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Prediction of flexural strength of FRC pavements by soft computing techniques

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ABSTRACT

Purpose: The mechanical characteristics of concrete used in rigid pavements can be improved by using fibre-reinforced concrete. The purpose of the study was to predict the flexural strength of the fibre-reinforced concrete for ten input variables i.e., cement, fine aggregate, coarse aggregate, water, superplasticizer/high range water reducer, glass fibre, polypropylene fibre, steel fibres, length and diameter of fibre and further to perform the sensitivity analysis to determine the most sensitive input variable which affects the flexural strength of the said fibre-reinforced concrete.

Design/methodology/approach: The data used in the study was acquired from the published literature to create the soft computing modes. Four soft computing techniques i.e., Artificial neural networks (ANN), Random forests (RF), Random trees RT), and M5P, were applied to predict the flexural strength of fibre-reinforced concrete for rigid pavement using ten significant input variables as stated in the 'purpose'. The most performing algorithm was determined after evaluating the applied models on the threshold of five statistical indices, i.e., the coefficient of correlation, mean absolute error, root mean square error, relative absolute error, and root relative squared error. The sensitivity analysis for most sensitive input variable was performed with out-performing model, i.e., ANN.

Findings: The testing stage findings show that the Artificial neural networks model outperformed other applicable models, having the highest coefficient of correlation (0.9408), the lowest mean absolute error (0.8292), and the lowest root mean squared error (1.1285). Furthermore, the sensitivity analysis was performed using the artificial neural networks model. The results demonstrate that polypropylene fibre-reinforced concrete significantly influences the prediction of the flexural strength of fibre-reinforced concrete.

Research limitations/implications: Large datasets may enhance machine learning technique performance.

Originality/value: The article's novelty is that the most suitable model amongst the four applied techniques has been identified, which gives far better accuracy in predicting flexural strength.

Keywords: Flexural strength, Fibre reinforced concrete, Artificial Neural Network, Random Forest, Random Tree, M5P based model

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METHODOLOGY OF RESEARCH, ANALYSIS AND MODELLING

1. Introduction

Plain cement concrete (PCC) is the most widely used construction material, which is highly brittle in nature [1]. Reinforcement bars are conventionally used in pavement construction where high flexural strength and toughness are required. Another method to increase flexural strength is to provide fibre as reinforcement [2]. Cement and concrete components contain a variety of fibres. Glass, carbon, aramid, polypropylene, and basalt fibres are the most prevalent in the category. Because of their small dimensions, fibres exhibit amazing structural perfection [3]. Because of its large surface area-to-weight ratio and strong strength qualities to unit cost ratio, glass fibre (GF) is favoured over other varieties. However, it was discovered that glass fibre, which was initially employed in combination with cement, was impacted by the alkaline state of the cement [4]. Fibres improve the mechanical properties of concrete. With an increase in fibre amount, there is an improvement in mechanical properties. Adding fibre increases the surface cracking resistance of concrete pavement [5]. Fibres are used to check the cracks in concrete pavements, decrease the slab thickness, and increase the joint spacing [6]. Fibres help resist cracks in tensile and bending stresses due to their extremely high elastic modulus. Flexural strength of Normal Strength Concrete (NSC) was increased to 51%, 22.6%, and 32.2% at 1% volume fraction of steel, polypropylene, and glass fibre, respectively, and High Strength Concrete (HSC) was increased to 55.8%, 26.5%, and 36.3% [7]. Some studies on the usage of steel fibre in cement concrete pavement have recently been conducted. Steel fibres are widely used in fibre-reinforced concrete in the field [8]. Steel fibres used in fibre-reinforced concrete are manufactured from cold-drawn wire and other types of steel. These fibres are used to increase the flexural toughness of concrete [9]. Various studies on the effect of steel fibre on the mechanical properties of fibre-reinforced concrete have been conducted in the literature [10,11]. Fibre-reinforced concrete (FRC) is also used for overlays. Concrete overlays, specifically with FRC, are one of the most efficient methods for rehabilitating pavement systems. Since 2004, FRC overlays have become popular in the road construction industry. Fibres help in preventing adhesion loss between the overlay and existing pavement in the bonded combined system. They also reduce the overlay thickness and increase the pavement service life. The flexural toughness factor of the FRC beams exhibits their ability to absorb energy during bending and is the most significant property of FRC [12]. Adding glass fibres may increase the compressive strength by only 0.3 to 0.6%. According to the findings, the optimum range for reinforced concrete with steel fibre is 0.3 per cent to 0.9 percent, and the best range for reinforced concrete with glass fibre is 0.3 to 0.6% by volume fraction to increase the strength of concrete. The tensile and flexural strengths of concrete might be described as 8% and 13% of the compressive strength [13]. The compressive and flexural strengths of cement mortars with glass fibre were increased when marble dust was added as exceptionally fine sand. This outcome might be due to one underlying reason: marble dust has a significantly smaller grain size than extremely fine sand, allowing it to fill in the spaces [14]. The impact of glass fibre and polypropylene fibre on concrete mechanical and durability qualities has been investigated. Compressive and flexural tests were performed to ensure that the fibre improved the mechanical characteristics of concrete. The findings of the experiments show that hybrid fibre-reinforced concrete has the greatest impact on concrete characteristics [15]. In the field of self-compacting concrete, significant progress has been made by partially replacing coarse aggregates (CA) with recycled coarse aggregates (RCA) derived from demolished building debris. Steel fibres were added to concrete in the study to improve the mechanical characteristics of Self-Compacting Concrete (SCC) so that it could be used in beam-column joints [16].

