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Original Article

Predicting pavement condition index based on the utilization of machine learning techniques: A case study

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HIGHLIGHTS

- Pavement condition index is mainly used for automated data collection.
- Development models by using three techniques of a machine learning based model are used for the PCI.
- Validation of the developed PCI results for maintenance work between 2018 and 2021 affected road performance.
- Evaluating the performance model among the three techniques for the developed index compared to the PCI.

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ABSTRACT

Pavement management systems (PMS) are used by transportation government agencies to promote sustainable development and to keep road pavement conditions above the minimum performance levels at a reasonable cost. To accomplish this objective, the pavement condition is monitored to predict deterioration and determine the need for maintenance or rehabilitation at the appropriate time. The pavement condition index (PCI) is a commonly used metric to evaluate the pavement's performance. This research aims to create and evaluate prediction models for PCI values using multiple linear regression (MLR), artificial neural networks (ANN), and fuzzy logic inference (FIS) models for flexible pavement sections. The authors collected field data spans for 2018 and 2021. Eight pavement distress factors were considered inputs for predicting PCI values, such as rutting, fatigue cracking, block cracking, longitudinal cracking, transverse cracking, patching, potholes, and delamination. This study evaluates the performance of the three techniques based on the coefficient of determination, root mean squared error (RMSE), and mean absolute error (MAE). The results show that the R^2 values of the ANN models increased by 51.32%, 2.02%, 36.55%, and 3.02% compared to MLR and FIS (2018 and 2021). The error in the PCI values predicted by the ANN model was significantly lower than the errors in the prediction by the FIS and MLR models.

1. Introduction

1.1. Background

The pavement performance is determined by observing and recording the characteristics identified on the pavement surface and the structural condition. In addition, the pavement condition surveys are a comprehensive assessment of pavement conditions and are probably the first pavement management system (PMS) component adopted on a large scale by several factors which are including the types of pavement, traffic volume, climate, and pavement maintenance history (Shon et al., 2022). PMS utilizes traditional pavement management tools such as visual

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inspections, pavement condition surveys, and pavement distresses to assess the overall performance of a pavement system. It generates the data required to make decisions regarding the pavement network's preservation (Heidari et al., 2018). The distresses caused by heavy traffic result in structural failure of the pavement, and functional failure occurs when pavements fail to provide a smooth riding surface. Uneven pavement causes driver and passenger discomfort and increases vehicle operating costs (Lu and Tolliver, 2012). The factors considered when assessing pavement condition and serviceability include the present serviceability index (PSI), pavement condition index (PCI) and international roughness index (IRI) (Abu Dabous et al., 2021; Al-Omari and Darter, 1994; Shah et al., 2013). Several studies have developed the index for evaluating concrete pavement conditions, such as PCI, IRI, PSI and PSR. These indices require converting the pavement distress data into a more practical index since PCI is the most common index for pavement evaluation based on visual observation and inspection (Haas et al., 1994; Kulkarni and Miller, 2003). Therefore, it is a widely used measure of pavement performance, and it is used to evaluate the need for maintenance and rehabilitation investments. The PCI is calculated using a combination of visual assessments, laboratory tests, and other measurements of pavement distress, such as cracking, rutting, skidding, and surface defects. In addition, it can assess the performance of pavement materials and designs, identify pavement maintenance needs, and prioritize pavement rehabilitation projects (Shahnazari et al., 2012).

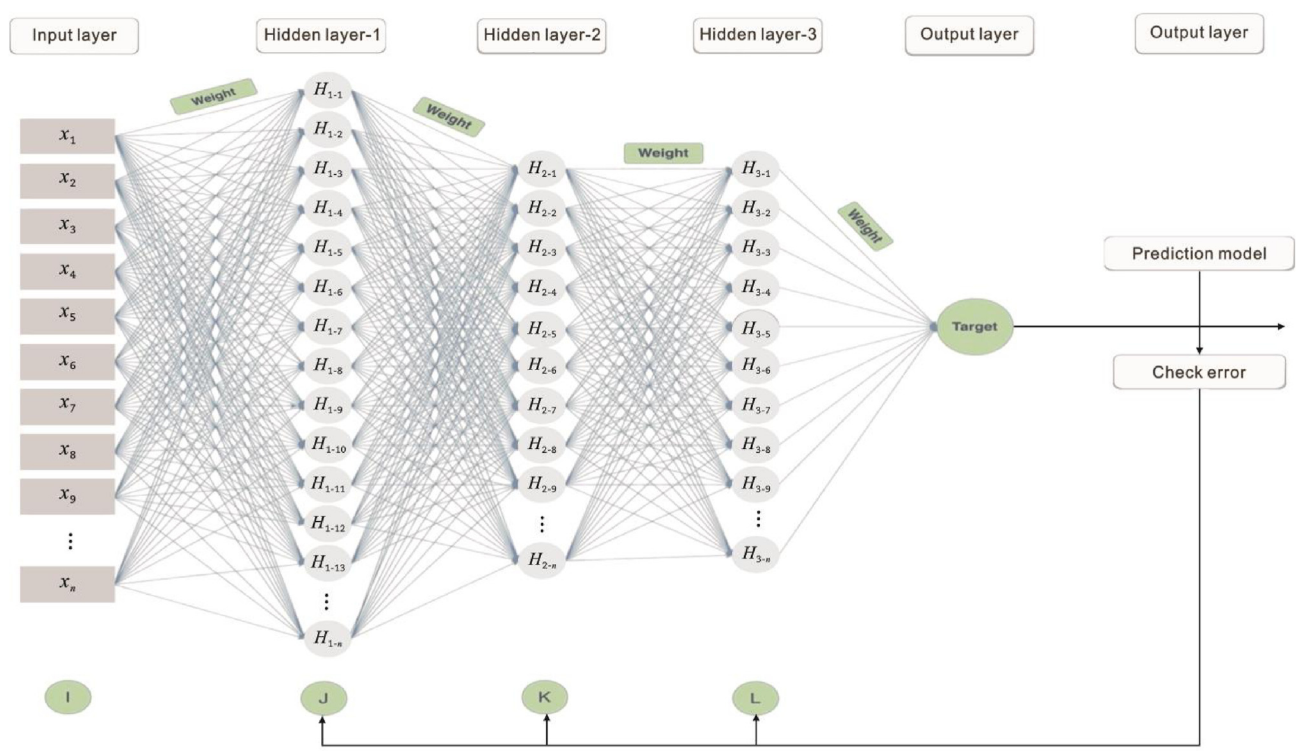

Fig. 1. Schematic representation of ANNs.

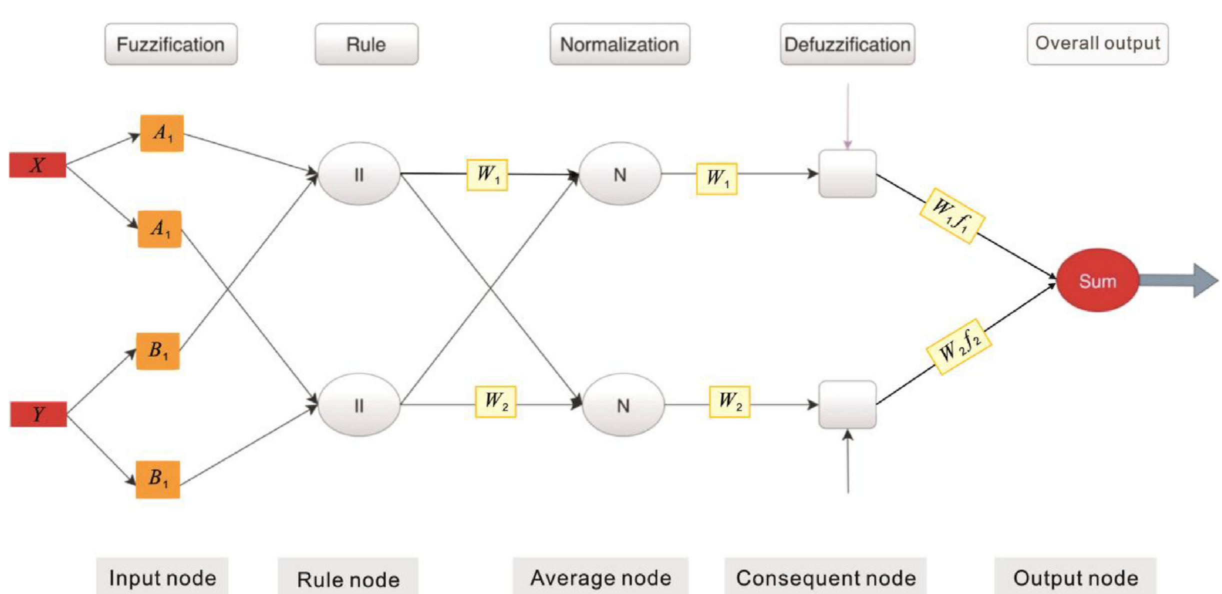

Fig. 2. Schematic representation of a fuzzy system.

