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A study of glass and carbon fibers in FRAC utilizing machine learning approach

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Abstract. Asphalt concrete (AC), is a mixture of bitumen and aggregates, which is very sensitive in the design of flexible pavement. In this study, the Marshall stability of the glass and carbon fiber bituminous concrete was predicted by using Artificial Neural Network (ANN), Support Vector Machine (SVM), Random Forest (RF), and M5P Tree machine learning algorithms. To predict the Marshall stability, nine inputs parameters i.e., Bitumen, Glass and Carbon fibers mixed in 100:0, 75:25, 50:50, 25:75, 0:100 percentage (designated as 100GF:0CF, 75GF:25CF, 50GF:50 CF, 25GF:75CF, 0GF:100CF), Bitumen grade (VG), Fiber length (FL), and Fiber diameter (FD) were utilized from the experimental and literary data. Seven statistical indices i.e., coefficient of correlation (CC), mean absolute error (MAE), root mean squared error (RMSE), relative absolute error (RAE), root relative squared error (RRSE), Scattering index (SI), and BIAS were applied to assess the effectiveness of the developed models. According to the performance evaluation results, Artificial neural network (ANN) was outperforming among other models with CC values as 0.9147 and 0.8648, MAE values as 1.3757 and 1.978, RMSE values as 1.843 and 2.6951, RAE values as 39.88 and 49.31, RRSE values as 40.62 and 50.50, SI values as 0.1379 and 0.2027 and BIAS value as -0.1 290 and -0.2357 in training and testing stage respectively. The Taylor diagram (testing stage) also confirmed that the ANN-based model outperforms the other models. Results of sensitivity analysis showed that the fiber length is the most influential in all nine input parameters whereas the fiber combination of 25GF:75CF was the most effective among all the fiber mixes in Marshall stability.

Keywords: artificial neural network; carbon fiber; glass fiber; M5P Tree-based model; Marshall stability; random forest; support vector machine

1. Introduction

The prevalent use of asphalt concrete pavements in highways leading to road transportation in most countries has necessitated the determination of these structures' performance characteristics,

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which usually require huge investments. Poor infrastructure leads to faster deterioration of asphalt concrete pavements, stability issues, and a negative effect on the predicted life span (Yildirim and Karacasu 2019). The pavement is often damaged by repeated pressures and strains. A fatigue crack occurs as a small fracture in the pavement system that grows larger under load (Honarmand *et al.* 2019). However, when axle load and traffic continue to rise, premature damage to asphalt pavement causes various distress and structural failure, which results in serious problems such as moisture damage, rutting, and fatigue etc. The efficiency of asphalt pavement may be enhanced by incorporating additives such as polymers and fibers into the mixture, which generally improves bitumen flexibility and engineering properties.

Fibers have gained increasing attention among the modifiers of asphalt mixtures due to their great improvement effects as well as their advantages of ease of construction and low cost (Zheng *et al.* 2011). Different types of fibers have been investigated by the researchers such as Polymeric fibers (polyester, polypropylene (Pamudji *et al.* 2021), polyacrylonitrile), organic fibers (cellulose, lignin, date-palm, oil-palm), mineral fibers (asbestos, rock wool), waste fibers (nylon, scrap tyre, textile), and other (glass, carbon, steel). The fibers enhanced the material's ductility through its increased elasticity, resistance, toughness, distortion, crack reduction, durability improvement, and better absorption of energy (Mawat and Ismael 2020, Upadhya *et al.* 2021a, Mazloom and Mirzamohammadi 2019, Touahri *et al.* 2020). Therefore, glass and carbon fibers could be an adequate substitute for bitumen modification, due to their compatibility with asphalt cement and its structural characteristics. It was observed that adding glass fiber to bituminous mixes affects the flow as well as the voids in the mix. As a result, flexible pavements, crack resistance, and deformation persist for a longer period, thus enhancing their fatigue life (Khater *et al.* 2021). Ji *et al.* (2007) found that the addition of glass fiber enhances the primary feature of hot mix asphalt (HMA). Results of Ameri *et al.* (2019) found that adding 0.1% glass fiber resulted in a 13% improvement in Marshall stability. It was discovered that the addition of glass fiber with a 12 mm length has a substantial influence on the Marshall Resistance, Marshall Strength, and asphalt mix performance (Zarei and Janmohammadi 2018). In one of the studies, it was found that fiberglass offered greater rutting resistance, increased the Marshall ratio, and reduced rutting (Khabiri and Alidadi 2016). It was also found that the higher carbon fibers content increased bituminous mix stability and decreased flow values (Geckil and Ahmedzade 2020). It has been revealed that the addition of carbon fibers to asphalt concrete significantly improves the mechanical performance of asphalt pavement (Nejad *et al.* 2014). Application of milled carbon fibers, chopped carbon fiber, and graphite powder into the mix which improved the tensile strength and rutting resistance of asphalt mixes (Vo *et al.* 2016). It is also observed that polyester and polyacrylonitrile (PAN) fibers have a higher impact than lignin and asbestos fibers, in enhancing the strength of flexible pavement (Chen and Wu 2010). Carbon-enhanced asphalt mixes were predicted to boost stiffness and resistance to permanent deformation, as well as improve the mixture's fatigue properties (Shanbara 2011). Due to the high tensile strength of carbon fiber, it was expected that the asphalt mixture would also perform better at low temperatures.

The rising complexity of modern-day technologies makes traditional control system approaches increasingly difficult to govern. For example, many linear and nonlinear models with large time delays are difficult to regulate and stabilise using conventional approaches. The lack of accuracy in the model is one of the major causes (Ibrahim 2016). Because of features like nonlinear programming, optimization, intelligent control, and decision support, machine learning is an efficient way to operate this complicated machinery. It includes several techniques such as Fuzzy logic, Neural networks, Support vector machine (SVM), Tree-based algorithms, and evolutionary algorithms. All of these methods are complementary to one another and may be used in conjunction to tackle a specific problem (Jang *et al.* 1997, Buckley and Hayashi 1994, Thakur *et al.* 2021). It is regarded to be extremely successful and efficient to use an artificial neural networks (ANN) model and optimization technique to predict the ideal asphalt composition of HRS-Base asphalt hot mix (Simatupang *et al.* 2018). The development of multilayer perceptron artificial neural network (MLP-ANN), SVM, M5Prime model tree technique (M5P), and RF were used to compare the prediction performance of the hybrid RF-FFA model to that of frequently used solo ML models (Cook *et al.* 2020). The findings reveal that in terms of prediction accuracy, the hybrid model performs better than solo ML models. In one of the studies, the authors (Vadood *et al.* 2014) measure and estimate the resilience modulus of modified HMA hybrid samples which was found to be accurately predicted by the optimised ANN. According to Angelaki *et al.* (2018) in terms of performance evaluation parameters, the ANFIS model based on a triangle membership function beats the SVM and ANN models. However, both models provided reliable parameter estimates. According to study (Li *et al.* 2019) Random Forest classification (RFC) was used to forecast pavement deterioration. The results showed that the RFC had a greater accuracy, demonstrating its adaptability and application to the classification of multi-sample and high-dimensional data. A study (Behnood and Daneshvar 2020) findings show that the efficacy of the M5P model performs better than other generated models to determine the dynamic modulus of asphalt. Additionally, the performance of the model was significantly enhanced by the logarithmic adjustment of the dynamic modulus values. A study (Reddy 2017) employed an ANN model to assess the strength characteristics of various mineral admixtures. It was found that there was a strong correlation between the predicted and the actual data generated by ANN application. This shows that ANN is an effective technique for examining the strength properties of concrete mixes.

In this study, glass and carbon fiber are used in the asphalt mixture separately and in combination with in different ratios to obtain Marshall stability. For the prediction of Marshall Stability, four distinct modeling approaches using Artificial Neural Networks (ANN), Support vector machine (SVM) Random forest (RF), and M5P tree-based models were adopted to estimate the Marshall value.