In the present study, four soft computing techniques have been applied to develop machine learning models, i.e., Artificial Neural Network, Random Forest, Random Tree, and M5P, for predicting the flexural strength of fibre-reinforced concrete. The comparison of the performance evaluation parameters has led to the conclusion that the best modelling technique (ANN) in predicting flexural strength of fibre reinforced concrete has been determined. Results of the sensitivity analysis show that polypropylene fibre (FPP) has the most significant impact on predicting the flexural strength of fibre-reinforced concrete.

2. Literature review

Many studies have been conducted to predict the mechanical properties of concrete, particularly for compressive and flexural strength, by applying machine learning techniques [17]. Ali et al. [18] not only predicted the compressive strength of concrete but also the flexural and splitting tensile strengths through the M5P model. In the study, the mechanical properties of concrete were predicted by the M5P model. Six input parameters were considered to predict four output parameters. The results indicated the successful use of the M5P algorithm in generating reasonable, simple predictive models for various properties of concrete containing waste foundry sand. A more inclusive dataset containing information on the properties of the constituents of concrete would be suggested to improve the performance of models. Saridemir [19] predicted the compressive strength of concrete containing metakaolin and silica fume using an Artificial Neural Network technique. The study indicated that an artificial neural network has the strong potential to predict the compressive strength of concrete containing metakaolin and silica fume. Ayaz et al. [20] predicted the compressive strength and ultra-pulse velocity of high-volume mineral concrete by using the M5 rule and M5P classifier. The results indicated that the M5 rule and tree model M5P perform well in estimating the compressive strength and ultra-pulse velocity of concrete. Kang et al. [21] conducted the study to predict the flexural and compressive strengths of steel fibre-reinforced concrete by applying machine learning techniques such as Linear regression, Ridge regression, Lasso regression, K Nearest neighbours regressor, Decision tree regression, Random forest regressor, AdaBoost regressor, Gradient boosting regressor, Extreme gradient boosting, Support vector regression and Artificial neural network with a dataset consisting of seven input variables and two output variables. Results indicated that the models with tree-based machine learning techniques and boosting techniques exhibit fairly good results. Marani et al. [22] used ten input and one output data variable to predict the compressive strength of phase change materials integrated into cementitious composites. Results indicated that the gradient boosting model showed the highest accuracy. Malek et al. [23] investigated the mechanical properties of cement mortar from scattered glass-fibre reinforcement. Glass fibres have been identified to improve the properties of mortar. The concrete containing glass fibres1800 g/m^3 showed the best mechanical properties compared to the control sample. Maximum compressive strength improved by 29.9%, flexural strength increased by 29.9%, and split tensile strength increased by 97.6%.

Over the last several decades, soft computing techniques such as Artificial neural networks (ANN), Adaptive neuro-fuzzy inference systems (ANFIS), Support vector machines (SVM), Gaussian process regression (GP), Fuzzy logic, and Tree-based algorithms such as random forest (RF), random tree (RT), M5P Tree-based model, and others have risen to prominence in tackling various engineering issues related to the prediction of various strengths in flexible and rigid pavements.

3. Machine learning techniques

3.1. Artificial Neural Network

Artificial neural networks work similar to a human brain. It is smaller in size when compared to the human brain. It is used for information processing because it is like the human brain. It is the most common learning algorithm and is widely used [24]. An artificial neural network is a numerical and mathematical model which consists of many artificial neurons. It is also called a multilayer perceptron, which consists of three layers: the input layer, the hidden layer, and the output layer [25,26]. In the majority of cases, an artificial neural network is an adjusting system that can modify its model according to related information that flows through the network during the learning phase. It can be used to develop any model that has a complex relationship between input and output data [27].

3.2. Random Forest

It is a combination of tree predictors in which each tree depends on observations of a random vector that is sampled separately [28,29]. In a random forest, regression trees are combined with decreasing the variation in individual trees. The decision trees are assembled to construct a forest as per bagging theory, which helps in combining a trained model for training data. One of the most important benefits of the random forest method is that it reduces instability [21]. The RF model is helpful in a variety of decision trees by randomly changing the combination of predictors in different tree evolutions. Random Forest exhibits satisfactory performance and is widely used in many situations. This model can be applied for classification and regression purposes [30].

3.3. Random Tree

A single decision tree is easy to conceptualize but will typically suffer from high variance, which makes them not competitive in terms of accuracy. This limitation is reduced by generating many variants of a single decision tree. It is executed by selecting a different subset of the same training set every time in the context of randomization-based ensemble methods [28]. A Random Tree is a type of classifier which belongs to a class of machine learning techniques in which ensemble classification takes place. It will also be helpful for the interpretation of the outcomes.

