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Research Article

Application of Artificial Intelligence Models to Predict the Tensile Strength of Glass Fiber-Modified Cemented Backfill Materials during the Mine Backfill Process

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Cemented backfill coal mining technology is gradually becoming a key technology for green mining of coal resources. And cemented backfill materials generally have congenital defects such as poor crack resistance, poor durability, and high brittleness, which restrict the promotion and application of cemented backfill coal mining technology. Due to the complex stress environment of in situ stress, mining stress, water pressure, and gas pressure, cemented backfill materials need to have good mechanical properties, and glass fiber is usually used to mix into cemented backfill materials to improve its performance, but there are many problems including complex testing process, high cost, and long time-consuming in the study of mechanical properties of glass fiber-modified cemented backfill materials (GFCBM) by laboratory tests. Consequently, this study proposed and compared four artificial intelligence models to forecast the tensile strength of GFCBM. Firstly, the laboratory tests of tensile properties of GFCBM under different influence factors were implemented to supply the prediction model with dataset. The input variables are aeolian sand content, cement content, glass fiber length, and glass fiber content, and the output variable is the tensile strength of GFCBM. The correlation coefficient (R), mean absolute error (MAE), and root mean square error (RMSE) are selected to assess the estimated performance of the hybrid intelligent model. The results indicate that the four hybrid artificial intelligence models show a latent capacity for forecasting the tensile strength of GFCBM, and according to the order from high to low, the prediction ability of the four prediction models is as follows: ABC-SVM, GA-SVM, SSA-SVM, and DE-SVM, and the corresponding R values are 0.9555, 0.9539, 0.9413, and 0.9359, respectively. The research findings are beneficial to promote the application of cemented backfill coal mining technology.

1. Introduction

The surface subsidence, soil erosion, and other ecological environment damage caused by coal mining have been a major problem, which seriously restricts the harmonious development of coal exploitation and ecoenvironment protection [1, 2]. As a key technology for coal resource green mining, backfill mining technology uses the supporting function of backfill body to control the overlying strata movement and reduce surface subsidence, which has become one of the important ways to achieve safe, efficient, economic, and sustainable development of coal resources [3, 4]. Because of its low cost and mature technology, cemented backfill mining technology has been extensively used in mining areas in the Northwest of China [5]. As a typical cement-based material, cemented backfill materials generally have congenital defects such as poor crack resistance, poor durability, and high brittleness. Since the cemented backfill body has the "arching effect" after it is backfilled into the goaf, it requires not only sufficient compressive strength, but also good tensile and shear properties [6]. At present, simply increasing the amount of cement to make up for the above shortcomings not only brings huge economic and safety costs to the mine but also largely restricts the wider promotion and application of cemented backfill mining technology.

Researchers have proposed that adding glass fiber materials to the cemented backfill materials can increase the strength, toughness, and ductility of the materials and optimize its mechanical properties [7, 8]. The role of glass fiber materials in cemented backfill materials can be summarized as crack resistance, reinforcement, and toughening. The specific reinforcement effect is related to the orientation, the ratio of length to diameter, and the volume content of the glass fiber materials. Qin et al. [9] analyzed the feasibility of polypropylene fiber fabrics to enhance the mechanical properties of concrete and compared the compressive strength and multiscale failure characteristics of ordinary concrete and fiber-modified concrete, and it is found that polypropylene fiber fabric is beneficial to improve the compressive strength of concrete. Elkatatny et al. [10] tested the effect of glass fiber materials on the tensile strength, porosity, and permeability of cement under high temperature and high pressure. The results show that glass fiber materials do not significantly affect the rheology, density, and water content of cement but can significantly improve its tensile strength and compressive strength. Yi et al. [11] studied the internal failure mechanism of cemented backfill materials with glass fiber through uniaxial compression test and X-ray computed tomography (CT), and the results indicate that the mechanical strength of cemented backfill materials with glass fiber is increased by about 70%~90%, and the glass fiber can effectively prevent the propagation of internal cracks. It can be seen that the incorporation of glass fiber materials is able to indeed change the mechanical properties of cemented backfill materials, and the means of its optimization process is mainly laboratory test. However, this method is currently faced with the problems of complex test process, high cost, and long time-consuming, which restrict the development of this research. Therefore, how to find other methods to conveniently obtain the changes in the properties of glass fiber-modified cemented backfill materials (GFCBM) is of great significance.