2. Study objectives

Glass and Carbon fibers have high potential in imparting stiffness and flexural strength to the asphalt mix. On one hand, Glass has high stiffness properties and on the other, carbon has high tensile strength and its hydrocarbon properties are compatible with asphalt. Therefore, these fibers when used in combination may enhance the strength properties of the asphalt mixture. As a result, the objectives were:

1. To predict the Marshall Stability of glass and carbon fibers in the asphalt concrete by exploring soft computing models i.e., Artificial Neural Networks (ANN), Support vector machine (SVM), Random forest (RF), and M5P tree-based model.
2. To optimize soft computing models that can predict the Marshall Stability of Glass and Carbon Fibrous asphalt concrete.
3. To perform the sensitivity analysis of an asphalt mix with nine inputs parameters i.e. Bitumen, Glass and Carbon fibers mixed in 100:0, 75:25, 50:50, 25:75, 0:100 percentage (designated as 100GF:0CF, 75GF:25CF, 50GF:50 CF, 25GF:75CF, 0GF:100CF), Bitumen grade (VG), Fiber length (FL), and Fiber diameter (FD) influencing Marshall Stability.

Table 1 Glass and carbon fiber combination in asphalt concrete

Designated Glass and Carbon fiber combination used in the asphalt concrete				
100GF: 0CF	75GF:25CF	50GF:50CF	25GF:75CF	0GF:100CF
100: 0 (%) Glass: Carbon Fiber (%)	75:25 (%) Glass: Carbon Fiber (%)	50:50 (%) Glass: Carbon Fiber (%)	25:75 (%) Glass: Carbon Fiber (%)	0:100 (%) Glass: Carbon Fiber (%)

Table 2 Gradation of coarse aggregate

Sieve size (mm)	25	20	16	12.5	10	4.75
Mesh passing (%)	100	97.67	67.47	30.07	8.27	0

Table 3 Fine aggregate gradation

Sieve size (mm/micron)	10	4.75	2.36	1.18	600	300	150	7
Passing (%)	98.4	93.6	89.8	86.0	76.9	19.9	7.4	4.8

Table 4 Physical characteristics of aggregates

Index	Coarse aggregate (%)	Fine aggregate (%)	Standard
specific gravity (gm/cm^3)	2.63	2.42	ASTM C-128
Apparent specific gravity (gm/cm^3)	2.83	2.47	
Water absorption (%)	2.75	0.33	
Bulk specific gravity (gm/cm^3)	1.51	1.68	
Aggregate crushing value	23.43	-	ASTM C-127
Aggregate impact value	7.95	-	ASTM C-127
Los angles abrasion value	34.34	-	ASTM C-131
Flakiness (FI) and Elongation index (EI)	14.64, 8.64	-	BS-812/ASTM D 4791

Table 5 Binder properties

Property	Standard	Unit	Value
Specific Gravity @ 25 ºC	ASTM D70	%	0.99
Penetration (25 ºC, 100 gm, and 5 sec)	ASTM D5	0.1 mm	97.66
Flash point	ASTM D92	ºC	281
Softening point (Ring and Ball test)	ASTM D36	ºC	39.2
Color	Visual	-	Black

2.1 Data collection

The Marshall Stability data was acquired utilizing two methods: (a) performing laboratory tests, (b) data derived from published articles. A total of 164 cylindrical specimens of size 101.6 mm in

Table 6 Physical and mechanical properties of glass and carbon fiber

Test properties	Glass fiber	Carbon fiber	Unit
Length	12	12	mm
Diameter	15	5	μm
Color	White	Black	-
Tensile strength	4700-4800	5790	MPa
Elongation	5.7	-	%
Density	2.46	1.80	gm/cc
Failure strain	-	2.0	%
Base	S- glass	Polyacrylonitrile (PAN)based carbon fiber	-

Fig. 1 Glass and carbon fiber used in this study

diameter and 63.5 mm in height were prepared using Glass and Carbon fibers mixed in 100:0, 75:25, 50:50, 25:75, 0:100 percentage (designated as 100GF:0CF, 75GF:25CF, 50GF:50 CF, 25GF:75CF, 0GF:100CF) as shown in Table 1.

3. Materials and methodology

3.1 Coarse and fine aggregates

The asphalt mixture is prepared using coarse aggregate with a nominal size of 20 mm. Tables 2 and 3, shows the gradation of coarse and fine aggregates was determined according to (ASTM D6913-04). Table 4 summarizes the physical characteristics of coarse and fine aggregates. Natural sand (10% of the weight of coarse aggregate) was utilized as a filler ingredient for the consistency of the asphalt mixture.

3.2 Binder

The asphalt used in this study was purchased from the Himachal Pradesh Public Works Department in Solan, India, with a penetration grade of 80-100 (VG 10) and the basic components of the asphalt are shown in Table 5.

3.3 Fibers utilized

Chopped glass fiber (GF) and Chopped carbon fiber (CF) were used in this study. Five different types of asphalt mix (Glass and Carbon fibers mixed in 100:0, 75:25, 50:50, 25:75, 0:100 percentage (designated as 100GF:0CF, 75GF:25CF, 50GF:50 CF, 25GF:75CF, 0GF:100CF), were prepared. The fiber percentage (by the weight of bitumen content) was added to the asphalt mix. Table 6 summarizes the physical and mechanical properties of glass and carbon fibers. The glass and carbon fibers that have been added to the asphalt mixture are shown in Fig. 1.

4. Marshall specimen preparation

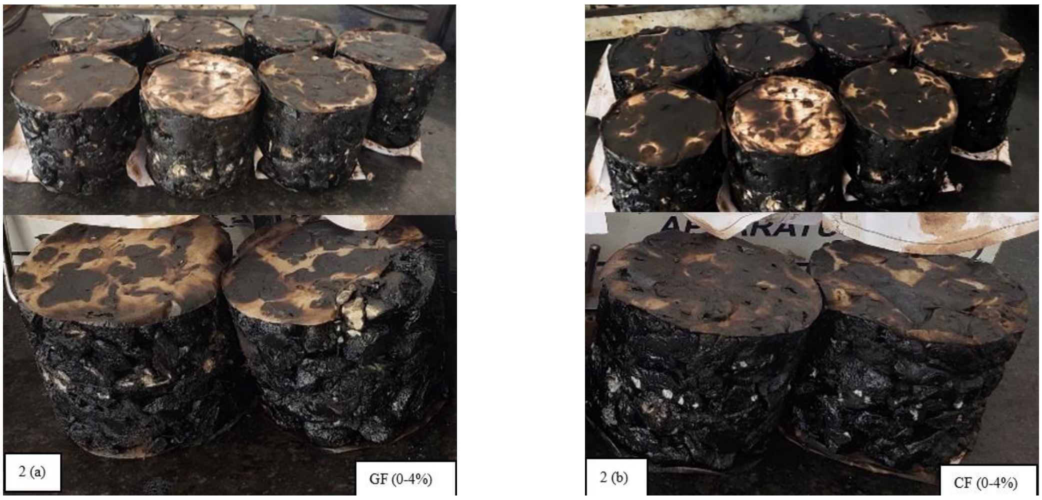
A total of 1200 gm of coarse aggregates was dried for 24 hours at 170-190°C in the oven and asphalt mixes were prepared following ASTM D1559 for Marshall Stability. Total 164 cylindrical asphalt concrete specimens were made in the Shoolini University laboratory using Glass and Carbon fibers in combination as 100GF: 0CF, 75GF:25CF, 50GF:50CF, 25GF:75CF, 0GF:100CF, along with control asphalt mix. The glass and carbon fibers were added in the prescribed quantity to 20 mm nominal size aggregate with filler material heated to a temperature of 160°C, followed by asphalt heated to a temperature range from 121 to 138°C to achieve a homogeneous asphalt mix. The quantity of fiber added in the asphalt mix was varied from 0%-4% by weight of bitumen content. The binder concentration varied from 4.5% - 6% in each asphalt mix with a bitumen content interval of 0.5%. The aggregate-fiber mixture was properly mixed until it was uniform in color and distribution of the fibers. The mixing time was kept between 2 to 5 minutes. The asphalt mixture was then poured into the Marshall moulds, which had been pre-heated. Each sample was given 75 blows of hammer on each side used to compact the samples. The specimens were stored at room temperature for 24 hours. The samples were then extracted and analyzed at 60°C, as per standard procedure. Figs. 2(a)-(b) shows the Glass, Carbon fibrous asphalt mix specimens respectively and Fig. 3 and Figs. 4(a)-(b) show glass and carbon fiber (50GF:50CF, 75GF:25CF and 25GF:75CF) asphalt mix specimens with fiber concentrations ranging from 0% to 4%.

5. Machine learning algorithm

A variety of machine learning is currently accessible, a few of them are discussed as under.