3.4. M5P

This algorithm is a modified version of the M5P algorithm. This model tree uses a vast number of data sets with a high number of attributes and dimensions. The M5P technique is initiated by dividing input space into several subspaces to develop a tree. The standard deviation of the observations is used to measure the variability. A tree is developed by using the standard deviation reduction factor, which helps in enhancing the expected error reduction at a node. When the tree is built, a linear regression model is developed. After that, a pruning technique is applied to overcome the training problem [18].

4. Methodology and dataset

The information for this study was acquired from "eleven" published research articles, as shown in Table 1. In total, 120 observations of flexural strength were used. The dataset contains ten input variables, i.e., Cement, Fine Aggregate, Coarse Aggregate, Water, Superplasticizer/high range water reducer (SP/HRWR), Glass fibre, Polypropylene Fibre (FPP), Steel fibres (SF), Length of fibre (Lf), Diameter of fibre (Df) and Flexural strength (MPa) as an output parameter. Each input variable influences flexural strength. The data set is randomly divided into two sets, i.e., training and testing data sets, in 70:30 ratio, Out of total observations, 84 were used for the training stage and 36 for the testing stage. In this study, Weka 3.9 software was used to analyze the input parameters to predict the flexural strength of concrete. This contains programming language, which was developed at the University of Waikato in New Zealand. It consists of graphical user interfaces (GUI) that simplify access to many operations, such as data analysis and predictive modelling, as well as a set of visualization tools and methods for conducting data analysis. Weka is currently being used for a wide range of new applications, in education and research being the most prominent. (Saad et al. [31]; Wang et al. [32]; Keles et al. [33]).

Summary statistics for training and testing datasets are shown in Tables 2 and 3.

Table 1.
Observations details (taken from literature)

No.	Author	No. of observations
1	Hesami et al. (2016) [34]	3
2	Hasani et al. (2020) [12]	7
3	Kim et al. (2017) [35]	15
4	Altoubat et al. (2008) [6]	5
5	Babar et al. (2020) [2]	7
6	Hussain et al. (2020) [7]	8
7	Soulioti et al. (2011) [36]	7
8	Al-Gemeel et al. (2018) [37]	8
9	Akbari and Abed (2020) [13]	28
10	Kelestemur et al. (2014) [14]	16
11	Liu et al. (2019) [15]	16
	Total	120

Table 2.
Summary statistics for the training dataset

	Cement, kg/m^3	Fine aggregate, kg/m^3	Coarse aggregate, kg/m^3	Water, kg/m^3	Super plasticizer, kg/m^3	Glass fibre, %	FPP, %	SFRC, %	Length of fibre (Lf), mm	Diameter of fibre (Df), mm	Flexural strength, MPa
Minimum	292.00	203.60	0.00	126.00	0.00	0.00	0.00	0.00	0.00	0.00	1.65
Maximum	605.00	1225.00	1253.80	338.60	13.28	1.50	1.00	1.50	60.00	15.00	14.00
Mean	386.79	790.84	908.51	181.33	2.72	0.24	0.09	0.24	20.37	0.62	5.89
Standard deviation	80.66	256.11	328.16	50.79	2.68	0.41	0.24	0.40	19.40	2.28	3.44
Kurtosis	0.63	0.04	2.18	2.88	3.68	1.70	7.84	1.11	-0.88	37.51	-0.01
Skewness	0.91	-0.82	-1.67	1.67	1.66	1.61	2.91	1.50	0.75	6.14	1.04

Table 3.
Summary statistics for a testing dataset

	Cement, kg/m^3	Sand, kg/m^3	Aggregate, kg/m^3	Water, kg/m^3	Super plasticizer, kg/m^3	Glass fibre, %	FPP, %	SFRC, %	Length of fibre (Lf), mm	Diameter of fibre (Df), mm	Flexural strength, MPa
Minimum	292.00	203.60	0.00	126.00	0.00	0.00	0.00	0.00	0.00	0.00	1.74
Maximum	544.00	1215.00	1253.80	304.80	8.68	1.50	1.00	1.00	60.00	0.92	13.56
Mean	373.00	804.79	929.52	173.59	2.08	0.23	0.07	0.19	23.07	0.31	5.58
Standard deviation	71.10	258.16	309.15	45.43	2.15	0.39	0.21	0.29	20.28	0.36	3.31
Kurtosis	-0.18	0.33	3.29	2.04	1.26	2.41	11.62	0.75	-1.32	-1.43	0.54
Skewness	0.66	-0.98	-1.82	1.42	1.21	1.73	3.40	1.33	0.51	0.63	1.23

Table 4.
Statistical performance measures for modeling approaches

Approaches	Training dataset					Testing dataset				
	CC	MAE, MPa	RMSE, MPa	RAE, %	RRSE, %	CC	MAE, MPa	RMSE, MPa	RAE, %	RRSE, %
ANN	0.9751	0.5106	0.7592	19.04	22.19	0.9408	0.8292	1.1285	31.14	34.42
RF	0.9741	0.5059	0.7756	18.87	22.67	0.9378	0.8139	1.1470	30.56	34.99
RT	0.9822	0.3017	0.6433	11.25	18.80	0.9214	0.9879	1.3141	37.09	40.08
M5P	0.9326	0.9724	1.2636	36.27	36.93	0.9252	1.0007	1.2460	37.57	38.01

