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Development of International Roughness Index from Pavement Distress Using Artificial Neural Networks (ANNs)

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ABSTRACT

Roughness index forecasts are essential for optimizing pavement rehabilitation and treatment programs. The main objective of this study is to investigate the effect of pavement distress on pavement performance and develop International Roughness Index models (IRI) for dry no freeze regions in the U.S. Data for this research was collected from the Long-Term Pavement Performance (LTPP) database. The data include a total of 138 records of pavement distress with no maintenance and rehabilitation. Based on these data, IRI prediction models were developed using two modelling approaches: Multiple Linear Regression analysis (MLR) and Artificial Neural Networks (ANNs). The proposed models predict the IRI as a function of pavement distress variables such as or including fatigue cracking, block cracking, edge cracking, longitudinal cracking, transverse cracking, potholes, patching, bleeding, and ravelling. This study showed that the (ANNs) model yielded a higher prediction accuracy than the (MLR) model.

Keywords: Pavement Performance; Artificial Neural Networks (ANNs); Pavement Condition Index (PCI); International roughness index (IRI); Multiple Linear Regression analysis (MLR).

1 INTRODUCTION

The performance of a pavement deteriorates with time. Nevertheless, the deterioration rate can be slowed down by performing regular maintenance. As an essential first step in designing pavement maintenance treatments, it is imperative to understand the actual road conditions on the ground. The International Roughness Index (IRI), Present Serviceability Rating (PSR), and Pavement Condition Index (PCI) are some of the well-established parameters to describe road conditions, and transportation agencies have used them for the last four decades.

2 Literature Review

Choosing an effective maintenance and rehabilitation strategy contributes to ride comfort and traffic safety. However, it also significantly impacts the environment and reduces vehicle operating costs and construction costs [1]. Different pavement condition indicators are used widely in the world, such as International Roughness Index (IRI), Pavement Condition Index (PCI), and Present Serviceability Rating (PSR). Pavement Condition Indicators are crucial to Pavement Management Systems. It is typical to select a method for conducting surveys that is unbiased, repeatable, and preferably relatively simple to perform in the field. One of the most common techniques is the IRI method. The IRI was developed in 1986 by the World Bank. It is calculated by dividing the cumulative vibrations or vertical movements by the profile length. A laser profiler measures it and is reported as a non-dimensional index (m/km) [2]. ASTM D6433-18 defines pavement roughness as a "deviation of a surface from the true planar surface with characteristic dimensions that affect vehicle dimensions and ride quality" [3]. According to Kaavianipour et al. [4] pavement roughness significantly impacts safety. Previous studies have also examined the relationship between IRI and pavement distress [5,6,7]. IRI can be viewed as the reflection of the pavement performance index, and it is possible to present the change in the pavement life cycle as the change in IRI. According to the Federal Highway Administration, high-speed pavements with IRI values exceeding 2.7 m/km are considered "poor"[8]. Table (1) shows pavement ride quality categories based on IRI-measured values. Elbagalati et al. [9] used ANNs to develop predictive models for subgrade resilient modulus. Badawy et al. [10] studies were conducted to develop predictive models for the asphalt dynamic modulus predictions using ANNs. ANNs emerged as an efficient tool for modelling purposes.

Most historical IRI models were based on linear or non-linear regression techniques. Ali et al. [11] evaluated pavement performance using the pavement condition index (PCI) and international roughness index (IRI) for 58 km of St. John's, Newfoundland, Canada road. Recent models were based on artificial neural networks (ANNs). ANNs (also referred to as Neural Networks) were one of the machine learning techniques. Its concept was biologically inspired by the human brain, thus mimicking brain behaviour [12].

ANNs provide entirely accurate solutions to develop empirical models for complex datasets with non-linear behaviours and not fitting at known mathematical functions [13]. ANNs operate with a high degree of parallelism, mimicking the human brain [14].

Table 1: Pavement ride quality based on roughness.

Category	IRI Rating (m/Km), by Highway Type		Interstate and Noninterstate Ride Quality
	Interstate	Noninterstate	
Very Good	<1	<1.0	Acceptable 0–2.0
Good	1.0-1.5	1.0-1.50	
Fair	1.5-1.90	1.50-2.70	
Poor	1.9-2.70	2.70-3.50	-
Very Poor	>2.70	>3.5	Less than acceptable >2.70

3 Objectives

The main goals of this study are to evaluate the performance of traditional techniques and machine learning techniques used to predict the International Roughness Index (IRI) based on pavement distress. Traditional techniques models in this study use multiple linear regression (MLR), while machine learning techniques models utilize Artificial neural networks (ANN). The data used in the study were collected from the Long-Term pavement Performance (LTPP) database for dry no-freeze region in the U.S.