5.1 Artificial neural network (ANN)

The ANN concept works similarly to biological neuron cells in the brain. It estimates an output as a mechanism for unknown functions using a database of input values. One of the most significant benefits of ANN is that it can analyze and solve exceedingly complex and nonlinear problems using only fundamental mathematical procedures (Bas¸yigit *et al.* 2010, Cavaleri *et al.* 2017). A neural network is made up of input, hidden, and output layers. Each layer may have many units that are completely connected with the next layer, and each connection in the system has its weight. The data is received by the nodes in the input layer, which are then processed and given to the nodes in



(a) GF (0-4%) (b) CF (0-4%)

Fig. 2 Laboratory specimens using glass and carbon fiber with different percentages of fibers (0-4%)

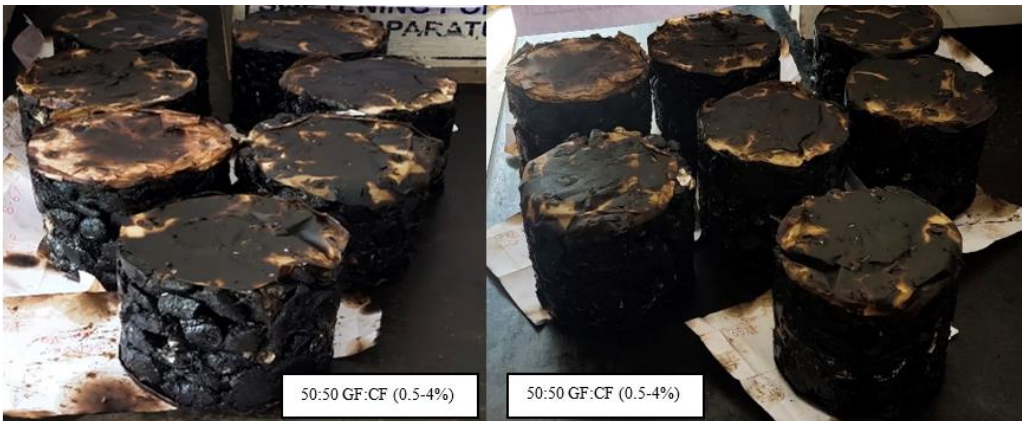
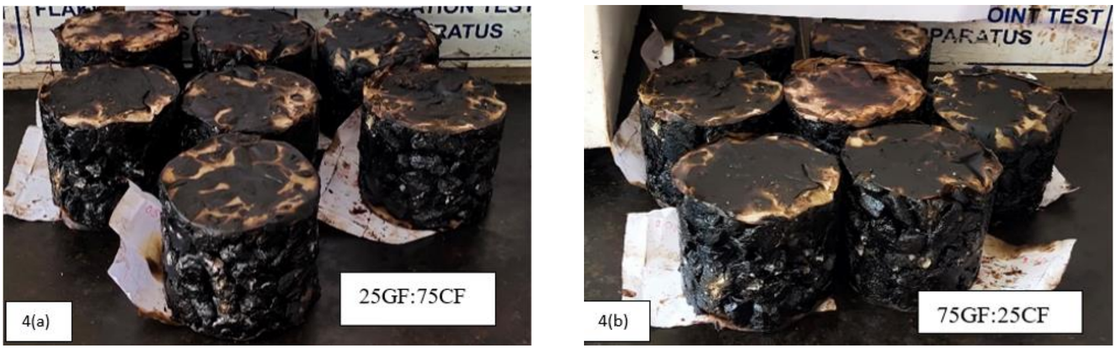


Fig. 3 Laboratory specimen in combination with glass and carbon fiber using different percentages of bitumen (0.5-4%)



(a) 25GF:75CF (b) 75GF:25CF

Fig. 4 Laboratory specimens (glass and carbon fiber) using bitumen (0.5-4%)

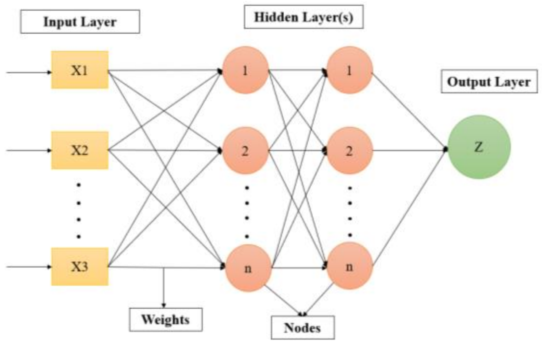


Fig. 5 ANN model

the hidden layer (Ahmadi *et al.* 2017, Upadhya *et al.* 2021b). However, generating a realistic ANN network requires empirical experience and its effectiveness is entirely based on the trial-and-error process. This approach is black-box and therefore, the nature of the prediction equation is not known. In this study performance of the ANN model was done to obtain the desired output by taking five input parameters (Vyas *et al.* 2020). The notation represents the frequency at which each layer returns data to the network. The number of times the training data is cycled through is measured in epochs (Demirel *et al.* 2009). Because of the network's complex interconnections, ANNs have a few restrictions, such as an exponential increase in the training phase as dataset size grows (Zealand *et al.* 1997, Upadhyay *et al.* 2021c). The processing of the ANN model is shown in Fig. 5.

5.2 Support vector machines (SVMs)

The Support Vector Machine (SVM) is a method of supervised learning that is used for classification and regression. In discriminative classifiers, a line is drawn across data clusters, which allows them to distinguish between them. The notion of decision planes, which establish decision bounds, underpins Support Vector Machines (Abd and Abd 2016). The SVM technique uses a kernel trick to perform data categorization, indirectly translating inputs into high-dimensional feature spaces. The SVM technique employs an effective separation by a hyperplane with the greatest distance to the nearest training data point and the smallest generalization error, allowing the SVM to achieve superior generalization. Over other machine learning algorithms, the SVM approach has a number of advantages, including a unique optimization strategy, effective use of higher dimensional spaces, and computational learning theory (Park *et al.* 2019). The SVM analysis approach includes training and testing data sets with input and output parameters. SVM analysis may be done in two ways. The optimum margin classifier (linear classifier), for example, splits the decision surface into two parts (Salcedo-Sanz *et al.* 2014). The primary objective of SVM regression is to reduce the upper bound of the generalization error via structural risk reduction (SRM) (Yan and Shi 2010). When the kernel mapping is applied to actual data, the information separates linearly across a high-dimensional feature with no change in the input data space (Goh and Goh 2007).

5.3 Random forest (RF)

The random forest algorithm was initially proposed by Breiman (1996). It's a flexible method that has been successfully used for a wide range of engineering challenges. The random forest (RF)

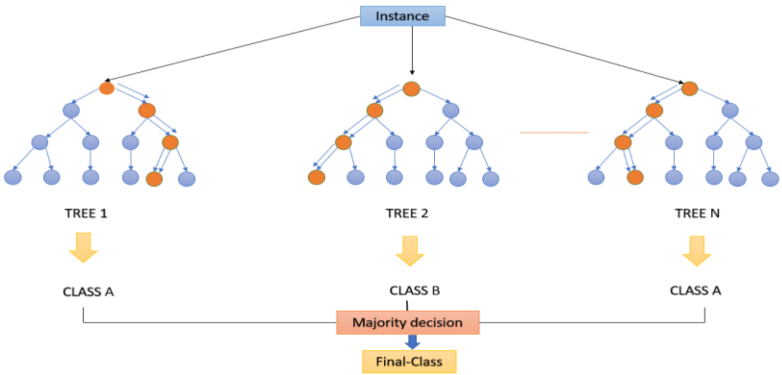


Fig. 6 Random forest model

regression approach employs several tree predictors, each of which is generated from a randomly chosen input vector. To construct a tree, random forest regression employs a random selection of input variables or a combination of variables at each node (Upadhya *et al.* 2021). RF consists of a number of tree-based predictors, each of which is formed from a random vector, i.e., utilizing input vector sampled separately and in various ways. Bagging is the process of randomly dividing a dataset into training data sets. In random forest regression, the number of trees to be formed (k) and the number of input variables used at each node to construct a tree (m) are two user-defined parameters. To determine the optimal split, only a few criteria are examined at each node. As a result, the RF regression consists of many (k) trees (Singh *et al.* 2019, Thakur *et al.* 2020). Out-of-bag samples are used to validate the model. The technique is carried out again and again until the requisite accuracy is achieved (Farooq *et al.* 2020). Weka software 3.9 is used to anticipate Marshall Stability. The random forest model is shown in Fig. 6.

