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Prediction of Binder Content in Glass Fiber Reinforced Asphalt Mix Using Machine Learning Techniques

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ABSTRACT Several researchers have reported the results of adding a variety of fibers to asphalt concrete described as fiber-reinforced asphalt concrete (FRAC). This research paper finds the most suitable prediction model for Marshall Stability and the optimistic bitumen content useful in glass fiber-reinforced asphalt mix by performing Marshall Stability tests and further analyzing the data in consonance with published research. Four machine learning approaches were used to find the best prediction model i.e., Artificial Neural Network, Support Vector Machine, Gaussian Process, and Random Forest. Seven statistical metrics were used to evaluate the performance of the applied models 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. Test results of the testing stage indicated that the Support Vector Machine (SVM_PUK) model performs the best in validation amongst all applied models with CC values as 0.8776 MAE as 1.2294, RMSE as 1.9653, RAE as 38.33%, RRSE as 55.22%, SI as 1.0648 and Bias as 0.5005. The Taylor diagram of the testing dataset also confirms that the model based on SVM outperforms the other models. Results of sensitivity analysis show that the bitumen content of about 5% has a significant effect on the Marshall Stability.

INDEX TERMS Glass fiber, Marshall stability, artificial neural network, support vector machine, Gaussian process, random forest.

I. INTRODUCTION

The asphalt concrete pavements are extensively used in advanced highways/runways/parking places; therefore, the cost of the bitumen influences the project cost to a greater extent. It is significant to have information of an optimum binder content which is helpful in achieving the higher Marshall steadiness values for better performance of asphalt concrete (AC) paved roads. In the initial scientific approach, methods for determining and discovering the physical features of pavements have been elaborated by researchers [1] that AC is the most popular form of pavement, and it can be found everywhere from local roads to expressways, parking lots to harbor facilities and bike paths to airport runways. Cracking, ravelling (structural failure), stripping (aggregate separation from the AC mixture), and potholes are common problems with AC mixes. Heavy traffic loads and adverse environmental or weather conditions are to blame for these annoyances. Distresses on road pavements might lead to the structure of the pavement failing [2]. Incorporating additives is one of the important strategies for enhancing the quality of pavement structures and reducing distresses - related problems. For specific purposes, additives are added to the asphalt binder to give it desirable qualities, resulting in new classes of compounds that may be employed to mitigate various asphalt pavement distresses [3]. Fiber modifiers include cellulose, polyester, and glass fibers, as well as mineral fibers (asbestos, rock wool), and waste fibers. Nylon, waste tires, and textiles are commonly utilized in various types of asphalt concrete and pavement [4]. Khattak and Baladi [5], studied

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the polymeric materials which make asphalt more resistant to loading and less susceptible to heat fluctuations, according to the consequences of utilizing polymers as modifiers. Although additives may improve the technical characteristics of the asphalt mix, they would have been difficult to employ in the asphalt if they were not cost-effective. For example, two types of additives, ethyl vinyl acetate (EVA) and glass fibers can be utilized in the asphalt if they are subject to economic viability.

Glass fiber is a modern industrial material with a wide range of applications. Moreover, it improves the mixture's efficiency and sensitivity to fracture propagation. Glass fiber can withstand pavement fractures at low temperatures because it has a potential resistance to fracture initiation [6]. Glass fiber-reinforced polymer. (GFRP) is popular because of its inherent compatibility with asphalt and strong mechanical properties and improves structural performance and fatigue characteristics while also enhancing ductility [7]. As a reinforcing material, glass fiber has certain unique features e.g., it is both durable and adaptable. At asphalt mix temperature of 200°C, it is thermally and chemically inert. De-icing salt, gasoline, or bitumen does not affect it. At 20°C, Young's modulus of glass fiber is 70 GPa, which is more than 20 times that of conventional asphalt concrete as well as high tensile strength. As a result, the axial stiffness which is necessary to divert fracture energy is provided by glass fiber [8]. Glass fibers have shown promise in reducing rutting and cracking in asphalt mixes. Glass fibers in asphalt mixes have also been shown to increase healing capabilities, rutting resistance, moisture resistance, and fatigue resistance [9]. Serfass and Samanos [11], examined the influence of fiber-modified asphalt in asphalt mixtures on asbestos, rock wool, glass wool, and cellulose fibers. Among the tests carried out in the investigations were resistive modulus, low-temperature direct stress, rutting resistance, and fatigue resistance. Fiber-modified mixtures conserved the greatest number of voids as compared to untreated asphalt and two elastomer-modified mixes. It was also discovered that it promotes improved drainage in porous combinations, resulting in a lower vulnerability to moisture-related distress. Zarei *et al.* [10], investigated that Glass fiber length has a significant influence on Marshall Resistance and asphalt mix performance, with 6 mm glass fiber lengths lowering the Marshall strength and 12 mm glass fiber lengths increasing Marshall strength. Furthermore, the robust modulus findings show that at two temperatures, with a fixed proportion of fiber and a rising lignin rate, it behaves differently. In the study conducted by Geckil and Ahmedzade [12], carbon fibers were used in four different percentages by weight of bitumen: 0%, 0.30%, 0.50%, and 0.70%. With the inclusion of carbon fiber, Marshall's steadiness and Flow experiments demonstrated an increase in the steadiness of bituminous mixes as well as a reduction in mixture flow values. The findings of another study conducted by Guo *et al.* [13], showed that adding diatomite and glass fiber to a bituminous mix did not influence the tensile strength, but it did have a positive impact on the tensile strain; therefore, preventing micro-crack development. Luo *et al.* [14], presented a review article on the effect of adding lignin or glass fiber to asphalt mixes, concluding that the overall performance of an asphalt mixture cannot be improved by adding a single admixture, as lignin fiber enhances low-temperature cracking; glass fiber improves excellent productivity, and both types of fibers have a good impact on durability properties. Mahrez *et al.* [15], used glass fiber, it has been observed that adding fiber to bituminous mixes alters their properties by reducing their steadiness and increasing the flow value as well as voids in the mix improving fracture resistance and persistent deformation resistance to extend fatigue life. Overall, the results showed that adding glass fiber to the flexible pavement improves several of the flexible pavement key properties.

To address the complex engineering problems, several studies were conducted, and mathematical principles were used. Machine learning technologies are increasingly being applied to fight the problem of pavement erosion. Supervised learning techniques are widely used to develop models and manage data difficulties to provide precise and consistent model sensitivity prediction [16]. To deal with problems related to optimization, intelligent control, and decision-making, machine learning has shown to be a cost-effective way. Machine learning incorporates a range of regression approaches such as fuzzy logic, neural networks, Gaussian Process regression, Support Vector Machine (SVM), Tree-based algorithms random forest, random Tree, M5P, and evolutionary algorithms, rather than being a single methodology. All of these approaches are complementary to one another and may be utilized in tandem to solve an issue (Jang *et al*. [17], Buckley and Hayashi [18], Thakur *et al.* [19]. To assess the sustainability of asphaltic concrete mixtures, Saif *et al.* [20] employed a conventional Back- Propagation Neural Network (BPNN) and Support Vector Machine (SVM) and the results show that SVM beats BPNN when it comes to forecasting the steadiness of asphaltic concrete mixes. Khuntia *et al.* [21], used a variety of input factors such as polypropylene, bitumen, and aggregates, a NN (neural network), and LS-SVM (least squares support vector machine) based model for predicting Marshall Steadiness was developed. When the performance of the two approaches was evaluated, it was observed that the NN-based model performed better and was more reliable than the LS-SVM model. Behnood and Daneshvar [22], found the effectiveness of the developed models which were calculated and compared to ANN models. In the study Xiao *et al.* [23], a typical statistical approach was used to predict the fatigue performance of various combinations. In estimating the fatigue life of changed mixtures, the data demonstrated that ANN approaches are more successful than typical statistical-based prediction models. In the research, Seitllari *et al.* [24], demonstrated that asphaltene aging indices, a basic asphalt property used to evaluate asphalt mixture qualities under various aging conditions, demonstrated a good relationship with the prediction model constructed using the ANN technique. Boscato *et al.* [25] utilized members made of Glass Fiber Reinforced Polymer (GFRP) to analyze numerical and experimental data based on Gaussian Processes Regression. Vadood *et al.* [26], investigated regression and artificial neural networks which were used to analyze and estimate the resilience modulus of modified HMA (Hot Mix Asphalt) samples constructed with polypropylene and polyester fibers (hybrid and single modes). Cook *et al.* [27], analyzed the support vector machine (SVM), multilayer perceptron artificial neural network (MLP-ANN), M5Prime model tree approach (M5P), and RF models were utilized to evaluate the performance of the hybrid RF-FFA model to those of regularly used solo ML models. The findings reveal that in prediction accuracy, the hybrid RF-FFA model regularly outperformed solo ML models.

