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

Ankita Upadhya1, M. S. Thakur2, Arwa Mashat3, Gaurav Gupta4, Mohammed S. Adbo5*

1Department of Civil Engineering, Shoolini University, Solan, Himachal Pradesh, zip code 173229, India.
2Faculty of Computing and Information Technology, King Abdulaziz University, P.O. box 344, Rabigh, Saudi Arabia.
3Yogananda School of Artificial Intelligence Computer and Data Sciences, Shoolini University, Solan, Himachal Pradesh, zip code 173229, India.
4Department of Mathematics, Hodeidah University, Al-Hudaydah, Yemen

Corresponding author: (e-mail: msabdo@hoduniv.net.ye).

ABSTRACT Several researchers have been 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: 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 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 Bitumen content, 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] AC is the most popular form of pavement, and it can be found everywhere from local roads to expressways, parking lots to harbour 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 (2001) [5] studied the polymeric materials which make asphalt more impervious 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’ve 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 flow 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. 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 (1996) [10] examined the influence of fiber-modified asphalt in asphalt mixtures on asbestos, rock wool, glass wool, and cellulose fibers was investigated. Among the tests carried out in the investigations were resistive modulus, low-temperature direct stress, rutting resistance, and fatigue resistance. Fiber-modified mixtures conserves 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., 2018) [11] 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 (2020), [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., (2015) [13] results 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., (2015) [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 and Karim (2005) [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., 1997, Buckley and Hayashi 1994, Thakur et al., 2021) [17] [18] [19]. To assess the sustainability of asphaltic concrete mixtures, Saif et al. (2013) [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., (2014) [21] used a variety of input factors such as polypropylene, bitumen, and aggregates, a NN (neural network), and LS-SVM (least
square 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 (2020) [22] found the effectiveness of the developed models which were calculated and compared to ANN models. In the study Xiao et al., (2009) [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, Seițlari et al., (2019) [24] demonstrated that asphaltenes 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 ANFIS technique. Boscato et al., (2020) [25] utilized members made of Glass Fiber Reinforced Polymer (GFRP) were used to analyze numerical and experimental data based on Gaussian Processes Regression. Vadood et al., (2014) [26] investigated regression and artificial neural networks which were used to analyze and estimate the resilience modulus of modified HMA samples constructed with polypropylene and polyester fibers (hybrid and single modes). Cook et al., (2020) [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 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 with 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%, 7(BC) %, (BC) 4.6%, (BC) 4.7%, Glass fiber (GF), Bitumen grade (VG), Fiber length (FL), Fiber diameter (FD), and based on these inputs, determined the optimum bitumen content from the range of binder content with glass fiber. For predicting the Marshall steadiness of asphalt concrete using glass fibers, machine learning techniques such as ANN, SVM, GP, and RF-based models were used to evaluate the Marshall strength of asphalt concrete. To the best knowledge, the prediction of Marshall steadiness 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.
I. STUDY OBJECTIVES

1) 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.
2) To optimize soft computing models that can predict the Marshall Stability precisely.
3) To determine the optimistic binder content in the asphalt mix by performing the sensitivity analysis.
4) 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).

II. DATA COLLECTION

The Marshall Stability prediction data was acquired by (a) performing laboratory tests using glass fiber asphalt specimens with diameter of 101.6 mm and heights of 635 mm (b) adopting data from previously published work.

III. 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 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 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 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.
mm was made and evaluated 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 temperatures of 121°C to 138°C, and the appropriate amount of asphalt was mixed completely into the heated aggregate at a temperature of 160°C. The amount of glass fiber was chosen 0%, 1%, 2%, 3% and 4% with a 0.5 percent fiber content interval. In both the control and carbon fiber modified asphalt mixtures, the binder concentration varied at 4.5%, 5%, 5.5%, 6% 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 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.