5.4 M5P model tree

It was developed in 1992 by Quinlan to predict statistics parameters. The M5P model tree structure is employed in high-dimensional applications for qualitative and continuous variables, as well as missing data. The M5P model allows a tree to estimate continuous mathematical characteristics. In this approach, pruning is used to reduce the risk of over-fitting. To obtain better information with less divergence in the cross-functional and cross-class values in each branch, a separation method is used. The three key steps of the M5P preparation process are tree growth, pruning, and smoothing (Ali *et al.* 2020, Almasi *et al.* 2017). The M5P approach is used to generate a model tree. The goal is to build a network that links the target values of the training examples to the values of their input attributes. The accuracy with which the model forecasts the unknown target values will determine the model's performance (Deepa *et al.* 2010). The M5P tree approach can handle very high dimensions and is better suited to continuous rather than discrete situations. It displays the piecewise features of each linear model that was created to approximate the nonlinear connection in the data set (Blaifi *et al.* 2018). The splitting ends when the values of all examples reaching a node differ slightly or there are only a few instances left, and the changeability is determined by the predicted decrease in error as a result of checking each variable at that node, which is defined as the standard deviation of the values reaching that node from the roots to the branches (Upadhya *et al.* 2021b).

Table 7 Data description

S. No.	Bitumen Content BC (%)	Glass Fiber GF (%)	50GF: 50CF	75GF: 25CF	25GF: 75CF	Carbon Fiber CF (%)	Bitumen Grade (VG)	Fiber Length (mm)	Fiber Diameter (FD) (5-15) µm	Marshall Stability (kN)	Obser-vations (No.)	Data Source
Range of dataset												
1.	5-7	0-2.5	-			-	0-30	0	0-0.5	6.3-7.6	5	Pasha *et al.* (2017)
2.	4.5-6.5	0-0.3	-			-	0-20	0-10	0-10	2.26-3.59	20	Alidadi and Khabiri (2016)
3.	5.5	0.2-0.6				-	0-30	0-12	0-2	13.5-14.4	4	Taherkhani (2016)
4.	4.6-4.7	0-0.3	-			-	0-30	0-6	0-10	13-14.3	4	Ji *et al.* (2007)
5.	5.34	-				0-1	0	0-12	0-7	11-11.4	3	Yoo *et al.* (2018)
6.	4.9-5.3	-	-			0-0.7	0-10	0-12.5	0-6.5	2.23-2.97	4	Geckil and Ahmedzade (2020)
7.	4.5-6.5	-	-			0-0.3	0-20	0-10	0-6	2.26-3.59	20	Alidadi and Khabiri (2016)
8.	4.2-4.3	-	-			0-2	0-30	0-10	0-5	12.8-13.5	2	Xiaoming and Shaopeng (2011)
9.	4.5-6	0-4	-	-	-	-	0-10	0-12	0-10	5.61-15.06	36	Collection of data from current research +(experimental)
10.	4.5-6	-	-	-		0.5-4	0-10	0-12	0-10	6.65-19.43	32	
11.	4.5-6	-	0.5-4	-	-	-	0-10	0-12	0-10	12.05-23.5	32	
12.	4.5-6	-	-	0.5-4	-	-	0-10	0-12	0-10	13.4-18.32	32	
13.	4.5-6	-	-		0.5-4	-	0-10	0-12	0-10	2.74-19.20	32	
Total observations											226	

6. Methodology and dataset

To develop a model for the prediction of Marshall stability a total of 226 (Table 7) observations in which 164 were obtained from laboratory experiments and 62 from previous research articles were incorporated for analysis. The data set was bifurcated in 80/20 ratio for training and testing data sets. For the prediction of Marshall stability of asphalt concrete reinforced, four soft

Table 8 Statistical features of dataset

Training										
	Bitumen Content BC (%)	Glass Fiber GF (%)	50GF: 50CF	75GF: 25CF	25GF: 75CF	Carbon Fiber CF (%)	Bitumen Grade (VG)	Fiber Length (mm)	Fiber Diameter (5-15) µm	Marshall Stability (kN)
Mean	5.3106	0.3370	0.2983	0.3232	0.3122	0.3481	12.3204	10.0497	9.6094	13.3619
Standard Error	0.0454	0.0656	0.0648	0.0672	0.0659	0.0659	0.4510	0.2908	0.3267	0.3382
Median	5.5000	0.0000	0.0000	0.0000	0.0000	0.0000	10.0000	12.0000	10.0000	13.9200
Standard Deviation	0.6114	0.8820	0.8721	0.9047	0.8870	0.8870	6.0669	3.9130	4.3949	4.5495
Kurtosis	-0.8690	7.4784	8.2928	7.3136	7.5787	7.0435	3.3099	2.0877	0.1943	0.3527
Skewness	0.1878	2.8946	3.0381	2.8892	2.9263	2.8034	1.9525	-1.8974	-0.3172	-0.6514
Range	2.8000	4.0000	4.0000	4.0000	4.0000	4.0000	30.0000	12.5000	20.0000	21.7700
Minimum	4.2000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	2.5300
Maximum	7.0000	4.0000	4.0000	4.0000	4.0000	4.0000	30.0000	12.5000	20.0000	24.3000
Confidence Level (95.0%)	0.0897	0.1294	0.1279	0.1327	0.1301	0.1301	0.8898	0.5739	0.6446	0.6673
Testing										
	Bitumen Content BC (%)	Glass Fiber GF (%)	50GF: 50CF	75GF: 25CF	25GF: 75CF	Carbon Fiber CF (%)	Bitumen Grade (VG)	Fiber Length (mm)	Fiber Diameter (5-15) µm	Marshall Stability (kN)
Mean	5.2244	0.3511	0.4000	0.3000	0.3444	0.3778	11.1111	10.5889	9.7000	13.2913
Standard Error	0.0875	0.1408	0.1487	0.1305	0.1411	0.1436	0.5705	0.4998	0.5542	0.8045
Median	5.0000	0.0000	0.0000	0.0000	0.0000	0.0000	10.0000	12.0000	10.0000	14.1400
Standard Deviation	0.5867	0.9445	0.9977	0.8752	0.9464	0.9632	3.8271	3.3529	3.7179	5.3969
Kurtosis	-1.1365	7.7390	5.5788	8.9838	7.7414	6.9898	14.5242	4.9550	0.6462	-0.1393
Skewness	0.1892	2.9100	2.5518	3.0722	2.9126	2.8051	3.7298	-2.4252	-0.5759	-0.4399
Range	2.0000	4.0000	4.0000	4.0000	4.0000	4.0000	20.0000	12.5000	15.0000	21.2400
Minimum	4.5000	0.0000	0.0000	0.0000	0.0000	0.0000	10.0000	0.0000	0.0000	2.2600
Maximum	6.5000	4.0000	4.0000	4.0000	4.0000	4.0000	30.0000	12.5000	15.0000	23.5000
Confidence Level (95.0%)	0.1763	0.2838	0.2997	0.2629	0.2843	0.2894	1.1498	1.0073	1.1170	1.6214

computing methods, namely Artificial neural network, Support vector machines, and Random forest and M5P tree were used in this study, which was implemented using Weka 3.9. Nine inputs parameters i.e., Bitumen, Glass and Carbon fibers mixed in 100:0, 75:25, 50:50, 25:75, 0:100 percentage (designated as 100GF:0CF, 75GF:25CF, 50GF:50 CF, 25GF:75CF, 0GF:100CF), Bitumen grade (VG), Fiber length (FL), and Fiber diameter (FD) were utilized to obtain the predicted values of Marshall Stability. Table 8 shows the statistical characteristics of the input