In a previously published article [4], the dataset was analyzed by considering the 5 input parameters i.e., Bitumen content, Glass fiber, Bitumen grade, Fiber length, and Filler to predict Marshall stability as an output parameter. The various ML techniques were applied i.e., ANN, RF, RT, and ANFIS. It was found that result of ANFIS outperformed other applied models. Sensitivity analysis was carried out with the best performing model i.e., ANFIS for all five applied input parameters which showed that Bitumen grade was the most sensitive to the Marshall Stability of asphalt concrete. In the current study, the 12 input parameters mainly of bitumen content varying from 4.5% to 7.0% were considered to determine the most sensitive bitumen content to predict the Marshall stability. Other input parameters were glass fiber content, fiber length, and type of bitumen grade. Sensitivity analysis showed that 5.0% BC is the most sensitive to Marshall Stability of asphalt concrete.

This study investigated the most appropriate machine learning algorithm which can be applied in the twelve input variables i.e., Bitumen content: (BC) 4.5%, (BC) 5%, (BC) 5.5%, (BC) 6%, (BC) 6.5%, (BC) 7.0%, (BC) 4.6%, (BC) 4.7%, Glass fiber (GF), Bitumen grade (VG), Fiber length (FL), Fiber diameter (FD), to determine the optimum bitumen content from the range of binder content with glass fiber for the highest Marshall strength. For predicting the Marshall stability of asphalt concrete using glass fibers, four machine learning techniques such as ANN, SVM, GP, and RF-based models were used. To the best knowledge, the prediction of Marshall stability utilizing glass fibers with twelve input variables and identification of the optimal bitumen content is yet to be explored. Consequently, the present investigation is to abridge this gap by performing experiments and adopting data inputs from published work.

II. STUDY OBJECTIVES

To select the most suitable machine learning techniques to develop different models for the prediction of the wide range of binder content using the most appropriate machine learning approaches.

1) To optimize soft computing models that can predict the Marshall Stability precisely.

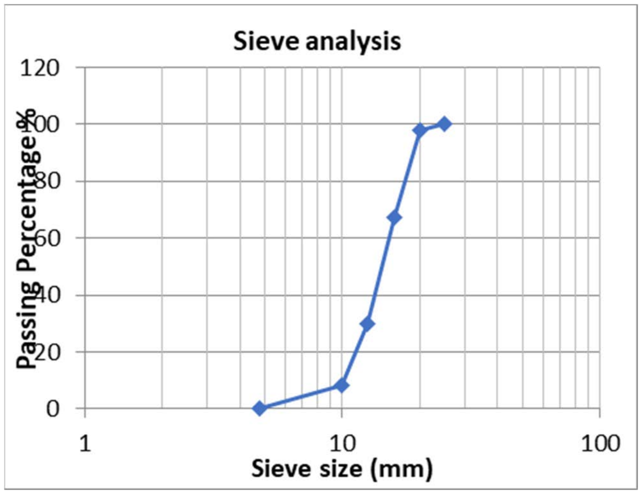

FIGURE 1. Coarse aggregate gradation.

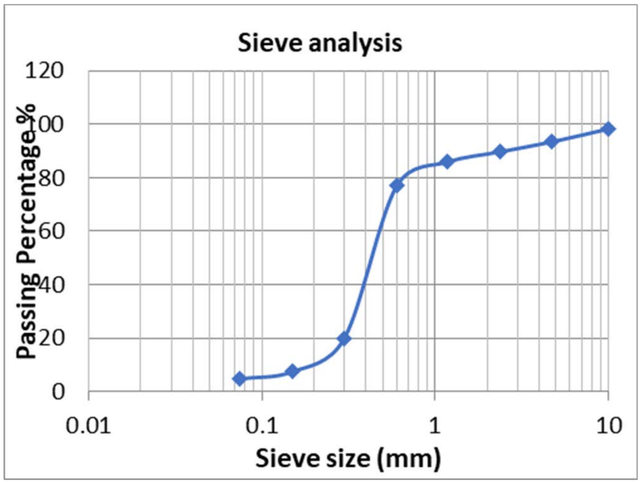

FIGURE 2. Fine aggregate gradation.

2) To determine the optimistic binder content in the asphalt mix by performing the sensitivity analysis.
3) To assess the importance of the twelve input variables in an asphalt mix i.e., eight Bitumen Content (BC) inputs, Glass fiber (GF), Bitumen grade (VG), Fiber length (FL), and Fiber diameter (FD).

III. DATA COLLECTION

To predict the Marshall Stability, the data was acquired by (a) performing laboratory tests using glass fiber asphalt specimens with a diameter of 101.6 mm and height of 63.5 mm (b) adopting data from previously published work.

IV. MATERIALS AND METHODOLOGY

Various types of material were used in the experimental work. i.e., 20 mm nominal size coarse aggregate, fine sand as filler, asphalt of grade VG10. The details of the materials are as under: -

A. AGGREGATE (COARSE AND FINE)

A coarse aggregate with a nominal size of 20 mm is used to prepare the asphalt mixture. Figures 1 and 2, show the

TABLE 1. Physical characteristics of aggregates.

Index	Coarse aggregate	Fine aggregate	Standard
Bulk Specific gravity (gm/cm^3)	2.64	2.47	ASTM C-128 [29]
Apparent specific gravity (gm/cm^3)	2.85	2.53	
Water absorption (%)	2.77	0.6	
Bulk density (gm/cm^3)	1.50	1.66	
Aggregate crushing value (%)	23.43	-	ASTM C-127 [30]
Aggregate impact value (%)	7.95	-	
Los angles abrasion value (%)	34.34	-	ASTM C-131 [31]
Flakiness (FI) and Elongation index (EI) (%)	14.64, 8.64	-	ASTM D- 4791 [32]

TABLE 2. Bitumen properties.

Properties	Standard	Value
Specific Gravity@ 25^0C %	ASTM D70 [33]	0.99
Penetration (25^0C,100 gm, and 5sec)	ASTM D5 [34]	97.66
Flash point test ^{0}C	ASTM D92 [35]	281^0c
Softening point Ring and Ball test) ^{0}C	ASTM D36 [36]	39.2

FIGURE 3. Glass fiber utilized in this study.

gradation of coarse and fine aggregates according to (ASTM D6913-04) [28]. Table 3 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.

B. BITUMEN

The bitumen VG-10 utilized in this investigation was acquired from the HPPWD (Himachal-Pradesh-Public-Works-Department) in Solan, India, with a penetration grade of (80-100), and the basic components of the asphalt are shown in Table 2.