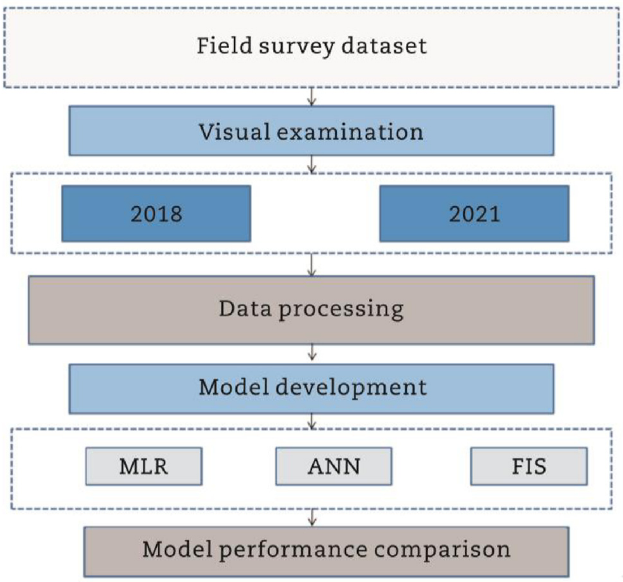

Fig. 3. The framework for model development.

1.2. Literature review

In order to achieve the challenges of computer vision algorithms that use machine learning models, an alternative to traditional techniques has been proposed for pavement performance. In fact, recent progress in machine learning has led to substantial improvements in our ability to analyze huge amounts of data concerned with preserving their valuable road assets for a longer period of time in order to save on maintenance costs. However, Basheer and Maha (2000) stated that ANN models could solve many problems because they use a learning algorithm to process unknown input patterns. Unlike traditional statistics, ANN models do not require a linearity assumption by detecting the similarities and differences between inputs. ANN models can use unsupervised learning to assign similar patterns to the same clusters, and multilinear ANN models can determine the relationship between the input and output data. Adeli (2001) published an extensive review of the neural network model from 1989 to 2000 and contended that ANN models are suitable for modelling complex problems in structural engineering, construction engineering and management.

Terzi (2007) pointed out that predicting the PSI for pavement distress is possible and used the ANN and multiple regression models to predict the stress intensity factors in pavement cracks. Civil engineering researchers who used ANN models in their studies have achieved good outcomes (Karlaftis and Vlahogianni, 2011). Shahnazari et al. (2012) examined a 1250-km national highway in Iran to predict PCI using ANN and genetic programming (GP). The ANN model produced more robust and accurate results than the GP-based model. The results demonstrated that ANN outperformed several regression models in prediction accuracy (Wu et al., 2014). Ceylan et al. (2014) summarised an extensive review of the implementation of artificial neural networks (ANN) in pavement engineering. They focused on specific subjects concerning new challenges and changing situations. Kırbaş and Karaşahin (2016) demonstrated that the ANN-based model performed better than the multivariate adaptive regression splines (MARS) and regression analysis in predicting PCI value. Plati et al. (2016) used ANNs and falling weight deflectometer (FWD) data to assess pavement structural conditions and found that they predicted pavement conditions accurately. Predicting pavement performance were through the use of regression models based on machine learning techniques to assess and diagnose pavement problems and recommend the most appropriate maintenance action for road pavement surfaces (Suh et al., 2017; Yang et al., 2021).

Golshani et al. (2018) compared the predictive effectiveness of traditional statistical models and neural network models for modelling two critical trip-related decisions, travel mode and departure time. Their study revealed that neural network models performed better and were easier and faster to implement. Gong et al. (2018) investigated IRI prediction using the data for pavement structure, traffic, climate conditions and surface. Compared to the linear regression model, the RF has better predictive performance coefficients of determination (R^2) greater than 0.95 in training and testing.

1.3. Motivation of research

Based on the literature review showed that a number of studies succeeded in using machine learning techniques and IRI values to predict PCI values. For instance, the LTPP database does not include the PCI values, the world's largest road performance database (Cao et al., 2022; Chen et al., 2022; Kargah-Ostadi et al., 2010; Mazari and Rodriguez, 2016; Morris and Yang, 2021; Piryonesi and El-Diraby, 2018). Nabipour et al. (2019) employed the support vector machine (SVM) and genetic expression programming (GEP) methods to predict the remaining service life (RSL) of pavements. Imam et al. (2021) used gene expression programming (GEP) to predict PCI by employing the IRI. Several researchers investigated pavement distress using machine learning techniques such as SVM, ANN, RF, radial basis function neural network (RBFNN), the naive Bayesian classifier (NBC), classification tree (CT) and image

Table 1
Details of the study section.

Geometric type	Road name	Starting coordinate	Ending coordinate	Length (m)
Highway (divided)	Trans-Canada highway	47.613080, −52.693132	47.572898, −52.778936	8600
Urban (divided)	Prince Philip Dr	47.588916, −52.720251	47.561888, −52.749006	3900
	Portugal Cove Rd	47.595724, −52.726608	47.609546, −52.765798	3800
Urban (undivided)	Kenmount Rd	47.563756, −52.739265	47.586281, −52.708537	3500
	Elizabeth Ave Rd	47.560475, −52.749060	47.533357, −52.831811	7000
	Torbay Rd	47.599852, −52.711999	47.638361, −52.724715	4500
	Blackhead Rd	47.598178, −52.698031	47.581270, −52.704083	2000
	Logy Bay Rd	47.580354, −52.704381	47.571455, −52.701725	1000
	Kenna's Hill	47.570864, −52.697512	47.562220, −52.709403	1300
	Water St	47.577570, −52.703921	47.571912, −52.701928	1000
	King's Bridge Rd	47.539661, −52.712965	47.522431, −52.660019	8200
	Newfoundland Dr	47.595526, −52.725829	47.591908, −52.687005	3600
	Newtown Rd	47.569411, −52.731490	47.566484, −52.716049	1300
	Freshwater Rd	47.563767, −52.717459	47.561518, −52.745447	2200
	MacDonald Dr	47.590916, −52.718891	47.593944, −52.701323	1400
	Aberdeen Ave	47.619806, −52.718596	47.612738, −52.711725	1000
	Empire Ave	47.572286, −52.713828	47.565904, −52.729028	1400
	The Blvd	47.577727, −52.703588	47.584444, −52.684521	1600
	Highland Dr	47.604463, −52.717754	47.610121, −52.708517	1000

processing techniques. Other studies used GPR, SVM, ensemble, ANN and regression tree approaches to model pavement performance (Hoang and Nguyen, 2018, 2019; Hoang et al., 2019; Waseem et al., 2019; Yamany et al., 2019; Zeiada et al., 2020). In their study published in 2021, Yu et al. (2021) examined the potential of a support vector machine (SVM) to predict back-break caused by blasting and random forest (RF) technique for important parameter selection to predict the back break. Emad et al. (2022) investigated the use of four soft computing techniques, namely pure quadratic, nonlinear relationship (NLR), artificial neural networks (ANNs), and M5P-tree (M5P) to predict the compressive strength of ultra-high performance fibre reinforced concrete (UHPFRC). Therefore, the motivation for utilizing ANN and ANFIS in this study is to understand the complicated modelling of the predictor and dependent variable relationships (Abdolrasol et al., 2021). Several countries adopted the PCI developed by the United States Army Corps of Engineers in pavement condition and performance assessment. The U.S. Department of Defense (DOD) and the American Public Works Association adopted a pavement condition indicator (ASTM, 2018; Shahin and Walther, 1990). Furthermore, the literature review of the existing PCI prediction models for asphalt pavement revealed that.