4 Methodology and Data Collection

This study used MLR and ANNs techniques to develop reliable and accurate roughness (IRI) prediction models for dry no freeze climate regions. The database contains 12 road sections, including 138 observations of pavement distress. This data was randomly divided into three sets: training, testing, and validating. Figure (1) illustrates the flowchart of the research methodology used in this study.

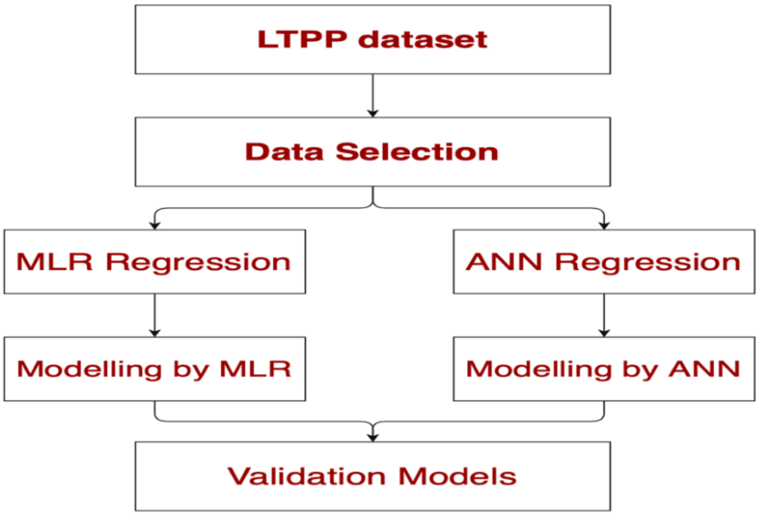

Fig.1 Research methodology flowchart.

4.1 Data collection and processing

Pavement distress is a significant variable that affects pavement performance during the pavement cycle. Data mining was performed as the first step to gather and consolidate the available data in the dry no-freeze region. This study used 138 observations from 12 road sections to develop IRI prediction models. Figure (2) shows the geographic distribution of the sections considered in the analysis. To fulfill the objectives of this study, data were collected for ten variables of pavement distresses; Age of pavement, fatigue cracking, block cracking, edge cracking, longitudinal cracking, transverse cracking, potholes, patching, bleeding, and ravelling were collected from 12 pavement sections for dry no freezing climate regions in the United State. Table (2) lists the specifications of the collected data.

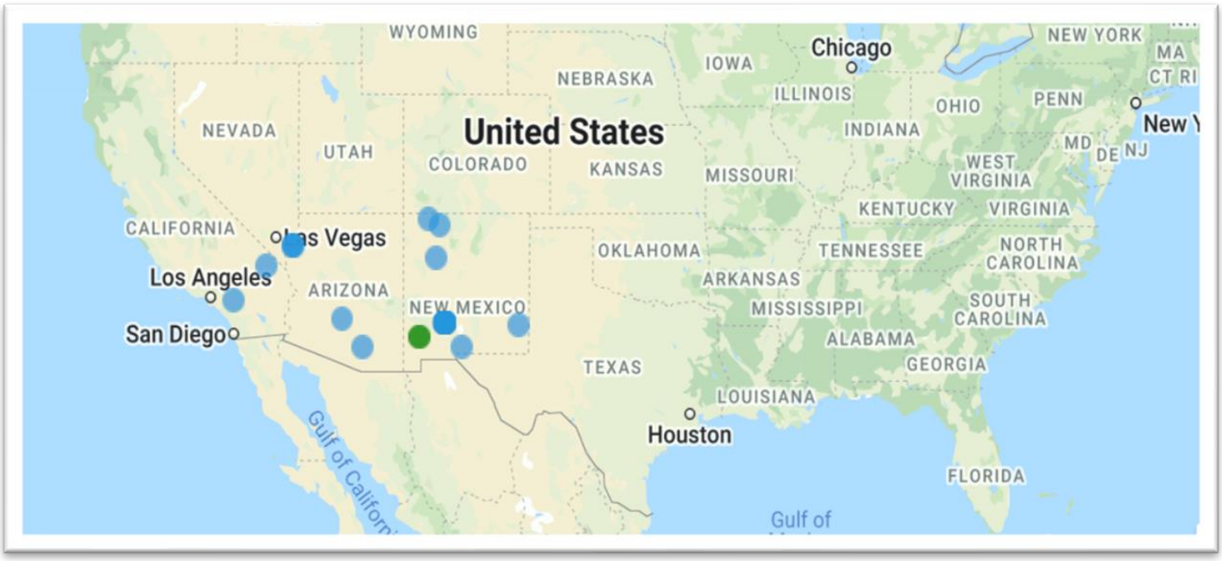

Fig.2 Locations of the LTPP sections [15].

Table 2: Gathered pavement distress data from dry no freeze region.

