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Combined effect of glass and carbon fiber in asphalt concrete mix using computing techniques

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Abstract. This study investigated and predicted the Marshall stability of glass-fiber asphalt mix, carbon-fiber asphalt mix and glass-carbon-fiber asphalt (hybrid) mix by using machine learning techniques such as Artificial Neural Network (ANN), Support Vector Machine (SVM) and Random Forest (RF), The data was obtained from the experiments and the research articles. Assessment of results indicated that performance of the Artificial Neural Network (ANN) based model outperformed applied models in training and testing datasets with values of indices as; coefficient of correlation (CC) 0.8492 and 0.8234, mean absolute error (MAE) 2.0999 and 2.5408, root mean squared error (RMSE) 2.8541 and 3.3165, relative absolute error (RAE) 48.16% and 54.05%, relative squared error (RRSE) 53.14% and 57.39%, Willmott's index (WI) 0.7490 and 0.7011, Scattering index (SI) 0.4134 and 0.3702 and BIAS 0.3020 and 0.4300 for both training and testing stages respectively. The Taylor diagram also confirms that the ANN-based model outperforms the other models. Results of sensitivity analysis show that Carbon fiber has a major influence in predicting the Marshall stability. However, the carbon fiber (CF) followed by glass-carbon fiber (50GF:50CF) and the optimal combination CF + (50GF:50CF) are found to be most sensitive in predicting the Marshall stability of fibrous asphalt concrete.

Keywords: artificial neural network; carbon fiber; glass fiber; marshall stability; random forest; support vector machine

1. Introduction

Modifying asphalt mixes to increase performance and pavement service life has become increasingly popular. Because asphalt is a viscoelastic substance, its performance is primarily affected by three factors i.e., axle loads, weather conditions, and moisture (Mohammed *et al.* 2020). One of the most common failures in asphalt pavements is moisture damage. Moisture can

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decrease the adhesion between aggregates and bitumen, separating them from one another. This is known as stripping, and it can result in holes in the road surface, as well as traffic accidents (Hosseinian *et al*. 2020). Pavement materials must be sturdy and secure to avoid deconstruction. Nowadays, research is focused on developing technological innovations for asphalt mixture properties in order to achieve an optimal and functional performance of road pavements for long-term sustainability (Celauro and Pratico 2018). Many researchers have added lignin, polymer, glass, carbon polyester, mineral, rubber, basalt, charcoal, rock, wool, plastic, and other fibers to asphalt mixes to increase the lifespan of the pavement (Zhao *et al*. 2020, Upadhya *et al*. 2021a). In most cases, adding chemicals improves stiffness and increases temperature susceptibility. The increased rigidity improves the asphalt pavement’s rutting resistance in high-temperature conditions and allows for the use of more flexible asphalt. In addition, adding fibres to an asphalt mix enhances the mixture's characteristics and adds to sustainability by lowering road maintenance costs and increasing the life of the road. Fibers increase the mechanical performance of asphalt mixtures by forming a multidimensional network that reinforces hot mix asphalt and promotes adhesion in the mix (Saleem and Ismael 2020). Among asphalt modifiers, fibers have gotten a lot of attention because of their outstanding improving impact. However, due to its outstanding mechanical characteristics, minimal water absorption, and high melting point, a new ecologically friendly i.e., glass fiber has garnered a lot of interest from environmentalism. Glass fiber reinforced polymer (GFRP) offers outstanding performance features such as lightweight, high strength, design flexibility, superior antishock efficiency, fatigue and corrosion resistance, and effective protection and concealment. (Wang *et al*. 2019, Liu *et al*. 2014). Luo *et al*. (2019) investigated the use of lignin and glass fiber as a modifier in bituminous mixtures to assess rutting, low temperature cracking resistance, moisture damage resistance, and fatigue resistance of asphalt mixtures treated with lignin or glass fiber, as well as to investigate rutting, low temperature cracking resistance, moisture damage resistance, and fatigue resistance. The addition of 0.2-0.6 percent glass fibre to asphalt mixes considerably increased the resilience to high temperatures. Ji *et al*. (2007) found that the inclusion of glass fiber improves the main characteristic of HMA. By comparing experimental results, the interaction mechanism of the glass fibre on the HMA is investigated to improve the asphalt pavement design.

Carbon fibers, owing to their intrinsic compatibility with asphalt cement and mechanical characteristics, may potentially play an important role in bitumen modification. Polymer-modified binders that increase the characteristics of hot asphalt mixes are more competitive than carbon modified binders. (Jahromi 2015, Rahimipour *et al*. 2016). Carbon fibre enhanced asphalt mixes were predicted to boost stiffness and resistance to permanent deformation, as well as improve the mixture fatigue properties. The cold temperature behavior of the asphalt mixture was also predicted to improve due to the high tensile strength of carbon fiber (Shanbara 2011). Jahromi and Khodaii (2008) Carbon fibers were investigated for their order to withstand structural distress in the pavement in the face of increasing traffic loads, and thus improve fatigue by increasing resistance to cracks or fatigue cracking, as well as an increase in its stability, a lowering in the flow value, and an enhance in voids in the mix. Mawat and Ismael (2020) found that Carbon fibers were shown to improve the performance of asphalt mixes, including increased stability, decreased flow value, and an increase in voids in the mixture. Vo *et al*. (2016) used a combination that included milled carbon fibers, chopped carbon fiber, and graphite powder for improving thermal properties, etc. The tensile strength and rutting resistance of the amended asphalt mixture are also enhanced. The Marshall stability test is used to determine the optimum binder content which affects the flexural strength, fatigue performance, anti-cracking, tensile ratio, etc. of the asphalt concrete.

Since Marshall stability also affects the performance of the fiber-asphalt mix, that is why this test was used. Many researchers have used Marshall stability as the main test with a fiber-asphalt mix which has the connection with the mechanical characteristic described above. According to (Mahrez and Karim 2005) used glass fiber, it was discovered that adding fiber to bituminous mixes affects their characteristics by lowering their stability and increasing the flow value as well as the voids in the mix, enhancing fatigue life via increasing fracture resistance and persistent deformation resistance. Higher Marshall stability contributes toward the higher flexural strength. In some published results it has been found that the fibers enhance flexural strength and anti-cracking resistance (Yu and Sun 2010). In one of the research works, asphalt mixes modified with lignin fiber combined with diatomite improved the RMS (Residual Marshall stability) and lignin fiber can improve the cracking resistance of asphalt mix (Abdelsalam *et al*. 2020). Mrema *et al*. (2020) have performed a Marshall stability test with glass-wool fibers and found that the addition of glass wool fibers to the Asphalt concrete (AC) improves the performance of AC in terms of tensile strength, toughness, rutting resistance, moisture susceptibility, and fatigue. Liu *et al*. (2016) found that Marshall test evaluation method for anti-cracking material was accurate and reliable. Ganesh and Prajwal (2019) found that the Marshall stability test was used to measure the fatigue performance of the asphalt mixture and to identify the optimal bitumen concentration and optimum nano-silica content. The results of Cong *et al*. (2016) Marshall stability test revealed that an asphalt mixture comprising reclaimed SBS modified asphalt pavement had improved moisture susceptibility, rutting resistance, dynamic modulus, low-temperature anti-cracking performance, and fatigue resistance. Shukla *et al*. (2014) also conducted the Marshall stability test with fiber modified asphalt mixtures have shown increased stiffness and permanent deformation. Fatigue characteristics of the mixer were also improved.

