree	2.53	4.54	0.898
Random forest	4.24	5.68	0.844
XGBoost	2.65	4.55	0.898
CatBoost	4.25	5.63	0.844
Gradient Boosting	4.32	5.76	0.836
AdaBoost	7.46	8.02	0.672

Table 3. Ensemble models metrics.

tion from actual values, while R-squared quantifies an independent variable's explanatory power on data variability in a dependent variable [30].

In Table 3 and Figure 4, the performance of various ensemble models is evaluated based on the metrics of MAE, RMSE, and R-squared value. Among these models, the decision tree and XGBoost showed better performance in predicting the PCI based on IRI. The high R-squared value, close to 0.90, indicates the strong performance of these models in capturing the underlying patterns in the data. Additionally, the lower MAE and RMSE values further support the superior performance of the decision tree and XGBoost models compared to other models, such as Adaboost, which exhibited a lower R-squared value. The accuracy results of all the models reinforce the notion that transitioning from linear regression to ensemble models, specifically Boosting methods, allows to capture the non-linear relationships present in the data. This, in turn, leads to improved prediction accuracy for the targeted problem.

Figure 4 shows that the decision tree and XGBoost models exhibit the highest accuracy in predicting the PCI, with an R-squared approaching 0.90. This finding suggests that there is a minimal linear relationship between the IRI and PCI due to the characteristics of the dataset and the complex nature of their relationship. The dataset contains abrupt changes in some values, which can affect the accuracy of calculations for sensitive algorithms such as Adaboost. As a result, this model produced a low R-squared and high MSE and RMSE. Conversely, other algorithms showed significantly more accurate predictions on the test data, mainly due to their ability to capture the non-linear nature of the dataset. The superior performance of the decision tree and XGBoost models can be attributed to their ability to capture complex and non-linear relationships between IRI and PCI. The lower MSE and RMSE values achieved by the decision tree and XGBoost models further validate their superior performance in capturing the complex relationships between the IRI and the PCI.

In Figure 5, the relationship between the predicted PCI values and the corresponding field-measured values for the entire dataset is showed. By examining the distance between the points and the fitted line, comparisons across different algorithms can be made. It is notable that the decision tree and XGBoost models show a smaller number of points deviating sig-

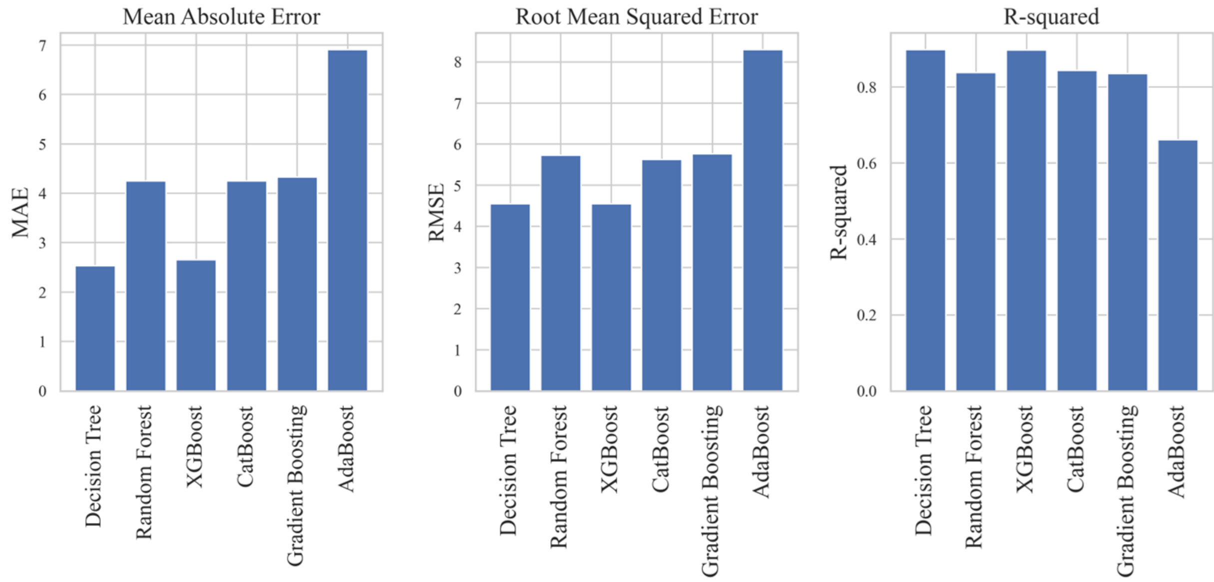

Figure 4. Ensemble models evaluation metrics.