IV. PREPARATION OF MARSHALL DESIGN MIX
The asphalt mix was prepared according to ASTM-D 1559 [37] standards. A total of 72 asphalt mixes cylindrical specimens with diameters of 101.6 mm and heights of 635

---

| Base | S-glass |
|------|---------|

---

FIGURE 3. GLASS FIBER UTILIZED IN THIS STUDY

FIGURE 4. GLASS FIBER REINFORCED ASPHALT SPECIMENS

FIGURE 5. MARSHALL STEADINESS APPARATUS USED IN TESTING

V. 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.

D. 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 account for the interaction of numerous parameters [40]. A self-learning artificial neural network is a multilayerperceptron 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 optimum percentage of bitumen content with glass fiber is predicted using WEKA 3.9 software. Figure 6 shows the basic functional mechanism of the ANN technique/model.

E. 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 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].

F. 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 (x) and the kernel function (y, y’) are the two major functions in the Gaussian process (x). According to the Gaussian process, (x) is:

\[ l(y) \sim GP(m(y), \sigma(y,y')) \]

(1)

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

\[ z = l(y) + \sigma \]

(2)

Where, is a Zero mean and variance Gaussian noise (σ²), i.e. σ ~ L(0, σ²). Then eq. 1 is developed to eq. 3: l(y) ~ GP(m(y), \sigma(y,y'+σ²)),

(3)

Where- I represent the identity matrix.
G. 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.

VI. 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, a total of 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 been used in predicting the best output [50] [51] [52] [53] [54] [55] [56] indicating that the model performs better with higher correlation and lower 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%, (BC) 5.5%, (BC) 6% used in experimental data and (BC) 6.5%, (BC) 7%, (BC) 4.6%, (BC) 4.7% was obtained from the published results. The additional input parameters were 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.
| S. No. | Bitumen content BC (%) | Glass fiber GF (%) | Bitumen grade (VG) | Fiber length FL (mm) | Fiber diameter FD (µm) | Marshall Stability (kN) | Observations (No., %) | Authors                           |
|-------|------------------------|--------------------|--------------------|---------------------|------------------------|--------------------------|------------------------|----------------------------------|
| 1.    | 5-7                    | 0-2.5              | 30                 | 0                   | 0.3-0.6 mm             | 6.26-9.23                | 5                      | Pasha et al., (2017)[57]          |
| 2.    | 4.5-6.5                | 0-0.3              | 20                 | 10                  | 15 µm                  | 1.88-3.83                | 20                     | Ailidadi and Khabiri (2016) [58] |
| 3.    | 5.5                    | 0.2-0.6            | 30                 | 12                  | 20 µm                  | 13.84-14.4              | 4                      | Taherkhani. H (2016) [59]         |
| 4.    | 4.6-4.7                | 0-0.3              | 30                 | 6                   | 10 µm                  | 13-14.3                 | 4                      | Ji et al., (2007) [60]            |
| 5.    | 5                      | 0-0.4              | 30                 | 12                  | 10 µm                  | 9.12-10.98              | 5                      | Jannmohammadi et al., (2020) [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**                  |                        |                                  |

### TABLE 5

**STATISTICAL FEATURES OF DATASET**

#### TRAINING

| 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      | 0.8780  | 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 | -1.069L |
| 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    | 6.4000    | 4.7000 | 4.0000 | 30.0000 | 15.0000 | 20.0000 | 18.7000 |
| Sum       | 72.0000 | 100.000   | 115.5000| 108.0000  | 19.5000 | 7.0000    | 9.2000    | 4.7000 | 117.1000 | 1240.000 | 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 | 10.0000 | 0.0000 | 0.0000 | 0.0000 | 1.8800 |
| Maximum   | 4.5000  | 5.0000    | 5.5000  | 6.0000    | 6.5000  | 7.0000    | 6.4000    | 4.0000 | 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 |
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:

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

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} |D - E|
\]  
(5)

