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Predicting Pavement Condition Index Using Machine Learning Algorithms and Conventional Techniques

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ABSTRACT

Government agencies and transportation engineers use pavement management systems (PMS) to evaluate pavement performance and keep pavement above the minimum acceptable performance standards. The Pavement Condition Index (PCI) and the international roughness index (IRI) are among the most commonly used indices to evaluate pavement conditions. Due to IRI data collection being more accessible and less expensive than collecting pavement distress data, this study aims to develop PCI models that can successfully estimate the PCI values based on IRI for flexible pavement using two Machine Learning techniques (ML), namely: Random Forest (RF), and Support Vector Machine (SVM), and three conventional techniques, namely: linear, quadratic, and cubic regression. The study was carried out with the database collected from the Long-Term Pavement Performance (LTPP) program. The results of the dataset reveal that both ML models (RF and SVM) have strong prediction ability with high values of coefficient of determination (R^2 = 99.7 and 96.8) %, and low values of Root Mean Squared Error (RMSE = 1.095 and 3.569) % and Mean Absolute Error (MAE = 0.474 and 2.244). In conclusion, the goodness of fit of the proposed ML models was compared with conventional techniques models previously developed. The results showed that the ML models yielded higher prediction accuracy than conventional techniques.

التنبؤ بمؤشر حالة الرصف باستخدام خوارزميات التعلم الآلي والأساليب التقليدية

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الكلمات المفتاحية:

التقنيات التقليدية
مؤشر الخشونة الدولي
تقنيات التعلم الآلي
مؤشر حالة الرصيف

الملخص

تستخدم الوكالات الحكومية ومهندسو النقل أنظمة إدارة الرصف (PMS) لتقييم أداء الرصف والحفاظ على الرصف فوق الحد الأدنى من معايير الأداء المقبولة. يعتبر مؤشر حالة الرصف (PCI) ومؤشر الخشونة الدولي (IRI) من أكثر المؤشرات استخدامًا لتقييم ظروف الرصف. نظرًا لكون جمع بيانات IRI أكثر سهولة وأقل تكلفة من جمع بيانات اضرار الرصف، تهدف هذه الدراسة إلى تطوير نماذج PCI يمكنها تقدير قيم PCI بنجاح استنادًا إلى IRI للرصف المرن باستخدام تقنيتين للتعلم الآلي (ML)، وهما: الغابة العشوائية (RF) وخوارزمية آلة المتّجه الداعم (SVM)، وثلاث تقنيات تقليدية وهي: الانحدار (الخطي -التربيعي -التكعيبي). تم إجراء الدراسة باستخدام قاعدة البيانات التي تم جمعها من برنامج أداء الرصف طويل المدى (LTPP). بينت نتائج مجموعة البيانات أن كلا نموذجي (RF& SVM) يتمتعان بقدرة تنبؤ قوية مع قيم عالية لمعامل التحديد (99.7 و 96.8) % وقيم

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منخفضة لمتوسط خطأ الجذر التربيعي (1.095 و 3.569) %و متوسط الخطأ المطلق (0.474 و 2.244
%. في النهاية، تمت مقارنة جودة ملاءمة نماذج ML المقترحة مع نماذج التقنيات التقليدية التي تم تطويرها
مسبقًا. أظهرت النتائج أن نماذج ML أعطت دقة تنبؤ أعلى من التقنيات التقليدية.

Introduction and related work

A maintenance and rehabilitation strategy enhances and improves traffic safety and ride comfort and reduces vehicle operating expenses and environmental and building costs [1]. The Pavement Condition Index (PCI), Present Serviceability Rating (PSR), Pavement Quality Index (PQI), and International Roughness Index (IRI) are commonly used pavement performance indicators in many countries. The PCI indicator created by the United States Army Corps of Engineers in the 1970s is a widely utilized technique. The PCI indicator is based on a composite index of the flexible pavement's structural integrity and operational requirements. The PCI is computed by combining nineteen different pavement distress degrees and intensities.