Parameters	Unit	Minimum	Maximum	Mean	Std. Deviation
Age	Year	2.00	24.00	10.24	4.17
Fatigue Cracking	m^2	0.00	436.20	43.62	105.93
Block Cracking	m^2	0.00	557.60	10.11	63.63
Edge Cracking	(m^2)	0.00	0.00	0.00	0.00
Longitudinal Cracking	m^2	0.00	306.60	82.09	97.02
Transverse Cracking	(m^2)	0.00	281.30	25.66	55.36
Patching	m^2	0.00	1.00	0.01	0.09
Potholes	Number	0.00	0.00	0.00	0.00
Bleeding	m^2	0.00	152.50	1.98	13.31
Raveling	m^2	0.00	564.30	58.76	102.03
IRI	(m/km)	0.59	3.14	1.56	0.58

4.2 Research Analysis Approaches

This research examined two techniques: Multiple Linear Regression (MLR) and Artificial neural networks (ANNs).

- **Multiple Linear Regression (MLR) Model**

The research was conducted in the dry no-freeze region in the U.S. to evaluate the effects of different pavement distresses on IRI indicator values, using 12 pavement sections from the LTPP carried out using the IBM SPSS Statistics package (IBM 27). MLR is typically used to research the relationship between independent and dependent variables. The conventional regression method is a comprehensive and reasonable evaluation of relationships between independent and dependent parameters. Equation (1) represents a basic equation for prediction models to find the Influence of pavement distress on IRI value.

$$\mathbf{IRI}=\mathbf{C}+a_1X_1+a_2X_2+a_3X_3+a_4X_4+a_5X_5+a_6X_6+a_7X_7+a_8X_8+a_9X_9+a_{10}X_{10} \quad \mathbf{(1)}$$

Where: C= Constant, IRI =International Roughness Index, X_1= Age, X_2= Fatigue, X_3= Block Cracking, X_4=Edge Cracking, X_5=Longitudinal Cracking, X_6=Transverse Cracking, X_7=Patching, X_8=Potholes, X_9=Bleeding, X_{10}=Raveling, $a_1, a_2, a_3 \dots \dots \dots \dots a_{10}$= Coefficients.

- **Artificial Neural networks (ANNs)Model**

Typically, ANNs consist of the input layer, output layer and several hidden layers in which the non-linear, sophisticated operations were executed, as shown in Figure (3). Each layer contains a set of neurons. All neurons were connected through synapses. These synapses (connections) have initial weights changing over the iterative process of the whole network. A typical solution for almost any neural network starts with the training process. Then, cross-validation and testing stages take place in which the predicted output is compared to the actual output. The final solution is considered a black box since ANNs deal with data that do not follow a casual mathematical relationship. Therefore, it was adopted in this research to predict IRI in terms of pavement distresses.

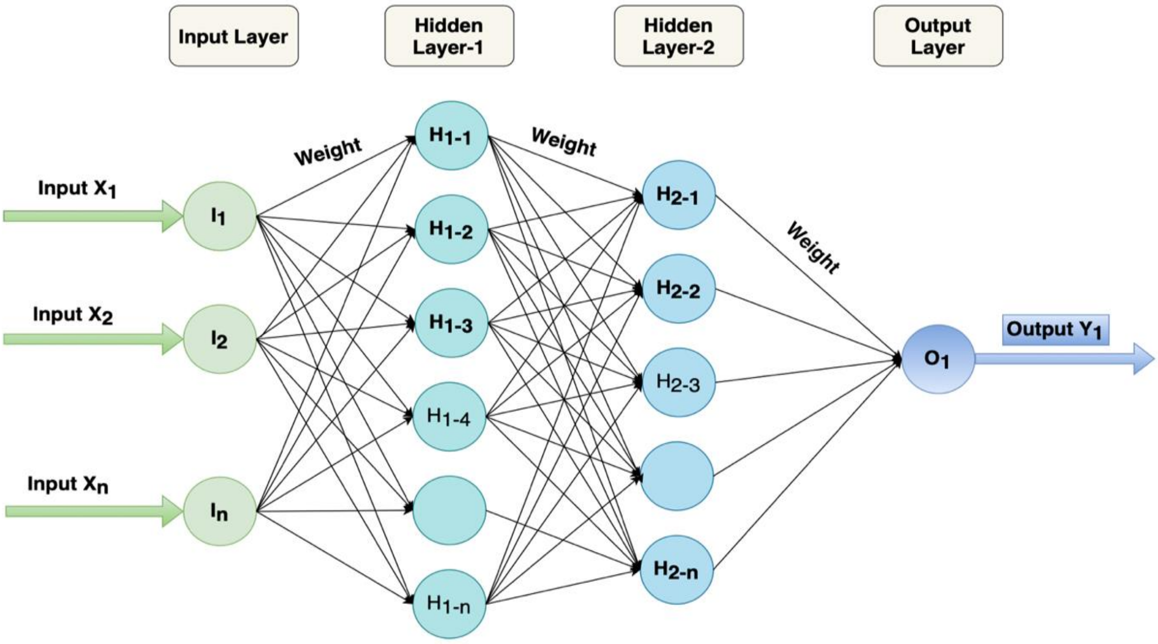

Fig.3 Schematic diagram of ANNs structure.