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (D - E)^2}
\]  
(6)

\[
RAE = \frac{\sum_{i=1}^{n}|D - E|}{\sum_{i=1}^{n}|D - \bar{D}|}
\]  
(7)

\[
RRSE = \sqrt{\frac{\sum_{i=1}^{n}(D - E)^2}{\sum_{i=1}^{n}(D - \bar{D})^2}}
\]  
(8)

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

\[
BIAS = \frac{\sum_{i=1}^{n}(D_i - E_i)}{\sum_{i=1}^{n} D_i}
\]  
(10)

\[D = \text{Observed values}\]

\[E = \text{Average of observation}\]

\[\bar{E} = \text{Predicted value}\]

\[n = \text{number of observations}\]

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:

**H. 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 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).

\[
f(x) = \frac{1}{1+e^{-x}}
\]  
(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 ±40% error range in training and testing stages.
I. PERFORMANCE OF SVM_PUK BASED MODEL

The Pearson Kernel function (PUK), used with the SVM model which incorporates user-defined parameters such as omega (Ω=1.0) and sigma (Σ=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 suggest 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 2.0229 and 1.8011, RMSE value as 2.0229 and 1.8011, RAE value as 55.93% and 56.16%, RRSE value as 56.71% and 54.35%, and SI as 0.9984 and 0.9931 for both training and testing stages. 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 experimental algorithm’s predicted values are between ±30% error range in training and testing stages.

J. PERFORMANCE OF GP_PUK BASED MODEL

Gaussian Processes is a regression process consists of the Pearson VII function-based universal kernel (PUK), with some user-defined parameters such as Omega (Ω=1.0) and Sigma (Σ=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 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%, and SI as 0.9984 and 0.9931 for both training and 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.
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 experimental algorithm’s predicted values are between the ±30% and error range in the training and testing stage.

FIGURE 11(a, b). PREDICTION IN GP_PUK MODEL (IN TRAINING & TESTING STAGES)

K. 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.

FIGURE 12(a, b). PREDICTION IN RF MODEL (IN TRAINING & TESTING STAGES)
VII. 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: (BC: content) 4.5 percent, (BC) 5 percent, (BC) 5.5 percent, (BC) 6 percent, (BC) 6.5 percent, (BC) 7 percent, (BC) 4.6 percent, (BC) 4.7 percent, GF, VG, FL, FD, and MS as an output parameter for the prediction of Marshall Stability. The performance evaluation parameters as given in following Equations 4-10 and obtained from the models are shown in Table 6 for training and testing stages. Results of
Table 6 Show the comparison of the applied models and it is found that 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 seen that the RF-based model is also in accordance and giving the best results as compared to other regression models in both the 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.

| 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  | 2.0239   | 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 |
The diagram shows a comparison of predicted and actual Marshall Stability values. The x-axis represents the Actual Marshall Stability (kN), while the y-axis represents the Predicted Marshall Stability (kN). The legend includes ANN, SVM_PUK, GP_PUK, and RF. The graph indicates that the predicted values are close to the actual values, with some data points falling above +30% and below -30% of the actual values. The Testing section is marked with +30% and -30% annotations.
FIGURE 13(a, b). PREDICTION IN ANN, SVM_PK, GP_PUK AND RF MODELS (IN TRAINING & TESTING STAGES)

FIGURE 14(a, b). RELATIVE ERROR IN ANN, SVM_PK, GP_PUK AND RF MODELS (IN TRAINING & TESTING STAGES)

L. TAYLOR DIAGRAM

The performance of the regression models in Figure 15 was illustrated 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.