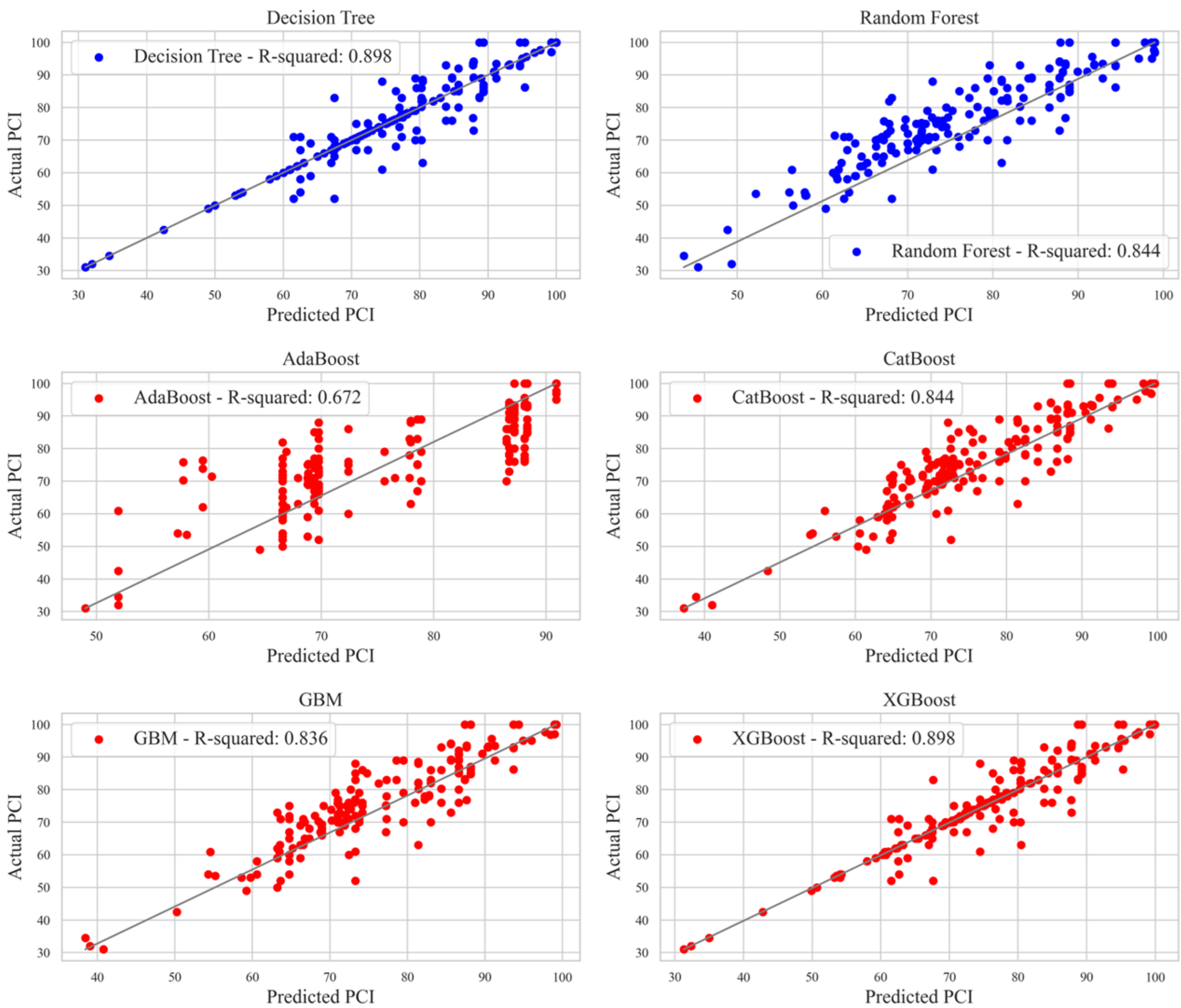

Figure 5. Predicted vs Actual values of the PCI for the different models.