5. Performance evaluation parameters

To measure the performance of developed models, various performance parameters were used, which included coefficient of correlation (CC), mean absolute error (MAE), root mean square error (RMSE), relative absolute error (RAE), and root relative squared error (RRSE). Their formulas are presented as follows:

$$CC = \frac{N\sum_{i=1}^{N} uv - \sum_{i=1}^{N} u \sum_{i=1}^{N} v}{\sqrt{[(N\sum_{i=1}^{N} u^2) - (\sum_{i=1}^{N} u^2)][(N\sum_{i=1}^{N} v^2) - \sum_{i=1}^{N} v^2)]}} \quad (1)$$

$$MAE = \frac{1}{N} \cdot \sum_{i=1}^{N} (|v - u|) \quad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (v-u)^2}{N}} \quad (3)$$

$$RAE = \frac{\sum_{i=1}^{N} |v-u|}{\sum_{i=1}^{N} |u-\overline{u}|} \quad (4)$$

$$RRSE = \sqrt{\frac{\sum_{i=1}^{N} (v-u)^2}{\sum_{i=1}^{N} \overline{(u-u)}^2}} \quad (5)$$

where:
u, v are the actual and predicted values,
$\overline{u}, \overline{v}$ are the mean of the actual and predicted values,
N = No. of observations.

6. Results and discussion

The results obtained from the total dataset were analyzed on Weka 3.9 software in exploring the performance of four models as per the details in the following sections.

6.1. Assessment of Artificial Neural Network (ANN) based model results

The parameters applied for developing the ANN model consist of 15 hidden layers, 0.1 momentum, 0.2 learning rate, and 5000 training time. The statistical performance of the models is shown in Table 4. Results of Table 4 show that the high value of CC exhibits that the ANN-based model is suitable for predicting the flexural strength of fibre-reinforced concrete with values: CC = 0.9751 & 0.9408, MAE = 0.5106 & 0.8292, RMSE = 0.7592 & 1.1285, RAE = 19.04 & 31.14% and RRSE = 22.19 & 34.42% for both training and testing stage, respectively. Figures 1 and 2 indicate agreement plots between actual and predicted values of flexural strength of fibre-reinforced concrete.

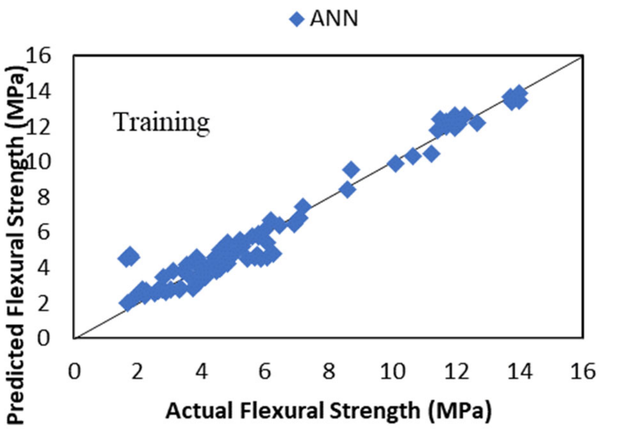

Fig. 1. Actual vs. predicted flexural strength with ANN model for the training dataset

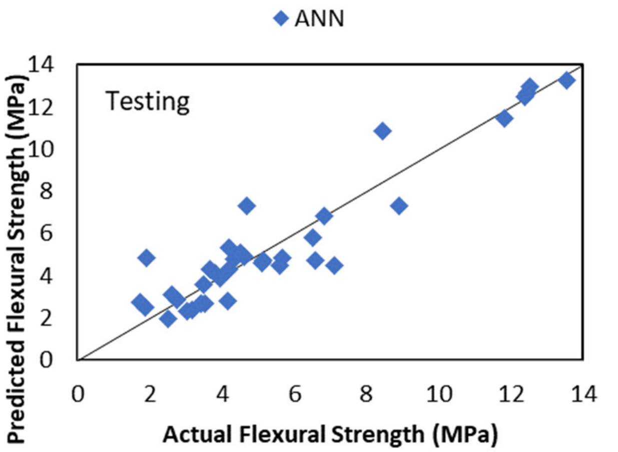

Fig. 2. Actual vs. predicted flexural strength with ANN model for the testing dataset

6.2. Assessment of Random Forest (RF) based model results

For developing the Random Forest model, the parameters used were a seed, the number of iterations (I), and the number of features (K). The performance of the model depends upon the CC value. Results of Table 4 show the statistical performance of all the models in which the Random Forest based model outperforms for predicting the flexural strength of fibre reinforced concrete with values: CC = 0.9741 & 0.9378, MAE = 0.5059 & 0.8139 MPa, RMSE = 0.7756 & 1.1470 MPa, RAE = 18.87 & 30.56% and RRSE = 22.67 & 34.99% for both training and testing stages, respectively. Figures 3 and 4 show the scatter graph plotted between actual and predicted flexural strength values of fibre-reinforced concrete using the Random Forest model.