C. GLASS FIBER

In this study, chopped glass fiber (GF) was utilized as an ingredient in the asphalt mixture to increase the asphalt's toughness and fatigue characteristics. The varying percentages of glass fibers were occupied by the weight of bitumen. Figure 3 shows the glass fibers which has been used in asphalt mixture and Table 3 lists the physical and mechanical characteristics of glass fibers.

TABLE 3. Mechanical/physical properties of glass fiber.

Test Properties	Glass-Fiber	Unit
Length	12	mm
Diameter	15	µm
Color	White	-
Tensile strength	4700-4800	MPa
Elongation	5.7	%
Density	2.46	gm/cc
Base	S- glass	-

V. PREPARATION OF MARSHALL MIX DESIGN

The asphalt mix was prepared according to ASTM-D 1559 [37] standards. A total of 72 asphalt mix cylindrical specimens with a diameter of 101.6 mm and height of 63.5 mm were prepared for which about 1200 gm of coarse aggregate was used and completely dried in the oven for 24 hours at 170 - 190°C. The asphalt was heated to a temperature of 121°C to 138°C, and the appropriate amount of asphalt was mixed completely into the heated aggregate at a temperature of 160^0C. The amount of glass fiber was chosen 0%, 1%, 2%, 3%, and 4% with a 0.5 percent fiber content interval by weight of bitumen. In both the control and glass fiber modified asphalt mixtures, the binder concentration varied at 4.5%, 5.0%, 5.5%, 6.0% with a 0.5 percent content interval. Glass fiber was mixed with heated aggregate and filler together in the modified mixture before the binder is

FIGURE 4. Glass fiber reinforced asphalt specimens.

FIGURE 5. Marshall steadiness apparatus used in testing.

added. The mixture is put into a mould and compacted with 75 blows on each side followed by the extraction of the mould by using a sample extractor. Figure 4 shows specimens with varying percentages of glass fiber, ranging from 0 to 4 %. The Marshall Stability device which was used in the testing of specimens is shown in Figure 5.

VI. MACHINE LEARNING TECHNIQUES

The following machine learning techniques were utilized for finding a solution for complex engineering problems with numerous input data. This section gives a summary of such techniques/models used in this research.

A. ARTIFICIAL NEURAL NETWORK (ANN)

It usually comprises a complicated framework of processing units. The input is processed using an artificial neural network (ANN). The ANN concept works similarly to biological neuron cells in the brain which estimates an output in a mechanism applicable for various inputs with estimated unknown functions using a database of input values. One of the most important features of ANN is its ability to analyze and solve extremely complicated and nonlinear problems using just basic mathematical processes [38]. The input layer, which specifies all input variables, the hidden layer, which describes the number of neurons, and the output layer, which creates the desired output, are the three basic layers of an ANN [39]. The neural network's approach may be used to develop prediction models of asphalt mixture fatigue life that accounts for the interaction of numerous parameters [40]. A self-learning artificial neural network is a multilayer perceptron artificial neural network (MLP-ANN). One input layer with a collection of neurons representing the input variables, one or more hierarchical hidden layers with computational neurons that refine and pass on the information from the previous layer, and one output layer with a computation node that provides the final prediction [41], [27], [42]. The training data set is used to apply the artificial neural network approach, while the testing data set is utilized for validation. This approach assists in the efficient solution of difficult problems as well as the correct calculation of findings. The Marshall Stability of an optimum percentage of bitumen content with glass fiber is predicted using weka 3.9.5 software. Figure 6 shows the basic functional mechanism of the ANN technique/model.

B. SUPPORT VECTOR MACHINES (SVM)

Cortes and Vapnik initially developed the support vector machine in 1995, and it is a powerful tool for machine learning for binary classification. SVM converts a non-linear problem into a linear problem by employing kernel function to move the original data spaces into a new feature space with more dimensions, allowing for the detection of unique global solutions that are not constrained by many local minima [42]. Data sets for training and testing, as well as input and output

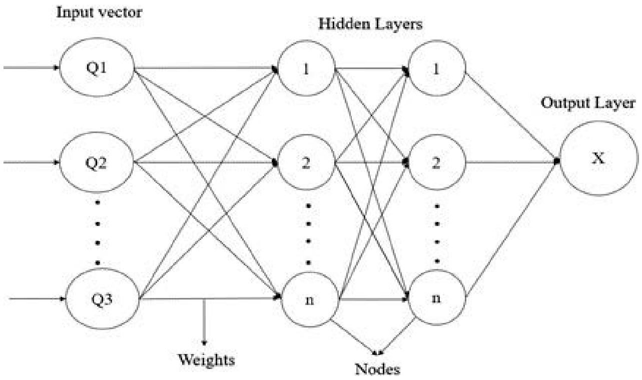

FIGURE 6. The basic functional mechanism of ANN.

parameters, are part of the SVM analysis technique. There are two ways for SVM analysis. The decision surface is separated using an optimal margin classifier (linear classifier). The kernel function approach, which calculates the products of two vectors, is another option. The input data is first mapped using n-dimensional features, then a non-linear kernel function is fitted in high-dimensional space using the fixed mapping process. The information separates linearly throughout a high-dimensional feature when the kernel mapping is applied to actual data, with no change in the actual input space [43]. A dot product of input data points is the kernel function that has been transformed into a higher dimensional feature space. Certain kernel functions have a gamma parameter that can be changed. By far the most prevalent kernel type utilized in Support Vector Machines is the RBF (Radial basis function). This is due to their limited and localized reactions throughout the whole range of the real x-axis [44]. The kernel variables should always be specifically selected since they have a significant impact on the accuracy and complexity of the SVM solution. Because the performance of SVMs is determined by the kernel function utilized, selecting the appropriate kernel function and kernel parameters for each application problem is critical to achieving outstanding results [45].

C. GAUSSIAN PROCESSES (GP)

The concept of Gaussian processes is named after Carl Friedrich Gauss (normal distribution) because it is predicated on the notion of the Gaussian distribution. Gaussian processes are multivariate normal distributions with an unlimited number of dimensions. The Gaussian process is a type of machine learning that interprets models using kernels. It presents a practical way to learn kernel machines. The hyperparameters of the kernel are optimized by maximizing the log-marginal-likelihood (LML) based on the passed optimizer during Gaussian Process Regressor fitting. It's a group of random variables in which every finite variable has a joint normal distribution. The mean function m(x) and the kernel function n (y, y') are the two major functions in the Gaussian process l(x). According to the Gaussian process, l(y) is:

$$\mathrm{l(y)} \sim \mathrm{GPm(y), n(y, y')}), \tag{1}$$

The function's main objective is to determine how input variables may be used to achieve the target. Every goal value, such as z, is coupled to an arbitrary regression function l(x) and independent Gaussian noise (ɜ) with the same distribution.

$$\text{i.e. } \mathrm{z} = \mathrm{l(y)} + ɜ \tag{2}$$

where, ɜ is a Zero mean and variance Gaussian noise $(\sigma \mathrm{n})^2$. i.e. ɜ $\sim \mathrm{L}(0, \sigma \mathrm{n}^2)$. Then eq. 1 is developed to eq. 3:

$$\mathrm{l(y)} \sim \mathrm{GP(m(y), n(y, y')} + \sigma \mathrm{n}^2 \mathrm{I}), \tag{3}$$

where- I represent the identity matrix.

D. 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, for every bootstrap sample, regression trees are generated, and the final results are established by voting after the classification tree predictions have been integrated. Both regression and classification may be done with RF [46]. The RF model is a modeling technique that combines several classification trees that are independent of one another. On the assumption that the calculation is not considerably expanded, the method can enhance forecast accuracy [47]. 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 received is used to calculate the prediction probability [48]. The out-of-bag samples are utilized to validate the model in this scenario. The procedure is repeated until the desired precision is obtained. Random Forest tree model 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 [49]. The random forest regression was applied for various parameters by using weka 3.9.5 version software. Figure 7, illustrates the fundamental function of the RF tree model.