The PCI method is a Standard ASTM Test technique, specifically ASTM D6433-18. PCI values range from zero to one hundred, with zero indicating failed pavements and a hundred meaning excellent performing pavements [2,3]. Similarly, the IRI is a globally used indicator of ride quality or smoothness. The IRI, which the World Bank developed in 1986, is calculated by dividing the cumulative vibrations or vertical movements by the profile length [4]. Machine learning applications (ML) have wide applications in civil and infrastructure engineering. The application of ML includes transportation, pavement engineering, structure, and environment. ML uses a nonlinear statistical technique inspired by how the human brain works to model complex relationships between inputs and outputs [5,6].

This study aimed to assess the performance of conventional and machine learning techniques used to predict the (PCI) from the (IRI). Conventional techniques models considered in this study include regression analysis (linear, quadratic, and cubic), while machine learning techniques models include RF and SVM. The data used in the study were collected from the LTPP database for different climate regions in the U.S. and Canada. It is expected that the findings of this study may reduce the time required to gather, examine, and process distress images for PCI determination and reduce the human opinion in the assessment of pavement distress. Furthermore, the cost of collecting and evaluating field data for defining the PCI will be reduced.

Overview of the Conventional Techniques Used in Performance Modelling

Over the last three decades, researchers proposed several pavement condition indices based on IRI. Some of these models were derived based on the (LTPP) database, while others were developed based on research teams' measurements or the local agency database. Table (1) presents some studies used to model pavement performance.

Table 1: Summary of some conventional models available in the literature.

Authors	Year	Model Equation	R^2
Dewan, Smith [7]	2002	IRI = 0.0171(153 - PCI)	53
Park et al. [8]	2007	log(PCI) = 2 – 0.436log(IRI)	59
Shah et al. [9]	2013	$PCI = 1.28(IRI)^2 - 17.73 \times IRI + 100$	-
Arhin et al. [10]	2015	$PCI = -0.224xIRI + 120.02$	82
Elhadidy et al. [11]	2019	$PCI = \frac{1}{0.048} \times \ln(\frac{79.933}{IRI} - 14.061)$	-
Ali et al. [12]	2021	PCI = 85.657 − 11.386 × IRI	89.5

Overview of the Machine Learning Techniques Used in Performance Modelling

Applying Machine Learning techniques for pavement modelling has become a significant focus of several pavement engineering researchers. Several researchers have explored, analyzed, and modelled indicators like the IRI, PCI, and fatigue cracking using ML techniques. The purpose of these studies was frequently to improve standard pavement management practices. Table (2) presents a few examples of these initiatives. The following subsections cover the main aspects of ML algorithms and their architecture (as determined by the model hyperparameters):

- **Random Forest (RF)**

The Random Forest technique gathers the results from several decision trees, in which the trees in the forest run in parallel with no interactions between them. This method ensures that the model is not overly reliant on a single feature. Because each tree employs a random sampling mechanism to draw data from the original dataset while producing its splits, it provides a better foundation for preventing overfitting than ANNs [12].

- **Support Vector Machine (SVM)**

SVM algorithms identify optimum hyperplanes in a high-dimensional space which classify the data points. Regression is applied to data points within the decision boundary lines surrounding the hyperplane. These algorithms employ various mathematical functions to transform the input data into the desired form.

Table 2: Summary of some Machine Learning models available in the literature.

Authors	Year	ML Technique
Marcelino et al. [13]	2019	Random Forest (RF)
Karballaeezadeh et al. [14]	2019	Support Vector Machine (SVM)
Hoang et al. [15]	2019	1- Support Vector Machine (SVM) 2-Artificial Neural Network (ANN) 3- Random Forest (RF)
Hoang et al. [16,17]	2018	1-Support Vector Machine (SVM) 2-Artificial Neural Network (ANN) 3- Random Forest (RF) 4- Radial Basis Function Neural Network (RBFNN) 5- Naïve Bayesian Classifier (NBC) 6-Classification Tree (CT)
Nabipour et al. [18]	2019	Genetic Expression Programming
Inkoom et al. [19]	2019	1- Bootstrap Forest 2- Gradient Boosted Trees 3- K Nearest Neighbours 4- Naïve Bayes 5- Multivariable Linear Regression
Cao et al. [20]	2020	1-Artificial Neural Network (ANN) 2- Support Vector Machine (SVM)
Yamany et al. [21]	2020	1-Artificial Neural Network (ANN) 2- Linear Regression (LR) 3- Random Parameter Regression