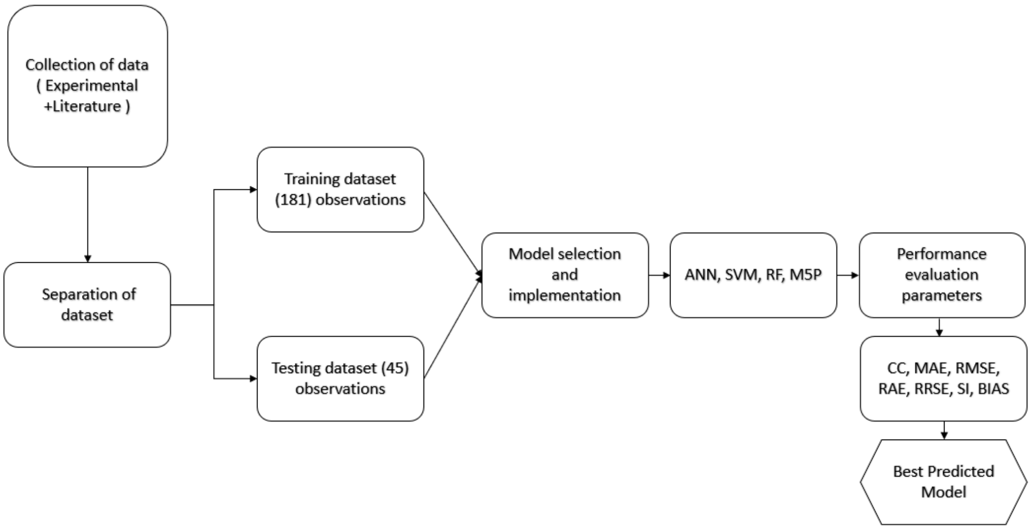


Fig. 7 Flow chart: Optimization process for ANN, SVM, RF, M5P

parameters, and Fig. 7 depicts the flow chart for determining the optimum model approach. Statistical indices such as correlation (CC), mean absolute error (MAE), root mean squared error (RMSE), relative absolute error (RAE), root relative squared error (RRSE), Scattering index (SI), and BIAS were assessed to evaluate the predicted output i.e., Marshall stability of asphalt concrete.

7. Performance evaluation parameters

The performance of each model was assessed using seven statistical metrics i.e., coefficient of correlation (CC), mean absolute error (MAE), root mean squared error (RMSE), relative absolute error (RAE), root relative squared error (RRSE), Scattering index (SI) and BIAS respectively. Both the root-mean-square error (RMSE) and the mean absolute error (MAE), Scattering index (SI), and BIAS (average difference between actual and predicted values). These statistics quantify the difference between actual and values for the same behavior, i.e., a lower calculated error predicts better output outcomes. This may be calculated using a formula that has been shown in the following Eqs. (1)-(7).

$$\mathrm{CC} = \frac{\sum_{i=1}^{n}(S_i-\bar{S})(T_i-\bar{T})}{\sqrt{\sum_{i=1}^{n}(S-\bar{S})^2}\sqrt{\sum_{i=1}^{n}(T_i-\bar{T})^2}} \tag{1}$$

$$\mathrm{MAE} = \left(\frac{1}{n}\sum_{i=1}^{n}|S-T|\right) \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S-T)^2} \tag{3}$$

$$\mathrm{RAE} = \frac{\sum_{i=1}^{n}|S-T|}{\sum_{i=1}^{n}(|S-\bar{S}|)} \tag{4}$$

Table 9 Performance assessment of ANN, SVM_PUK, RF, and M5P Tree-based model

Models applied	CC	MAE (kN)	RMSE (kN)	RAE (%)	RRSE (%)	SI	BIAS
Training Dataset							
ANN	0.9147	1.3757	1.843	39.88	40.62	0.1379	-0.1290
SVM_PUK	0.9345	1.0066	1.6234	29.18	35.78	0.1366	0.0589
RF	0.9796	0.6832	0.9619	19.80	21.20	0.1385	0.0450
M5P	0.957	0.8652	1.3161	25.08	29.01	0.1383	-1.1049
Testing Dataset							
ANN	0.8648	1.978	2.6951	49.31	50.50	0.2027	-0.2357
SVM_PUK	0.8542	2.0115	2.7853	50.14	52.19	0.1992	0.0516
RF	0.8561	2.1544	2.8003	53.71	52.47	0.2035	-0.1004
M5P	0.8597	1.98	2.7767	49.36	52.03	0.2012	-0.4146

$$\mathrm{RRSE} = \sqrt{\frac{\sum_{i=1}^{n}(S-T)^2}{\sum_{i=1}^{n}(|S-\bar{T}|)^2}} \tag{5}$$

$$\mathrm{SI} = \sqrt{\frac{\sum_{i=1}^{n}[(T_i-\bar{T})-(S-\bar{S})^2}{\sum_{i=1}^{N} S_i^2}} \tag{6}$$

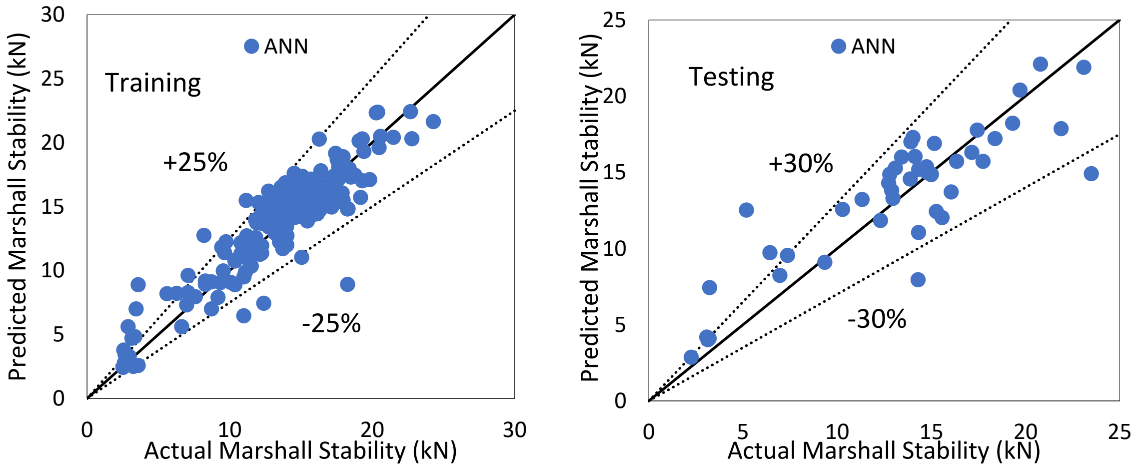
$$\mathrm{BIAS} = \frac{\sum_{i=1}^{n}(S_i-T_i)}{\sum_{i=1}^{n} S_i} \tag{7}$$

Where,
S=Observed values
T=Average of observation
$\bar{T}$=Predicted value
n=number of observations

8. Performance evaluation of developed model

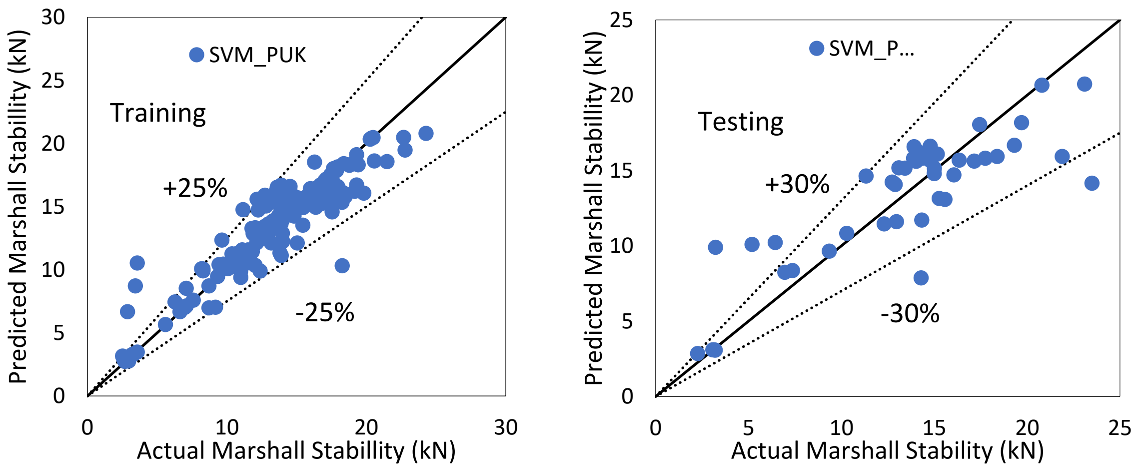
8.1 ANN-based model

The development of an ANN-based model is an iteration process that uses a multilayer perceptron model as a framework. Several attempts were conducted to arrive at the optimal value, i.e., the maximum defined CC value with the least errors for both the training and testing data for the predictions assessment of the developed models. Seven different performance assessment indices were applied to get the best predictive model as shown in Table 9. Results of Table 9 suggests that an ANN-based model outperforms other applied models for the prediction of Marshall Stability corresponding to nine input variables with CC value as 0.9147 and 0.8648, MAE value as 1.3757 and 1.978, RMSE value as 1.843 and 2.6951, RAE value as 39.88 and 49.31, RRSE value as 40.62 and 50.50, SI values as 0.1379 and 0.2027 and BIAS value as -0.1290 and -0.2357 for both training