Table 2
PCI determination based on pavement distresses.

Elizabeth Ave Road	Type of distress	Rutting	Block cracking	Fatigue cracking	Longitudinal cracking	Transverse cracking	Delamination	Pothole	Patching
	Unit	mm	m^2	m^2	m^2	m^2	m^2	No.	m^2
Section: I (1440 m^2)	Quantity	4.80	0	2.00	26.00	0	18.00	5.00	118.00
	Severity	Mb	Mb	–	Lc	–	Ha	Lc	Mb
	Density (%)	0.33	0	0.14	1.81	0	1.25	0.35	8.19
	Deduct value	5	0	4	22	0	9	38	41
	Total deduct value	118							
	Corrected deduct value	80							
	PCI (%)	100−80 = 20 (very poor)							
Section: II (1440 m^2)	Quantity	4.4	0	1.5	47.5	0	13.5	7.0	96.0
	Severity	Mb	Lc	–	Mb	–	Mb	Lc	Mb
	Density (%)	0.3	0	0.1	3.3	0	0.9	0.5	6.7
	Deduct value	10.0	0	4.0	28.0	0	16.0	41.0	37.0
	Total deduct value	136							
	Corrected deduct value	88							
	PCI (%)	100−88 = 12 (very poor)							

Note: Ha means high severity, Mb means medium severity, Lc means low severity.

Table 3
Gathered pavement distress data for 2018 and 2021 (37 sections).

Parameter	2018					2021				
	Range		Mean		Std. deviation	Range		Mean		Std. deviation
	Minimum	Maximum	Statistic	Std. error		Minimum	Maximum	Statistic	Std. error	
Rutting (mm)	2.2	35.0	8.7	1.8	7.8	3.0	33.0	8.8	1.6	6.8
Fatigue cracking (m^2)	0.0	7.0	2.1	0.4	1.9	0.0	8.2	2.4	0.6	2.4
Block cracking (m^2)	0.0	5.0	0.9	0.4	1.6	0.0	4.0	0.6	0.3	1.2
Longitudinal cracking (m^2)	6.2	43.0	16.9	2.1	9.4	5.8	47.5	18.8	2.5	10.4
Transverse cracking (m^2)	0.0	23.5	5.0	1.8	7.7	0.0	33.0	3.2	1.9	8.0
Patching (m^2)	0.0	36.0	5.2	1.8	7.7	0.0	7.0	3.8	0.5	2.0
Pothole	0.0	235.0	63.0	14.2	61.8	0.0	121.0	51.0	8.4	35.6
Delamination (m^2)	0.0	18.0	5.5	1.3	5.7	0.0	16.5	5.7	1.4	5.8
PCI (%)	13.0	75.0	41.4	4.3	18.7	11.0	74.0	43.6	4.5	18.9

Table 4
The PCI models based on the surface pavement distress data.

Model	2018				2021			
	Unstandardised coefficient		Standardised coefficient (Beta)	*t*-stat	Unstandardised coefficient		Standardised coefficient	*t*-stat
	B	Std. error			Std. error	Beta	B	
Constant	39.73	7.675	–	5.851	36.29	6.786	–	6.458
Rutting	0.84	0.495	0.325	1.689	0.972	0.437	0.298	1.550
Fatigue cracking	1.24	1.714	0.147	0.744	1.367	1.515	0.236	1.189
Block cracking	0.04	2.457	−0.004	−0.021	−0.161	2.172	−0.102	−0.546
Longitudinal cracking	−0.10	0.313	−0.065	−0.392	0.628	0.277	0.021	0.125
Transverse cracking	0.10	0.352	0.046	0.314	−0.975	0.312	−0.133	−0.899
Patching	−0.08	0.061	−0.223	−1.342	0.036	0.054	−0.154	−0.926
Pothole	0.22	0.470	0.063	0.441	−0.008	0.416	−0.048	−0.337
Delamination	−1.29	0.593	−0.384	−2.124	−2.552	0.524	−0.421	−2.324
R-squared (*p*-value)	0.48 (0.05)				0.63 (0.05)			
RMSE	14.051				9.932			
MAE	11.368				7.844			

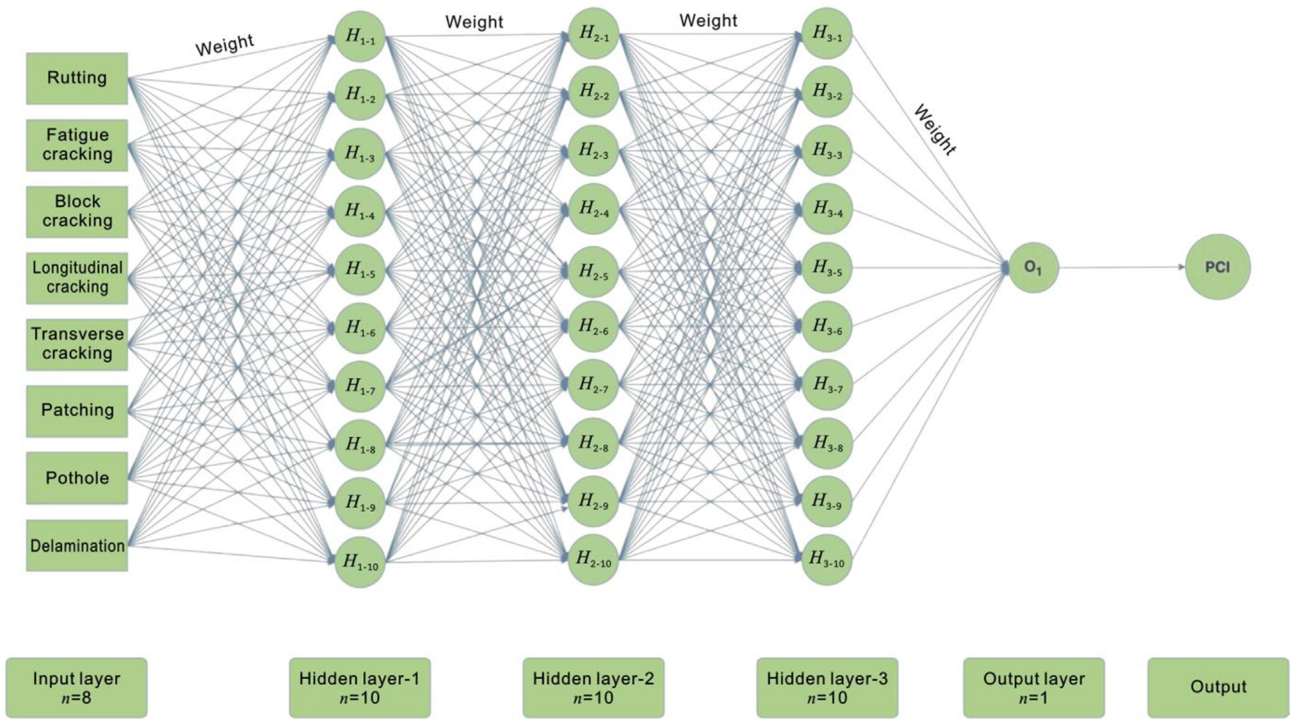

Fig. 4. Architecture of the ANNs model (Model B).

- ML models provided good performance in predicting pavement condition index.
- The relationship between PCI and pavement distresses provided reasonable and effective methods to estimate PCI.
- Many of these models were created using a limited database, making them unsuitable worldwide.

1.4. Objective of the research

This study aims to develop a model for predicting asphalt pavement conditions based on several factors, such as type of distress, quantity, severity, density (%), and deduct value. The data was collected from the field surveys conducted in St. John's, Newfoundland, Canada, over the last few years. This data will then be used to train a machine learning algorithm to predict the PCI accurately. In addition, this study could be used to help pavement engineers better assess pavement conditions and make better decisions on the maintenance and repair of existing pavements.