Methodology

In this study, conventional and ML techniques were used to develop a reliable and accurate PCI based on IRI. This database can be found in the LTPP dataset. Figure (1) shows the methodological framework adopted in this research. The plan of the study was divided into four steps, as follows:

1- **Data Collection:** In this step, data were collected from the LTPP dataset.

2- **Data Preprocessing**: All data collected in this research were used to estimate the existing PCI for each road section based on the ASTM 6433–18 standard.

3- **Model Development**: This step is divided into two phases:

- **Phase 1(Conventional Techniques):** This phase used three conventional methods to predict PCI from IRI based on the data obtained from the previous step and IRI data from the LTPP dataset.

- **Phase 2 (Machine Learning):** This phase was devoted to developing two Machine Learning techniques to predict the PCI value.

4- **Comparison and Validation:** In this step, models developed using different methods were compared and validated. (Conventional Techniques and Machine Learning).

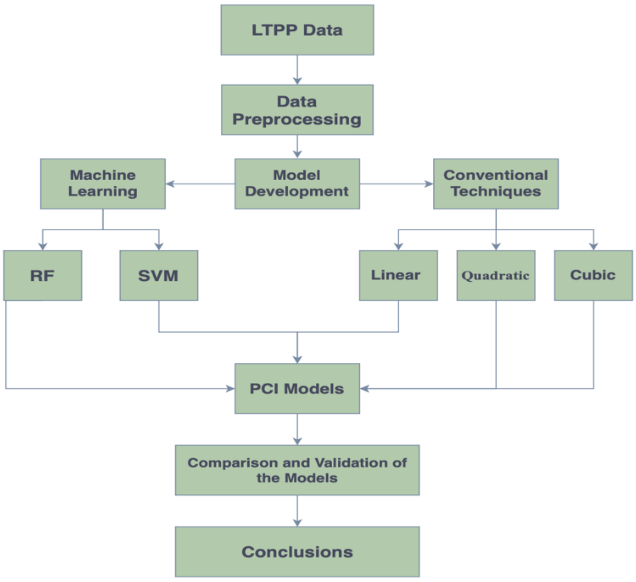

Fig 1. Methodological flow chart of this study.

Data Description and Preprocessing

Data used in this study were collected from the LTPP database. The LTPP programme is one of the significant sources of pavement performance data for researchers, which was established from 1987 to 1991 to collect pavement condition data as one of the principal research areas of the Strategic Highway Research Program (SHRP). The Federal Highway Administration (FHWA) has continued to oversee and finance the initiative from 1992 to the present. The LTPP programme has two essential classes of studies, the General Pavement Study (GPS) and Specific Pavement Studies (SPS). In this research, the information concerning asphalt pavement sections located in different climate regions without any maintenance or rehabilitation activities was received from the LTPP database. The LTPP makes the data available for free use on its website, https://infopave.fhwa.dot.gov

- **International Roughness Index**

In this research, data and measurements were collected from the LTPP database: IRI, pavement age, and nine types of distress, including rutting, fatigue cracking, block cracking, longitudinal cracking, transverse cracking, patching, potholes, bleeding, and ravelling.
Table (3) illustrates the descriptive statistics for 60 sections (400 observations) of the data obtained from the LTPP database.

- **Pavement Condition Index**

Based on the data obtained from the LTPP dataset of the 60 road sections, PCI values were calculated using the ASTM D6433-18 method.

Table 3: Descriptive statistics for 60 sections of the measured deterioration.