Several studies were conducted to combat the problem of pavement deterioration, machine learning methods are increasingly being used. In order to offer precise and reliable model sensitivity prediction, supervised learning techniques are frequently utilized to construct models and handle data problems (Upadhya *et al*. 2021b), Thakur *et al*. 2021, Upadhya *et al*. 2021c). Numerous artificial intelligence techniques such as genetic programming, M5P model tree, support vector machine (SVM), random forest (RF), random tree (RT), Artificial neural network (ANN), Adaptive neuro fuzzy inference system (ANFIS), and Gaussian Process regression (GP) have become very popular and are widely used by various researchers (Singh *et al*. 2019). According to the Angelaki *et al*. (2018), the ANFIS model based on a triangle membership function outperforms the SVM and ANN models in terms of performance assessment parameters. On the other hand, SVM and ANN models give accurate parameter estimations. Khuntia *et al*. (2014) using multiple input variables such as polyethylene, bitumen, and aggregate, a neural network (NN) and least square support vector machine (LS-SVM) based model for the prediction of Marshall Stability was constructed. Sangeetha and Shanmugapriya (2020) found that the compressive strength of concrete columns covered with GFRP using an ANN model. Ozgan (2011) developed an artificial neural network (ANN) technique to predict the stability of asphalt concrete under different temperatures, exposure durations, and physical characteristics. According to the Li *et al*. (2019) pavement distress was predicted using random forest classification (RFC). Morova *et al*. (2012) showed that when compared the results of the generated ANN model with experimental data to find CC. (Saffarzadeh and Heidaripanah 2009) found that ANN's analysis methods were effective in predicting deflection. In the study (Xiao *et al*. 2009) the fatigue life of these combinations was predicted using a standard statistical technique. Seitllari *et al*. (2019) demonstrated that the prediction model created using the ANN method to evaluate asphalt mixture characteristics under

Table 1 Performance or characteristics of fibers

S.no.	Author	Additives used	Characteristics of fiber	Volume fraction (%)	Increase and decrease in strength properties
1	Abdi *et al.* (2021)	PET polyester fibers	Melting point (˚C) - 250-260< Yield strength (MPa)- 75 Ultimate tensile strength (MPa)- 154 Denier (gr)- 1980	0.1, 0.2, 0.3 and 0.4%	0.4% of polyester fibers has higher Marshall strength by 20% compared to the sample without fibers and also 48% more flow than the base sample. 0.2% to 0.5% give best result on asphalt mix
2	Aliha *et al.* (2015)	Poly phosphoric acid (PPA)	Melting point (˚C) - 20-30 Viscosity- 25 ˚C- 840 Density-25 ˚C- 2.02 Boiling point- ˚C- 275>	1 wt.% (i.e., weight percentage	CR and SBS enhances fracture toughness value of modified asphalt materials. Decreases air void percentage from 3% to 7%. PPA modifier had no significant influence on the performance of asphalt mixture against cracking. Sasobit, a small increase in fracture toughness. Anti-stripping agent, shows higher tensile strength.
		Styrene Butadiene Styrene (SBS)	Toluene soluble viscosity- 5 Toluene insoluble materials- <0.1 Ash content- <0.35	5 wt.% of the bitumen	
		Anti-stripping agent	Viscosity @ 50 ˚C- 6.4 Density @ 15 ˚C (kg/L)- 0.975 Boiling point ˚C- 275> Flammability ˚C >140	0.4 wt.% of base bitumen	
		Crumb rubber (CR)	Moisture content (%) -0.1 Maximum grain size (mm) -0.4 Unit weight (g/cm^3)- - 0.31 Ash content (%)- 10	15 wt.% of the base bitumen.	
		F-T paraffin wax (Sasobit)	Congealing point ˚C- 106 Penetration @ 25 ˚C dmm- <1 Penetration @ 65 ˚C dmm- 6 Diameter (mm)- 1	2.5 wt.% of base bitumen	
3	Aliha *et al.* (2017a)	Polyolefin-Aramid fiber (FORTA)	Specific gravity (g/cm^3)- 0.91-1.44 Length (mm)- 20 Tensile strength (MPa)- 490-2800 Melting point (˚C)- 100-427	0, 0.3%, 0.5% and 0.7%	0.3% fiber shows Highest effect of fiber on pure mode I loading conditions. Containing 0.5% and 0.7% Jute fibre enhanced fracture toughness. FORTA fibre outperformed other fibres in terms of increasing low-temperature fracture development characteristics.
		Jute fiber	Length (mm)- 20 Tensile strength (MPa)- 200-400	0, 0.3%, 0.5% and 0.7%	
4	Aliha *et al.* (2017b)	Lucobit	Density at 23˚C (g/cm^3)- 0.97 Apparent Density (g/l)- 500 Melting point (˚C)- 165-195 Modulus of Elasticity (MPa)- 17 Elongation at break at 23˚C (%)- 700-800	Lucobit 4% of base binder	The nano-clay component had the greatest impact in increasing fracture toughness. Nano-clay was added to the mixture, which resulted in a 30% increase.

		Nanoclay	Organic modifier - 2M2HT Moisture (%)- >2 Weight loss on ignition (%)- 43 Anion - Chloride Density (g/mL)- 1.66	4% of base binder	
		Crumb rubber (CR)	Moisture content (%)- 0.1 Maximum grain size (mm)- 0.4 Unit weight (g/cm^3)- 0.31 Ash content (%)- 10	15% of base binder.	
		Styrene Butadiene Styrene (SBS)	Toluene soluble viscosity (Pa.s)- 5 Toluene insoluble materials (%)- <0.1 Ash content (%) <0.35	5% of base binder	
		Nano-silica	Purity (%)- 99 Maximum diameter of particles (Nm)- 10 Specific area (m2 /gr)- 600 Density (g/cm^3)- 4.2 Apparent density (g/cm^3)- 1	4% of wt. fraction	
5	Aliha *et al.* (2018)	Synthetic forta-ferro (SFF) fibers	Length (mm)- 54 Diameter (mm)- 0.34 Density (kg/m^3)- 910 Elastic modulus (GPa)- 4.7 Melting point (˚C)- 162-168 Tensile strength (MPa)- 570-660	0.1%, 0.3%, and 0.5% by weight	SFF fibre percentage was increased by 0.3%, the K_{Ic} decreased slightly up to 8%, but further increase in the fiber content has no positive effect on the mode I crack growth resistance of the SFF fiber reinforced concrete.
6	Tabar *et al.* (2021)	Recycled polyethylene terephthalate (PET)epoxy resin	Elastic modulus (GPa)- 2.9 ± 0.02 Ultimate tensile strength (MPa)- 45.35 ± 0.76	100:12	By adding of 4 wt% of fine and coarse PET fillers, the fracture toughness of polymer concrete was enhanced by 8.5% and 16.3% respectively.
7	Daneshfar *et al.* (2017)	Polyolefin	Melting point (˚C)- 120 Flash point (˚C)-590 Elastic modulus (GPa)- 4.2 Tensile strength (MPa)- 570-660 Diameter (mm)- 0.3 Length (mm)- 38 Density (g/cm3)- 0.91-0.96	0.2, 0.4, and 0.6 by volume	Flexural and tensile strength were increased by 19.6-81.69% and 0.84-34.29%. Compressive strength and elasticity modulus are reduced by 4.57-26.32% and 12.48-37.08% respectively, when additional fibre is added.
8	Fakhria and	Crumb Rubber	Density (T/M3)- 1.21 Particle size (mm)- 10	10% and 25% by wt. of aggregates	Rubber showed higher fracture toughness values, compared with the