- **Criteria for Assessing Model Performance**

Three statistical criteria have been applied to validate the findings of this study, including the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE) [16]. Equations 2, 3 and 4 listed below were used to apply these criteria:

$$\boldsymbol{R^2 = 1 - \frac{\sum_i (t_i - o_i)^2}{\sum_i (o_i)^2}} \quad \textbf{(2)}$$

$$\textbf{MAE}=\boldsymbol{\frac{1}{n}\sum_i^n |t_i - o_i|} \quad \textbf{(3)}$$

$$\textbf{RMSE}=\boldsymbol{\sqrt{\frac{\sum_i (t_i - o_i)^2}{n}}} \quad \textbf{(4)}$$

where, o_i= actual value observation I, t_i = predicted value of observation I, and n = number of observations.

5 Results and Discussion

5.1 Multiple Linear Regression (MLR) Results

Table (3) shows the result of the regression analysis for IRI. The IRI is negatively correlated with fatigue cracking and patching, while IRI is positively correlated with age, longitudinal and transverse cracking. Figure (4) shows the relationship between actual IRI and predicted IRI. Equation (5) shows the relationship between the IRI and pavement distress as follows:

$$\mathbf{IRI=0.562+0.086X_1-0.001X_2+0.001X_4+0.003X_5-0.350X_6} \quad \mathbf{(5)}$$

This relationship's correlation coefficient (R^2) is **63.8%.**

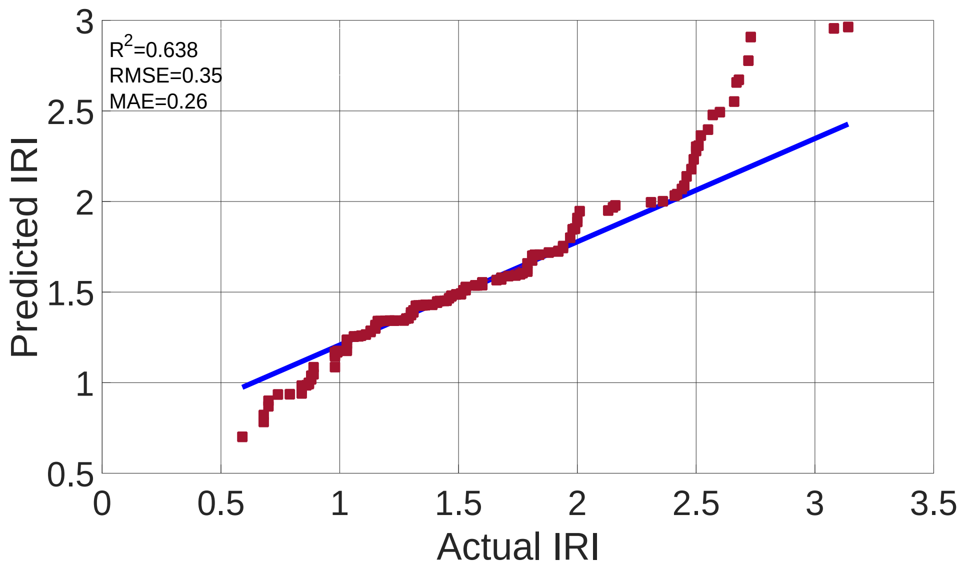

Fig. 4 MLR prediction results.

Table 3: The IRI model summary.

Model	Unstandardized Coefficients		Standardized Coefficients	t-stat	R^2	RMSE	MAE
	B	Std. Error	β				
(Constant)	0.562	0.09	-	6.437	63.8	0.35	0.26
Age	0.086	0.01	0.611	9.422			
Fatigue Cracking	-0.001	0	-0.125	-2.21			
Block Cracking	0	0.001	0.028	0.342			
Edge Cracking	0.001	0	0.143	2.284			
Longitudinal Cracking	0.003	0.001	0.321	5.622			
Transverse Cracking	-0.35	0.55	-0.051	-0.64			
Patching	0.001	0.002	0.012	0.219			
Potholes	0	0	-0.049	-0.84			
Bleeding	0.562	0.087	-	6.437			
Raveling	0.086	0.009	0.611	9.422			