Parameters	Minimum	Maximum	Mean	Std. Deviation
Age	1	32	14.3	6.66
Rutting	0	29	7.22	4.64
Fatigue Cracking	0	377.90	18.3	50.59
Block Cracking	0	0	0	0
Longitudinal Cracking	0	2300.4	75.5	149.97
Transverse Cracking	0	293	22.3	40.25
Patching	0	1.50	0	0.07
Potholes	0	0	0	0
Bleeding	0	350.80	6.53	40.38
Ravelling	0	564.30	13.7	74.38
IRI	0.62	4.01	1.35	0.58
PCI	8	100	73.6	20.40

Accuracy Validation

Three of the most commonly used metrics to measure accuracy for continuous variables are the R^2, RMSE, and MAE [22]. The mathematical representation of the three implemented measures is shown in Table (4).

Table 4. Mathematical illustration for performance metrics.

Measure Models	Formula	Variables Description
Determination Coefficient	$R^2 = 1 - \frac{\sum_i (t_i - o_i)^2}{\sum_i (o_i)^2}$	o_i=Actual value observation I,
Mean Absolute Error	MAE=$\frac{1}{n}\sum_i^n \lvert t_i - o_i \rvert$	t_i = Predicted value of observation I, n = Number of observations.
Root Mean Squared Error	RMSE=$\sqrt{\frac{\sum_i (t_i - o_i)^2}{n}}$	

Results and Discussions

Developing Conventional Techniques Models

Three conventional techniques were used in this research (linear, quadratic, and cubic) to predict PCI based on the IRI indicator for flexible pavement. The PCI indicator has been taken as a dependent variable, while the IRI indicator has been considered as an independent variable. The data were extracted from the IBM SPSS Statistics package (IBM 27). The correlation was assessed using R^2, RMSE, and MAE values. Table (5) summarised the regression models and presented the relation between (PCI& IRI).
According to Table (5), equations from (1) to (3) presented the regression models and the relation between (PCI& IRI) as follows:

- **Linear Regression Method**

$$\mathbf{PCI=117.72-32.70(IRI)} \qquad \textbf{(1)}$$

The correlation coefficient (R^2) of this relationship is **87.2%.**

- **Quadratic Regression Method**

$$\mathbf{PCI=129.1-47.75(IRI)+4.2(IRI)^2} \qquad \textbf{(2)}$$

The correlation coefficient (R^2) of this relationship is **88.3%.**

- **Cubic Regression Method**

$$\mathbf{PCI = 129.1 - 49.4(IRI) + 5.1(IRI)^2 - 0.2(IRI)^3} \qquad \textbf{(3)}$$

The correlation coefficient (R^2) of this relationship is **88.5%.**

Equations (1), (2) and (3) showed that the R^2 were 87.2 %, 88.3 % and 88.5 %, respectively. Based on this, IRI data can easily predict PCI values. Figure (2) presents the relationship between PCI and IRI in three conventional techniques: linear, quadratic, and cubic. The R^2, RMSE, and MAE statistical error measures were used for

validating the developed regression model for the three mathematical methods mentioned above. Results showed that the R^2 was good, while the RMSE and the MAE values in all cases were acceptable.
The results showed that the cubic models' R^2, RMSE, and MAE values improved by 1.46%, 4.67%, and 9.23% compared to the linear models.
The results obtained from the regression analysis showed that the three regression models could be used for estimating the PCI values based on the IRI. Cubic model results provided the best fit with a minor error between the observed and predicted values, compared to linear and quadratic models. As a result, the difference between the quadratic and cubic regression models was relatively small.

Table 5: Summary of correlation between IRI & PCI.