FIGURE 15. TAYLOR DIAGRAM (TESTING STAGE)
M. 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 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.

| Input parameters | Marshall Stability related output |
|------------------|----------------------------------|
|                  | CC  | RMSE  |
| (BC) 4.5%        |     |       |
| (BC) 5.0%        |     |       |
| (BC) 5.5%        |     |       |
| (BC) 6.0%        |     |       |
| (BC) 6.5%        |     |       |
| (BC) 7.0%        |     |       |
| (BC) 7.5%        |     |       |
| (BC) 8.0%        |     |       |
| (BC) 8.5%        |     |       |
| (BC) 9.0%        |     |       |
| (VG)             |     |       |
| (FL) mm          |     |       |
| (FD) µm          |     |       |
| CF               |     |       |
| RMSE             |     |       |

VIII. Discussion

The objective of this study was to determine the binder content i.e., BC which is highly sensitive to the Marshall value. Therefore, 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 (4) parameters of Glass Fiber content, Glass fiber length and type of bitumen (VG) were selected in the asphalt mix tested for Marshall stability specimens. These twelve input parameters were responsible for generating output as Marshall stability values. The sensitivity analysis was performed by applying the most effective model which is SVM_PUK in this case. Now to arrive at the most effective model, it was imperative to test many models in the sensitivity analysis to determine the most appropriate model i.e., ANN, SVM_PUK, GP_PUK, and RF based model. The performance of all four machine learning models 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. The most sensitive binder content in the input parameters was BC5%, that shows highest sensitivity to the Marshall value. In the study, [61] found that the bitumen content of BC5% imparts the highest Marshall Stability with glass fiber which aligns with the results of the sensitivity analysis. This implies that the Marshall value with Bitumen content as binder is contributing highly for the Marshall stability values. Therefore, the use of said bitumen content can be useful in attaining the good Marshall strength vis-à-vis flexible pavement strength.
IX. 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, 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.
ACKNOWLEDGMENT

We, the authors, would like to express our gratitude to the researchers whose findings we have mentioned in this work.