5.2 Artificial Neural networks (ANNs) Results

The purpose of developed models is to predict the performance of a pavement network for the following years to evaluate the outcome of a given set of maintenance decisions, thus optimizing the maintenance plan. The network architecture consists of one input layer including ten neurons, one output layer including one neuron and three hidden layers in between with fifteen neurons each (10-20-15-15-1), as presented in Figure (5). Out of the 138 data observations, 70% of the data was used for training, 15% of the data was testing, and the remaining 15% of the data was used for validation. The trained ANNs models were statistically evaluated using all 138 data to obtain the overall predictive accuracy of the developed IRI ANNs model. The performance models were assessed using three standard methods R^2 Value, RMSE, and MAE. Table (4) summarizes the results of the ANNs technique. Figure (6) presents the ANN prediction results for IRI models. Table (4) presents R^2, RMSE and MAE values of the IRI model for the (12) flexible pavement sections in the dry climate regions in the U.S. The R^2 value was (96.8) %. The RMSE and MAE values for IRI are (0.087) and (0.071).

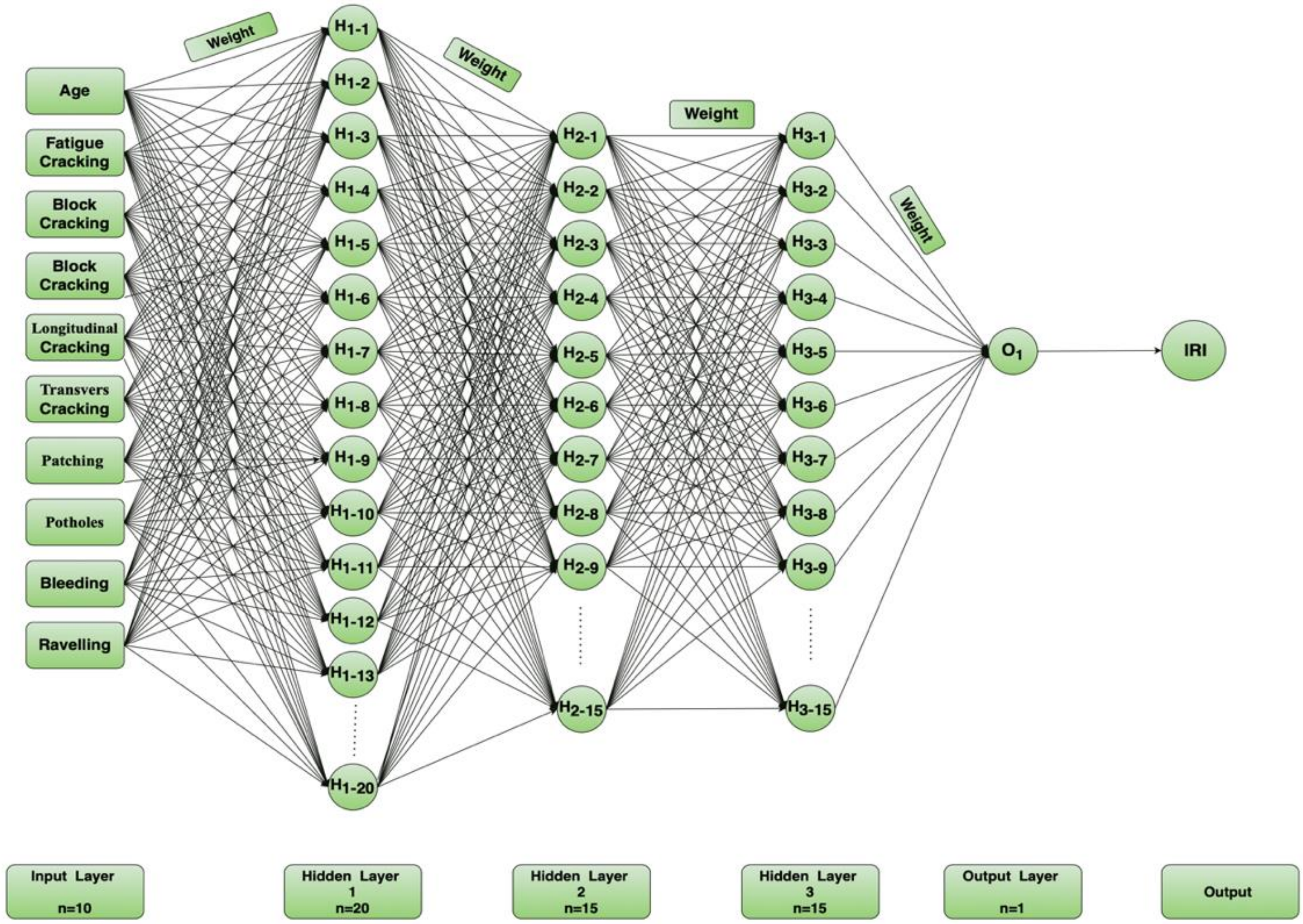

Fig.5 Neural network architecture.

Table 4: Performance of ANN model.