	Amoosoltani (2017)	RAP	Particle size (mm)- 25	0%, 25%, 50% and 100% by wt. of aggregates	mixtures containing RAP. 12% to 20%, increase in fracture toughness
9	Ziari *et al.* (2020)	Glass fiber	Specific gravity (g/cm^3)- 1.18 Length (mm)- 12 Diameter (mm)- <0.13 Tensile strength (MPa)- >1000 Melting point (˚C)- 800-900 Water absorption (%)- 0	0, 0.06%, 0.12%, and 0.18% by wt. of total mix	Adding 0.12% to 0.18% glass fiber decrease crack resistance of asphalt mixtures.
10	Rooholamini *et al.* (2018)	Macro Synthetic (twisted bundle) Polyethylene Roller-compacted concrete pavement (RCCP)	Crosssection- (circular) Length (mm)-3.8 Specific gravity (g/cm^3)- 0.91 Tensile capacity (Mpa)- 610 Modulus of elasticity (Gpa)- 9.5	0.25%, 0.5% and 0.75% by volume fraction	High flexural strength RCCP with 0.25% volume fraction. Hardening of the post-cracking can be caused by 0.5% of fibre in high flexural strength RCCP.
11	Rizvi *et al.* (2021)	High strength low steel (HSLA)	Yield strength (MPa)-315 Ultimate strength % (MPa)- 478 Elongation (%)-50 Toughness (J)- 105 Hardness (HV)- 90	steel plate of 200 mm 60 mm × 10 mm size	weld metal increases while ultimate tensile strength decreases.
12	Motamedi *et al.* (2020)	Polyolefin	Shape Twisted strings and single-stranded Specific gravity (g/cm^3)- 0.91 Tensile strength (psi)- 70,000 Length (mm)- 19 Colour- Black Resistance Acid/Base- Ineffective Melting Point ˚C -100	0%, 0.025%, 0.05% and 0.1% (75% by weight)	0.1 wt.% fibres increase fracture strength by 8 to 35%. Increases fracture toughness of asphalt by 25% and 26% for control and 0.1%
		Aramid	Shape- Single-stranded Specific gravity (g/cm^3)- 1.44 Tensile strength (psi)- 400,000 Length (mm)- 19 Colour- Yellow Resistance Acid/Base- Ineffective Melting Point ˚C -427	0%, 0.025%, 0.05% and 0.1 (25% by weight)	

different ageing circumstances.

The purpose of the study is to predict the Marshall stability of glass-fiber asphalt mix, carbon-fiber asphalt mix and glass-carbon-fiber asphalt mix by using the machine learning techniques. For which the dataset was obtained from the experimental work and the literature to identify the significant parameters in asphalt mix. Three distinct modelling approaches i.e., Artificial Neural Networks (ANN). Support vector machine (SVM) and Random Forest (RF) based model were used to predict the Marshall stability in fibrous asphalt concrete mix. Sensitivity analysis was carried out by using Machine learning techniques to find the sensitive parameters.

Many researchers, have investigated the impact of the additives on flexural strength, compressive strength, fracture resistance, toughness, rutting, anti-crack resistance and modulus of elasticity in the asphalt/cement concrete, which is shown in Table 1.

2. Objective of study

1. To determine the Marshall stability of asphalt mix each of glass, carbon and glass-carbon (hybrid) respectively.
2. To find a suitable model for the prediction of Marshall stability by applying Machine learning algorithms in order to determine the optimum model.
3. To assess the significance of the input parameters such as bitumen content, bitumen grade, glass, and carbon fiber content separately, Glass and Carbon in combination, fiber length, and fiber diameter, etc in an asphalt mix.
4. To perform sensitivity analysis to identify the sensitive parameters.

3. Data collection

1. The necessary data for the Marshall Stability prediction was collected from experiments performed in the laboratory i.e., 72 specimens of glass-fiber asphalt mix, 72 specimens of carbon-fiber asphalt mix, and 64 specimens of carbon-fiber asphalt mix.
2. Data were collected from the published results.

4. Materials and methodology

4.1 Coarse and fine aggregates

In the preparation of the asphalt mixture, coarse aggregate with a nominal size of 20 mm has been used. As shown in Tables 2 and 3, the particle size distribution of coarse and fine aggregates was determined according to (ASTM D6913-04). Table 4 summarises the physical characteristics of coarse and fine aggregates. Natural sand was utilized as a filler ingredient for the consistency of the asphalt mixture, 10% of the weight of coarse aggregate.

4.2 Asphalt binder

The asphalt used in this study was purchased from the Himachal Pradesh Public Works Department in Solan, India, with a performance grade (PG 58-22) (VG 10) and the basic components of the asphalt are shown in Table 5.

4.3 Fibers (GF and CF)

Two types of fibers were used: Chopped glass fiber (GF) and Chopped carbon fiber (CF). Three

Table 2 Coarse aggregate gradation

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

Table 3 Fine aggregate gradation

Sieve size	10 mm	4.75 mm	2.36 mm	1.18 mm	600 micron	300 micron	150 micron	7 micron
Mesh 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	2.56	2.81	ASTM C-128
Apparent specific gravity gm/cm^3	2.74	2.86	
Water absorption %	2.65	0.5	
Bulk specific gravity gm/cm^3	1.53	1.56	
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 Properties of asphalt

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

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	visual


Fig. 1 Glass and carbon fiber used in this study

Fig. 2 Distribution of fibers in asphalt specimen

Fig. 3 Fractured specimen

types of asphalt mix were prepared i.e., glass-fiber asphalt mix, carbon-fiber asphalt mix, and glass-carbon-fiber asphalt (hybrid) mix. Table 6 summarises 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.

5. Preparation of Marshall specimen

A total of 1200 gm of coarse aggregates was dried in the oven for 24 hours at temperature 110 ± 5˚C and asphalt mixes were prepared in accordance with ASTM D1559 for Marshall Stability. 144 cylindrical specimens were made using glass and carbon fiber separately and 72 specimens were prepared with the combination of glass and carbon fiber. A total of 208 specimens, as well as control asphalt mix, were prepared in the laboratory. The glass and carbon fibers were added in the prescribed quantity to 20 mm nominal size aggregate with filler 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 by percentage starting from 0 to 4% by weight of bitumen content added in each asphalt aggregate mixture. The binder content varied from 4.5 - 6% in each mix containing glass and carbon fibers with an interval of 0.5%. The aggregate-fiber asphalt mixture was properly mixed until it was uniform in color and aggregates were fully coated with asphalt. 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 a 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 the standard procedure. Fig. 2 shows the distribution of both the fibers inside it and Fig. 3 shows the fractured surface of the broken specimen.

6. Machine learning models

This section gives a summary of the machine learning models used in this research.

6.1 Multilayer perceptron Artificial Neural Network (ANN)

ANN stands for artificial neural networks, and it is a powerful computing tool modeled after biological neural networks. They may approach and estimate unknown functions using a database of input values. One of the primary advantages of ANN is that it can decompose and solve extremely complicated and nonlinear problems using only basic mathematical procedures (Seitllari *et al*. 2019, Nguyen and Suong 2020). The neural networks technique may be utilized to create predictive models of asphalt mixture fatigue life that take into account the interplay of several factors (Xiao *et al*. 2009). The multilayer perceptron artificial neural network (MLP-ANN) is a type of artificial neural network that is capable of self-learning. The hierarchical structure of MLP-ANN consists of one input layer; which contains a set of neurons representing the input variables; one or more hierarchical hidden layers, which contain computational neurons to refine and pass on the information received from the previous layer; and one output layer, which contains a computation node to produce the final prediction (Cook *et al*. 2019, Ayat *et al*. 2018). The technique of computing the gradient for nonlinear multilayer networks is known as back-propagation. Backpropagation is a set of learning rules that explain the backward propagation of