2. Applications of machine learning models

2.1. Multiple linear regression

MLR is a popular technique for examining the relationship between the input and output variables. A classic regression approach is a comprehensive tool for assessing the input and output parameter correlations. Because collinearity between variables can cause inaccurate predictions, Sousa et al. (2007) assumed that the error values are independent across the observations. One of the most often used statistical techniques is linear regression (Bunce, 1985). The following Equation is the traditional linear regression model.

$$Y = C + a_1X_1 + a_2X_2 + \cdots + a_nX_n \tag{1}$$

where Y is dependent variable, C is constant, X is independent variable ($X = X_1, X_2, \cdots, X_n$), and $a_1, a_2, \cdots, a_n$ are coefficients.

Table 5
Summary of the PCI models of the developed ANNs models.

ANN model	2018			2021		
	R^2 (%)	RMSE (%)	MAE (%)	R^2 (%)	RMSE (%)	MAE (%)
8-8-8-8-1-1 (Model A)	97.5	1.490	2.230	97.3	2.480	2.112
8-10-10-10-1-1 (Model B)	98.6	0.888	0.734	99.3	0.720	0.592
8-20-10-10-1-1 (Model C)	96.8	2.872	2.731	97.1	2.673	2.267

2.2. Artificial neural network

ANNs are computational models inspired by the biological characteristics of the brain. They can approximate and estimate functions

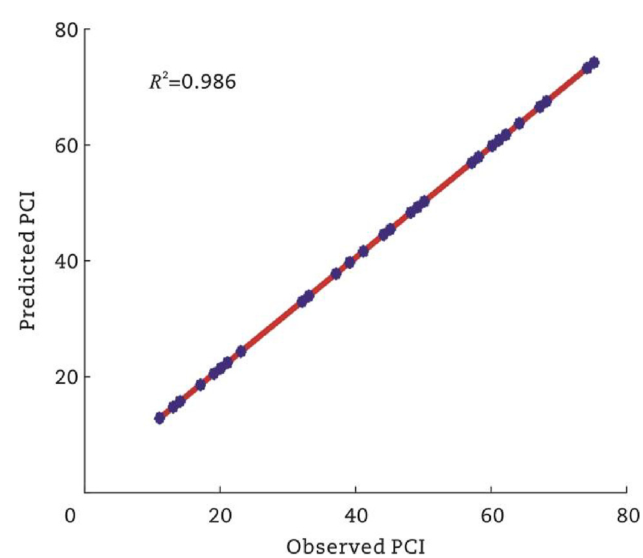

Fig. 5. The goodness-of-fit for PCI values by the ANN model (2018).

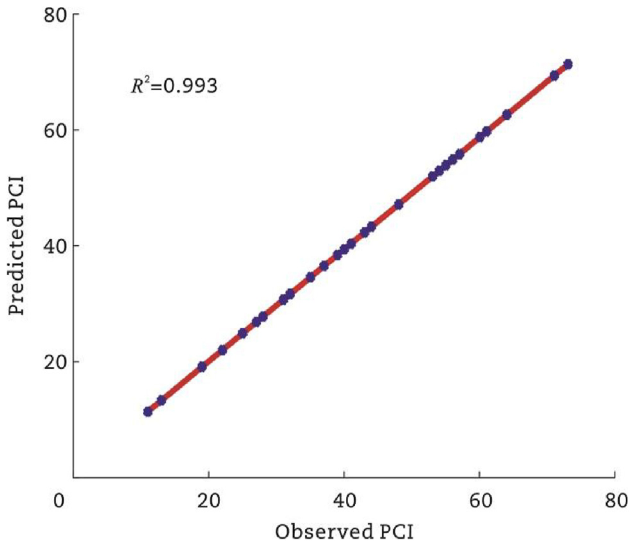

Fig. 6. The goodness-of-fit for PCI values by the ANN model (2021).

by using many different independent values. A vital feature of these techniques is that they can solve complicated problems using simple mathematical procedures (Graupe, 2013). ANN models solve optimization problems efficiently by maximizing or minimizing an objective function subject to constraints. Fig. 1 shows that these layers comprise the input layer, several hidden layers, and an output layer. Each neuron in the ANN functions as a processing unit that receives inputs and passes the output to the following layer (Huang and Moore, 1997). The neurons in one layer are linked to the neurons in the next layer. ANN's nonlinear relationship between input and output layers necessitates using a function to establish a link between the neurons. Three transfer functions, log-sigmoid, tan-sigmoid and linear, provide the computation between the neurons of different layers (Demuth and Beale et al., 1992). The following equations expressed the functions in Eqs. (2)–(4).

$$\mathrm{logsig}(x)=\frac{1}{1+\mathrm{e}^{-x}} \tag{2}$$

$$\mathrm{tansig}(x)=\frac{2}{1+\mathrm{e}^{-2x}}-1 \tag{3}$$

$$\mathrm{purelin}(x)=x \tag{4}$$

The processing of each neuron is a weighted summation transferred via the activation function given by Eq. (5).

$$Y_j=f\sum_{i=1}^{n}x_iw_{ij} \tag{5}$$

where Y_j is the output of jth neuron, f is the activation function, n is the number of inputs in this layer, x_i is the ith input, and w_{ij} is the connection weight between the ith input and the neuron.

2.3. Fuzzy inference system (FIS)

The term fuzzy means a lack of clarity, and the fuzziness is due to using a complex mathematical pattern to model the most similar human inference. A fuzzy system is a system that converts human knowledge into mathematical formulas using linguistic variables, the "if-then" fuzzy rules, and a mapping system (fuzzy engine). Fuzzy systems are based on knowledge and rules (McNeill and Thro, 2014). The core of a fuzzy system is a knowledge base of fuzzy "if-then" rules. The first step in developing a fuzzy system is collecting a set of fuzzy "if-then" rules from expert knowledge or studying the relevant literature and converting the rules into mathematical forms (Moazami et al., 2011). Fuzzy logic is an approach for dealing with uncertainties in a model or data. Fuzzy inference systems use fuzzy rules known as fuzzy "if-then" rules. Fuzzy inference systems are also known as fuzzy models, fuzzy associative memory and fuzzy logic controller (Jang et al., 1997). To provide a scheme for handling diverse problems. The inference under consideration employs the fuzzy set operations obtained by generalizing the classical set operations. Fig. 2 illustrates the five layers of a general fuzzy system. The FIS structure comprises the following five layers (Zadeh, 1965).

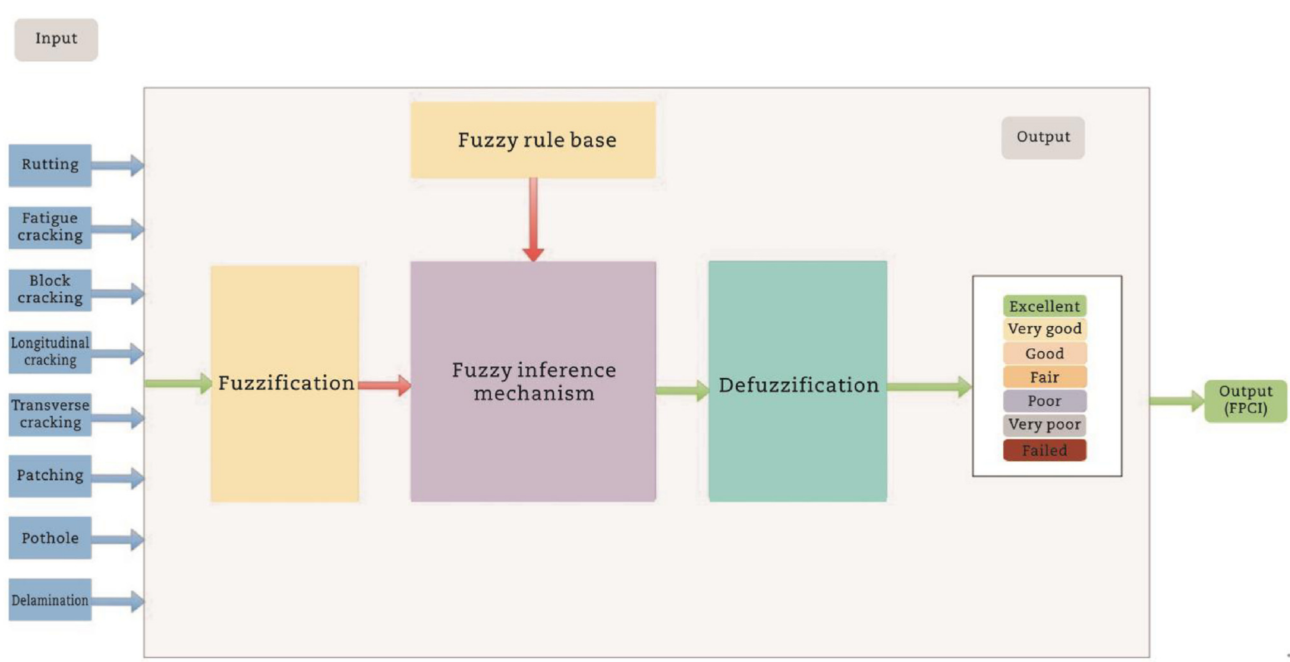

Fig. 7. Diagram of the pavement classification in FIS.