VII. METHODOLOGY AND DATASET

It was decided that the experimental data which is of 72 observations to be blended with 38 observations obtained from published research articles. Total 110 observations have been used for developing a model for the prediction of optimum binder content from the set of the applied binder content in the studies. As for the model prediction, a large number of datasets is required but in several research articles, the small/limited number of datasets has also been used in predicting the best output [50]–[56], indicating that the model performs better with a higher correlation and lower

TABLE 4. Dataset information.

S. No.	*Bitumen content BC (%)*	*Glass fiber GF (%)*	*Bitumen grade (VG)*	*Fiber length FL (mm)*	*Fiber diameter FD*	*Marshall Stability (kN)*	*Observations (No.)*	*Authors*
Range of Dataset								
1.	5-7	0-2.5	30	NA	0.3-0.6 mm	6.26-9.23	5	Pasha *et al.* [57]
2.	4.5-6.5	0-0.3	20	10	15 μm	1.88-3.83	20	Alidadi and Khabiri [58]
3.	5.5	0.2-0.6	30	12	20 μm	13.84-14.4	4	Taherkhani. H [59]
4.	4.6-4.7	0-0.3	30	6	10 μm	13-14.3	4	Ji *et al.* [60]
5.	5	0-0.4	30	12	10 μm	9.12-10.98	5	Janmohammadi *et al.* [61]
6.	4.5-6	0-4	10	12	15 μm	3.74-14.65	72	Data obtained from current research experiments
Total observations							110	

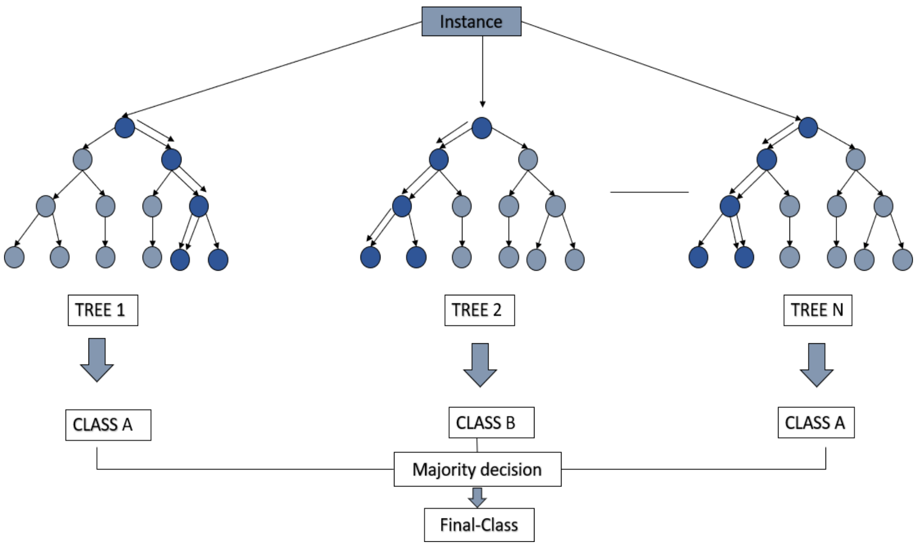

FIGURE 7. Working of random forest-based model.

errors. Therefore, total observations were then randomly divided into two subsets, each with a 75:25 proportion i.e., 83 observations were in training and 27 in the testing dataset. The experimental and literature data sets are summarized in Table 4 with input parameters such as (BC: Bitumen Content) 4.5%, (BC) 5.0%, (BC) 5.5%, (BC) 6.0% used in experimental data and (BC) 6.5%, (BC) 7.0%, (BC) 4.6%, (BC) 4.7% as were obtained from the published results. The Glass-fiber (GF) Bitumen-grade (VG), Fiber length (FL), Fiber diameter (FD) braced up for output as Marshall stability (MS). Table 5 shows the statistical characteristics of the input parameters. The input parameters are assessed via statistical metrics 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 to predict the output i.e., Marshall stability. Figure 8 shows the flow chart for determining the optimum performance model approach.

VIII. PERFORMANCE EVALUATION PARAMETERS

The performance of each model was assessed using seven statistical metrics i.e., CC MAE, RMSE, RAE, RRSE, SI, and BIAS respectively. This may be calculated using the formula which has been shown in the following Equations:

$$CC = \frac{\sum_{i=1}^{n}(D_i - \bar{D})(E_i - \bar{E})}{\sqrt{\sum_{i=1}^{n}(D - \bar{D})^2}\sqrt{\sum_{i=1}^{n}(E_i - \bar{E})^2}} \tag{4}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|D - E| \tag{5}$$

TABLE 5. Statistical features of dataset.

	BC (4.5%)	*BC (5%)*	*BC (5.5%)*	*BC (6%)*	*BC (6.5%)*	*BC (7%)*	*BC (4.6%)*	*BC (4.7%)*	*GF (%)*	*(VG)*	*FL (mm)*	*FD (µm)*	*MS (kN)*
TRAINING													
Mean	0.8780	1.2195	1.4085	1.3171	0.2378	0.0854	0.1122	0.0573	1.4280	15.1220	8.6829	11.8512	8.3180
Standard Error	0.1981	0.2386	0.2667	0.2759	0.1356	0.0854	0.0788	0.0573	0.1501	0.8544	0.4441	0.6646	0.4545
Standard Deviation	1.7943	2.1604	2.4154	2.4988	1.2278	0.7730	0.7140	0.5190	1.3589	7.7370	4.0212	6.0183	4.1156
Kurtosis	0.4678	-0.5373	-0.7220	-0.0967	23.8747	82.0000	38.3991	82.0000	-1.0922	-0.4020	1.0118	0.1175	-1.0691
Skewness	1.5675	1.2151	1.1385	1.3807	5.0292	9.0554	6.2819	9.0554	0.5692	1.1059	-1.4062	-1.3380	0.1177
Minimum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	10.0000	0.0000	0.0000	2.0200
Maximum	4.5000	5.0000	5.5000	6.0000	6.5000	7.0000	4.6000	4.7000	4.0000	30.0000	15.0000	20.0000	18.7000
Sum	72.0000	100.0000	115.5000	108.0000	19.5000	7.0000	9.2000	4.7000	117.1000	1240.0000	712.0000	971.8000	682.0800
Confidence Level (95.0%)	0.3943	0.4747	0.5307	0.5490	0.2698	0.1699	0.1569	0.1140	0.2986	1.7000	0.8835	1.3224	0.9043
TESTING													
	BC (4.5%)	*BC (5%)*	*BC (5.5%)*	*BC (6%)*	*BC (6.5%)*	*BC (7%)*	*BC (4.6%)*	*BC (4.7%)*	*GF (%)*	*(VG)*	*FL (mm)*	*FD (µm)*	*MS (kN)*
Mean	0.6923	1.5385	1.2692	1.1538	0.5000	0.0000	0.1769	0.0000	1.5346	14.6154	9.4231	13.0942	8.3854
Standard Error	0.3247	0.4615	0.4635	0.4729	0.3464	0.0000	0.1769	0.0000	0.2640	1.4916	0.6081	0.9940	0.7038
Standard Deviation	1.6558	2.3534	2.3632	2.4115	1.7664	0.0000	0.9021	0.0000	1.3464	7.6057	3.1006	5.0686	3.5889
Kurtosis	2.3283	-1.3247	-0.1766	0.8075	10.1563	0.0000	26.0000	0.0000	-1.1285	0.1851	5.9399	3.3146	-1.1537
Skewness	2.0383	0.8852	1.3576	1.6587	3.3732	0.0000	5.0990	0.0000	0.5249	1.3218	-2.1835	-2.0310	-0.2924
Minimum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	10.0000	0.0000	0.0000	1.8800
Maximum	4.5000	5.0000	5.5000	6.0000	6.5000	0.0000	4.6000	0.0000	4.0000	30.0000	15.0000	20.0000	14.1000
Sum	18.0000	40.0000	33.0000	30.0000	13.0000	0.0000	4.6000	0.0000	39.9000	380.0000	245.0000	340.4500	218.0200
Confidence Level (95.0%)	0.6688	0.9506	0.9545	0.9740	0.7134	0.0000	0.3644	0.0000	0.5438	3.0720	1.2524	2.0473	1.4496