REFERENCES

[1] Z. B. Yıldırım, and M. Karacasu, “Modelling of weathered rubber and glass fiber with response surface method in hot mix asphalt”. Construction and Building Materials, 227, 117070. 2019.
[2] A. H. Mrema, S. H. Noh, O. S. Kwon and J.J. Lee, J. J., “Performance of Glass Wool Fibers in Asphalt Concrete Mixtures”. Materials, 13(21), 4699.2020.
[3] M. Enieh, M. A. Diab and X. Yang, “Short -and long-term properties of glass fiber reinforced asphalt mixtures”. International Journal of Pavement Engineering, 2 2 (1), 6 4 - 76. 2021.
[4] A. Upadhy, M.SThakur, N. Sharma, and P. Shag, “Assessment of Soft Computing-Based Techniques for the Prediction of Marshall Stability of Asphalt Concrete Reinforced with Glass Fiber”. International Journal of Pavement Research and Technology, 1-20. https://doi.org/10.1016/j.matdes.2014.10.033.
[5] M. J. Khattak and G. Y. Baladi, “Fatigue and permanent deformation models for polymer-modified asphalt mixtures”. Transportation Research Record, 1767(1), 135-145. https://doi.org/10.1141/1767-17.2001.
[6] A. Khater, D. Luo, M. Abdelsalam, Y. Yue, Y. Hou and M. Ghazy, “Laboratory Evaluation of Asphalt Mixture Performance Using Composite Admixtures of Lignin and Glass Fibers”. Applied Sciences, 11(1), 364. https://doi.org/10.3390/app11010364. 2021.
[7] A. A. R. Amer, M. M. A. B. Abdullah, L. Y. Ming and d M. F. M. Tahir, “Performance and properties of glass fiber and its utilization in concrete” A review. In AIP Conference Proceedings Vol. 2030, No. 1, p. 020296). AIP Publishing LLC. https://doi.org/10.1063/1.506937. November. 2018.
[8] M. L. Nguyen, J. Blanc, J. P. Kerzrého, and P. Hornych, P, “Review of glass fiber grid use for pavement reinforcement and APT experiments at IFSTTAR”. Road Materials and Pavement Design, 14(sup1), 208-308. 2013. https://doi.org/10.1080/16860629.2013.774763.
[9] H. Ziari, M. R. A. Ahiha, A. Movrika and Y. Saghafi, “Crack resistance of hot mix asphalt containing different percentages of reclaimed asphalt pavement and glass fiber”. Construction and Building Materials, 230, 117015. 2020.
[10] A. Zarei, M. Zarei and O. Jamomhammad, “Evaluation of fo t the effect of lignin and glass fiber on the technical properties of asphalt mixtures”. Arab J Sci Eng, 44(5), 4085-4094. https://doi.org/10.1007/s13369-018-2327-4. 2019.
[11] J. P. Serfass and J. T. Samanos, “Fiber-modified asphalt co ncrete characteristics, applications and behavior”. Asphalt Paving Technology, 65, 193-230. 1996.
[12] T. Geckil and P. Ahmedzade, “Effects of carbon fiber on property performance of asphalt mixtures. Baltic Journal of Road & Bridge Engineering (RTU Publishing House), 15(2), 2020. https://doi.org/10.7250/jbret.2020-15.472.
[13] Q. Guo, L. Li, Y. Cheng, Y. Jiao and C. Xu, “Laboratory evaluation on performance of diamonite and glass fiber compound-modified asphalt mixture”. Materials & Design (1980-2015), 6 6 , 51-59; https://doi.org/10.1016/j.matdes.2014.10.033.
[14] D. Luo, A. Khater, Y. Yue, M. Abdelsalam, Z. Zhang, Y. Li and D. T. Isley, “The performance of asphalt mixtures modified with lignin fiber and glass fiber: A review”. Construction and Building Materials, 209, 377-387. 2019. https://doi.org/10.1016/j.conbuildmat.2019.03.126.
[15] A. Mahrez, M.R. Karim, H. Y. Katman, H. Y., “Fatigue and deformation properties of glass fiber reinforced bituminous mixes”. Journal of the Eastern Asia Society for Transportation Studies, 2005, 6, 997-1007. https://doi.org/10.11175/easts.6.997.
[16] K. Golzar, J.A. Azam and N. Mahta “Statistical investigation on physical-mechanical properties of base and polymer modified bitumen using Artificial Neural Network,” Construction and Building Materials, 37, 822-831. 2012. https://doi.org/10.1016/j.conbuildmat.2012.08.011.
[17] J. S. R. Jang, C. T. Sun and E. Mizutani, E, “Neuro-fuzzy and soft computing—c a computer-aided approach to learning and machine intelligence” [Book Review]. IEEE Transactions on automatic control, 42(10), pp.1482-1484. 1997.
[18] J. J. Buckley and Y. Hayashi, Y, “Fuzzy neural networks: A survey”. Fuzzy sets and systems, 66(1), pp.1-13. 1994.
[19] M.S. Thakur, S. M. Pandhiani, V. Kashyap, A. Upadhy, and P. Shag, “Predicting Bond Strength of FRP Bars in Concrete Using Soft Computing Techniques”. Arabian Journal for Science and Engineering. 46(5),4951-4969. https://doi.org/10.1007/s1336-020-05314-8. 2021.
[20] M. A. Saif, M.S. El-Bisy and M. H. Alawi, “Application of So f t Computing Techniques to Predict the Stability of Asphaltic Concrete Mixes”. In Third International Conference on Soft Computing Technology in Civil, Structural and Environmental Engineering, Cagliari, Sardinia, Italy. 2013.
[21] S. Khuntia, A.K. Das, M. Mohanty and M. Panda, “Prediction of Marshall parameters of modified bituminous mixtures using artificial intelligence techniques”. International Journal of Transportation Science and Technology, 3(3), 211 -227. https://doi.org/10.102016/0030 3.3.211. 2014.
[22] A. Behnood and D. Daneshvar, “A machine learning study of the dynamic modulus of asphalt concretes: An application of a Simple Model tree algorithm”. Construction and Building Materials, 262, 120544. 2020. doi.org/10.1016/j.conbuildmat.2020.120544.
[23] F. Xiao, S. Amirkanian and C. H. Huang, “Prediction of fatigue life of rubberized asphalt concrete mixtures containing reclaimed asphalt pavement using artificial neural networks”. Journal of Materials in Civil Engineering, 21(6), 253-261. 2009. https://doi.org/10.1061/(ASCE)1090-0278(2009)21:6(253).
[24] A. Seiitlari, Y. S. Kumbargere, K. P. Biligiri and I. Boz, “A so f t computing approach to predict and evaluate asphalt mixture aging characteristics using asphaltene as a performance indicator”. Materials and Structures, 32(5), 1-11. 2019. https://doi.org/10.1617/s11527-019-1402-5.
[25] G. Boscato, M. Civera and L. Zanotti Fragonara, “Recursive partitioning and Gaussian Process Regression for the detec tion and localization of damages in pultruded Glass Fiber Reinfo ced Polymer material”. Structural Control and Health Monitoring, e2805. 2021. https://doi.org/10.1002/stc.2805.
[26] M. Vadood, M. S. Johari, A. Rahai, “Developing a hybrid artificial neural network-genetic algorithm model to predict resilient modulus of polypropylene/polyester fiber-reinforced asphalt concrete. The Journal of the Textile Institute, 1 06(11), 1239-1250. 2015. https://doi.org/10.1000/04050000.2014.985882.
[27] R. Cook, J. Lapeyre, H. Ma, and A. Kumar, “Prediction of compressive strength of concrete: critical comparison of performance of a hybrid machine learning model with standalone models”. Journal of Materials in Civil Engineering, 31(11), 04019255, 2019 https://doi.org/10.1061/(ASCE)MT.1943-5533.0002920.
[28] ASTM D6913-04, “Standard test methods for particle size distribution of soils,” American Society for Testing of Materials, Pennsylvania, PA, USA.
[29] ASTM C-128,” Standard Test Method for Specific Gravity and d Absorption of Fine Aggregate”. Annual Book of ASTM Standards USA,1992
[30] ASTM C 127,” Test Method for Specific Gravity and Adsorption of Coarse Aggregate”. Annual Book of ASTM Standards USA, 1992.
[31] ASTM C 131, “Standard test method for resistance to degradation of small-size coarse aggregate”, Annual Book of ASTM Standards USA.
A. Simultaneous