Original value		Ensemble models prediction					
ID	PCI	Decision tree	Random forest	XGBoost	CatBoost	GBM	AdaBoost
100	92	85.64	86.25	85.68	86.70	86.63	85.01
162	93	93	84.71	92.93	90.20	90.36	82.58
187	76	76	73.49	76.05	72.06	73.14	70.27
14	80.25	83.81	83.86	83.81	84.12	84.38	82.58
45	78.34	78.17	79.74	78.45	82.49	82.77	82.11
35	89.23	87.87	87.14	87.79	85.85	85.61	82

Table 4. Random selected prediction values.

Pavement condition	FHWA [31]	Sayer et al. [32]	Goenaga et al. [33]
Good	IRI < 1.5	2 < IRI < 3.5	2.8 < IRI < 3.5
Fair	1.5 < IRI < 2.68	3.5 < IRI < 6	3.5 < IRI < 4.3
Poor	IRI > 2.68	IRI > 8	IRI > 4.3

Table 5. Literature recommendation for pavement conditions based on the IRI values.

State	IRI	LS* Alligator Crack(Area)	MS** Alligator Crack(Area)	HS*** Alligator Crack(Area)	HS*** Block Crack(Area)	HS*** Edge Crack	Predicted PCI
Missouri	0.98	0	1	3	0	0	95.3
Kansas	3.39	9.199	88.69	63.79	394.29	106.80	75
Missouri	1.26	20.60	0.40	11.89	0	0	88.43
Nebraska	0.82	0	1	1	0	0	95.52

* Low severity.
** Medium severity.
*** High severity.

Table 6. Specific sections with their crack's information.

nificantly from the fitted line compared to the other methods. This observation suggested that these models possessed a higher predictive power for the specific dataset used in this research.

In Table 4, the comparison between the predicted values of the PCI and their corresponding original values is presented for different methods used in this research. Upon examination, it is evident that the prediction results were generally acceptable and closely aligned with the actual values, particularly for the decision tree and XGBoost models. For instance, in ID number 162 and 187, the predicted values from the decision tree and XGBoost models closely match the original values. This close alignment can be attributed to the accuracy and robustness of these algorithms in capturing the underlying patterns and relationships within the dataset.

4.1. Case study for evaluating the application of HFST

In this section, the performance of the predicted models was assessed, and the feasibility of HFST installation was proposed. This evaluation involved incorporating the IRI data, crack types and severity from specific sections retrieved from the Long-Term Pavement Performance (LTPP) database. Four sections from different states in the United States were selected based on their IRI data. The ensemble models developed in this research were then applied to predict the corresponding PCI for these sections based on their current conditions and IRI values.

These sections were then categorised into levels of suitability for HFST installation, including classifications such as good, fair, or poor, based on the criteria given in various literature sources, as shown in Table 5.

According to the FHWA and other literature recommendations, an IRI value of less than 1.5 is considered to indicate good asphalt pavement condition, while an IRI value between 1.5 and 2.68 suggests a fair condition. These IRI thresholds can serve as criteria to assess the suitability of HFST application, according to recommendations from various authorities, considering the significant impact of IRI on PCI and its consideration of pavement condition aspects, such as crack type and severity [3–5]. The predicted PCI values for the respective sections were examined and a comparison was made to the corresponding IRI thresholds to determine the recommended PCI status. For instance, in the case where the predicted PCI falls within the range associated with a good or fair condition based on the IRI thresholds, it indicates the suitability of HFST application for these sections.