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n}}\,(D-E)^2 \tag{6}$$

$$\mathrm{RAE} = \frac{\sum_{i=1}^{n}|D-E|}{\sum_{i=1}^{n}\left(\left|D-\bar{D}\right|\right)} \tag{7}$$

$$\mathrm{RRSE} = \sqrt{\frac{\sum_{i=1}^{n}(D-E)^2}{\sum_{i=1}^{n}(|D-E|)^2}} \tag{8}$$

$$\mathrm{SI} = \sqrt{\frac{\sum_{i=1}^{n}\left[(E_i-\bar{E})\,(D-\bar{D})\right]^2}{\sum_{i=1}^{n}D_i^2}} \tag{9}$$

$$\mathrm{Bias} = \frac{\sum_{i=1}^{n}(D_i-E_i)}{\sum_{i=1}^{n}D_i} \tag{10}$$

$D =$ Observed values
$E =$ Average of observation
$\bar{E} =$ Predicted value
$n =$ number of observations.

After performing the experimental work in the Highway Engineering laboratory and data from numerous specimens were obtained and observations were obtained from various literature as per Table 4. A total dataset was prepared and bifurcated into training and testing datasets. Four machine learning techniques (ANN, SVM, GP, and RF) were applied to get the Marshall Stability as output for the 12 input variables. The performance of each model has been discussed as under:-

A. PERFORMANCE OF ANN-BASED MODEL

The development of an ANN-based model is an iteration process that uses a multilayer perceptron model as a framework. Several operations were conducted to arrive at the optimal value of CC with the least errors in training and testing datasets for the prediction assessment. The user-defined parameters were used to optimize the model i.e., sigmoid functions were used as activation functions

TABLE 6. Performance assessment of models.

Models applied	CC	MAE (kN)	RMSE (kN)	RAE (%)	RRSE (%)	SI	Bias
TRAINING DATASET							
ANN	0.8851	2.1072	2.6494	58.26	64.62	1.2835	1.8243
SVM_PUK	0.879	1.1166	2.0112	30.87	49.05	2.0111	0.4437
GP_PUK	0.8632	2.0229	2.3254	55.93	56.71	2.3253	-0.0129
RF	0.9114	1.298	1.7185	35.89	41.91	1.7184	0.0955
TESTING DATASET							
ANN	0.8008	2.6052	3.3665	81.23	94.59	1.3689	2.2145
SVM_PUK	0.8776	1.2294	1.9653	38.33	55.22	1.0648	0.5055
GP_PUK	0.8518	1.8011	1.9345	56.16	54.35	0.9931	-0.0566
RF	0.8716	1.3708	1.7598	42.74	49.44	1.0272	0.2180

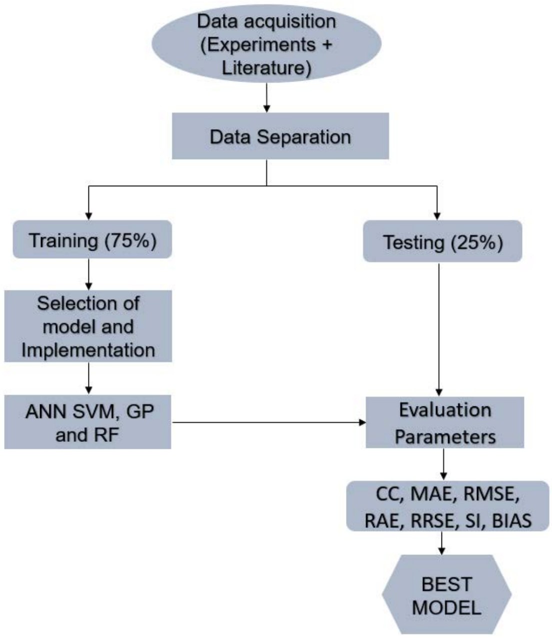

FIGURE 8. Flow chart for optimum performance model.

based on equation (11), Learning rate (L = 0.2), Momentum (M = 0.1), number of hidden layers (H = 1), Number of neurons (10) and Iterations (I = 10000).

$$f(x) = \frac{1}{1 + e^{-x}} \tag{11}$$

Seven different performance assessment metrics were applied to get the best predictive model as shown in Table 6. The outcome of Table 6 shows that the performance of an Artificial Neural Network model for predicting Marshall Stability is reliable with CC value as 0.8851 and 0.8008, MAE as 2.1072 and 2.6052, RMSE as 2.6494 and 3.3665, RAE as 58.26% and 81.23%, RRSE as 64.62% and 94.59%, SI as 1.2835 and 1.3689, and BIAS as 1.8243 and 2.2145 for both training and testing stages respectively. The training and testing phases are represented in Figure 9a, b with the agreement graph showing actual and predicted values using Artificial Neural Network-based models. The majority of the points in the said figures are centered on the line of perfect agreement, which shows the best possible match between actual and predicted outcome parameters, signifying more reliability. The majority of the experimental algorithm's predicted values are within the ±40% error range in the training and testing stages.

B. PERFORMANCE OF SVM_PUK-BASED MODEL

The Pearson Kernel function (PUK), used with the SVM model which incorporates user-defined parameters such as omega (O = 1.0) and sigma (S = 1.0) are used in this approach. After several applications, the ideal number was determined, i.e., the largest CC value with the minimum errors. Results of Table 6 suggests that an SVM_PUK based model outperforms all applicable models for the prediction of Marshall Stability of an optimum percentage of bitumen content with glass-fiber with CC value as 0.879 and 0.8776, MAE value as 1.1166 and 1.2294, RMSE value as 2.0112 and 1.9653, RAE value as 30.87% and 38.33%, RRSE value as 49.05% and 55.22%, SI values as 1.0567 and 1.0648 and Bias value as 0.4437 and 0.5005 for both training-testing phases accordingly. The training and testing phases are represented in Figure 10a, b with the agreement graph showing actual and predicted values using SVM_ PUK-based models. The majority of the predicted values are between the ±30% error range in the training and testing stages.

C. PERFORMANCE OF GP_PUK-BASED MODEL

Gaussian Processes is a regression process consisting of the Pearson VII function-based universal kernel (PUK), with some user-defined parameters such as Omega (O = 1.0) and Sigma (S = 1.0). Various trials have been carried out to reach the optimum value i.e., the maximum CC value and the minimum errors. Results of Table 6 suggest that an GP_PUK based model is consistent in the prediction of