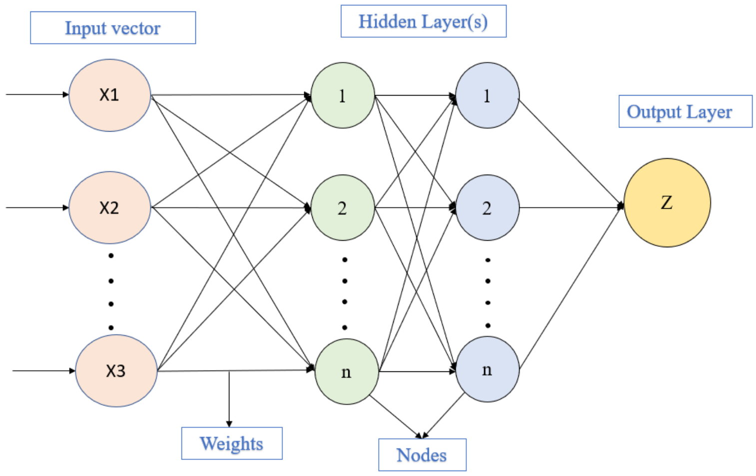


Fig. 4 Multilayer Perceptron Artificial Neural Network

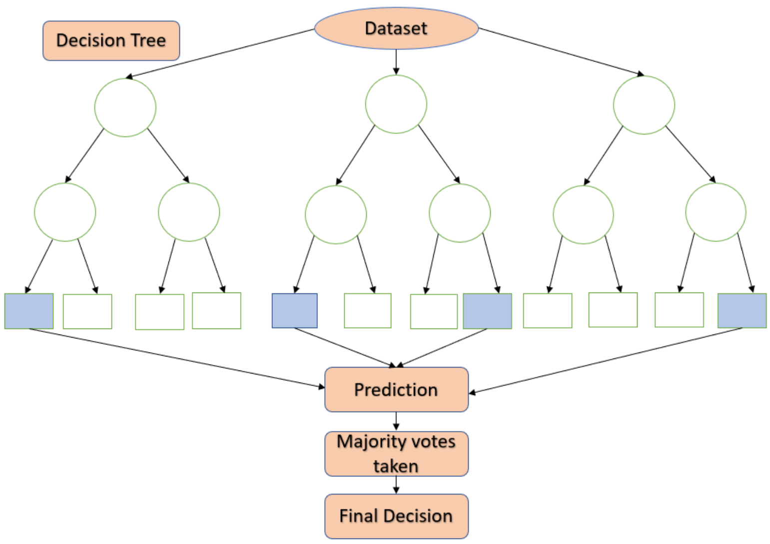


Fig. 5 Random Forest regression model

errors, calculate the error function in terms of weights, and ensure that the model is accurate. The sigmoid transfer function compresses the input, which can range from 0 to infinity (Yang *et al*. 2019). The basic structure of a Multilayer Perceptron ANN develops model as shown in Fig. 4.

6.2 Support Vector Machines (SVM)

A support vector machine (SVM) is a machine learning technique for simulating the mathematical connection between input variables and output of a dataset using an optimization algorithm rather than a regression approach to reduce costs (Cook *et al*. 2019). SVM transforms a non-linear issue into a linear problem by transferring the original input space into a new feature space with more dimensions using kernel functions, allowing for the identification of unique

Table 7 Dataset details

S. No.	Bitumen Content (BC %)	Fiber percentage (%)	Fiber Type	Bitumen Grade (VG)	Fiber Length (FL mm)	Fiber Diameter (FD µm)	Marshall Stability (MS kN)	Observations (No.)	Authors
				Range of dataset					
1.	5	0-0.4	GF	30	12	10	9.12-10.98	5	Janmohammadi *et al*. (2020)
2.	4.5-6.5	0-0.3	GF	20	10	10	1.88-3.83	20	Alidadi and Khabiri (2016)
3.	5.5	0.2-0.6	GF	30	12	20	13.84-14.4	4	Taherkhani. H (2016)
4.	4.6-4.7	0-0.3	GF	30	6	10	13-14.3	4	Ji *et al*. (2007)
5.	5.34	0-1	CF	0	12	7	11-11.4	3	Yoo *et al*. (2018)
6.	4.9-5.3	0-0.7	CF	10	12.5	6.5	18.29-20.26	4	Geckil and Ahmedzade (2020)
7.	4.5-6.5	0-0.3	CF	20	10	6	2.26-3.59	20	Alidadi and Khabiri (2016)
8.	4.2-4.3	0-2	CF	30	10	5	12.8-13.5	2	Xiaoming and Shaopeng (2011)
9.	4.5-6	0-4	GF	10	12	10	3.74-18.70	72	Collection of data from current research + (experimental)
10.	4.5-6	0-4	CF	10	12	10	6.23-24.63	72	
11.	4.5-6	0.5-4	50:GF50CF	10	12	10	9.35- 24.97	64	
			Total observations					270	

global solutions that are not limited by multiple local minima (Angelaki *et al*. 2018). 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. The SVM technique offers numerous benefits over other machine learning algorithms, including a novel optimization strategy, effective use of high-dimensional feature spaces, and computational learning theory (Park *et al*. 2019). SVM uses a pre-selected nonlinear mapping to convert a linear inseparable space into a high-dimensional linear separable space and then calculates the best classification plane in this feature space using the structural risk reduction principle. To considerably simplify the computation, define the suitable kernel function (Cao *et al*. 2013). Polynomial functions, radial basis functions (RBF), sigmoid functions, and other functions can be employed as the kernel of SVM. The RBF was used for this investigation because of its larger convergence domain (Yu *et al*. 2021).

6.3 Random Forest (RF)

Breiman proposed the Random Forest technique in 2001 as a well-known generalized, high-accuracy supervised machine learning strategy. In RF, the original data is resampled to produce a large number of samples, which is usually done via the bootstrap method. Following that, classification

Table 8 Statistical features of dataset

Training dataset								
	Bitumen content (BC%)	Glass fiber (GF%)	50GF:50CF	Carbon fiber (CF%)	Bitumen grade (VG)	Fiber length (FL mm)	Fiber diameter (FD μm)	Marshall stability (MS kN)
Mean	5.2485	0.5500	0.5324	0.5630	11.7593	10.4676	9.7917	11.8100
Median	5.0000	0.0000	0.0000	0.0000	10.0000	12.0000	10.0000	11.5300
Mode	5.0000	0.0000	0.0000	0.0000	10.0000	12.0000	15.0000	10.2900
Standard Deviation	0.5773	1.0860	1.1087	1.1109	5.2525	3.5288	4.9175	5.3837
Kurtosis	-1.1718	2.7051	2.6065	2.5295	6.0209	3.8371	-0.7550	-0.5883
Skewness	0.1464	1.9902	1.9870	1.9498	2.5114	-2.2823	-0.2956	-0.0359
Range	2.2000	4.0000	4.0000	4.0000	30.0000	12.5000	20.0000	23.3000
Minimum	4.3000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	2.2600
Maximum	6.5000	4.0000	4.0000	4.0000	30.0000	12.5000	20.0000	25.5600
Confidence Level (95.0%)	0.0774	0.1456	0.1487	0.1490	0.7044	0.4733	0.6595	0.7220
Testing dataset								
	Bitumen content (BC%)	Glass fiber (GF%)	50GF:50CF	Carbon fiber (CF%)	Bitumen grade (VG)	Fiber length (FL mm)	Fiber diameter (FD μm)	Marshall stability (MS kN)
Mean	5.3452	0.5741	0.5370	0.5630	11.6667	10.4167	9.3241	12.2798
Median	5.5000	0.0000	0.0000	0.0000	10.0000	12.0000	10.0000	12.7800
Mode	5.5000	0.0000	0.0000	0.0000	10.0000	12.0000	10.0000	10.6000
Standard Deviation	0.6102	1.1736	1.1237	1.0977	5.4079	3.6572	4.6512	5.8162
Kurtosis	-0.7760	2.5576	3.0172	2.5837	6.1385	3.9434	-0.8375	-0.7514
Skewness	0.1022	1.9805	2.0479	1.9581	2.3539	-2.2986	-0.2878	-0.2144
Range	2.3000	4.0000	4.0000	4.0000	30.0000	12.5000	15.0000	21.5000
Minimum	4.2000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.8800
Maximum	6.5000	4.0000	4.0000	4.0000	30.0000	12.5000	15.0000	23.3800
Confidence Level (95.0%)	0.1665	0.3203	0.3067	0.2996	1.4761	0.9982	1.2695	1.5875

trees are created for each bootstrap sample, and the final results are determined by voting once the classification tree predictions have been combined. RF may be used for both regression and classification (Dai *et al*. 2017). On the assumption that the calculation is not considerably expanded, the method can enhance forecast accuracy (Huang *et al*. 2020). Random forests have been widely utilized in transportation research, and models using a random forest classification model are frequently used to build models using a random forest classification model due to its flexibility and good performance even in small datasets. Each tree has a categorization, and the model chooses the forest with the most votes among all the trees in the forest. The fraction of 1s