Table 6 summarised these sections, providing valuable insights into their predicted PCI values, along with comprehensive information about crack length, type, and severity. The in-depth analysis of the pre-

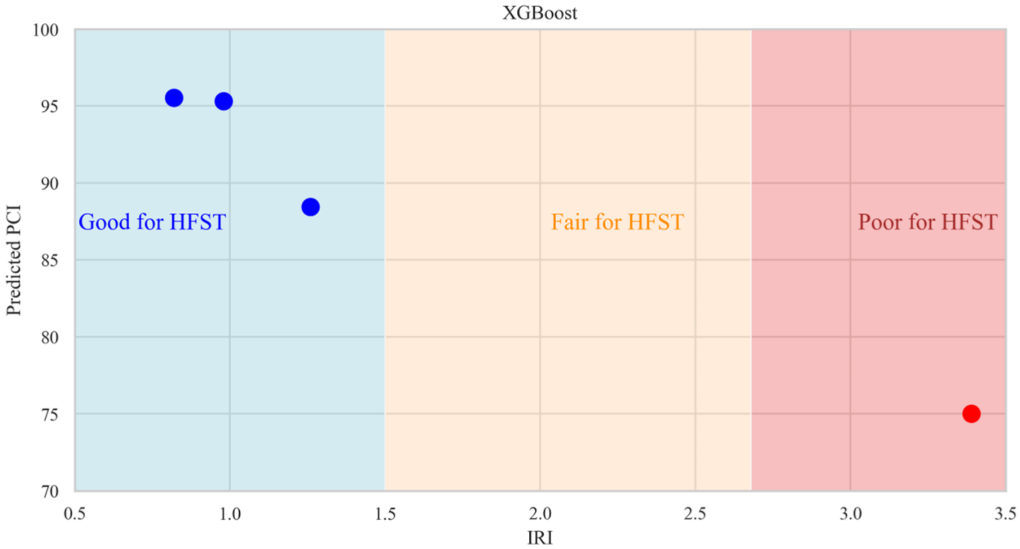

Figure 6. Pavement quality for the HFST application based on IRI and predicted PCI values.

dicted PCI based on IRI and subsequent HFST application recommendations revealed a strong correlation between the crack severity and the overall pavement condition, validating the effectiveness of the evaluation method. For instance, when examining the Kansas section with its high IRI and varying crack characteristics, the predicted and suggested model indicated that it is not a suitable candidate for HFST. Conversely, sections like Missouri, with lower IRI, lower crack severity, and higher predicted PCI values, exhibit promising attributes, making them excellent candidates for the HFST application.

The installation of HFST in the selected sections was suggested based on the Predicted PCI and HFST installation recommendations, as depicted in Figure 6. Both the Missouri and Nebraska sections emerged as good candidates for the HFST installation. However, the Kansas section was indicated as a poor candidate for the HFST application.

5. Conclusion

HFST provides superior friction levels that does not degrade over time. It is mainly used as a spot treatment for specific high-risk locations such as sharp curves and other critical areas, rather than for long stretches of pavement [1]. The selection of HFST locations is usually driven by high accident rates, although it can also be used as a systemic countermeasure. In addition, a thorough pavement condition assessment is essential to ensure that a location is suitable for HFST application.

The assessment of pavement condition for the HFST application is a complex task that requires considering multiple factors, such as distress, skid resistance, and roughness. This research aimed to address this challenge by using machine learning techniques to predict the PCI and evaluate the suitability of pavements for HFST applications. Incorporating IRI data and previous PCI information streamlined the evaluation process, eliminating the need for extensive distress evaluation. This approach not only saved cost and time, but also allowed for a comprehensive consideration of factors in determining the suitability of the HFST application. Previous research efforts have focused on predicting PCI using simple models based on IRI, but these models have lacked the necessary accuracy. In addition, there is a lack of research on evaluating the suitability of HFST and predicting pavement conditions using IRI and previous PCI. The suitability of HFST application based on the predicted PCI has been suggested through the use of ensemble models and consideration of various recommendations. This advanced approach improved the evaluation process and resulted in more reliable recommendations for the HFST application to pavements. It was observed that the decision tree and XGBoost models exhibited the highest accuracy in predicting the PCI, with an R-squared value approaching 0.90. This finding suggests that there is a minimal linear relationship between the IRI and PCI due to the dataset's characteristics and the complex nature of their relationship.

In the evaluation of the predicted models' performance, the IRI data from the LTPP database were incorporated. By comparing the predicted PCI values to the corresponding IRI thresholds, the recommended PCI status could be determined. If the predicted PCI fell within the range associated with good conditions based on the IRI thresholds, this indicated the suitability of the HFST application.

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