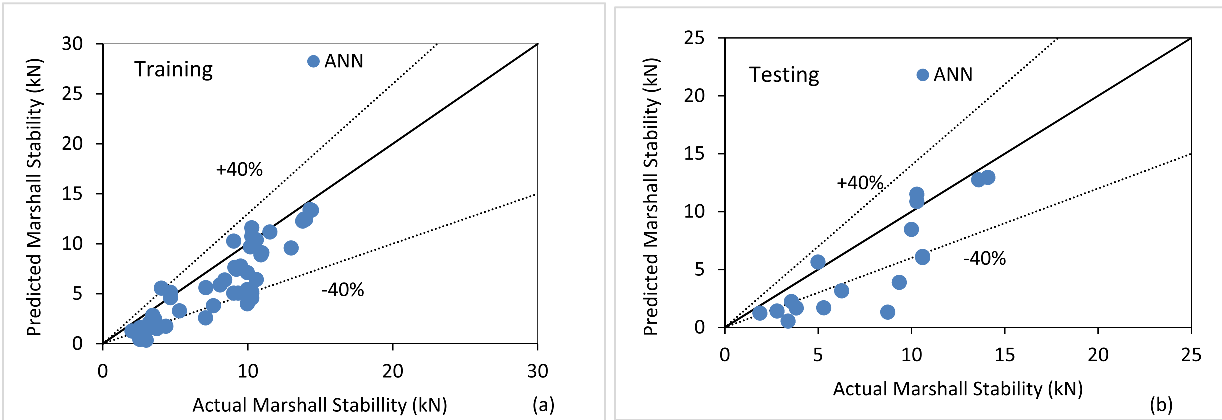

FIGURE 9. **(a, b). Prediction in ANN model (in training & testing stages).**

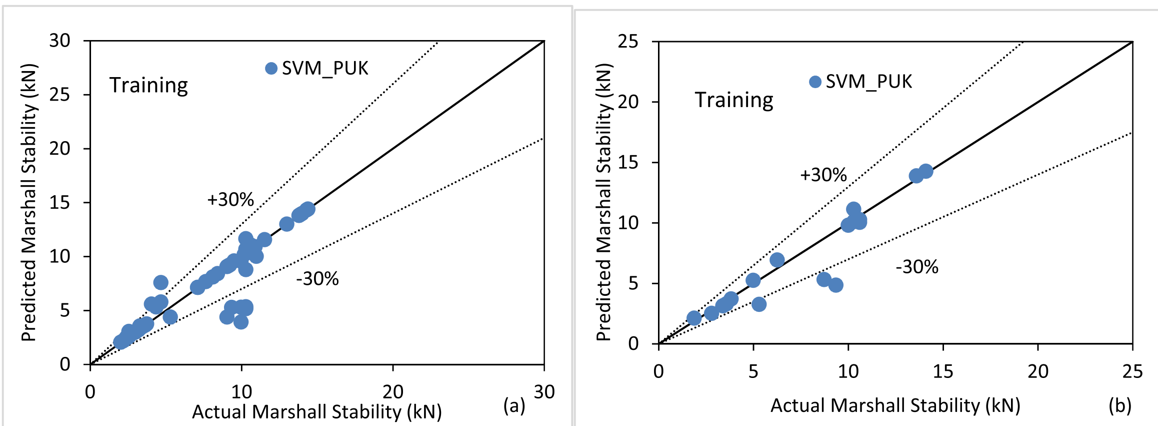

FIGURE 10. **(a, b). Prediction in SVM_PUK model (in training & testing stages).**

Marshall Stability with CC value as 0.8632 and 0.8518, MAE as 2.0229 and 1.8011, RMSE as 2.3254 and 1.9345, RAE as 55.93% and 56.16%, RRSE as 56.71% and 54.35%, SI as 0.9984 and 0.9931 and Bias as −0.0129 and −0.0566 for both training and testing stages respectively. The training and testing phases are represented in Figure 11a, b with the agreement functions showing the actual and the predicted values by using GP_PUK-based models. The majority of the machine learning algorithm predicted values are between the ±30% and error range in the training and testing stage.

D. PERFORMANCE OF 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 user-defined parameters used to optimize RF i.e., Numfeatures (K = 2), Iterations (I = 100), and Number of seed (S = 4). The performance evaluation parameters as listed in Table 6 show that the RF-based model gives better results in the prediction of Marshall Stability with CC as 0.9114 and 0.8716, MAE as 1.298 and 1.3708, RMSE as 1.7185 and 1.7598, RAE as 35.89% and 42.74%, RRSE as 41.91% and 49.44%, SI as 1.0117 and 1.0272 and Bias as 0.0955 and 0.2180 for both training and testing stages respectively. The majority of the points in these functions are centered on the line of perfect agreement, which shows the best possible match between actual and predicted results. The actual and predicted values and their deviation from the perfect agreement line for training and testing stages by using the RF model have been shown in Figure 12a, b. It was also discovered that the majority of the predicted values from the model are within the ±30% error range in both training and testing stages.

IX. RESULTS AND DISCUSSION

In this study, the prediction of Marshall stability at different binder and glass fiber contents has been investigated by implementing machine learning techniques using Regression and Tree-based models. Twelve attributes were used i.e., (BC) 4.5 percent, (BC) 5.0 percent, (BC) 5.5 percent, (BC) 6.0 percent, (BC) 6.5 percent, (BC) 7.0 percent, (BC) 4.6 percent, (BC) 4.7 percent, GF, VG, FL and FD whereas MS as an output parameter for the prediction of Marshall Stability. The performance evaluation parameters as given in Equations 4-10 as obtained from the models are shown in

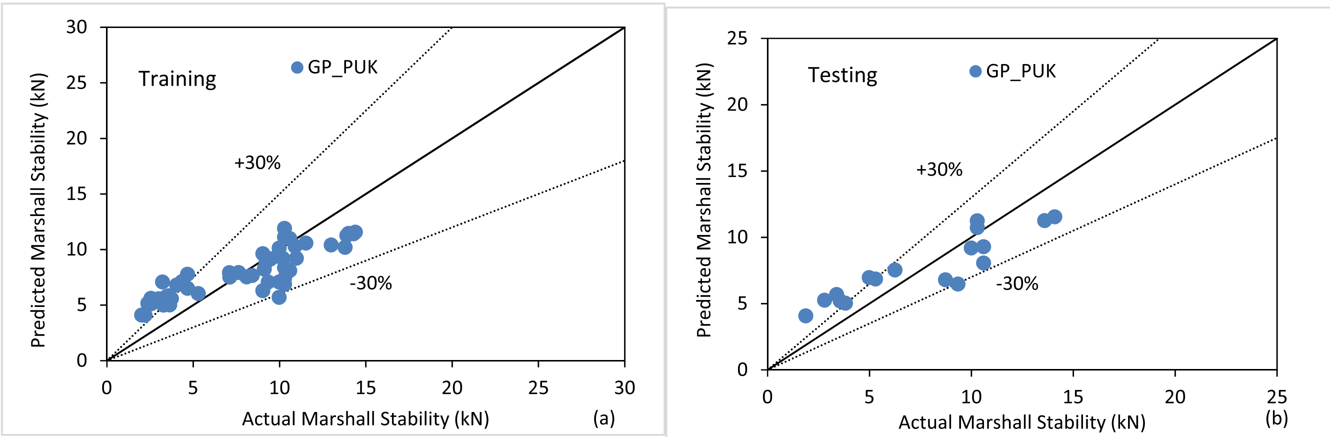

FIGURE 11. **(a, b). Prediction in GP_PUK model (in training & testing stages).**