Table 6
The distresses and the number of membership functions for evaluating the PCI.

Distress	Category	M.F.	Description
Rutting	Input	Minimal, moderate, severe	Extremely important
Fatigue cracking	Input	Minimal, moderate, severe	Relatively important
Block cracking	Input	Minimal, moderate, severe	Important
Longitudinal cracking	Input	Minimal, moderate, severe	Important
Transverse cracking	Input	Minimal, moderate, severe	Moderately important
Patching	Input	Minimal, moderate, severe	Moderately important
Pothole	Input	Minimal, moderate, severe	Relatively important
Delamination	Input	Minimal, moderate, severe	Relatively important
PCI	Output	Failed, very poor, poor, fair, good, very good, excellent	Extremely important

(1) The fuzzification layer is made up of the input parameters' membership functions (Manogaran et al., 2018).

$$\mu_{Ai}(x) = \exp\left(-\left(\frac{x-c_i}{2\delta_i^2}\right)^2\right) \tag{6}$$

where c_i and δ_i are the parameters of a membership function.

(2) The rule layer applies the fuzzy AND to the previous fuzzy rule.

$$\omega_i = \mu_{Ai}(x)\ \mu_{Bi}(x) \tag{7}$$

where Ai and Bi are the fuzzy sets.

(3) The normalization layer normalizes the membership functions.

$$\overline{\omega_i} = \frac{\omega_i}{\sum_i \omega_i} \tag{8}$$

(4) The defuzzification layer applies the outcome of the fuzzy rules.

$$\overline{\omega_i} f_i = \overline{\omega_i}(p_i x + q_i y + r_i) \tag{9}$$

where p_i, q_i, and r_i are linear variables, f_i $(i = 1, 2)$ are the outputs within the fuzzy region specified by the fuzzy rules.

(5) The output layer is calculated by summing the outputs of previous layers.

$$\sum_i \overline{\omega_i} f_i = \frac{\sum_i \overline{\omega_i} f_i}{\sum_i \omega_i} \tag{10}$$

2.4. Assessment of the developed models

The researchers compared the predicted PCI values with the observed values to determine the strengths and weaknesses of the models developed using MLR, ANNs, FIS, and the coefficient of determination (R^2), root mean squared error (RMSE), and mean absolute error (MAE). The mathematical representations for the measurements are as follows.

$$R^2 = 1 - \frac{\sum_i (t_i - o_i)^2}{\sum_i {o_i}^2} \tag{11}$$

$$\text{MAE} = \frac{1}{n}\sum_i^n |t_i - o_i| \tag{12}$$

$$\text{RMSE} = \sqrt{\frac{\sum_i (t_i - o_i)^2}{n}} \tag{13}$$

where o_i is the actual value for observation i, t_i is the predicted value for observation i, and n is the number of observations.

Table 7
The rules generation for the FIS technique.

Rule No	Distress type (input)								PCI (output)
	Rutting	Fatigue cracking	Block cracking	Longitudinal cracking	Transverse cracking	Patching	Pothole	Delamination	
1	Minimal	Minimal	Minimal	Minimal	Minimal	Minimal	Minimal	Minimal	Excellent
2	Minimal	Minimal	Minimal	Moderate	Minimal	Minimal	Minimal	Minimal	Excellent
3	Minimal	Minimal	Minimal	Severe	Minimal	Minimal	Minimal	Minimal	Very good
4	Minimal	Minimal	Minimal	Minimal	Severe	Minimal	Minimal	Minimal	Good
5	Minimal	Severe	Minimal	Moderate	Minimal	Minimal	Minimal	Minimal	Good
6	Minimal	Moderate	Minimal	Minimal	Severe	Minimal	Minimal	Minimal	Good
7	Minimal	Moderate	Minimal	Minimal	Minimal	Minimal	Minimal	Minimal	Good
8	Moderate	Minimal	Minimal	Minimal	Minimal	Minimal	Minimal	Minimal	Good
9	Minimal	Moderate	Minimal	Moderate	Severe	Minimal	Minimal	Moderate	Good
10	Minimal	Moderate	Minimal	Moderate	Minimal	Minimal	Minimal	Minimal	Fair
11	Minimal	Minimal	Minimal	Moderate	Moderate	Minimal	Minimal	Minimal	Fair
12	Minimal	Severe	Minimal	Minimal	Minimal	Minimal	Minimal	Moderate	Fair
13	Severe	Moderate	Minimal	Minimal	Minimal	Minimal	Minimal	Minimal	Poor
14	Minimal	Severe	Minimal	Minimal	Moderate	Minimal	Minimal	Minimal	Poor
15	Minimal	Moderate	Minimal	Minimal	Minimal	Moderate	Minimal	Minimal	Poor
16	Minimal	Minimal	Minimal	Moderate	Severe	Minimal	Minimal	Minimal	Poor
17	Minimal	Minimal	Minimal	Moderate	Moderate	Minimal	Minimal	Minimal	Very poor
18	Moderate	Moderate	Minimal	Minimal	Moderate	Minimal	Minimal	Moderate	Very poor
19	Minimal	Moderate	Minimal	Moderate	Severe	Minimal	Minimal	Moderate	Very poor
20	Moderate	Minimal	Minimal	Minimal	Moderate	Minimal	Minimal	Minimal	Very poor
21	Moderate	Severe	Minimal	Severe	Severe	Minimal	Minimal	Moderate	Very poor
22	Minimal	Moderate	Minimal	Moderate	Moderate	Minimal	Minimal	Minimal	Very poor
23	Moderate	Minimal	Minimal	Severe	Severe	Minimal	Minimal	Minimal	Very poor
24	Minimal	Moderate	Minimal	Minimal	Moderate	Minimal	Minimal	Minimal	Failed
25	Minimal	Severe	Minimal	Moderate	Severe	Minimal	Minimal	Minimal	Failed
26	Moderate	Moderate	Minimal	Moderate	Severe	Minimal	Minimal	Minimal	Failed
27	Severe	Severe	Minimal	Moderate	Moderate	Minimal	Minimal	Moderate	Failed

Table 8
Assessment of the fuzzy inference system configurations for 19 sections.

Inference	Year	Defuzzification	Statistical error measure			Improvement		
			R^2 (%)	RMSE (%)	MAE (%)	R^2 (%)	RMSE (%)	MAE (%)
Mamdani (triangular)	2018	Centroid	96.6[a]	3.456[a]	2.919[a]	–	–	–
		Bisector	96.6	3.652	3.149	–	–	–
		LOM	96.1	4.136	3.541	–	–	–
		SOM	95.9	4.751	3.595	–	–	–
	2021	Centroid	96.3	3.468	2.917	−0.31	−0.35	−0.07
		Bisector	96.0	3.680	3.167	−0.62	−0.76	−0.57
		LOM	96.1	4.110	3.500	0.00	0.63	1.58
		SOM	95.5	4.805	3.639	−0.42	1.19	−1.21

Note: [a] the best results for each fuzzy system in the column.

3. Model development

The model development comprises collecting the pavement distress parameters, analyzing the data using the developed techniques and comparing their performance. The performance indicator is the PCI. The study considered eight pavement distresses in the analysis and modelling. Fig. 3 shows the framework for the model development.