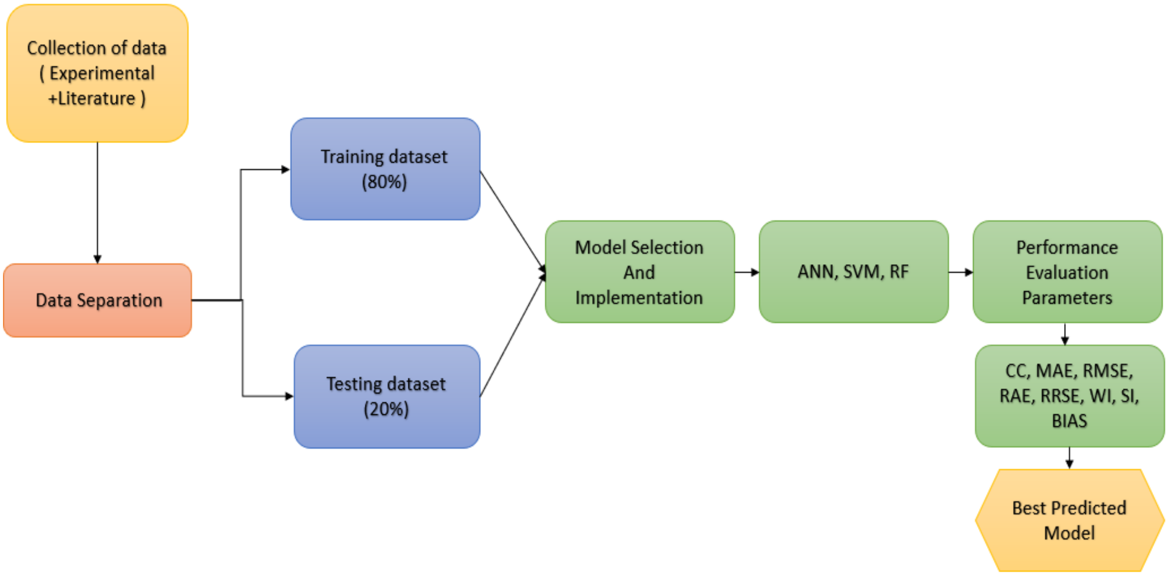


Fig. 6 Flowchart of the methodology

received is used to calculate the prediction probability. (Upadhya *et al*. 2021a). The out-of-bag samples are utilized to validate the model in this scenario. The procedure is repeated until the desired precision is obtained. RFR is unusual in that it has an in-built procedure for removing points for out-of-bag samples and using them for validation. At the conclusion, the total error for each expression tree is computed, revealing the efficiency of each expression tree (Farooq *et al*. 2020). The random forest regression applying the parameters was implemented using WEKA software. The RF tree model's fundamental function is illustrated in Fig. 5.

7. Methodology and dataset

To develop a model for the prediction of Marshall stability a total of 270 observations were incorporated (208 observations were obtained from laboratory experiments and 62 observations from previous research articles). The total observations were then randomly divided into two subsets, each with an 80 / 20 ratio. The experimental and literature data sets are summarised in Table 7. For the prediction of Marshall stability of asphalt concrete reinforced with glass and carbon fibers, three soft computing methods, namely Artificial neural network, Support vector machines, and Random Forest, were used in this study, which was implemented using Weka 3.9. The input parameters such as bitumen content (BC), glass fiber (GF), carbon fiber (CF), 50GF:50CF bitumen grade (VG), fiber length (FL), and fiber diameter (FD) are shown in Table 8 along with statistical characteristics of the input parameters. Fig. 6 shows the flow chart for determining the optimum model. Statistical parameters such as correlation (CC), mean absolute error (MAE), root mean squared error (RMSE), relative absolute error (RAE), root relative squared error (RRSE), Willmott's index (WI), Scattering index (SI), and BIAS are assessed to evaluate the input parameters to predict the output i.e., Marshall stability.

8. Evaluation parameters

The performance of each model with eight 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), Willmott's index (WI), Scattering index (SI), and BIAS (average difference between actual and predicted values) was evaluated. This may be calculated using a formula that has been shown in the following Equations:

CC:

$$= \frac{\sum_{i=1}^{n}(K_i - \bar{K})\,(L_i - \bar{L})}{\sqrt{\sum_{i=1}^{n}(K - \bar{K})^2}\,\sqrt{\sum_{i=1}^{n}(L_i - \bar{L})^2}} \tag{1}$$

MAE:

$$= \frac{1}{n}\sum_{i=1}^{n} |K - L|) \tag{2}$$

RMSE:

$$= \sqrt{\frac{1}{n}}\sum_{i=1}^{n}(K - L)^2 \tag{3}$$

RAE:

$$= \frac{\sum_{i=1}^{x}|K - L|}{\sum_{i=1}^{x}(|K - \overline{K}|)} \tag{4}$$

RRSE:

$$= \sqrt{\frac{\sum_{i=1}^{n}(K - L)^2}{\sum_{i=1}^{n}(|K - \overline{L}|)^2}} \tag{5}$$

WI:

$$= 1 - \left[\frac{\sum_{i=1}^{n}(K_i - L_i)^2}{\sum_{i=1}^{n}(|K_i - \bar{L}| + |L_i - \bar{L}|)^2}\right] \tag{6}$$

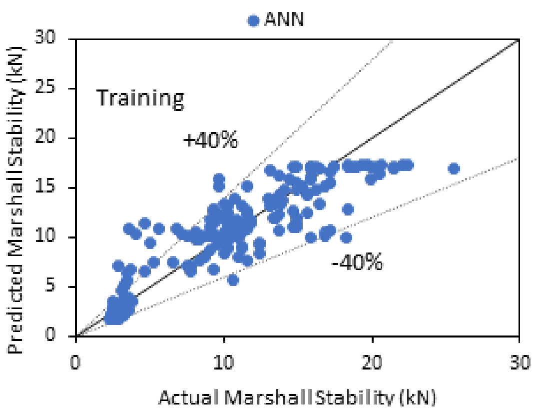
SI:

$$= \sqrt{\frac{\sum_{i=1}^{n}[(L_i - \overline{L}) - (K_i - \overline{K})^2}{\sum_{i=1}^{N} G_i^2}} \tag{7}$$

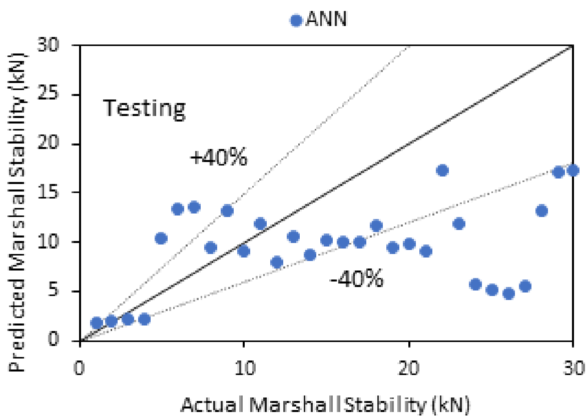
BIAS:

$$= \frac{\sum_{i=1}^{n}(K_i - L_i)}{\sum_{i=1}^{n} K_i} \tag{8}$$

where, K = Observed values; L = Average of observation; $\overline{L}$= Predicted value; n = number of observations



(a)



(b)

Fig. 7 Actual and predicted values using ANN-based models for training and testing stages