(a) (b)

Fig. 8 Actual and predicted values using ANN-based models for training and testing stages



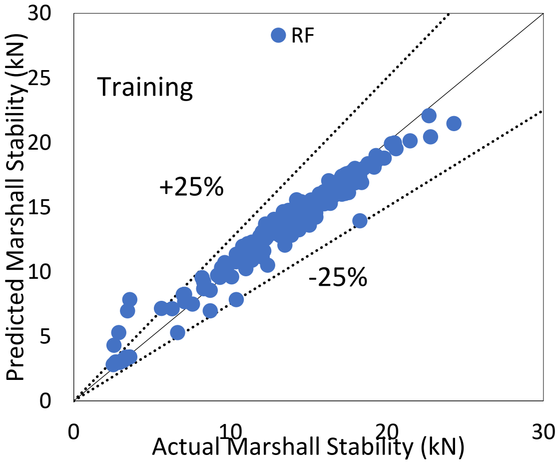
(a) (b)

Fig. 9 Actual and predicted values using SVM_PUK-based models for training and testing stages

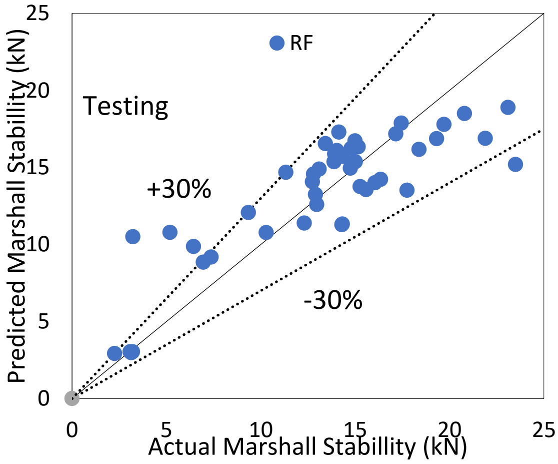
and testing stages respectively. The training and testing phases are represented in Figs. 8(a)-(b) with the agreement graph showing actual and predicted values using ANN-based models. The majority of the points in these graphs are centered on the line of perfect agreement, which shows the best possible match between actual and predicted outcome parameters, signifying more reliability. Most of the experimental algorithms' predicted values are within the ±25% and ±30% error range in the training and testing stages.

8.2 SVM_PUK model

The Pearson Kernel function (PUK), which incorporates user-defined parameters such as omega



(a)



(b)

Fig. 10 Actual and predicted values using RF-based models for training and testing stages

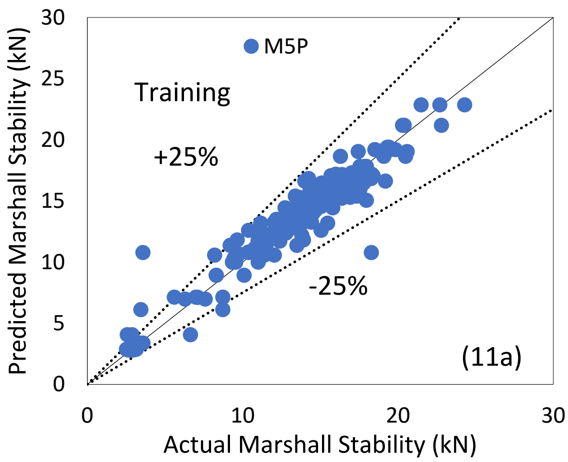
(O) and sigma (sigma), is used in this approach (S). After several applications, the ideal number was determined, i.e., the largest CC value with the minimum errors. Results of Table 9 suggests that an SVM_PUK-based model is reliable in predicting the Marshall Stability of asphalt concrete using glass and carbon fiber with CC value as 0.9345 and 0.8542, MAE value as 1.0066 and 2.0115, RMSE value as 1.6234 and 2.7853, RAE value as 29.18 and 50.14, RRSE value as 35.78 and 52.19, SI values as 0.1366 and 0.1992 and BIAS value as 0.0589 and 0.0516 for both training and testing stages respectively. The training and testing phases are represented in Figs. 9(a)-(b) with the agreement graph showing actual and predicted values using SVM_PUK based models. Most of the experimental algorithms' predicted values are within the ±25% and error range in the training and testing stages.

8.3 RF-based model

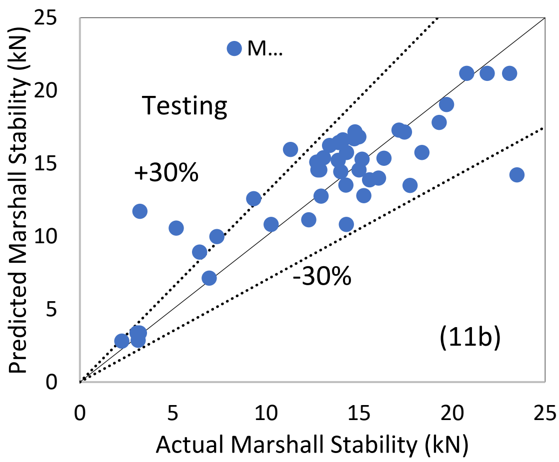
On a decision tree, the RF classifier is trained. A Random Forest-based model evolution is analogous to that of an ANN-based model. The performance evaluation parameters as listed in Table 9 show that the RF-based model is better in predicting the Marshall Stability of asphalt concrete with glass and carbon fiber reinforcement with CC values as 9.9796 and 0.8561 MAE values as 0.6832 and 2.1544, RMSE 0.9619 and 2.8003, RAE 19.80 and 53.71, RRSE 21.20 and 52.47, SI values as 0.2035 and 0.2035 and BIAS value as 0.0450 and -0.1004 for both training and testing stages respectively. The agreement graph plotting actual and predicted values using RF-based models is shown in Figs.10(a)-(b). It was also discovered that the majority of the predicted values from the model are within the ±25% and ±30% error range in both the training and testing stages.

8.4 M5P tree

The performance assessment of the M5P model tree shown in Table 9 which depicts that the M5P tree model is also accurate in predicting the Marshall Stability of asphalt concrete with nine input variables with CC value as 0.957 and 0.8597 MAE value as 0.8652 and 1.98, RMSE 1.3161

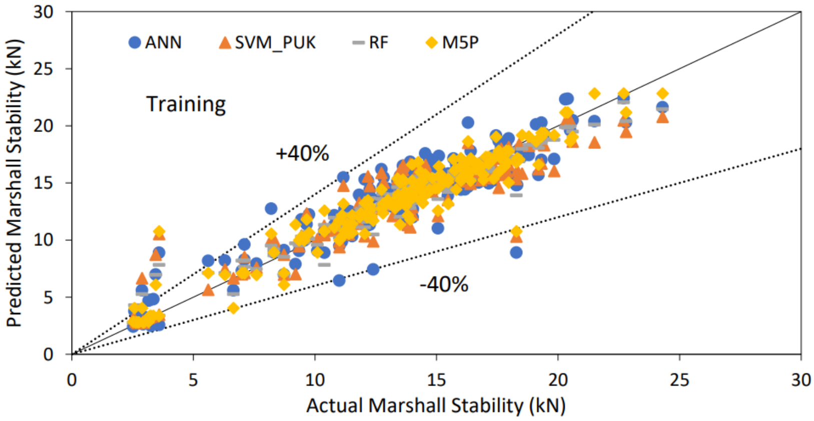


(a)