Procedure	**ANN Model**		
	R^2	**RMSE**	**MAE**
Training	93.8	0.112	0.089
Testing	97.8	0.073	0.065
Validation	98.6	0.021	0.015
All	96.8	0.087	0.071

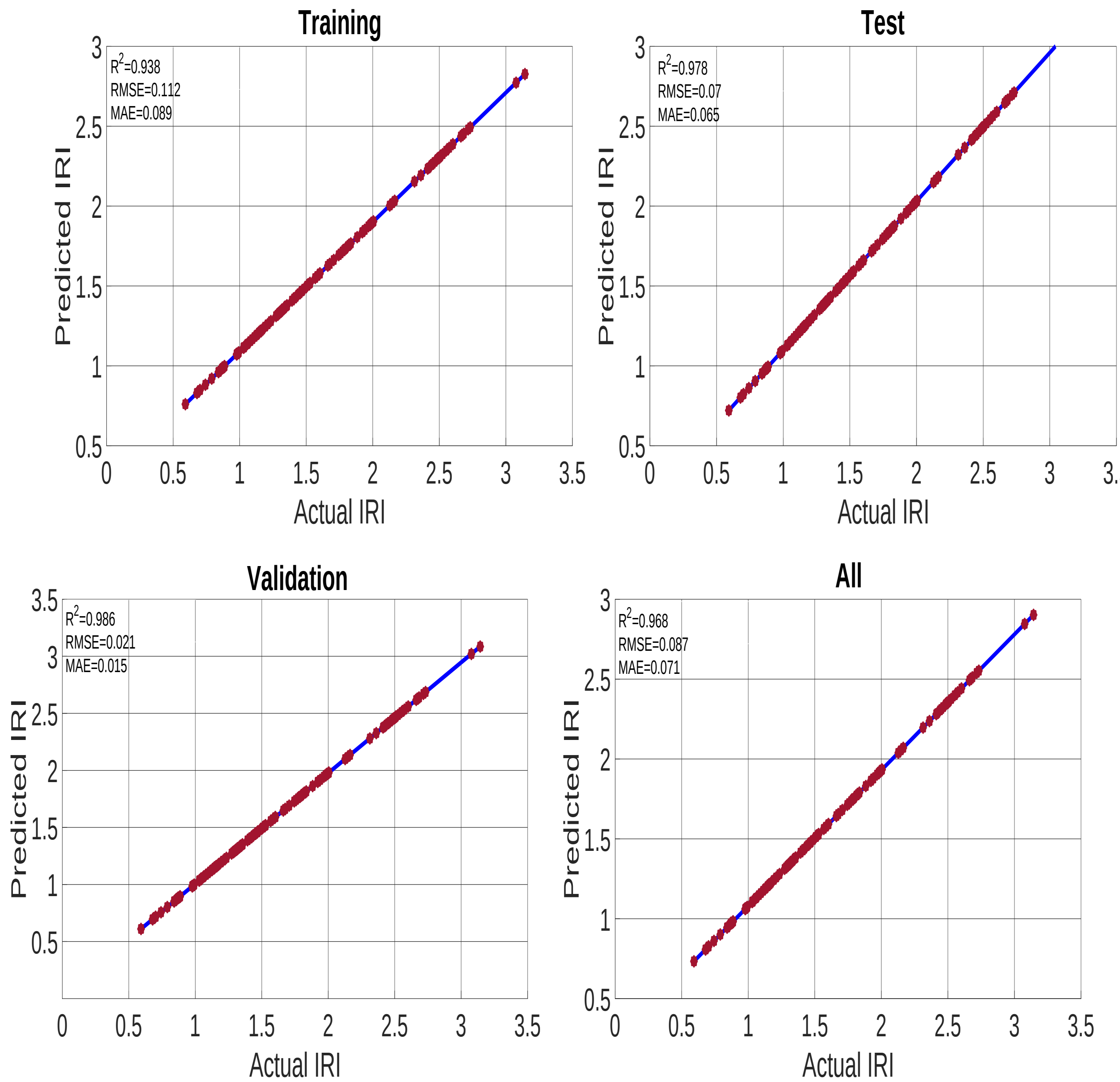

Fig.6 ANN prediction results.

6 Comparison of the MLR and ANN Generated Model

ANN model development was carried out using the same data used to develop the regression model. Comparing the ANN model to the MLR model, the ANN model fits better in the goodness of fit parameters, as shown in Table (5).

Table 5: Comparison between ANN and the MLR models.

Indicator	MLR Generated			ANN Generated			Improvement (%)		
	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE
IRI	63.8	0.35	0.26	96.8	0.087	0.071	34.09	75.14	72.7

Table (5) presents a comparison between MLR and ANN models and summarizes several points as follows:

- Prediction models using MLR and ANN techniques based on pavement distresses were developed in this study.
- ANN model provides more accurate predictions than the MLR model.
- Statistics showed that the R^2 value of the ANNs model is higher than the R^2value of the MLR model by **34.09%.**
- The RMSE value of the ANN model is less than the RMSE value of the MLR model by **75.14%.**
- The MAE value of the ANN model is less than the MAE value of the MLR model by **72.7%**.