3.1. Visual examination and data processing

The data acquisition comprises visual (human-based), automated, and semi-automated methods (Abou Chacra and Zelek, 2017; Sholevar et al., 2022). The surveys were carried out on 19 asphalt concrete pavements in St. John's, which stretch 58 km and comprise nine major roads (36.2 km), eight minor roads (13.5 km), and one highway (8.6 km).

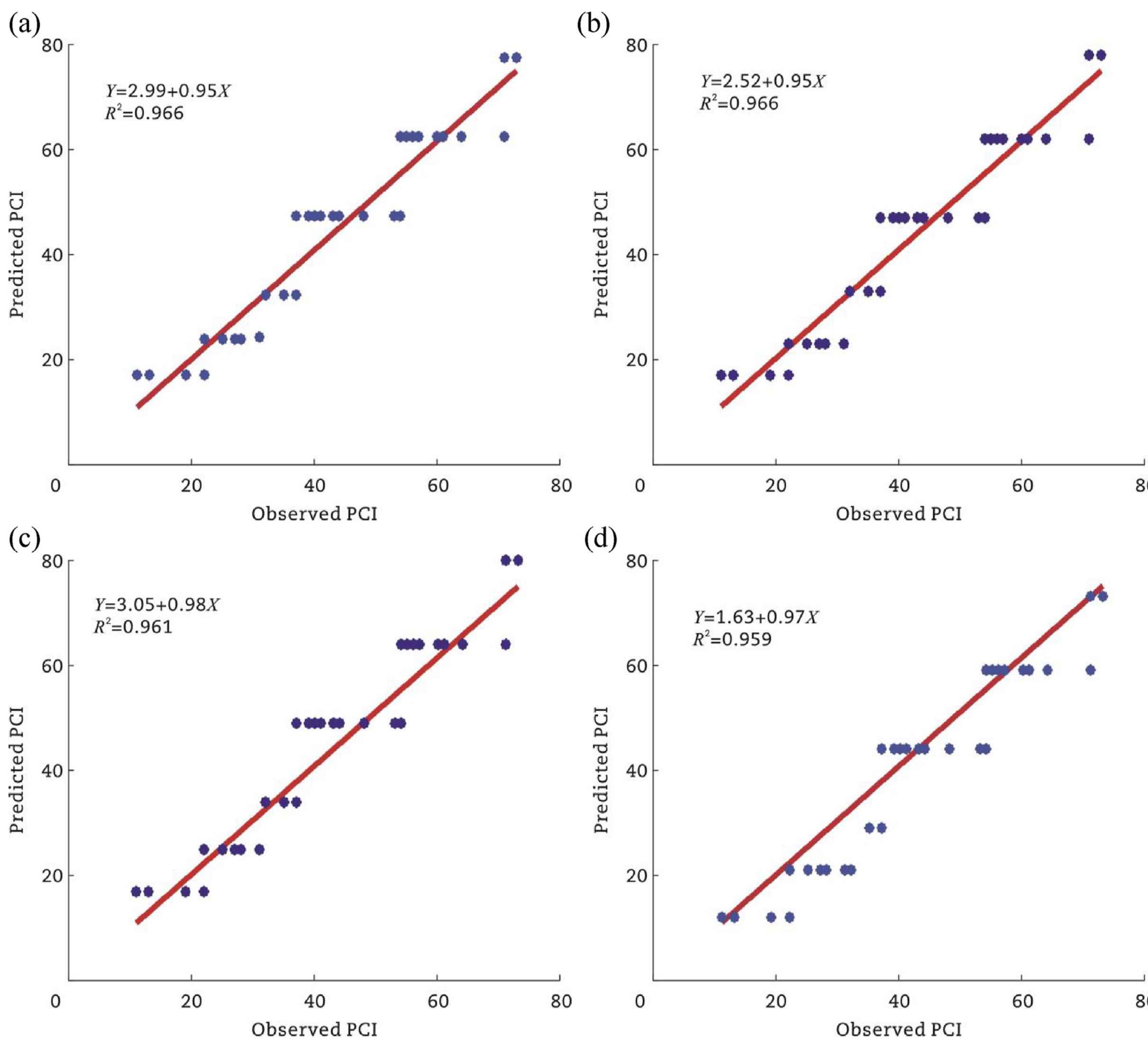

Fig. 8. Performance of the fuzzy inference system (2018). (a) Centroid. (b) Bisector. (c) LOM. (d) SOM.

The visual examination is used to obtain the PCI values for St. John's roads, which experience severe structural and functional distress. The researchers carried out the visual examination in two stages. In the first stage, the researchers drove along the major and local roads and took photos and videos of the road surfaces used to process and assess pavement performance. In the second stage, the survey team went to selected road sections for a closer examination of the road sections and collected data on their conditions. Developing improved prediction models classified and rated the distress types and severity. The researchers used the ASTM D6433-18 standard to determine the PCI values. Table 1 summarises the characteristics of the St. John's road network, and Table 2 presents the calculated PCI values for Elizabeth Ave Road. Table 3 presents the gathered pavement distress data for 2018 and 2021.

Ali et al. (2021) published the findings of a distress survey of various road segments in St. John's. Ali et al. (2018) did not consider the road examined, and presented their findings at the 2018 Canadian Society for Civil Engineering (CSCE) conference.

3.2. MLR model development

This study used MLR to determine the association between the pavement distress variables and the asphalt pavement performance index. The researchers used the survey data for 19 road sections and the MLR technique to develop two prediction models and the IBM SPSS Statistics package (IBM 27) to analyze the data. Eq. (14) gives the formula for determining how the pavement distress characteristics affect the PCI prediction models.

$$\mathrm{PCI} = C + a_1X_{\mathrm{age}} + a_2X_1 + a_3X_2 + a_4X_3 + a_5X_4 + a_6X_5 + a_7X_6 + a_8X_7 + a_9X_8 \tag{14}$$

where C is constant, X_1 is rutting, X_2 is fatigue cracking, X_3 is block cracking, X_4 is longitudinal cracking, X_5 is transverse cracking, X_6 is patching, X_7 is potholes, X_8 is delamination, and $a_1, a_2, \cdots, a_9$ are coefficients.

The input factors are eight surface pavement distresses, namely rutting, fatigue cracking, block cracking, longitudinal cracking, transverse cracking, potholes, patching, and delamination and output variable.

- **MLR (2018)**

Table 4 shows the PCI regression models developed using surface pavement distress data. The PCI (2018) model was negatively associated with rutting, fatigue cracking, block cracking, transverse cracking and potholes but positively correlated with longitudinal cracking, patching, and delamination. Eq. (15) describes the relationship between PCI and surface pavement distress.