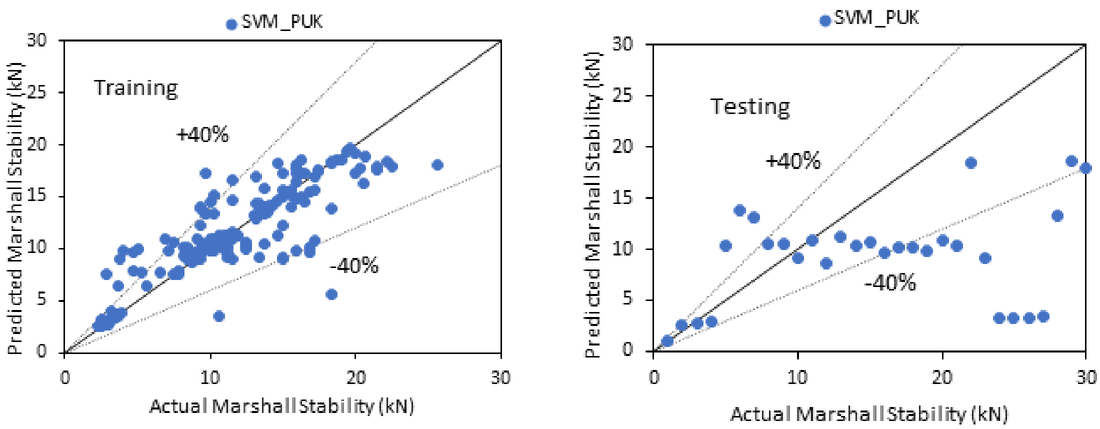
Table 9 Performance assessment of ANN, SVM_PUK, RF based model

Models applied	CC	MAE (kN)	RMSE (kN)	RAE (%)	RRSE (%)	WI (kN)	SI	BIAS
Training Dataset								
ANN	0.8492	2.0999	2.8541	48.16	53.14	0.7490	4.1378	0.3020
SVM_PUK	0.8485	1.7953	2.8491	41.18	53.04	0.7520	4.1451	0.1208
RF	0.9336	1.4473	1.9357	33.2	36.04	0.8850	6.1010	-0.0658
Testing Dataset								
ANN	0.8234	2.5408	3.3165	54.05	57.39	0.7011	3.7027	0.4300
SVM_PUK	0.8106	2.4853	3.4112	59.02	59.02	0.6874	3.5987	0.4369
RF	0.7725	2.6661	3.6869	56.72	63.77	0.6322	3.3307	0.3371

9. Results and discussion

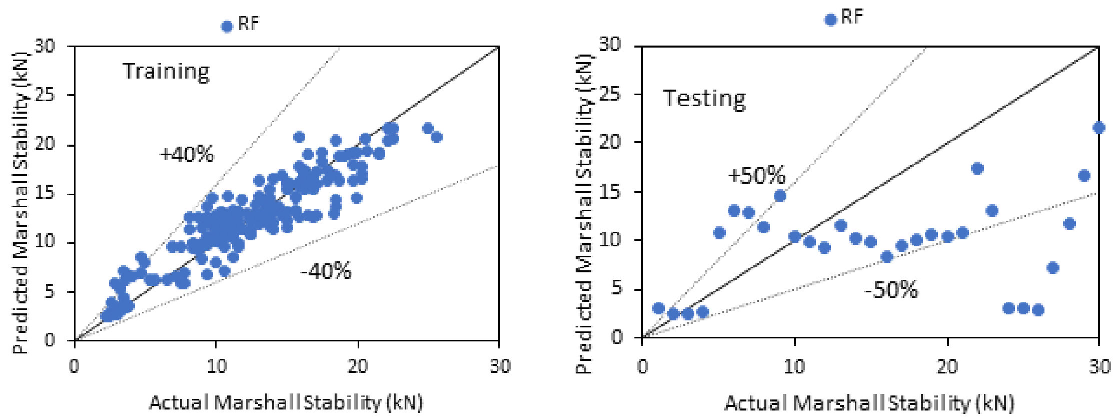
9.1 Performance of ANN-based model

The development of an ANN-based model is an iterative technique and is based on the multilayer perceptron model. Several trials were carried out to arrive at the ideal value, i.e., for the prediction assessment of the generated models the largest defined CC value with the minimum inaccuracies for both the training and testing datasets. Eight different performance assessment factors were applied to get the best predictive model as shown in Table 9. Results of Table 9 suggests that an ANN-based model outperforms for the prediction of Marshall Stability of asphalt concrete using glass, carbon and in combination with both the fibers with CC value as 0.8492 and 0.8234, MAE value as 2.0999 and 2.5408, RMSE value as 2.8541 and 3.3165, RAE value as 48.16% and 54.05%, RRSE value as 53.14% and 57.39%, WI value as 0.7490 and 0.7011, SI values as 4.1378 and 3.7027 and BIAS value as 0.3020 and 0.4300 for both training and testing stages respectively. The training and testing phases are represented in Fig. 7(a) and 7(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



(a) (b)

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



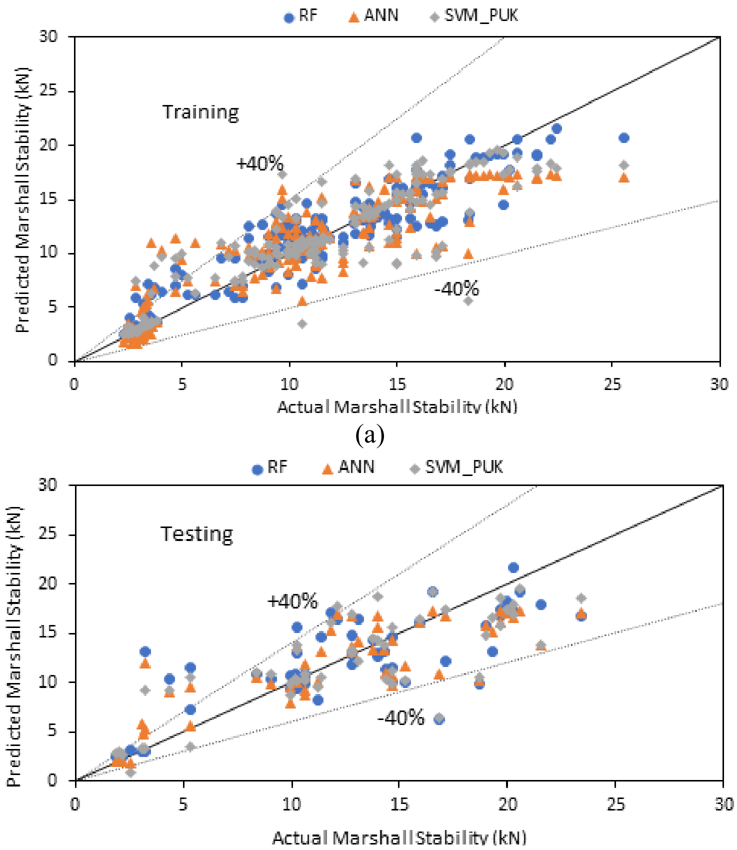
(a) (b)

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

actual and predicted outcome parameters, signifying more reliability. Most of the algorithm's predicted values are within the ± 40% error range in the training and testing stages.

9.2 Performance of SVM_PUK based model

The Pearson Kernel function (PUK) is employed in this algorithm, including certain user-defined parameters like omega (O) and sigma (S). After repeated applications, the ideal value, i.e., the maximum CC value with the minimum errors, was found. This technique's data was assessed using an O value of 2.0 and S value of 1.0. Results of Table 9 suggests that an SVM_PUK based model is reliable in predicting the Marshall Stability of asphalt concrete using glass, carbon and glass-carbon fiber combination with CC value as 0.8485 and 0.8106, MAE value as 1.7953 and 2.4853, RMSE value as 2.8491 and 3.4122, RAE value as 41.18% and 59.02%, RRSE value as 53.04% and 59.02%, WI value as 0.7520 and 0.6874, SI values as 4.1451 and 3.598 and BIAS value as 0.1208 and



(b)

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

0.4369 for training and testing stages respectively. The training and testing phases are represented in Fig. 8(a) and 8(b) with the agreement graph showing actual and predicted values using SVM_PUK-based models. Most of the experimental algorithm's predicted values are within the ±40% error range in the training and testing stages.