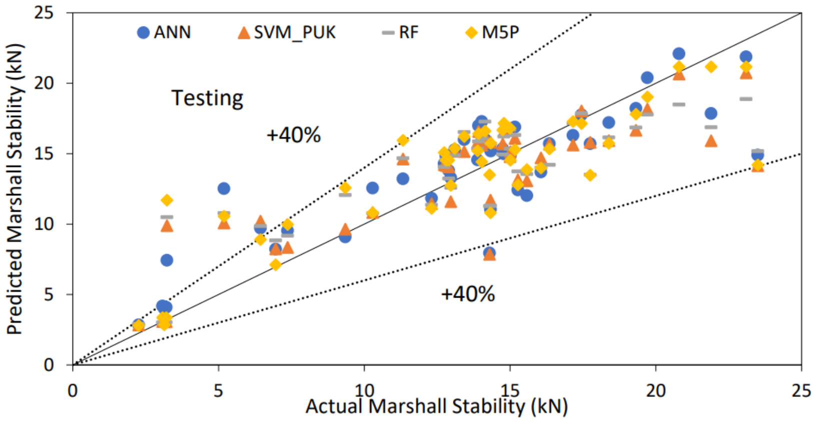


(b)

Fig. 11 Actual and predicted values using M5P-based models for training and testing stages



(a)



(b)

Fig. 12 Actual and predicted values using ANN, SVM_PUK, RF and M5P Tree based models for t raining and testing stages

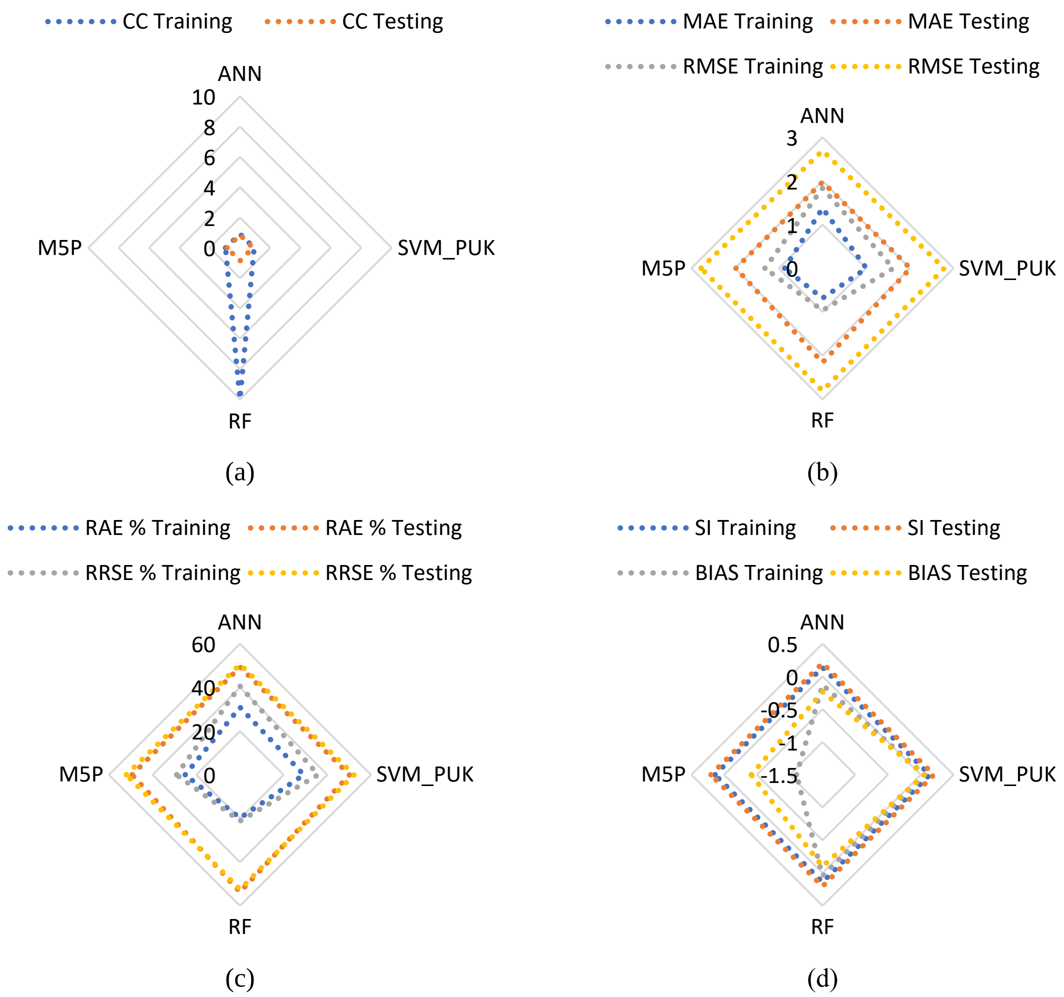
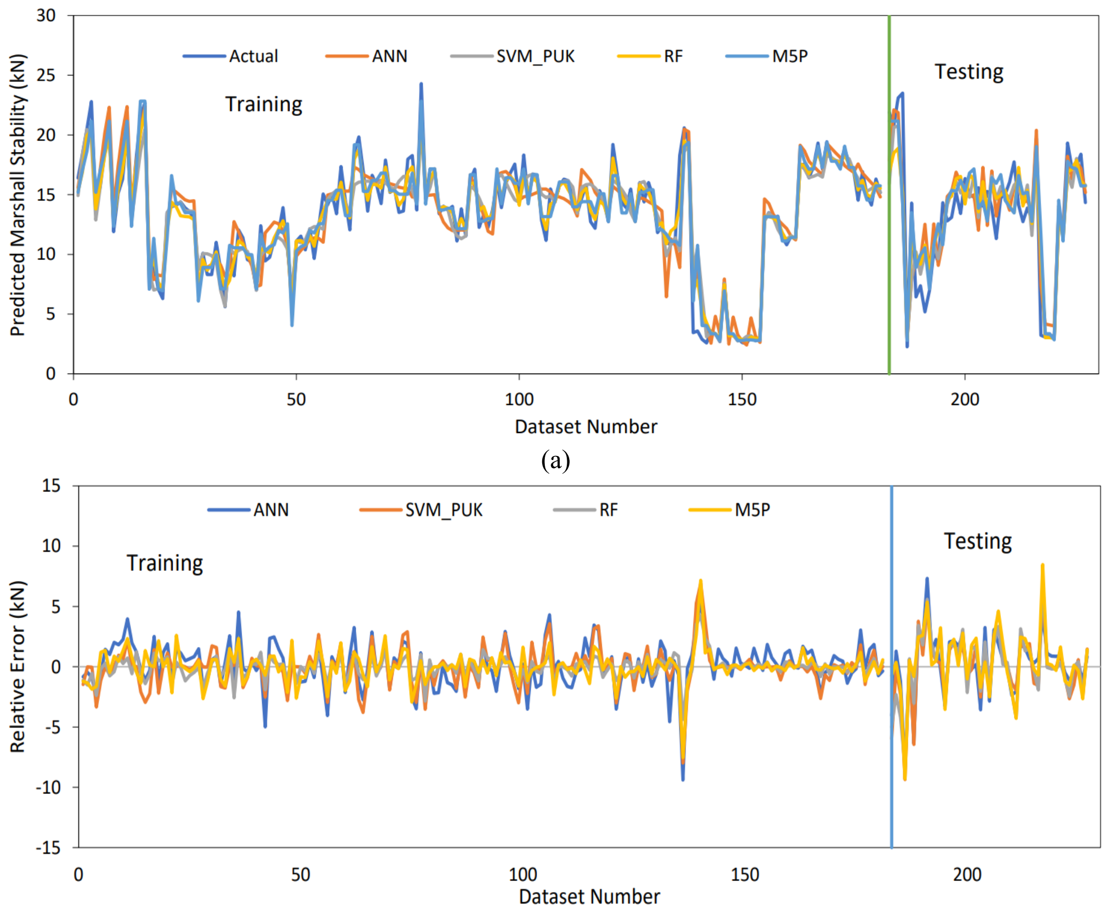


Fig. 13 Radial graph showing actual and predicted values for all applied models for training and testing stages

and 2.7767, RAE 25.08 and 49.36, RRSE 29.01 and 52.03, SI values as 0.1383 and 0.2012 and BIAS value as -1.1049 and -0.4146 for both training and testing stages respectively. The agreement graph plotting actual and predicted values using M5P-based models is shown in Figs.11(a)-(b). It was also discovered that the majority of the predicted values from the model are within the ±25% and ±30% error range in both the training and testing stage.