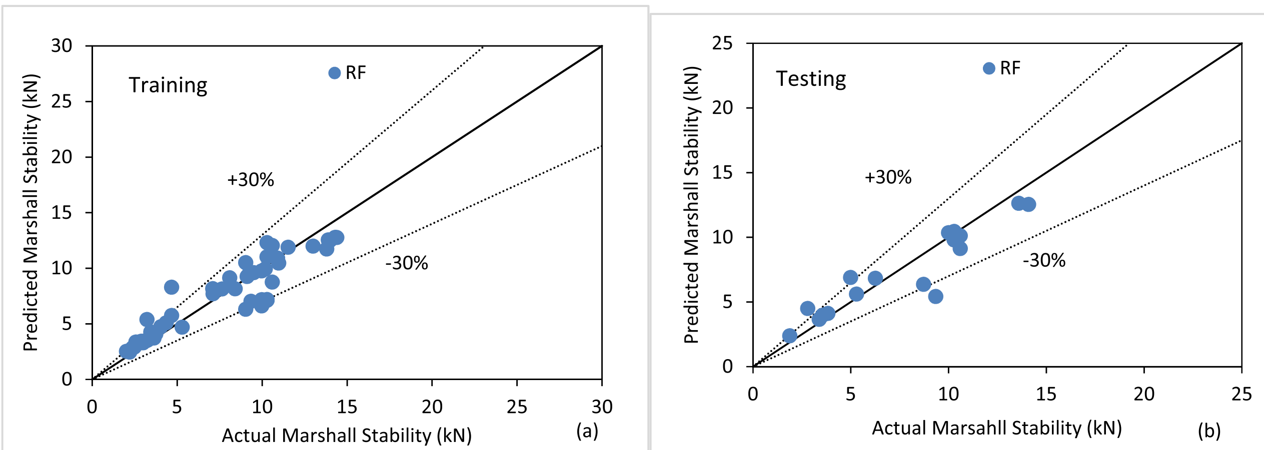

FIGURE 12. **(a, b). Prediction in RF model (in training & testing stages).**

Table 6 for training and testing stages. Results of Table 6 show the comparison of the applied models and it is found that the Support vector machine (SVM_ PUK) based model outperforms with CC value as 0.879 and 0.8776, MAE value as 1.1166 and 1.2294, RMSE value as 2.0112 and 1.9653, RAE value as 30.87% and 38.33%, RRSE 49.05% and 55.22%, SI values as 2.0111 and 1.0648 and Bias value as −0.4437 and 0.5055 for both training and testing stages respectively in the prediction of Marshall Stability. The majority of the points in these graphs are centered on the line of perfect agreement which shows an actual relationship between actual and predicted values. In the case of regression models i.e., ANN, GP_PUK, and RF-based model. It has been observed that the RF-based model is also competitive with respect to other regression models in both stages with a higher coefficient of correlation and lower errors. The performance evaluation of all the models employed for both stages is shown in Figure 13a, b, which demonstrates that the predicted values of the SVM_PUK-based model are closer to the actual data, resulting in a low error bandwidth i.e., ±50% error line. Figure 14a, b, show the predicted Marshall Stability with the total dataset and relative error for all applied models.

A. TAYLOR DIAGRAM

The performance of the regression models was illustrated in Figure 15 using the Taylor diagram for the testing stage. The accuracy of the implemented models was evaluated using two statistical metrics: standard error and correlations. According to the Taylor diagram, the orange point indicates that the SVM_PUK based model has the highest coefficient of correlation in comparison to the other employed models for the prediction of Marshall stability followed by ANN, GP_PUK, and RF-based model. As a consequence, the findings of the four applied models used are consistent with those of the Taylor diagram, indicating the best model.

B. SENSITIVITY ANALYSIS

To determine the importance of input parameters for the prediction of Marshall Stability with bitumen concentration, GF, VG, FL, FD, etc., a sensitivity analysis was

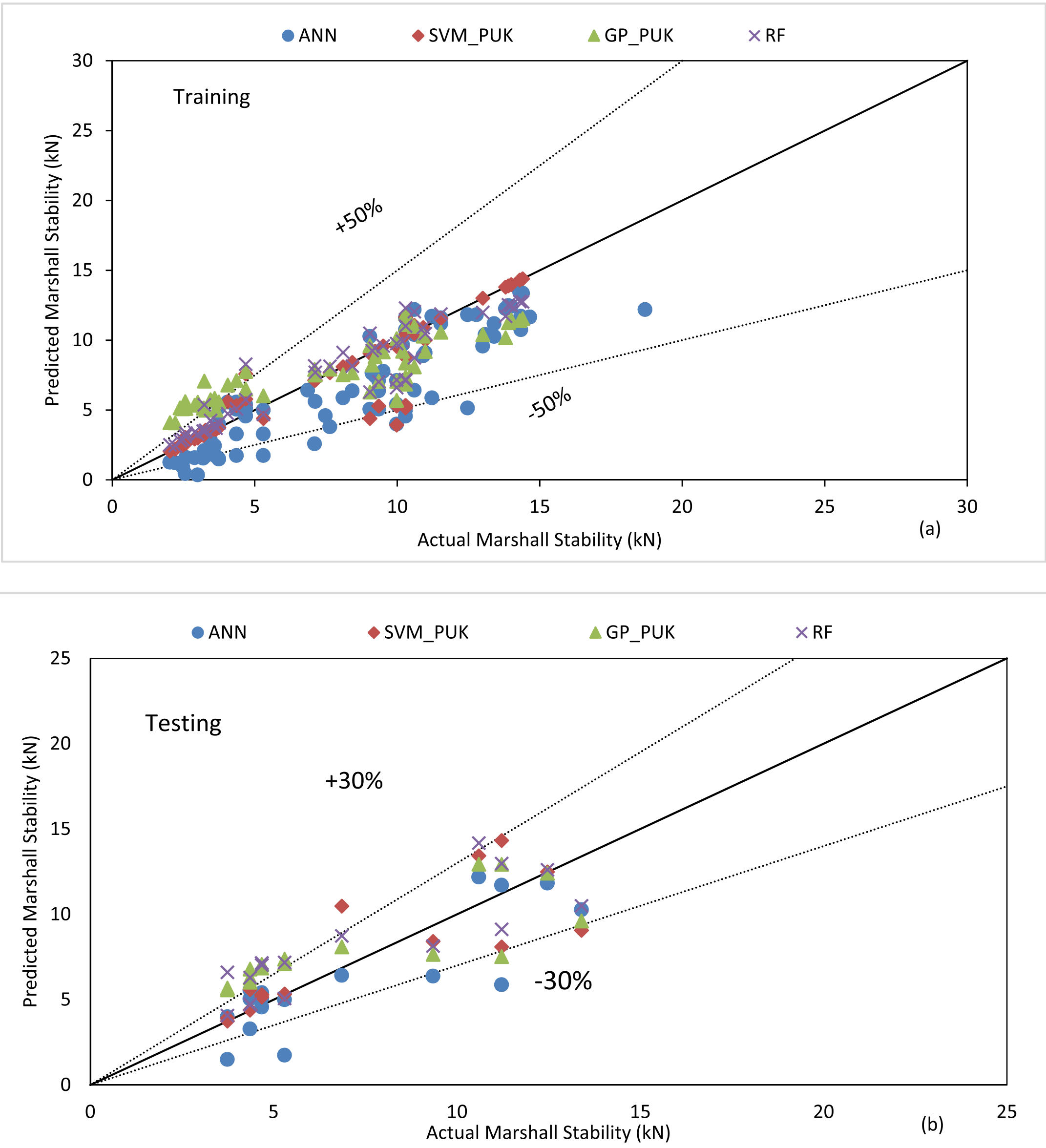

FIGURE 13. (a, b). Prediction in ANN, SVM_PUK, GP_PUK, and RF models (in training & testing stages).

performed. Twelve input parameters were used against the output of Marshall stability in this analysis as shown in Table 7. The black box represents the input parameter being removed under the column in the analysis. The said table shows that bitumen content (BC) of 5% has a major influence on the Marshall Stability of the asphalt concrete mix.