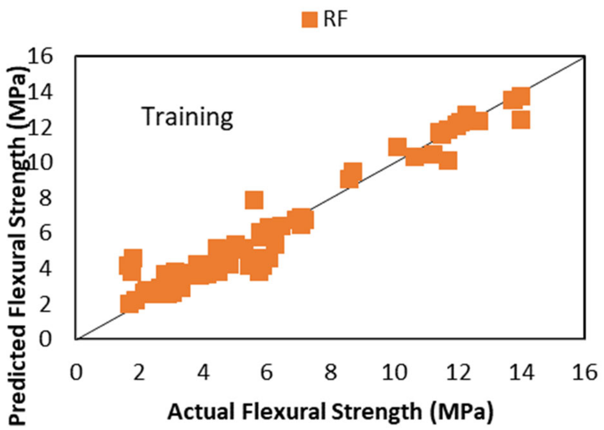

Fig. 3. Actual vs. predicted flexural strength with RF model for training dataset

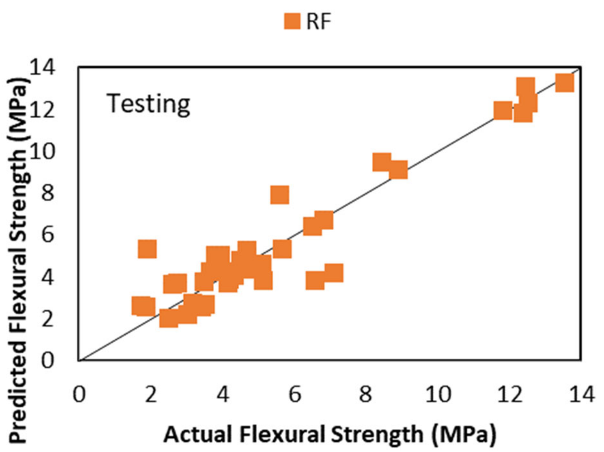

Fig. 4. Actual vs. predicted flexural strength with RF model for testing data

6.3. Assessment of Random Tree (RT) based model results

The parameters used for developing the model are the 'seed' and 'k' values. Table 4, with the statistical performance of all the four models shows that the Random Tree-based model is reliable for predicting the flexural strength of fibre-reinforced concrete with values: CC = 0.9822 & 0.9214, MAE = 0.3017 & 0.9879 MPa, RMSE = 0.6433 & 1.3141MPa, RAE = 11.25 & 37.09% and RRSE = 18.80 & 40.08% for both the training and testing stages, respectively. Figures 5 and 6 show the agreement plots between the actual and predicted values of fibre-reinforced concrete flexural strength in the training and testing datasets, respectively.

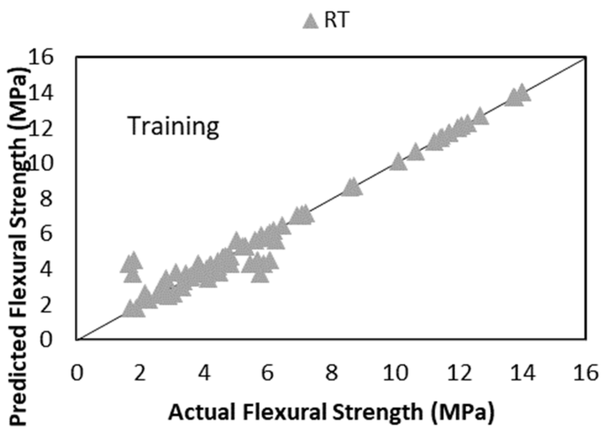

Fig. 5. Actual vs. predicted flexural strength with RT model for the training dataset

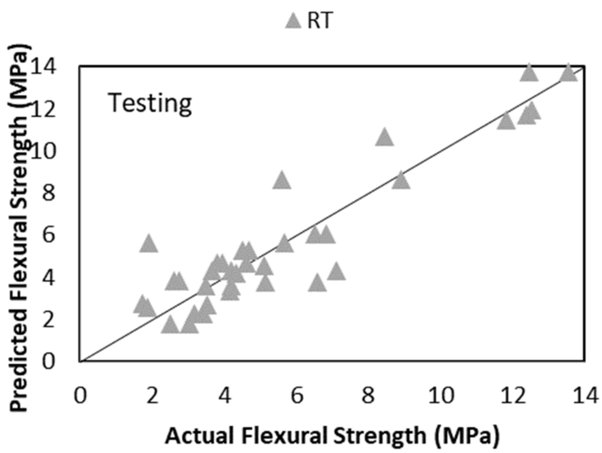

Fig. 6. Actual vs. predicted flexural strength with RT model for the testing dataset

6.4. Assessment of M5P-based model results

The performance assessment of the M5P based model, as per Table 4 is also nearly accurate in predicting the flexural strength of fibre reinforced concrete with values: CC =0.9326 & 0.9252, MAE = 0.9724 & 1.0007 MPa, RMSE = 1.2636 & 1.2460 MPa, RAE = 36.27 & 37.57% and RRSE = 36.93 & 38.01% for both training and testing stages, respectively. Figures 7 and 8 indicate agreement plots between actual and predicted values of flexural strength of fibre-reinforced concrete. Figure 8 reveals that the majority of the points lie closer to the line of perfect agreement, which indicates that the M5P model is suitable for predicting the flexural strength of fibre reinforced concrete.