9.3 Performance of RF-based model

The RF classifier is developed on a decision tree. 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 using glass, carbon and in combination with both the fibers with CC value as 0.9336 and 0.7725 MAE value as 1.4473 and 2.4853, RMSE 1.9357 and 3.6869, RAE 33.2% and 56.72%, RRSE 36.04% and 63.77%, WI value as 0.8850 and 0.6322 and SI values as 6.1010 and 3.330 and BIAS value as -0.0658 and 0.3371 for both training and testing stages respectively. The agreement graph plotting actual and predicted values using RF-based models is shown in Figs. 9(a) and 9(b). It was also discovered that the majority of the predicted values from the model are within the ±40% error range in the training and ±50% testing stage.

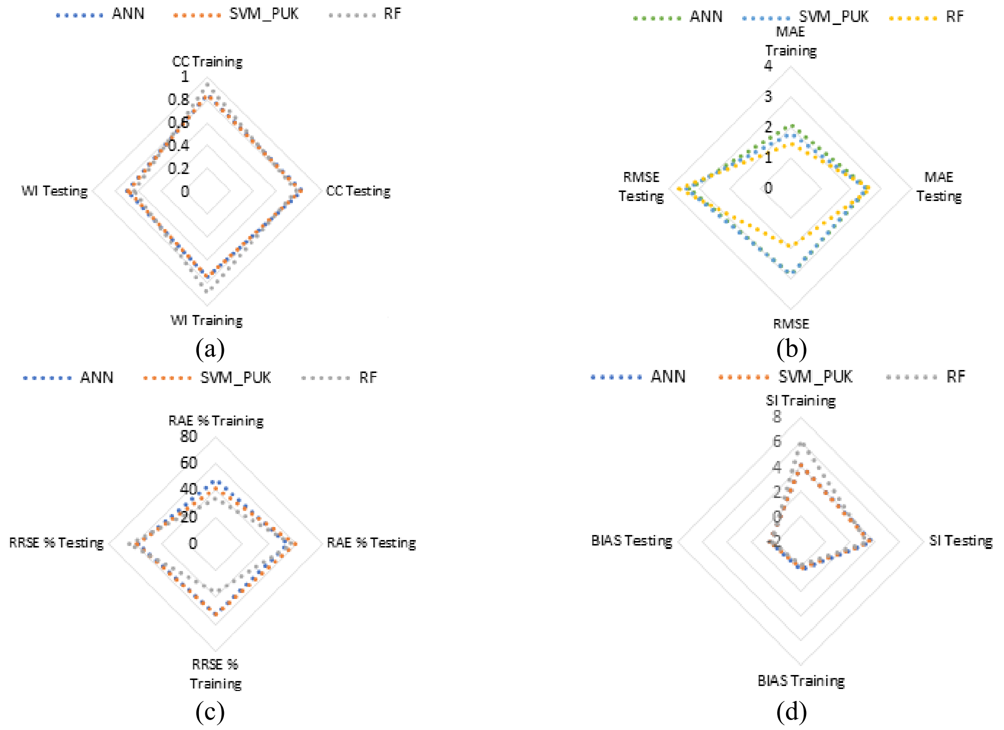


Fig. 11 Radial graph showing actual and predicted values for all applied models for training and testing stages

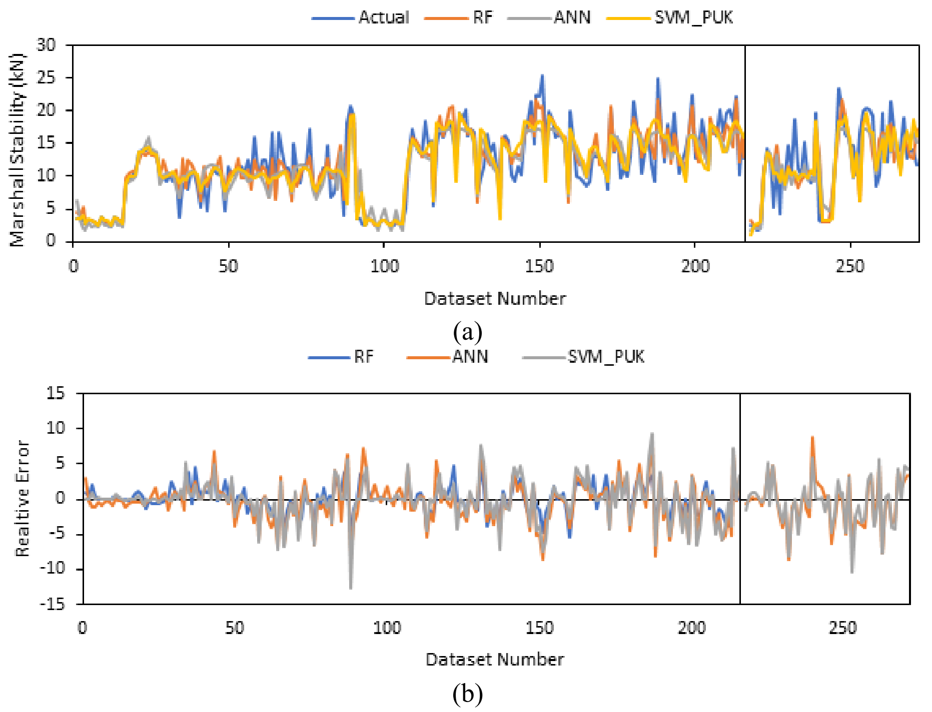


Fig. 12 Error graph between actual and predicted values using ANN, SVM_PUK and RF based models for training and testing stages

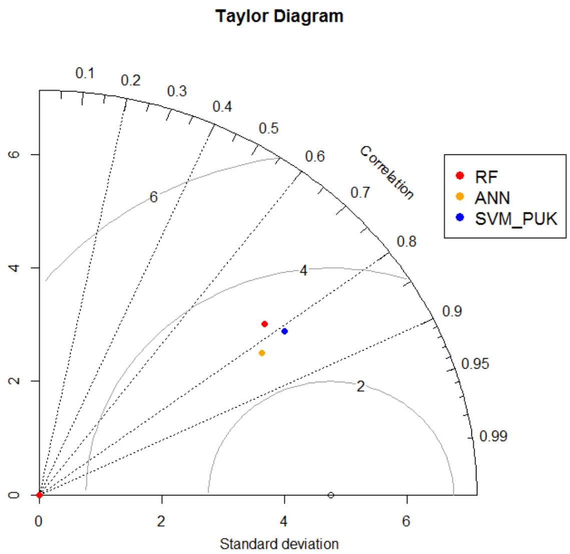


Fig. 13 Taylor diagram using a testing dataset

10. Comparison of models

In this study, Marshall's stability of asphalt concrete using glass and carbon fiber and with the combination of both the fibers has been investigated by implementing machine learning techniques. Seven attributes Bitumen content (BC), glass fiber (GF), carbon fiber (CF), 50/50 GF:CF, bitumen grade (VG), fiber length (FL), and fiber diameter (FD) have all been considered, as well as Marshall stability (kN) as an output parameter for the prediction of Marshall stability of asphalt concrete mix using glass and carbon fiber and in combination with the both and these attributes are assessed by performance evaluation parameters as given in following Eqs. (1)-(8). and performance of all the models executed as shown in Table 9. for both training and testing stages. Table 9 shows a comparison of all the models applied for shows that ANN-based model is outperforming with CC value as 0.8492 and 0.8234, MAE value as 2.0999 and 2.5408, RMSE value as 2.8541 and 3.3165, RAE value as 48.16% and 54.05%, RRSE value as 53.14% and 57.39%, WI value as 0.7490 and 0.7011, SI values as 4.1378 and 3.7027 and BIAS value as 0.3020 and 0.4300 for both training and testing stages respectively. Whereas the performance of the SVM_PUK and RF-based model also gives better results in predicting the Marshall stability of asphalt concrete using glass and carbon fiber with a higher coefficient of correlation and lower errors. The performance evaluation of all the models employed for both stages is shown in Figs. 10(a) and 10(b), which demonstrates that the predicted readings of the ANN-based model are near to the actual data, resulting in a low error bandwidth i.e., ±40% error line. Figs. 11(a)-11(d) radial graphs representing predicted values for all models with statistical parameters applied for both stages. Fig 12(a) and 12(b) shows the predicted Marshall stability with the total dataset and relative error for all applied models.