B. Dai, C. Gu, E. Zhao and X. Qin, “Statistical model optimized using artificial neural network.” Adv. Comput. Des, 3(3), 2007.

C. Basgıtay, I. Akkurt, S. Kilincarslan and A. Beycigölu, "Prediction of compressive strength of heavyweight concrete using ANN and FL models", Neural Computing and Applications, 19(4), 507-513, (2010). https://doi.org/10.1007/s00521-009-0292-9.

D. Huang, T. Duan, Y. Zhang, J. Liu, J. Zhang and Y. Lei, “Predicting the permeability of pervious concrete-based on the beetle antennae search algorithm and random forest model.” Advances in Civil Engineering, 2020. https://doi.org/10.1155/2020/8863181.

E. Upadhya, M.S. Thakur, S. M. Pandhian and S. Tayal, “Estimation of Marshall Stability of asphalt concrete mix using Neural Network and MSP Tree”. In Computational Technologies in Materials Science 223-236, 2012b, CRC Press.

F. Farooq, M. Nasir Amin, K. Khan, M. Rehan Sadiq, M. Faizal Javed, F. Aslam and R. Alyousef, “A comparative study of random forest and genetic engineering programming for the prediction of compressive strength of high strength concrete (HSC)”. Applied Sciences, 10(20), 7330, 2020. https://doi.org/10.3390/app10207330.