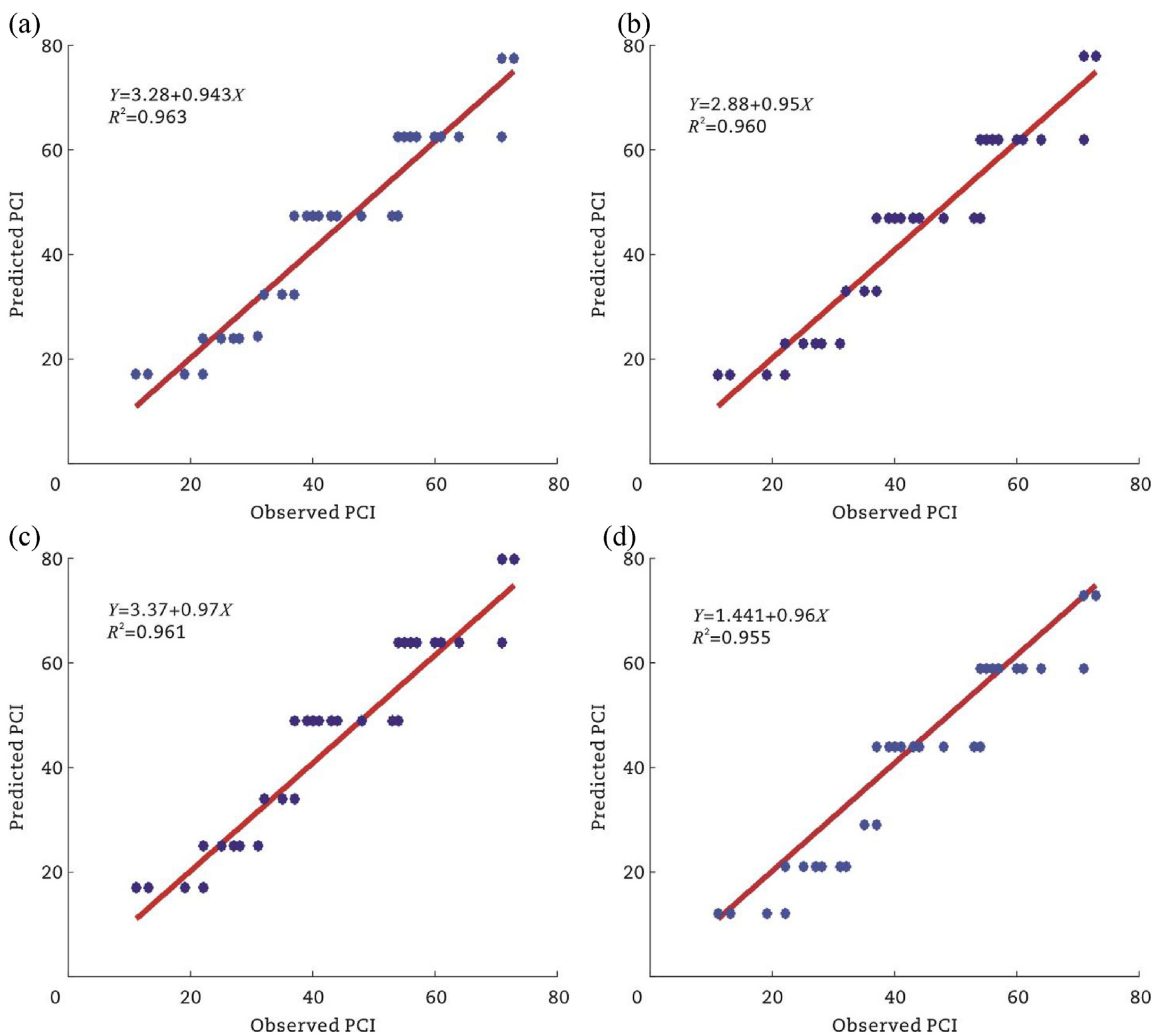

Fig. 9. Performance of the fuzzy inference system (2021). (a) Centroid. (b) Bisector. (c) LOM. (d) SOM.

Table 9
Comparison of the MLR, FIS and ANNs models.

Technique	2018			2021		
	R^2 (%)	RMSE (%)	MAE (%)	R^2 (%)	RMSE (%)	MAE (%)
MLR	48.0	14.051	11.368	63.0	9.932	7.844
FIS	96.6	3.456	2.919	96.3	3.468	2.917
ANNs	98.6	0.888	0.734	99.3	0.720	0.592

$$\begin{aligned}\mathrm{PCI}_{2018} = & 39.73 + 0.84X_1 + 1.24X_2 + 0.04X_3 - 0.10X_4 + 0.10X_5 \\ & - 0.08X_6 + 0.22X_7 - 1.29X_8\end{aligned} \tag{15}$$

The correlation coefficient (R^2) for this relationship is 48%.

- **MLR (2021)**

The PCI (2021) model is negatively associated with block cracking, transverse cracking, patching and delamination but positively correlated with rutting, fatigue cracking, longitudinal cracking and potholes. Eq. (16) describes the relationship between PCI and surface pavement distress.

$$\begin{aligned}\mathrm{PCI}_{2021} = & 36.294 + 0.972X_1 + 1.367X_2 - 0.161X_3 + 0.628X_4 \\ & - 0.975X_5 + 0.036X_6 - 0.008X_7 - 2.552X_8\end{aligned} \tag{16}$$

The correlation coefficient (R^2) for this relationship is 63%.

3.3. ANN model development

The primary goal for developing these models is to predict pavement performance and evaluate and optimize maintenance decisions. This research investigated three ANN architectures (Models A–C) to obtain the best results. The Model B ANN architecture produced the best results with eight inputs, three hidden layers of ten neurons, and one output layer (8-10-10-10-1-1). Fig. 4 represents the Model B ANN architecture. The data was divided into 70% for training, 15% for testing, and 15% for validation, and the results showed that the pavement distress models performed well. Three statistical metrics, maximum R^2 values and minimum RMSE and MAE values determined the selection of the best ANN network. Table 5 summarises the results of the ANNs approach. The highest R^2 values for 2018 and 2021 were 98.6% and 99.3%, the lowest RMSE values were 0.888% and 0.734%, and the lowest MAE values were 0.720%. Figs. 5 and 6 present the predicted PCI by the ANNs.

3.4. FIS model development

This section of the paper discusses applying the FIS technique to the data for 19 roads in St. John's. The fuzzy model generated the PCI models using the degradation severity from the field survey data as an input variable and the PCI as an output variable.

The FIS technique comprises the Fuzzification, Normalisation, and Defuzzification modules. The fuzzy modelling study considered eight input variables and one output (PCI) variable. Fig. 7 presents the main steps of the FIS technique.

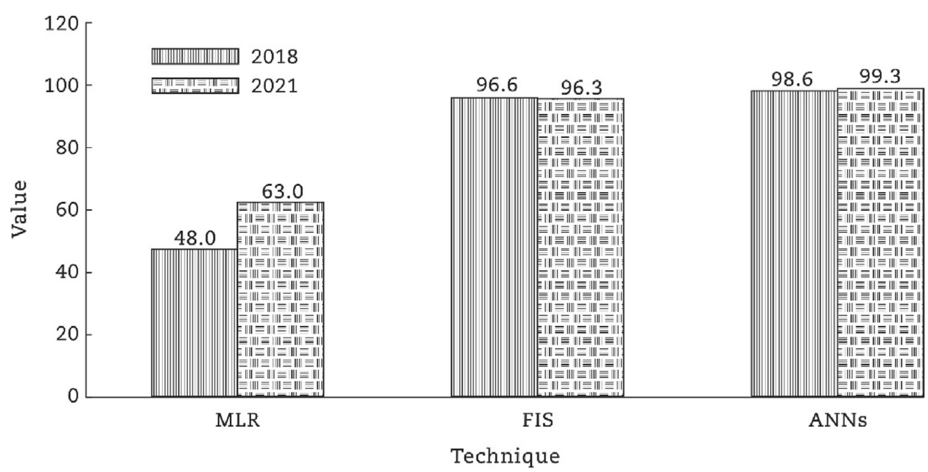

Fig. 10. The fitness of the MLR, FIS, and ANNs models for R^2 of PCI prediction.

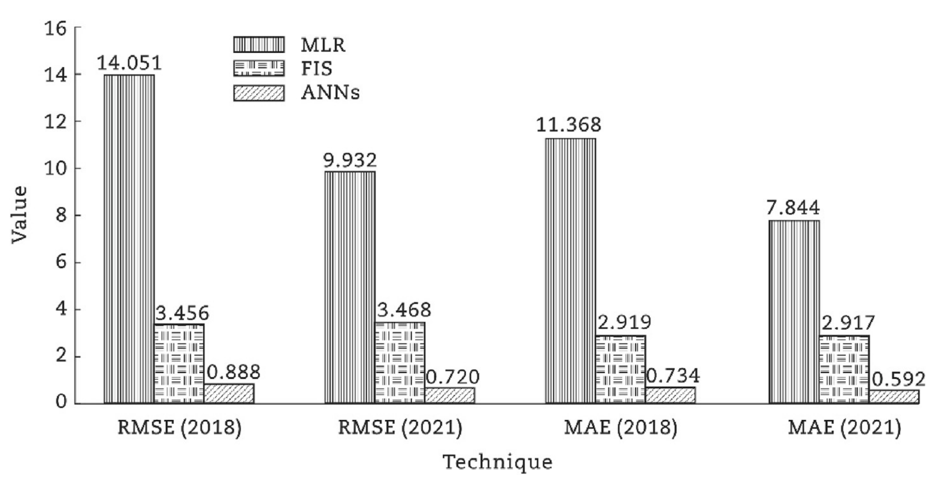

Fig. 11. The fitness of MLR, FIS, and ANNs models for RMSE and MAE of PCI prediction (2021).