At present, artificial intelligence technology has been gradually applied in many engineering fields [12, 13]. It can achieve better prediction results on the basis of comprehensive consideration of various influencing factors. Yan et al. [14] proposed an intelligence model named BPNN-GA-AdaBoost to predict the change of coal strength after CO_2 injection into coal seam; Han et al. [15] integrated random forest and particle swarm optimization algorithm to evaluate the fracture performance of concrete; Jalal et al. [16] estimated the swelling strength of expansive soil through ANN, GEP, and ANFIS methods. It can be seen that intelligent prediction has been used in various engineering directions and has achieved excellent results, but currently, it is still facing the following problems: (1) At present, there is almost no intelligence model to forecast the tensile performance of GFCBM, especially the use of support vector machine (support vector machine has obvious advantages in small sample data). (2) There is a lack of comparative studies on the tensile strength of cemented backfill materials using different prediction models. Therefore, it is of urgent significance to implement a comparative study on the intelligent prediction of the tensile properties of GFCBM.

This paper puts forward four hybrid artificial intelligence models, namely, ABC-SVM, DE-SVM, GA-SVM, and SSA-SVM, to predict the tensile strength of GFCBM. Among them, the support vector machine (SVM) is mainly employed in analyzing the function relation between the tensile strength of GFCBM and various influence parameters. The dataset of the model is gained through laboratory tests on tensile properties of GFCBM. The input variables of the model are aeolian sand content, cement content, glass fiber length, and glass fiber content, and the output variable is the tensile strength of GFCBM. The R, MAE, and RMSE were selected to evaluate and compare the prediction performance of these hybrid intelligent model. Finally, the optimal model for predicting the tensile performance of GFCBM was obtained. The research findings are beneficial to promote the application of cemented backfill mining technology.

2. Experiment

2.1. Materials. The aeolian sand and fly ash, together with a small amount of cement and quicklime, are chosen as the cemented backfill materials. The aeolian sand is mainly taken from the mining area in Northern Shaanxi, where the surface is covered with a large amount of aeolian sand, and the fly ash comes from the power plant. Glass fiber is selected as the doped fiber material, mainly considering the low cost. Among them, the length of glass fiber is 3 mm, 6 mm, and 15 mm, and the maximum tensile strength of single glass fiber is 2800 MPa. It is often used as the filler of cement or concrete to improve the strength, impact resistance, tensile strength, bending resistance, and durability of materials, and it is an ideal multifunctional reinforcing material. The photograph of glass fiber is shown in Figure 1.

2.2. Preparation Process. Firstly, glass fiber and raw materials of backfill materials (fly ash, aeolian sand, cement, and quicklime) were weighed, mixed, and stirred evenly, and then, water was added for mixing. Then, the mixed mortar was poured into self-made abrasives and put into the curing box for curing; eventually, a cube-like concrete specimen is formed. The size of the abrasive tool is $7.07 \times 7.07 \times 7.07$ cm, and the WAW-1000D servo press machine was selected to test the tensile strength of the cemented backfill materials at different ages.

2.3. Experimental Scheme. In current study, the influence of aeolian sand content, fly ash content, cement content, quicklime content, glass fiber length, and glass fiber content on the tensile strength of cemented backfill materials is mainly considered. The content of each material refers to the weight proportion, and the specific design scheme is shown in Table 1. Among them, there are 4 kinds of cemented backfill ratios, 3 kinds of glass fiber lengths, 5 kinds of glass fiber content, and a total of 60 schemes. Each scheme carries out 3 experiments for a total of 180 experiments.

Figure 1: The photograph of glass fiber.

Table 1: Experimental scheme design [17].

Group	Aeolian sand : fly ash: cement: quicklime (%)	Glass fiber length (mm)	Glass fiber content (‰)
1	47.5 : 35 : 12.5 : 5	3, 6, 15	1, 3, 5, 10, 15
2	55 : 35 : 5 : 5	3, 6, 15	1, 3, 5, 10, 15
3	21.5 : 35 : 38.5 : 5	3, 6, 15	1, 3, 5, 10, 15
4	30 : 35 : 30 : 5	3, 6, 15	1, 3, 5, 10, 15

The design of the experimental scheme is mainly based on the results of previous studies. Aeolian sand content, cement content, glass fiber length, and glass fiber content are the main variables in this scheme. Therefore, the input variable of the artificial intelligence prediction model selects the above variables. Since glass fiber can significantly modify the tensile strength of cemented backfill materials, this study mainly tests the tensile strength of GFCBM, and it is also the output variable of the artificial intelligence prediction model.