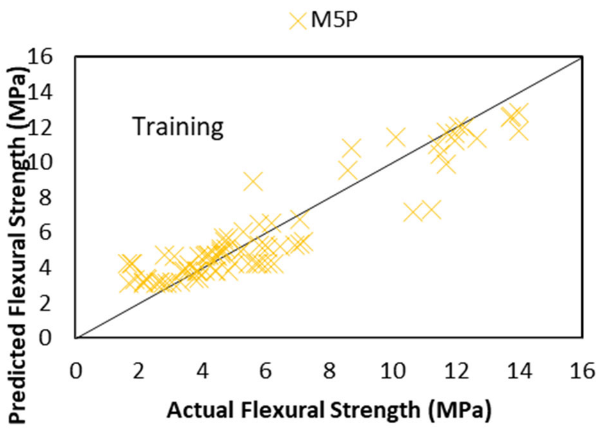

Fig. 7. Actual vs. predicted flexural strength with M5P model for the training dataset

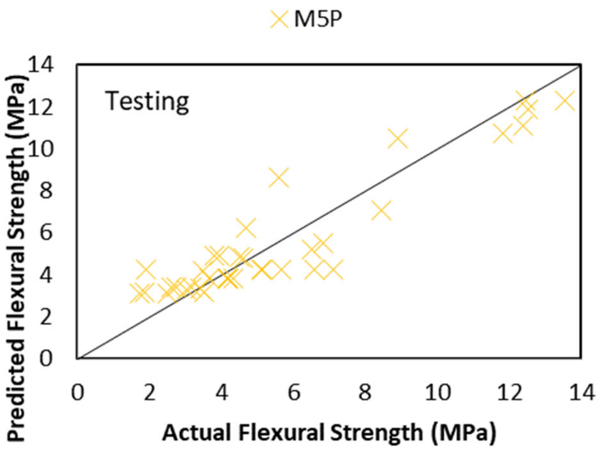

Fig. 8. Actual vs. predicted flexural strength with M5P model for the testing dataset

7. Comparative analysis for models

It is simple and time-saving to predict the flexural strength of fibre-reinforced concrete using machine learning techniques. Table 4 shows the performance measures of all the models for both the training and testing stages. Figures 9 and 10 show the results of training and testing datasets, respectively, for the four models. The said figures confirm that the ANN-based model outperforms other applied models with the following values: CC = 0.9751 & 0.9408, MAE = 0.5106 & 0.8292 MPa, RMSE = 0.7592 & 1.1285 MPa, RAE = 19.04 & 31.14 % and RRSE = 22.19 & 34.42% for both training and testing stages, respectively, for the prediction of the flexural strength of fibre-reinforced concrete.