Technique	Parameter Estimates	Unstandardized Coefficients		R^2	RMSE	MAE
		B	Std. Error			
Linear Regression	Constant	117.72	0.92	87.2	7.295	4.583
	b1	-32.70	0.63			
Quadratic Regression	Constant	129.1	2.00	88.3	6.956	4.176
	b1	-47.75	2.46			
	b2	4.2	0.66			
Cubic Regression	Constant	129.1	4.73	88.5	6.954	4.16
	b1	-49.4	8.59			
	b2	5.1	4.64			
	b3	-0.2	0.75			

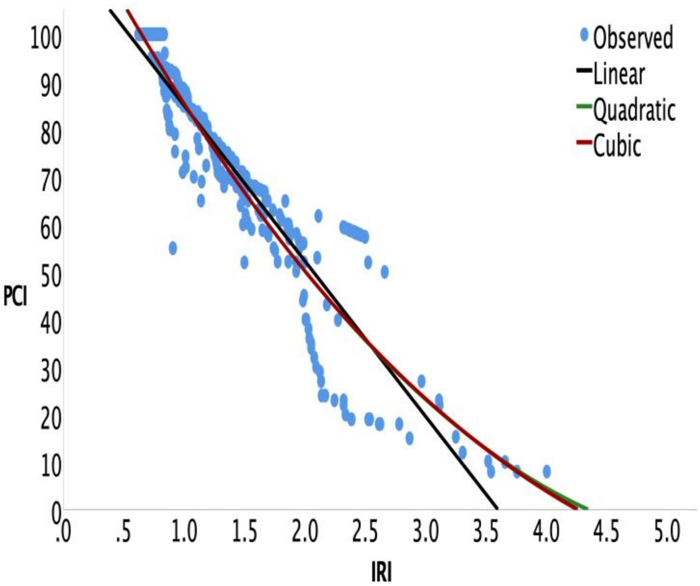

Fig 2. PCI versus IRI plot.

Developing Machine Learning (ML) Models

SVM and RF have been used to develop effective and accurate models. These techniques aim to predict the PCI value based on the IRI value obtained from the LTPP datasets in the U.S. and Canada. The model's performance was assessed using the three common R^2 values, RMSE and MAE methods. Table (6) summarizes the modelling results for this study's two machine learning techniques. Figures (3) and (4) present the SVM and RF prediction results for PCI models.

Table 6: Performance of PCI models using RF and SVM techniques based on IRI values.

ML technique	Statistical Error Measures		
	R^2	RMSE	MAE
SVM	96.8	3.659	2.244
RF	99.7	1.095	0.474

Table 6 and Figures 3 and 4 summarize the modelling results for this study's two machine learning techniques as follows:

Support Vector Machine (SVM): The SVM performing model scored R^2 =96.8%, RMSE =3.659%, and MAE = 2.244%.
Random Forest (RF): The RF performing model scored R^2= 99.7%, RMSE = 1.095%, and MAE = 0.474%.
Based on the results, the RF model was more accurate than the SVM model.

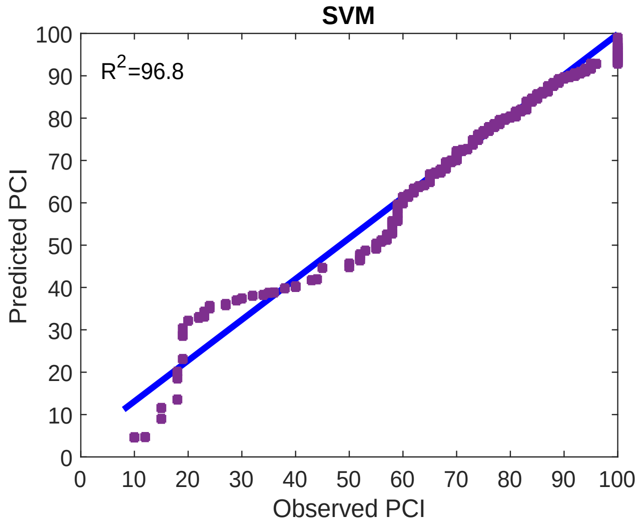

Fig 3. SVM prediction results for PCI model.