Table 10
Sensitivity analysis of the prediction models.

Parameter	R^2 (%)	
	2018	2021
Rutting	18.3	17.1
Fatigue cracking	13.3	14.4
Block cracking	2.5	1.2
Longitudinal cracking	11.4	8.1
Transverse cracking	0.4	4.1
Patching	19.0	16.6
Pothole	–	0.9
Delamination	19.1	19.0

3.4.1. *Data pre-processing and membership functions*

A fuzzy model was constructed by reviewing the data for 19 roads in St. John's and using eight independent parameters for pavement distress and one output (PCI). The membership functions (M.F.) for all input variables are classified as minimal, moderate or severe, while the PCI membership functions are classified as failed, very poor, poor, fair, good, very good and excellent for the output variables. Table 6 presents the types of pavement distress and the number of membership functions used to evaluate PCI.

3.4.2. *Fuzzy rule generation*

The challenge in the second phase of the FIS technique is developing the generation rules. The eight inputs and one output make the rule generation for the classification model a difficult and complex task. Table 7 presents the rules generation for the FIS technique.

3.4.3. *Results of the pavement section classification*

The system was evaluated for the datasets for two sections, each with 19 road sections. This method generated the membership functions and rules by measuring the efficiency of the fuzzy pavement classification. The R^2, RMSE and MAE were calculated using four defuzzified approaches, including centroid, bisector, smallest of maxima (SOM), and largest of maxima (LOM), to demonstrate the agreement of the PCI values. Table 8 presents the assessment of the fuzzy inference system configurations for 19 sections. Figs. 8 and 9 show the relationship between the observed and predicted PCI for the 19 sections.

Table 8 shows that the four methods predicted the PCI values accurately, although the centroid method gave a more accurate prediction than other methods for the 2018 and 2021 data (R^2 = 96.6% and 96.3%, RMSE = 3.456% and 3.468%, and MAE = 2.919% and 2.917%). The SOM technique was less accurate than the other methods in predicting the PCI for 2018 and 2021 (R^2 = 95.9% and 95.5%, RMSE = 4.751% and 4.805%, and MAE = 3.595% and 3.639%). The accurate prediction by all models means that the FIS technique is a reliable predictor of the PCI indicator.

4. Comparison and validation of the MLR, ANNs and FIS models

This research used statistical measures, namely minimum values of MAE and RMSE, and the maximum values of R^2, to compare and validate the results of the models. Table 9, Figs. 10 and 11 show the comparison among the three techniques.

The researchers draw the following conclusions from the data in Table 9, Figs. 10 and 11.

- PCI (2018): ANN has the best performance among the three techniques. The statistical measures for the ANN model are R^2 = 98.6%, RMSE = 0.888%, and MAE = 0.734%, and the worst-performing model was MLR, with an R^2 = 48.0%, RMSE = 14.051%, and MAE = 11.368%.
- PCI (2021): ANN has the best performance among the three techniques. The statistical measures for the ANN model are R^2 = 99.3%, RMSE = 0.720%, and MAE = 0.592%, and the worst-performing model was MLR, with an R^2 = 63.0%, RMSE = 9.932%, and MAE = 7.844%.

5. Model sensitivity analysis

A sensitivity analysis was carried out to identify the critical features in PCI evaluations and determine the influence of the input factors on the prediction models' effectiveness. The researchers performed the sensitivity analysis by creating models that consider each input while ignoring the influence of other variables. Table 10 and Fig. 12 present the sensitivity analysis results used as the basis to make the following conclusions.

PCI (2018): Table 10 and Fig. 12 show a strong positive correlation between delamination and PCI. Similarly, rutting, fatigue cracking, longitudinal cracking, and patching have a positive correlation with PCI. The PCI model has a weak positive association with block and transverse cracking and no correlation with potholes. The lack of correlation with potholes could be due to insufficient data for this variable in the field survey.

PCI (2021): Table 10 and Fig. 12 show a strong positive correlation between delamination and PCI. Similarly, rutting, fatigue cracking,

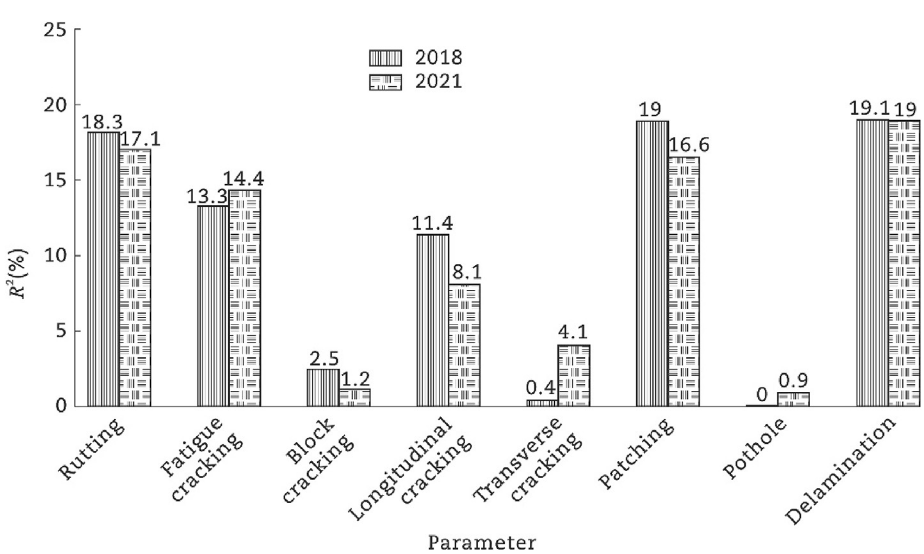

Fig. 12. Results of the sensitivity analysis of the prediction models (2018 and 2021).

longitudinal cracking, and patching have a positive correlation with PCI. The PCI model has a weak positive association with block cracking, transverse cracking and potholes.

6. Summary and conclusions

Machine learning techniques are useful for determining the correlation between surface pavement distress and PCI. This research has developed and evaluated the performance of MLR, ANNs and FIS methods in predicting pavement performance. Two studies in 2018 and 2021 evaluated 19 road sections (37 sections) in St. John's, Newfoundland, Canada, to determine the relationship between the PCI and eight independent factors. Eight surface pavement distresses, namely rutting, fatigue cracking, block cracking, longitudinal cracking, transverse cracking, potholes, patching and delamination, were identified using the performance indicator data (PCI). The key research findings are as follows.

(1) The extensive maintenance work carried out by the city of St. John's in 2018 and 2021 impacted the road performance. The appropriately maintained road showed improved performance, while those without proper maintenance showed declined performance.
(2) The ANN technique showed the best performance among the three techniques for the 2018 data. Compared to the MLR technique, the statistical measurements for ANN showed that the R^2 value increased by 51.32%, while the RMSE and MAE decreased by 93.7% and 93.54% compared to the MLR technique.
(3) Compared to the FIS technique, the statistical measurements for ANN showed that the R^2 value increased by 2.03%, and the RMSE and MAE decreased by 74.30% and 74.85%.
(4) The ANN technique showed the best performance among the three techniques for the 2021 data. Compared to the MLR technique, the statistical measurements for ANN showed that the R^2 value increased by 36.55%, and the RMSE and MAE decreased by 92.75% and 92.54%.
(5) Compared to the FIS technique, the statistical measurements for ANN showed that the R^2 value increased by 3.02%, and the RMSE and MAE decreased by 79.23% and 79.71%.
(6) Compared to FIS and MLR, ANN reduced errors considerably, and the FIS technique was better than the MLR in reducing errors.
(7) Generally, the ANN model performed better than the models developed using other modelling techniques. This conclusion is based on the data for this study and may not apply to other studies.

Data availability statement

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

Declaration of competing interest

The authors do not have any conflict of interest with other entities or researchers.

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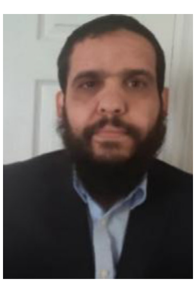

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