G. N.S. Singh, P. Sihag, and S. Luthra, “Performance evaluation of fuzzy-logic and BP-ANN methods for WEDM of aeronautics super alloy.” Methods X 5 (2018): 890-908. https://doi.org/10.1016/j.mex.2018.04.006.

H. Ayat, Y. Kellouche, M. Ghrici and M. Ahmadi, H. Naderpour and A. Kheyroddin, “ANN model for prediction of compressive strength of high strength concrete using support vector machine (SVM)”, Case Studies in Construction Materials, 1(1), 2017.

I. B. Topcu, A. R. Boğa, and F. O. Hocaoğlu, "Modeling corrosion currents of reinforced concrete using ANN", Automation in Construction, 18(2), 145 -152. F, 2009. https://doi.org/10.1016/j.autcon.2008.07.004.

J. M. Ahmad, H. Naderpour and A. Kheyroddin, “ANN model for predicting the compressive strength of circular steel co-fined concrete”, International Journal of Civil Engineering, 15(2), 213-221, 2017. https://doi.org/10.1108/ijc-04-2016-0096-0.

K. H. Ayat, Y. Kellouche, M. Ghrici and B. Boukhatem, “Compressive strength prediction of limestone filler con crete using artificial neural networks”. Adv. Comput. Des, 3(3), 2-9, 2018. DOI: http://dx.doi.org/10.12989/acd.2018.3.3.289.

L. Angelaki, A., Singh Nain, S., Singh, V., & Sihag, P., “Estimation of models for cumulative infiltration of soil using machine learning methods”, ISH Journal of Hydraulic Engineering, 27(2), 162-169, 2021. https://doi.org/10.1080/09715101.2018.1531274.

M. A. T. C. Goh and S. H. Goh, “Support vector machines: Their use in geotechnical engineering as illustrated using seismic liquefaction data”, Computers and Geotechnics, 34(5), 410 -42 1, 2007. https://doi.org/10.1016/j.compgeo.2006.10.001.

N. A. M. Abd, and S.M. Abd, “Modelling the strength of lightweight foamed concrete using support vector machine (SVM)”, Case studies in construction materials, 6, 8-15, 2017. https://doi.org/10.1016/j.cscm.2016.11.002.

O. M. Suthar, “Applying several machine learning approaches for the prediction of unconfined compressive strength of stabilized pond ashes”, Neural Computing and Applications. 2019. https://doi.org/10.1007/s00521-019-04411-6.

P. Dal, C. Gu, E. Zhao and X. Qin, “Statistical model optimized random forest regression model for concrete dam deformation monitoring”, Structural Control and Health Monitoring, 25 (6), e2170, 2018. https://doi.org/10.1002/stc.2170.

Q. J. Huang, T. Duan, Y. Zhang, J. Liu, J. Zhang and Y. Lei, “Predicting the permeability of pervious concrete-based on the beetle antennae search algorithm and random forest model.” Advances in Civil Engineering, 2020. https://doi.org/10.1155/2020/8863181.

R. A. Upadhya, M.S. Thakur, S. M. Pandhian and S. Tayal, “Estimation of Marshall Stability of asphalt concrete mix using Neural Network and MSP Tree”. In Computational Technologies in Materials Science 223-236, 2012b, CRC Press.

S. Farooq, M. Nasir Amin, K. Khan, M. Rehan Sadiq, M. Faizal Javed, F. Aslam and R. Alyousef, “A comparative study of random forest and genetic engineering programming for the prediction of compressive strength of high strength concrete (HSC)”. Applied Sciences, 10(20), 7330, 2020. https://doi.org/10.3390/app10207330.

T. N.S. Singh, P. Sihag, and S. Luthra, “Performance evaluation of fuzzy-logic and BP-ANN methods for WEDM of aeronautics super alloy.” Methods X 5 (2018): 890-908. https://doi.org/10.1016/j.mex.2018.04.006.