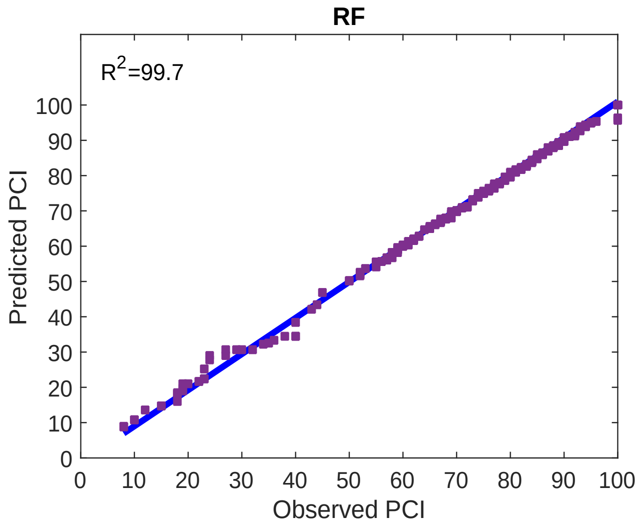

Fig 4. RF prediction results for PCI model.

Comparison with Conventional Techniques

In order to assess the efficiency of machine learning techniques versus conventional techniques, the R^2, RMSE, and MAE were used. Comparing the results generated by the conventional and ML techniques showed that all the models were accurate. Table (7) provides a comparison of the conventional and ML techniques. Figures (5) to (7) present the comparison between machine learning and conventional techniques.

Table 7: Comparison of the machine learning techniques and conventional techniques models.

Technique	Statistical Error Measures		
	R^2	RMSE	MAE
Linear Regression	87.2	7.295	4.583
Quadratic Regression	88.3	6.956	4.176
Cubic Regression	88.5	6.954	4.16
SVM	96.8	3.659	2.244
RF	99.7	1.095	0.474

Table (7) and figures from (5) to (7) present a comparison among machine learning techniques and conventional techniques models and summarize several points as follows:

- The conventional and ML techniques could successfully predict the PCI values based on IRI values.
- The ML models show higher performance compared to the conventional models.
- The calculated $R^2$was strong in all models, and RMSE and MAE values were acceptable.
- The results showed that the R^2 of the RF model improved by 12.53%, 11.43%, and 11.23%, compared to the linear, quadratic, and cubic models, respectively.
- The results showed that the RMSE value of the RF model was reduced by 84.99%, 84.26%, and 84.25%, compared to linear, quadratic, and cubic models, respectively.
- The results showed that the MAE value of the RF model was reduced by 89.66%, 88.65%, and 88.61%, compared to linear, quadratic, and cubic models, respectively.
- The results showed that the R^2of the RF model improved by 2.91%, while RMSE and MAE values were reduced by 70.07% and 78.88%, compared to the SVM model.
- According to the results, two machine learning and three conventional techniques estimate the PCI values based on the IRI with reasonable accuracy.
- Results showed that the RF technique had a better and higher accuracy with a minor error between observed and predicted values than the other techniques.
- Although the conventional techniques provided a predictive regression equation and showed the effect of the parameters and their interactions on a response the ML technique provided a strong correlation with PCI and distress in terms of error.

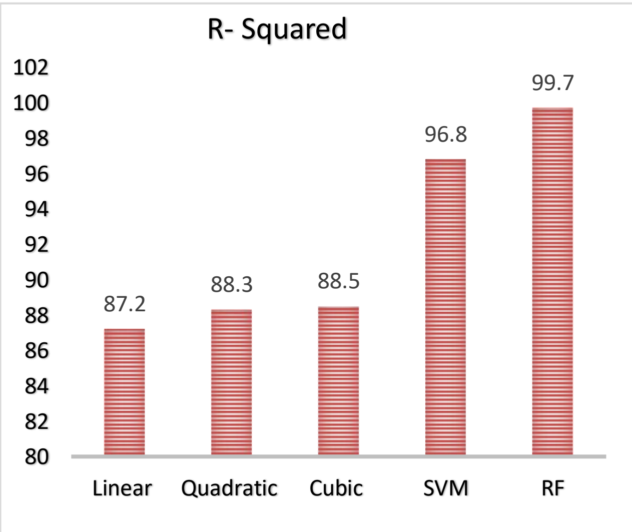

Fig 5. Comparison between the machine learning techniques and conventional techniques (R-Squared).