X. DISCUSSION

The objective of this study was to determine the binder content (BC) which is highly sensitive to the Marshall value in an asphalt mix. Therefore, the majority of the input parameter (8 No. of BC) consisted of different binder content (BC) in the range of 4.5-7.0 percent and other four parameters i.e., Glass fiber content, Glass fiber length, and type of bitumen (VG) were selected in the asphalt mix for predicting the Marshall stability of the mix. These twelve input parameters were responsible for predicting Marshall stability as output. The performance of all four machine learning models (ANN, SVM_PUK, GP_PUK, and RF-based model) was evaluated using statistical indicators, and it was discovered that the SVM_PUK outperformed the others. In the testing stage, the RF model was extremely competitive with SVM PUK, with its stats indices such as CC values of 0.8776, 0.8716. After carrying the sensitivity analysis with the SVM_PUK based model, it was found that the most sensitive binder content in the input parameters was (BC) 5%, which shows the highest sensitivity to the Marshall value. In the study, [61] found that the bitumen content of 5% imparts the highest Marshall Stability with glass fiber which aligns with the results

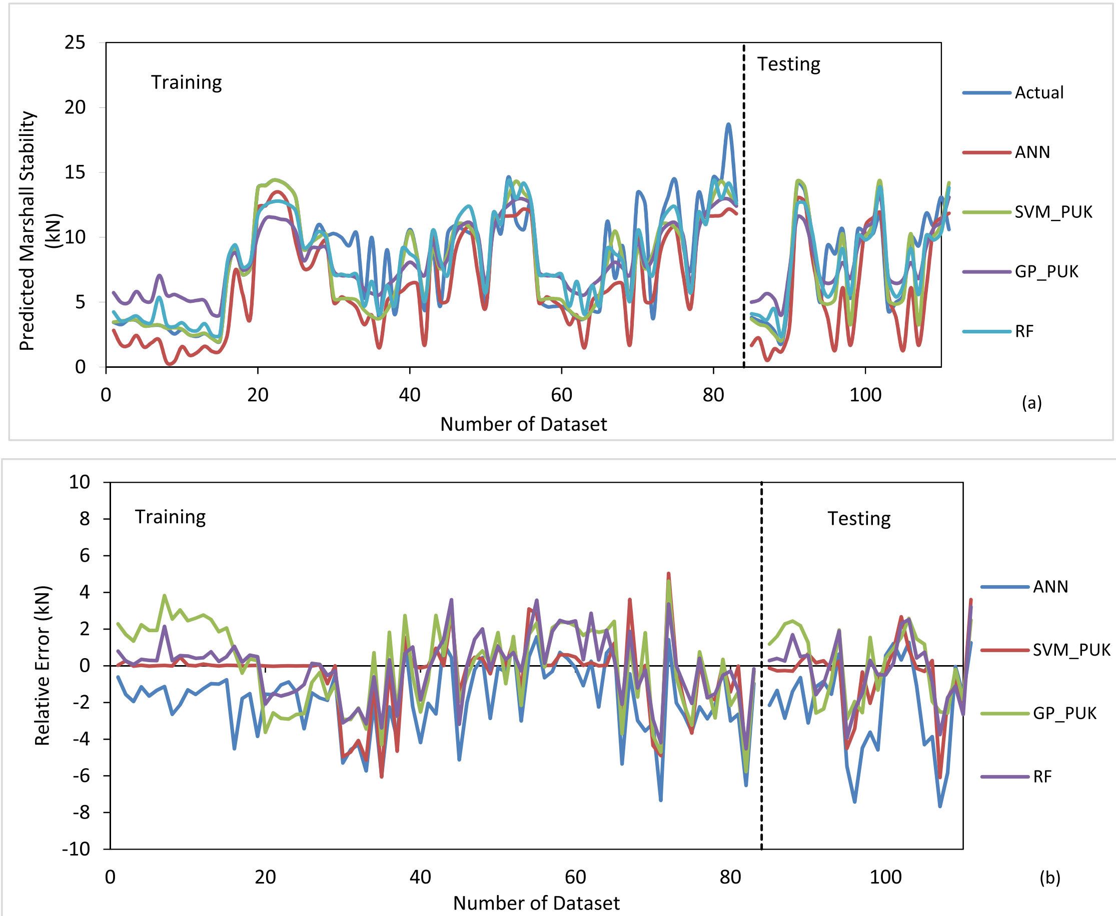

FIGURE 14. **(a, b). Relative error in ANN, SVM_PUK GP_PUK, and RF models (in training & testing stages).**

TABLE 7. **Sensitivity analysis with SVM_PUK based model.**

Input parameters												*Marshall Stability related output*	
(BC) 4.5%	*(BC) 5.0%*	*(BC) 5.5%*	*(BC) 6.0%*	*(BC) 6.5%*	*(BC) 7.0%*	*(BC) 4.6%*	*(BC) 4.7 %*	*GF (%)*	*(VG)*	*FL (mm)*	*FD (μm)*	*CC*	*RMSE*
	■											**0.6961**	**2.6307**
									■			0.7017	2.6212
		■										0.7202	2.5465
■												0.7204	2.5582
						■						0.7211	2.6966
							■					0.7322	2.6242
								■				0.7469	2.4808
											■	0.7917	2.323
										■		0.8012	2.2601
				■								0.8599	1.9425
					■							0.8605	1.9596
			■									0.8626	1.913

of the sensitivity analysis. This implies that the Marshall value with bitumen content as a binder is contributing highly to the Marshall stability values. Therefore, the use of said bitumen content (5%) can be useful in attaining the good Marshall stability vis-à-vis flexible pavement strength of the asphalt mix.

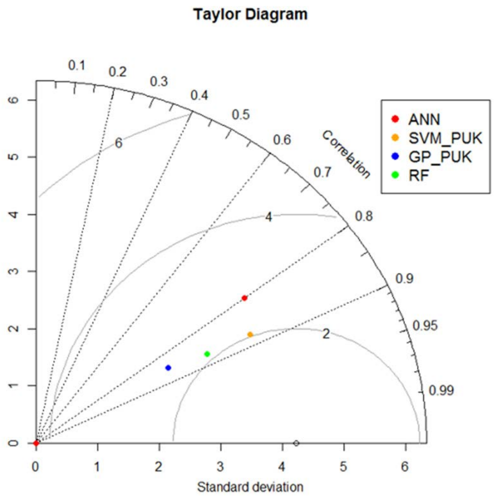

FIGURE 15. Taylor diagram (testing stage).

XI. CONCLUSION

The current study investigated the most appropriate machine learning algorithm with can be applied in the twelve input variables and based on these inputs, determined the optimum bitumen content in the range of binder content with glass fiber. Machine learning approaches i.e., ANN, SVM GP, and RF models were used to assess the Marshall strength of asphalt concrete. The performance of the developed models was assessed using seven different goodness of fit parameters 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 to assess the performance of these models. According to the performance evaluation results, the Support vector machine (SVM_ PUK) based model outperforms with CC value as 0.879 and 0.8776, MAE value as 1.1166 and 1.2294, RMSE value as 2.0112 and 1.9653, RAE value as 30.87% and 38.33%, RRSE 49.05% and 55.22%, SI values as 2.0111 and 1.0648 and BIAS value as −0.4437 and 0.5055 for both training and testing stages respectively. According to an agreement graph of the relationship between actual and predicted values, the SVM model has a small error band and is an optimal fitting for predicting the output. Taylor diagram also shows that the SVM model outperformed the other models and is suitable for the prediction of Marshall Stability of an optimum percentage of bitumen content with glass fiber in the range of 0-4% by weight of asphalt content. The results of the sensitivity analysis show that bitumen content about BC (5%) influences the Marshall strength to a greater extent for this dataset.

XII. FUTURE SCOPE

1) More research can be conducted to see how different types of fiber affect the mechanical qualities of asphalt at varying percentages of fiber and varying bitumen percentages and bitumen grades.
2) By using advanced machine learning hybrid approaches for prediction, such as linear regression, fuzzy logic, and ANFIS.
3) More input parameters such as filler content, varying the percentage of filler, aggregate size, etc. can be included in the future study.
4) To measure the strength qualities of asphalt pavement, several tests that evaluate the pavement's performance, such as indirect tensile test, rutting resistance, fatigue test, etc. can be performed on the glass-fiber asphalt mix.

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