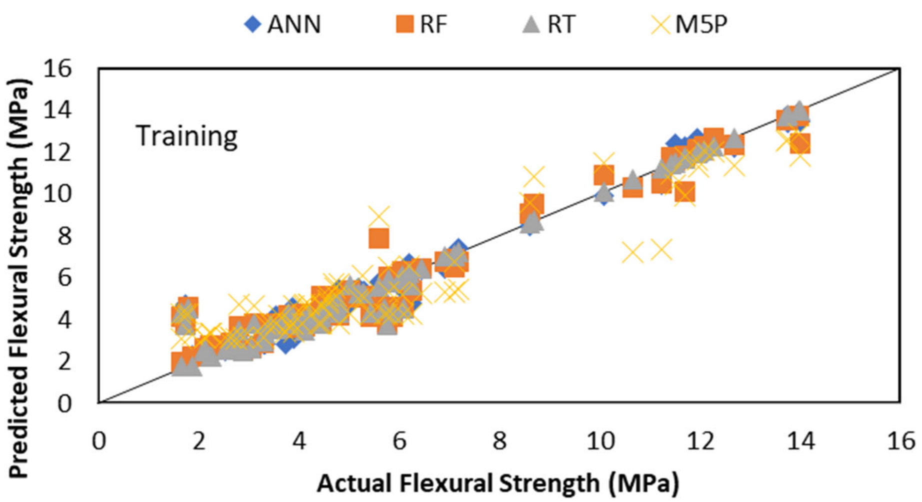

Fig. 9. Comparison of models for the training dataset

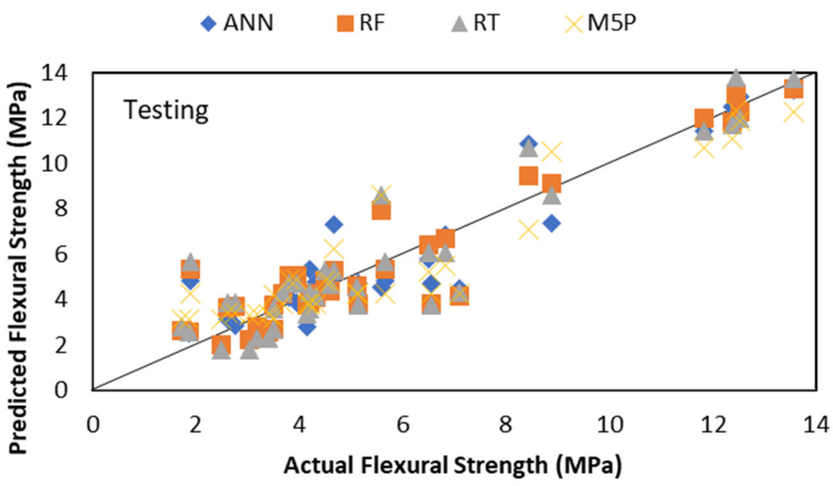

Fig. 10. Comparison of models for testing dataset

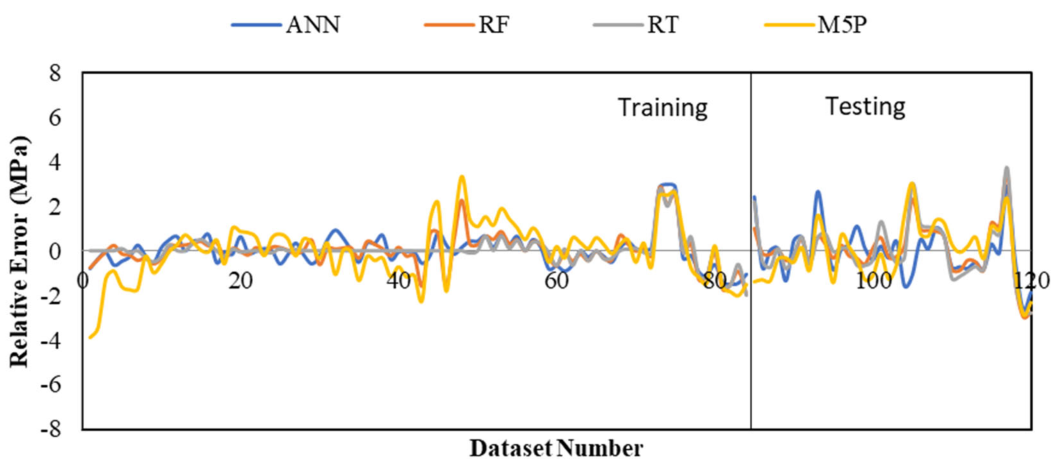

Fig. 11. Comparison of Errors in models for Training and Testing stages

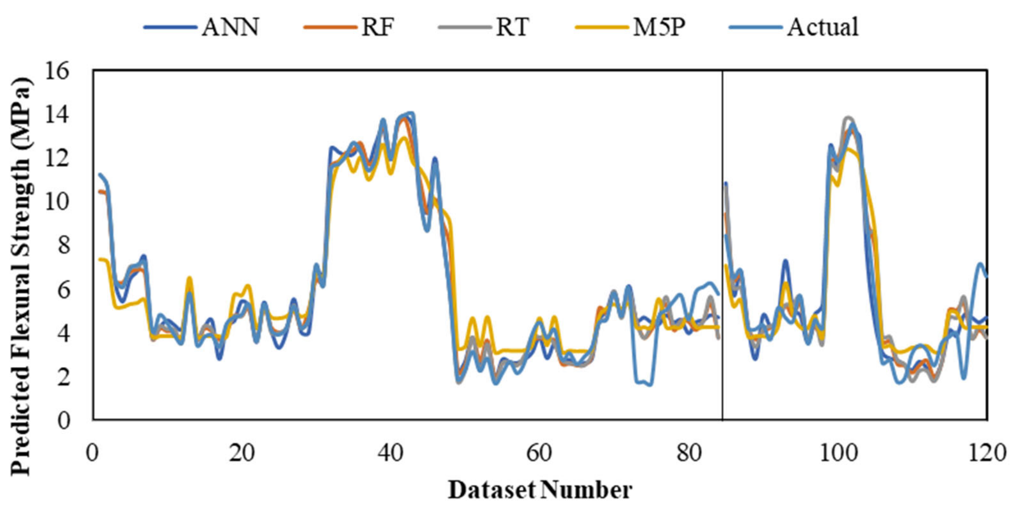

Fig. 12. Comparison of variation in predicted flexural strength with the total dataset