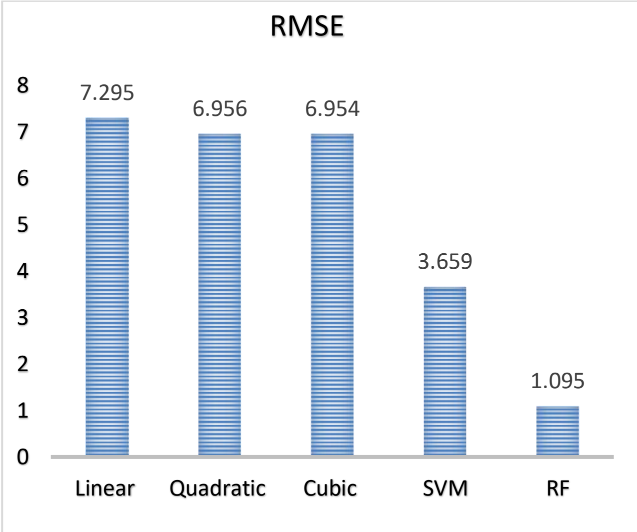

Fig 6. Comparison between the machine learning techniques and conventional techniques (RMSE).

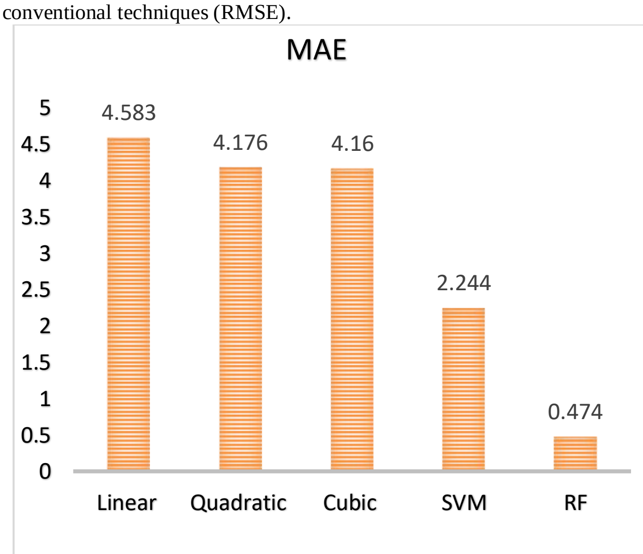

Fig 7. Comparison between the machine learning techniques and conventional techniques (MAE).

Conclusions

In this paper, the prediction of the PCI based on the IRI was developed using three conventional regression techniques, linear, quadratic, and cubic, and two machine learning techniques RF and SVM. Based on the results of this study, the following conclusions can be drawn:

- The present study focused on predicting PCI based on IRI using sixty road sections (400 observations) for flexible pavements selected in the U.S. and Canada from the LTPP dataset.
- A comparison was conducted between the machine learning and conventional techniques values using the LTPP dataset. The RF model was the most accurate compared to other models.
- A comparison was conducted between machine learning and conventional techniques. The ML techniques provided a more precise prediction compared to conventional regression techniques.
- An evaluation of the conventional regression techniques showed that the cubic technique provided a more precise prediction than the linear and quadratic techniques.
- An assessment of the ML techniques showed that the RF provided a more precise prediction than the SVM technique.
- Finally, based on the findings of this study, the ML techniques and conventional techniques were found to be viable modelling tools for PCI values prediction based on IRI values. Furthermore, this study demonstrated that both techniques could accurately predict PCI values, decrease

the need for visual examination of PCI values, and save budgets and time.

Data availability statement

The published article includes all data, models, and code generated or used during the study.

Declaration of Competing Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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