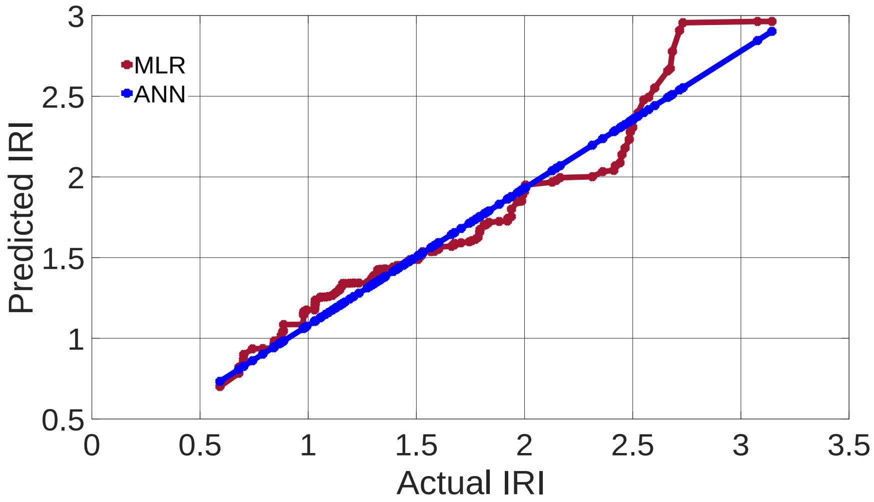

Fig.7 Comparison between the actual and predicted IRI using MLR and ANN models.

Several conclusions can be drawn from Figure (7):

- The MLR approach has a slight groove while ANN has a straight line, which explains why the ANN model tends to be more accurate.
- The Figure clearly shows that the ANN prediction model provided more accuracy than the MLR prediction model under different climate conditions.
- According to the results, MLR and ANN methods can predict the IRI models with reasonable accuracy.

7 Sensitivity Analysis

As a part of the IRI model evaluation, a sensitivity analysis was conducted to determine whether input variables positively or negatively affect the statistical prediction models. A backward elimination approach was used to determine the type of predictor (pavement distress) significantly affecting the dependent variable (IRI). All independent variables were included in the model, and the least essential variables were eliminated. The operation ends when the model does not contain any significant variables. Table (6) summarizes the results of the sensitivity analyses, and Figure (8) shows that graphically.

Table 6: Sensitivity analysis of prediction models.

Parameters	R^2
Age	49.8
Fatigue Cracking	-
Block Cracking	-
Edge Cracking	-
Longitudinal Cracking	25.7
Transverse Cracking	17.8
Patching	-
Potholes	-
Bleeding	-
Raveling	-

The following conclusions were drawn from Table (6) and Figure (8):

- Age of pavement is the variable that has the most significant effect on the prediction models compared to other variables.
- Longitudinal and transverse cracking have some influences on the prediction models compared to other variables.
- Fatigue cracking, block cracking, edge cracking, potholes, bleeding, and ravelling have no impact on the prediction model.