3. Machine Learning Algorithms

In this study, four artificial intelligence models are used to predict the tensile properties of GFCBM, which are ABC-SVM, DE-SVM, GA-SVM, and SSA-SVM. Among them, SVM is employed in analyzing the function relation between the tensile strength of GFCBM and various influence parameters, and ABC, DE, GA, and SSA are employed in optimizing the parameters of the SVM.

3.1. Support Vector Machine. Support vector machine (SVM) [18] is a machine learning means raised by Vapnik. It can be divided into support vector classification and support vector regression to solve classification and regression problems, respectively. As shown in Figure 2, the core idea of SVM is the conversion from low-dimensional spatial data points to high-dimensional spatial data points through nonlinear mapping and adopt the principle of structural risk minimization, and then, classify and predict the data in the high-dimensional space. SVM can effectively avoid the local extremum problem, maximize the prediction accuracy, and prevent the data from overfitting. According to the restricted sample data, it can obtain the optimal value between model complexity and forecast accuracy and improve its generalization ability.

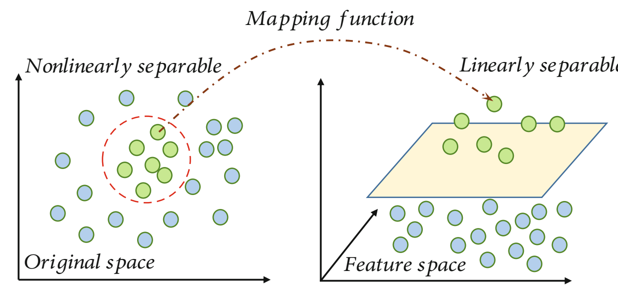


Figure 2: The SVM solution principle.

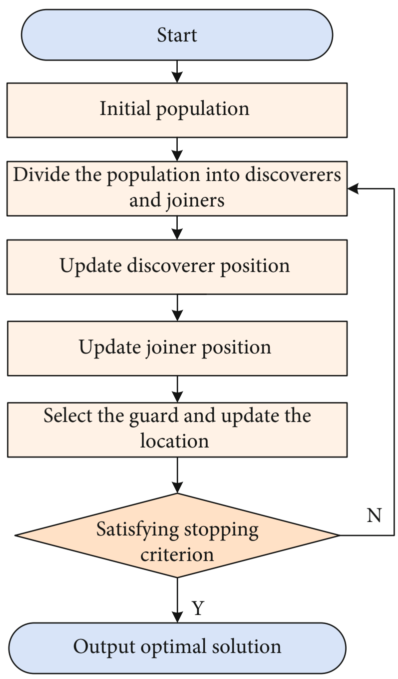


Figure 3: SSA algorithm flow chart.

The selection of kernel function and related parameter setting are the key of SVM. In this study, the SVR is selected, and the widely used RBF kernel function is adopted, because it is suitable for different samples and various dimension problems and has strong nonlinear mapping ability. The hyperparameters (C and g) of the SVM model are closely related to its predictive ability, and the optimal solution needs to be gained through optimization algorithms.

3.2. Artificial Bee Colony Algorithm. Artificial bee colony (ABC) is a new optimization algorithm in view of swarm intelligence put forward by Vasquez and Garro [19]. The artificial bee colony algorithm model mainly includes the following elements: one is the nectar source, that is, the group goal. The composition of the group is dedicated to

Table 2: Basic parameter statistics of the dataset.

Parameter	Minimum	Maximum	Unit	Variable
Aeolian sand content	21.50	55	%	Input
Cement content	5	38.50	%	Input
Glass fiber length	3	15	mm	Input
Glass fiber content	1	15	‰	Input
Tensile strength of GFCBM	0.17	1.23	MPa	Output

finding the best nectar source and continuously updated after mining; the second is the composition and division of the bee colony. The hired bee is dedicated to discovering and sharing nectar source information with the follower bees, while the scout bee is dedicated to the update of the nectar source. It is always transformed from the hired bee when the quality of the nectar source drops. The third is colony behavior, that is, the recruitment of new bees and the abandonment of low-value nectar sources.

3.3. Differential Evolution Algorithm. The DE algorithm was put forward by Yuan et al. [20]. This algorithm solves the optimization problem by means of the cooperation and competition of individuals in the whole population and has a strong global convergence potentiality. The process of DE algorithm is similar to other evolutionary algorithms, including mutation, selection, and crossover operations, but compared with other algorithms, DE algorithm runs stably, converges quickly and has low complexity. The DE algorithm begins from the initial population, after mutation, selection, and crossover operations; the best individual is saved in the new population and then iterates until the termination condition is met.