11. Taylor diagram

The performance of the regression models in Fig. 13 was illustrated using a Taylor diagram. The

Table. 10 Sensitivity analysis with ANN-based model

Input parameter (Coloured box shows the exit of the parameter under the column from the analysis)							Output	ANN based model		
Bitumen Content (BC %)	Glass Fiber (GF %)	50GF:50CF (%)	Carbon Fiber (CF%)	Bitumen Grade (VG)	Fiber Length (FL mm)	Fiber Diameter (FD µm)	Marshall Stability (kN)	CC	RMSE	MAE
							all	0.8234	3.3165	2.5408
							-	0.7266	4.1083	3.4481
							-	0.7616	3.7846	3.1182
							-	0.7641	3.7985	3.0057
							-	0.7673	4.0608	2.948
							-	0.7752	4.4407	3.9445
							-	0.7811	4.0927	3.2432
							-	0.7875	3.6002	2.7882

Table. 11 Sensitivity analysis with combination of input parameters using ANN based model

Input Parameter (Coloured box shows the removal of the parameter under the column from the analysis)							Combination of Input Parameters	Output	ANN based Model		
Bitumen Content (BC %)	Glass Fiber (GF %)	50GF:50CF (%)	Carbon Fiber (CF%)	Bitumen Grade (VG)	Fiber Length (FL mm)	Fiber Diameter (FD µm)		Marshall Stability (kN)	CC	RMSE	MAE
							CF	-	0.2597	5.7706	4.6386
							50GF:50CF + CF	-	0.406	5.4624	4.4419
							50GF:50CF + CF + FL	-	0.6876	4.3386	3.7215
							50GF:50CF + CF + FL + GF	-	0.7007	4.584	3.9956
							50GF:50CF + CF + FL + GF + VG	-	0.7004	4.1695	3.3654
							50GF:50CF + CF + FL + GF + VG + FD	-	0.7895	3.5926	2.7706
							50GF:50CF + CF + FL + GF + VG + BC	ALL	0.8234	3.3165	2.5408

accuracy of the implemented models was evaluated using two statistical metrics: standard error and correlations. According to the Taylor diagram, (Orange point) indicates that the ANN-based model has the highest coefficient of correlation when compared to the other employed models for predicting Marshall Stability of asphalt concrete using glass and carbon fibers, as well as a mixture of both fibers, followed by SVM_PUK and RF. As a consequence, the findings of the three models used are consistent with those of the Taylor diagram, indicating the best model.

12. Sensitivity analysis

Sensitivity analysis was done to find the most relevant parameter among input parameters for predicting Marshall stability of glass-fiber, carbon-fiber, and glass-carbon-fiber asphalt mixes. Several input combinations-based models were developed, as shown in Table 10 and the blue colored box shows the elimination (from the analysis) of the parameter falling under the column. Table 10 shows that carbon fiber has been proven to be a more sensitive material, having a lower coefficient of correlation and higher error values in comparison to glass fiber. Table 11 shows the sensitivity analysis with the combination of input parameters. It has been found that carbon fiber seems to be more sensitive followed by the optimal combination of (50GF:50CF) + CF to Marshall stability of asphalt concrete mix. For the prediction of Marshall stability of hybrid mix, the ANN model is found to be an optimal fitting and suitable model. However, the significance of all input parameters: bitumen content (BC), glass fiber (GF), carbon fiber (CF), 50GF:50CF, bitumen grade (VG), fiber length (FL), and fiber diameter (FD) gives higher prediction accuracy.

13. Discussions

The maximum Marshall stability obtained with 2.5% glass-fiber asphalt mix was 18.7 kN at 4.5% bitumen content and as per literature, the maximum Marshall stability is 14.4 kN at bitumen content 5.5% with 0.6% glass fiber (Taherkhani 2016). The maximum Marshall stability of 3% carbon-fiber asphalt mix was 24.6 kN at 6.0% bitumen content and the result obtained by (Geckil and Ahmedzade 2020), the maximum Marshall stability was found to be 20.26 kN at bitumen content 5.1% with 0.5% of carbon fiber. The increase in Marshall stability by the carbon-fiber asphalt concrete over the glass-fiber asphalt concrete is to the extent of 31.55 % whereas as per the aforesaid cited literature it is 40.7% which is within the range of published results. This further shows that the use of carbon fiber is more beneficial than the glass fibers in the asphalt mix. However, the cost of the carbon fiber is quite high with respect to glass fiber, therefore it was idealized to use these two fibers in the combination of 50:50 in asphalt mix to observe the Marshall stability. The glass-carbon-fiber asphalt mix (hybrid) specimens were tested in the laboratory and it was found that the Marshall stability of 2.0% glass-carbon-fiber asphalt (hybrid) mix is 6.0% bitumen content is about 33.5% higher than the glass-fiber asphalt mix. This increase in Marshall stability of hybrid asphalt mix with respect to glass-fiber asphalt mix shows sustainability. The said hybrid mix, not only will increase the Marshall stability but also be cost-effective in flexible pavements due to the higher cost of carbon fiber.

14. Conclusions

The carbon-fiber asphalt mix has higher Marshall stability than the glass-fiber asphalt mix. However carbon fiber is more expensive than glass fiber, so the hybrid use of glass-carbon fiber in asphalt mix seems to be a better performer than glass-fiber asphalt mix due to 35.5% increase in Marshall stability. The hybrid mix can increase the Marshall stability and can be cost-effective in flexible pavements due to the low cost of glass fiber. For the prediction of Marshall stability of fibrous asphalt mix three machine learning techniques i.e., ANN, SVM_PUK and RF-based models were applied. Eight, different goodness of fit parameters were used to evaluate the performance of the generated models such as CC, RMSE, MAE, RAE, RRSE, WI, SI and BIAS to assess the performance of these models. The following are the results of this investigation:

• For the prediction of Marshall stability of hybrid mix, the ANN model is found to be an optimal fitting and suitable model. However, the significance of parameters: bitumen content (BC), glass fiber (GF), carbon fiber (CF), 50GF:50CF, bitumen grade (VG), fiber length (FL), and fiber diameter (FD) is well established by the three-machine learning algorithm ANN, SVM_PUK, RF with CC: 0.84, 0.84, 0.93 in training dataset and 0.82, 0.81,0.77 in testing dataset respectively.

• According to the performance evaluation results, the multilayer perceptron artificial neural network (ANN) outperformed model with CC as 0.8234, MAE as 2.5408, RMSE as 3.3165, RAE as 54.05%, RRSE as 57.39%, WI as 0.7011, SI as 3.7027 and BIAS as 0.4300 in the testing stage.

• Taylor diagram also shows that the ANN model outperformed the other models and is suitable for predicting the Marshall Stability of asphalt concrete.

• The carbon fiber (CF) followed by glass-carbon fiber (50GF:50CF) and the optimal combination CF + (50GF:50CF) are found to be most sensitive in predicting the Marshall stability of fibrous asphalt concrete. This demonstrates that more research on the use of glass-carbon fiber asphalt concrete is required.

15. Findings of the study

The carbon-fiber asphalt mix has higher Marshall stability than the glass-fiber asphalt mix. However, carbon fiber is more expensive than glass fiber, so the hybrid use of glass-carbon fiber in asphalt mix seems to be a better performer than glass-fiber asphalt mixes due to increase in Marshall stability. The hybrid mix, not only will increase the Marshall stability but also be cost-effective in flexible pavements due to the lower cost of glass fiber. For the prediction of Marshall stability of fibrous asphalt mix, the ANN model is found to be an optimal fitting and suitable model which has identified that carbon-fiber followed by glass-carbon fiber is the most sensitive parameter in the asphalt mix.

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Data availability statements

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

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