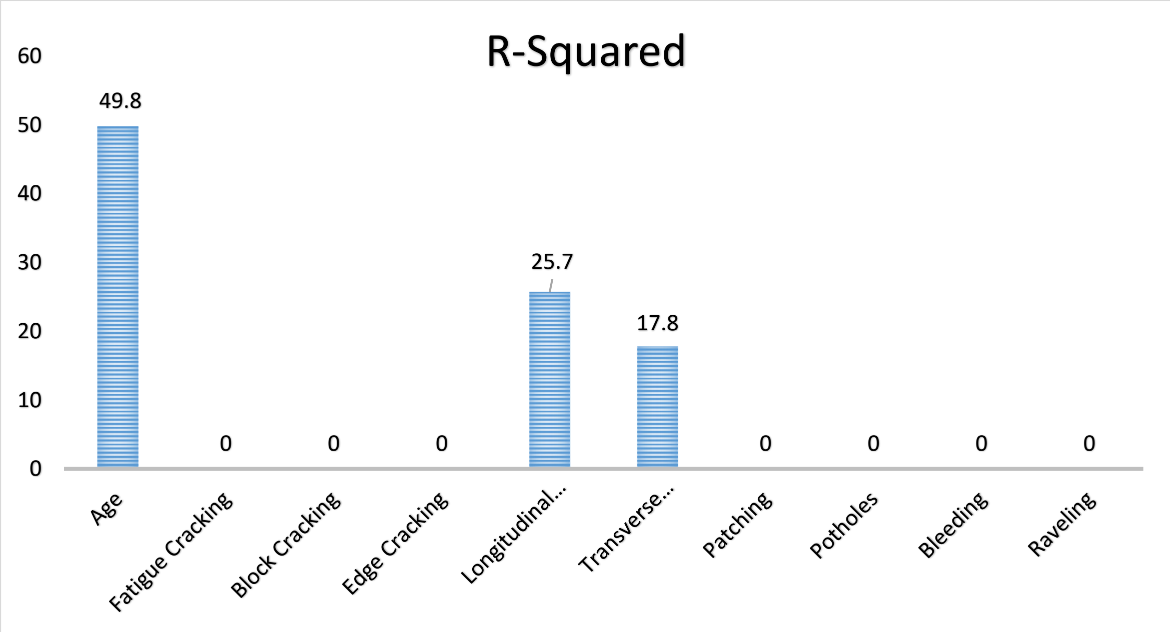

Fig.8 Sensitivity analysis of prediction models for IRI.

8 Conclusion

The authors of this paper proposed an approach to illustrate the theoretical relationship between (IRI) indicators in asphalt pavements and pavement distresses in a more precise and statistically reliable manner. The authors used soft computing such as MLR and ANN. This study investigates pavement distress parameters to predict the IRI of flexible pavements for dry freeze no regions. Several conclusions can be drawn from this study as follows:

- As part of the study, 12 road sections from an LTPP database (138 observations) and pavement distress data were collected, including fatigue block cracking, edge cracking, longitudinal cracking, transverse cracking, potholes, patching, bleeding, ravelling, and performance indicator data IRI.
- Results showed that the MLR model with 10 independent variables could predict pavement performance for dry no freeze climate regions, but the ANN models predicted the pavement condition with more accuracy, promising and lowest errors,
- This study concluded that pavement distress parameters helped predict IRI values.

9 Data Availability Statement

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

References

[1] Moazami D, Muniandy R, Hamid H, Yusoff ZH . "Developing a comprehensive pavement management system in Tehran, Iran using MicroPAVER." Electron. J. Geotech. Eng 15 (2010): 1782

[2] Sayers, M. W. "Transportation research record." Transp Res Rec1501 (1995): 1-12.

[3] ASTM International. "ASTM D6433-18 Standard Practice for Roads and Parking Lots Pavement Condition Index Surveys. (2018). " 10.1520/D6433-18, West Conshohocken, PA.

[4] Kavianipour, O., M. Montazeri-Gh, and M. Moazamizadeh. "Road profile measurement using the two degrees of freedom response-type mechanism." Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science 229.6 (2015): 1074-1087.

[5] Madanat, S. M., Ziad El Nakat, and Nakul Sathaye. "Development of empirical-mechanistic pavement performance models using data from the Washington State PMS database." (2005).

[6] Perera, R. W., and Starr D. Kohn. LTPP data analysis: Factors affecting pavement smoothness. Washington, DC: Transportation Research Board, National Research Council, 2001.

[7] Wen, Haifang. "Design factors affecting the initial roughness of asphalt pavements." International Journal of Pavement Research and Technology 4.5 (2011): 268.

[8] FHWA (Federal Highway Administration). What needs to be done? Rep. No.(2009) PHWA-HRT-09-052. Washington, DC: FHWA.

[9] Elbagalati, Omar, et al. "Development of an artificial neural network model to predict subgrade resilient modulus from continuous deflection testing." Canadian Journal of Civil Engineering 44.9 (2017): 700-706.

[10] El-Badawy, Sherif M., Ahmed M. Khattab, and Al Abbas Al Hazmi. "Using artificial neural networks (ANNs) for hot mix asphalt E* predictions." Geo-China (2016). 2016. 83-91.

[11] Ali, Abdualmtalab, et al. "Modeling pavement performance indices in harsh climate regions." Journal of Transportation Engineering, Part B: Pavements 147.4 (2021): 04021049.

[12] Chandra, Satish, et al. "Relationship between pavement roughness and distress parameters for Indian highways." Journal of transportation engineering 139.5 (2013): 467-475.

[13] Ceylan, Halil, Mustafa Birkan Bayrak, and Kasthurirangan Gopalakrishnan. "Neural Networks Applications in Pavement Engineering: A Recent Survey." International Journal of Pavement Research & Technology 7.6 (2014).

[14] Ye, Z., Xu, Y., Veneziano, D., & Shi, X. "Evaluation of winter maintenance chemicals and crashes with an artificial neural network." Transportation Research Record 2440.1 (2014): 43-50.

[15] (www.infopave.com).

[16] Guisan et al.. Effect of boundary layer conductance on the response of stomata to humidity. Plant, Cell & Environment, (2000) 8(1), 55–57. https://doi.org/10.1111/j.1365-3040.1985.tb01209.x