9. Results and discussion

In this study, the Marshall stability of asphalt concrete was predicted by implementing four machine learning techniques i.e. ANN, SVM, RF and M5P. with nine inputs parameters i.e., Bitumen, Glass and Carbon fibers mixed in 100:0, 75:25, 50:50, 25:75, 0:100 percentage (designated as 100GF:0CF, 75GF:25CF, 50GF:50 CF, 25GF:75CF,0GF:100CF), Bitumen grade (VG), Fiber



(a)

(b)

Fig. 14 Error graph between actual and predicted values using ANN, SVM_PUK RF and M5P based models for training and testing stages

length (FL), and Fiber diameter (FD) were utilized from the experimental and literary data. Seven statistical indices i.e. coefficient of correlation (CC), mean absolute error (MAE), root mean squared error (RMSE), relative absolute error (RAE), root relative squared error (RRSE), Scattering index (SI), and BIAS were applied to assess the effectiveness of the developed models and these attributes are assessed by performance evaluation parameters as given in following Eqs. (1)-(7) in testing stage. Whereas the performance of SVM_PUK, RF and M5P based model also gives reliable results in predicting the Marshall stability of asphalt concrete using glass and carbon fiber with higher coefficient of correlation and lower errors. The performance evaluation of all the models employed for both stages is shown in Figs. 12(a)-(b), which demonstrates that the predicted readings of the ANN-based model are closer to the actual data, resulting in a low error bandwidth i.e., ±40% error line. Figs. 13(a)-(c), and (d) presents radial graphs representing predicted values for all models with statistical parameters applied for both stages. Figs. 14(a)-(b) shows the predicted Marshall stability with the total dataset and relative error for all applied models. As a result, it can be inferred that all the four developed models (ANN, SVM, RF and M5P) can be utilized satisfactory for the prediction

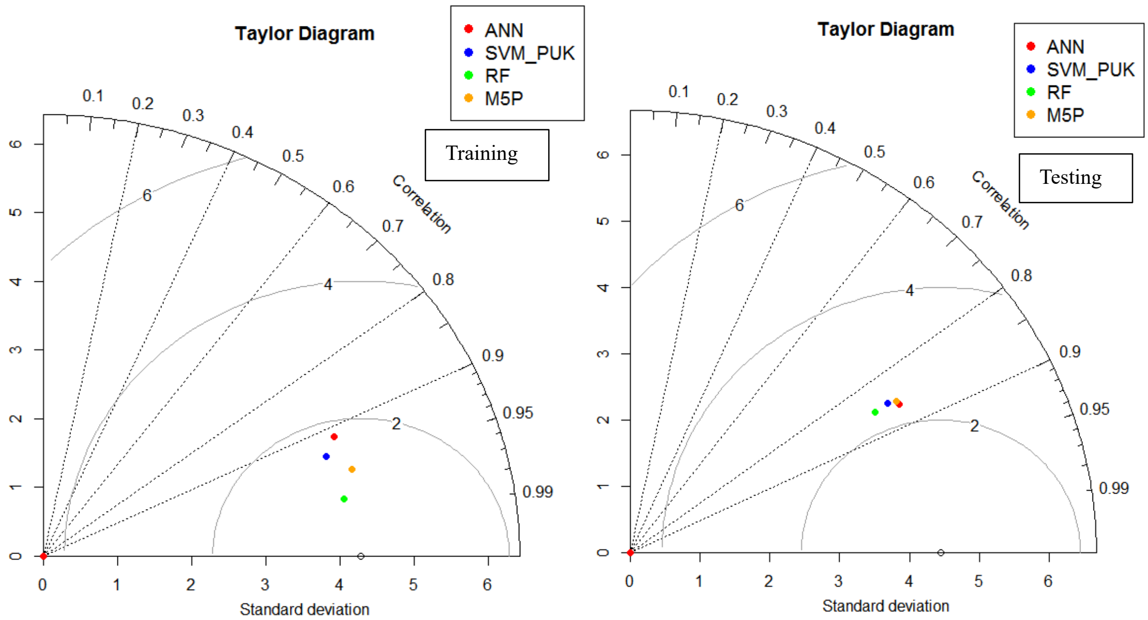


Fig. 15 Taylor diagram (Training and Testing stages)

of the Marshall Stability with nine input parameters for the dataset considered in the study.

10. Taylor diagram

The performance of the all four developed models (ANN, SVM, RF and M5P) as shown in Table 9 for CC values, is illustrated Taylor diagram Fig. 15. The accuracy of the implemented models was evaluated using two statistical metrics: standard deviation and correlations. In the Taylor diagram, (Red point) indicate that the ANN-based model has the highest coefficient of correlation in the testing stage when compared to the other developed models for predicting the Marshall Stability of asphalt concrete by utilizing nine inputs parameters i.e., Bitumen, Glass and Carbon fibers mixed in 100:0, 75:25, 50:50, 25:75, 0:100 percentage (designated as 100GF:0CF, 75GF:25CF, 50GF:50 CF, 25GF:75CF, 0GF:100CF), Bitumen grade (VG), Fiber length (FL), and Fiber diameter (FD). To validated the results of the four developed model (ANN, SVM, RF and M5P), the findings of the Taylor diagram are consistent with them.

11.Sensitivity analysis

Sensitivity analysis was performed to analyses the significance of each input parameters on the prediction output of the Marshall Stability. Nine inputs parameters i.e., Bitumen, Glass and Carbon fibers mixed in 100:0, 75:25, 50:50, 25:75, 0:100 percentage (designated as 100GF:0CF, 75GF:25CF, 50GF:50 CF, 25GF:75CF, 0GF:100CF), Bitumen grade (VG), Fiber length (FL), and Fiber diameter (FD) were utilized as shown in Table 10. The white box under the input parameter

Table 10 Sensitivity analysis with ANN-based model

Bitumen content BC (%)	Glass fiber GF (%)	50GF: 50CF	75GF: 25CF	25GF: 75CF	Carbon fiber CF (%)	Bitumen grade (VG)	Fiber length (mm)	Fiber diameter (5-15) µm	Marshall stability (kN)	ANN Model	
										CC	RMSE
										0.5453	4.7353
										0.6193	4.4693
										0.7551	3.8228
										0.7961	3.4285
										0.7969	3.3803
										0.8476	2.9255
										0.8507	3.145
										0.8532	2.9212
										0.8564	2.5327
										0.8648	2.6951

shows the its elimination from the rest of the input set in the analysis, resulting thereby change in CC and RMSE values for Marshall stability. The said table shows that Fiber length (FL) is the most sensitive to the Marshall Stability followed by fiber diameter, and Bitumen grade. While observing the effect of the different fiber mixes it is found that 25GF:75CF is the most sensitive to the Marshall Stability. Therefore, further studies related to this fiber mix may reflect its potential use in asphalt mixes.

12. Conclusions

The current study was focused on the prediction of the Marshall stability of asphalt concrete by developing four machine learning techniques i.e., ANN, SVM_PUK, RF, and M5P Tree-based models.

- Total nine inputs parameters i.e., Bitumen, Glass and Carbon fibers mixed in 100:0, 75:25, 50:50, 25:75, 0:100 percentage (designated as 100GF:0CF, 75GF:25CF, 50GF:50 CF, 25GF:75CF, 0GF:100CF), Bitumen grade (VG), Fiber length (FL), and Fiber diameter (FD) were utilized in the study.
- Seven different goodness of fit parameters were used to evaluate the performance of the generated models such as coefficient of correlation (CC), mean absolute error (MAE), root mean squared error (RMSE), relative absolute error (RAE), root relative squared error (RRSE), Scattering index (SI) and BIAS.
- From the performance evaluation results, the Artificial neural network (ANN) outperformed other models with CC values as 0.9147 and 0.8648, MAE values as 1.3757 and 1.978, RMSE values as 1.843 and 2.6951, RAE values as 39.88 and 49.31, RRSE values as 40.62 and 50.50, SI values as 0.1379 and 0.2027 and BIAS value as -0.1290 and -0.2357 testing stage.
- An agreement graph between actual and predicted values shows that the ANN has a small error band and is an optimal fitting for predicting the output. Taylor diagram also suggested that the ANN model outperformed the other models in testing stage.

• Results of the sensitivity analysis showed that Fiber length (FL) is the most sensitive to the Marshall Stability followed by fiber diameter, and Bitumen grade. While observing the effect of the different fiber mixes it is found that 25GF:75CF is the most sensitive to the Marshall Stability. Therefore, further studies related to this fiber mix may reflect its potential use in asphalt mixes.

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Data availability statement

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

Conflict of interest

There is no conflict of interest by the authors with anyone whosoever is connected with this research.

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