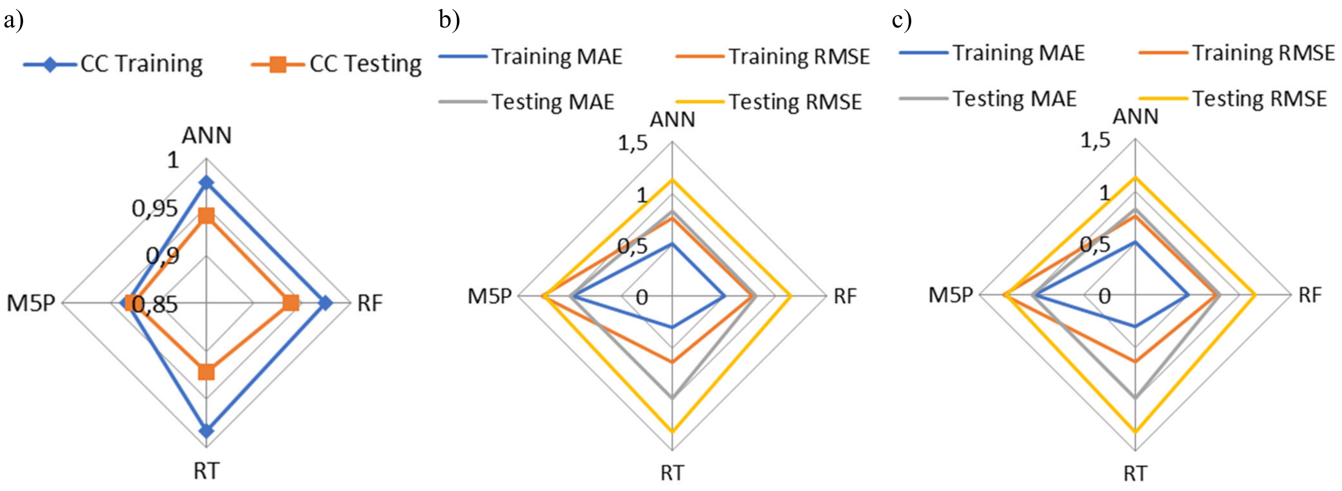

Fig. 13. Radial graphs show the evaluation parameters values of training and testing stages with applied models

The predicted values of flexural strength in the ANN model are remarkably close to the actual values. In the ANN -based model, the value of RRSE is the lowest among all the applied techniques. The CC value is above 0.8 in all models, which shows that all models are suitable for predicting the flexural strength of fibre-reinforced concrete. However, the ANN model with CC (0.9408) in the testing stage outperforms all other applied models. Figure 11 indicates the relative error with all applied models, which is the minimum in the ANN-based model as compared to other models. Figure 12 shows how consistent the model is with the observed values. This shows that all of the models are consistent with the observed values.

Figure 12 shows that the predicted flexural strength values in ANN-based model lie closest to the actual observations in a testing stage which confirms the congruity of the ANN-based model performing better than other applied models.

Figure 13 shows radial graphs showing the evaluation parameter values of training and testing stages with applied models.

8. Sensitivity analysis

A sensitivity analysis was performed with outperforming ANN model to determine the significance of the ten input parameters for predicting the flexural strength of fibre-reinforced concrete, and the results are shown in Table 5. The said table shows that FPP has a significant impact on predicting the flexural strength of fibre-reinforced concrete. In addition, the input parameter, i.e., water, also plays a crucial role in predicting the flexural strength of fibre-reinforced concrete. In the study undertaken by Ramesh et al. [38], it has been found that FPP enhances the strength of the concrete.

Table 5.
Sensitivity analysis with ANN-based model

Removed Parameter	ANN based model		
	CC	MAE	RMSE
-	0.9408	0.8292	1.1285
FPP, %	**0.8308**	**1.3077**	**2.0228**
Water, kg/m^3	0.8480	1.3346	1.8868
Fine aggregate, kg/m^3	0.9124	1.0776	1.4480
Coarse aggregate, kg/m^3	0.9194	1.0910	1.3569
SFRC, %	0.9263	0.9587	1.2710
Diameter of fibre (Df), mm	0.9355	0.8816	1.1694
Glass fibre, %	0.9371	0.8884	1.2189
Cement, kg/m^3	0.9420	0.9154	1.1399
Length of fibre (Lf), mm	0.9470	0.8238	1.0890
SP/HRWR, kg/m^3	0.9504	0.8098	1.0359

9. Conclusions

Flexural strength is one of the most important mechanical properties of fibre-reinforced concrete pavement. In this paper, four machine learning techniques were applied for the prediction of the flexural strength of fibre reinforced concrete with ten input variables and flexural strength as an output. Four goodness-of-fit parameters such as coefficient of correlation (CC), mean absolute error (MAE), root mean squared error (RMSE), relative absolute error (RAE), and root relative squared error

(RRSE), were used to evaluate the performance of the generated models. According to the performance evaluation results, the ANN-based model outperforms other models with CC = 0.9751 & 0.9408, MAE = 0.5106 & 0.8292 MPa, RMSE = 0.7592 & 1.1285 MPa, RAE = 19.04 & 31.14 % and RRSE = 22.19 & 34.42% for both training and testing stages, respectively. According to an agreement graph between actual and predicted values, the ANN has a lower error and optimal fitting for predicting the output, i.e., flexural strength (MPa). The results of the sensitivity analysis show that polypropylene fibre (FPP) has the most significant impact on predicting the flexural strength of fibre-reinforced concrete. This shows Polypropylene fibres (FPP) affect the flexural strength required for rigid pavement.

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Data availability statement

All data, models, and code generated or used during the study appear in the submitted article.

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