3.4. Genetic Algorithm. Genetic algorithm (GA) is a type of evolutionary calculation, which is a method to imitate Darwin's genetic selection and natural elimination of biotic evolution process [21]. The algorithm is simple, general, and robust and is suitable for parallel processing. The GA mainly transfers the better genes to the next generation by the means of the selection operator and expands the search range by the means of the crossover operator, and the mutation operator accelerates the convergence speed, so as to achieve the goal of global search.

3.5. Sparrow Search Algorithm. Sparrow search algorithm (SSA) is a latest swarm intelligence optimization algorithm, put forward in 2020 [22]. During the process of foraging for sparrows, it is compartmentalized into discoverers and joiners. The discoverers are responsible for finding food in the population and provide search directions for the whole population, while joiners use the discoverers' guidance to obtain food. In order to obtain food, sparrows can usually forage for food using two behavioral strategies: discoverer and joiner. Individuals in the population will be alert to the other individual behaviors, and attackers in the population will compete with high-intake companions for food resources to increase their predation rate. The specific flow chart is shown in Figure 3.

4. Methodology

4.1. Dataset Preparation. In current study, the tensile properties of GFCBM from the experimental test are used as the dataset for the artificial intelligence. As mentioned above, there are 180 series of data for training and testing. According to early research experience [23, 24], compared with other models such as ANN, SVM has obvious advantages in dealing with small samples and nonlinear problems. It is unnecessary to be large for the dataset required for the training and testing of SVM-based model, and the artificial intelligence models can be well trained and tested by the 180 series of data in this paper. According to the experimental scheme, the aeolian sand content and cement content in the GFCBM are variables, and the glass fiber length and content are also variables. Therefore, the input variables are aeolian sand content, cement content, glass fiber length, and glass fiber content, and the output variable is the tensile strength of GFCBM. Table 2 summarizes the data statistics for the whole dataset.

In the process of modeling, the whole dataset will be separated into a training set and a testing set on the basis of a certain ratio [25]. In this paper, the ratio is selected to be 7 : 3, that is, 126 series of data are selected for the training set, and the 54 series of data are selected for the testing set.

4.2. Model Establishment. Figure 4 presents four hybrid artificial intelligence models, that is, ABC-SVM, DE-SVM, GA-SVM, and SSA-SVM. Among them, SVM is employed in analyzing the function relation between the tensile strength of GFCBM and various influence parameters, and ABC, DE, GA, and SSA are employed in optimizing the parameters of the SVM. For comparison and analysis purposes, based on the optimal effect and stable convergence of various machine learning algorithms, it is better to keep the model parameters consistent. The kernel function of SVM is RBF radial basis function, the population size of each algorithm is given with 50, and the maximum number of iterations is given with 100.

4.3. Model Validation and Evaluation. The intelligence model validation and evaluation is an important link for the development of the model. In this study, for the sake of assessing the dependability of the hybrid model effectively, the function relationship between the predicted value and the measured value is described by the correlation coefficient (R), mean absolute error (MAE), and root mean

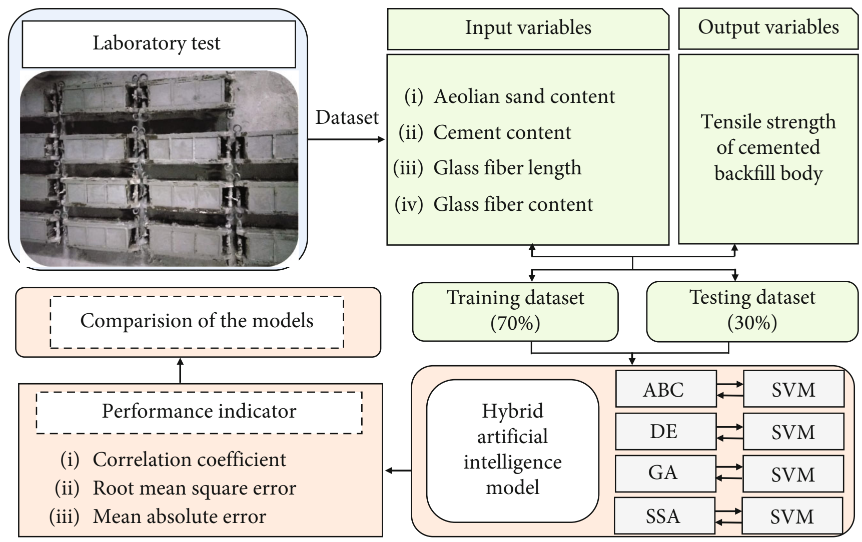
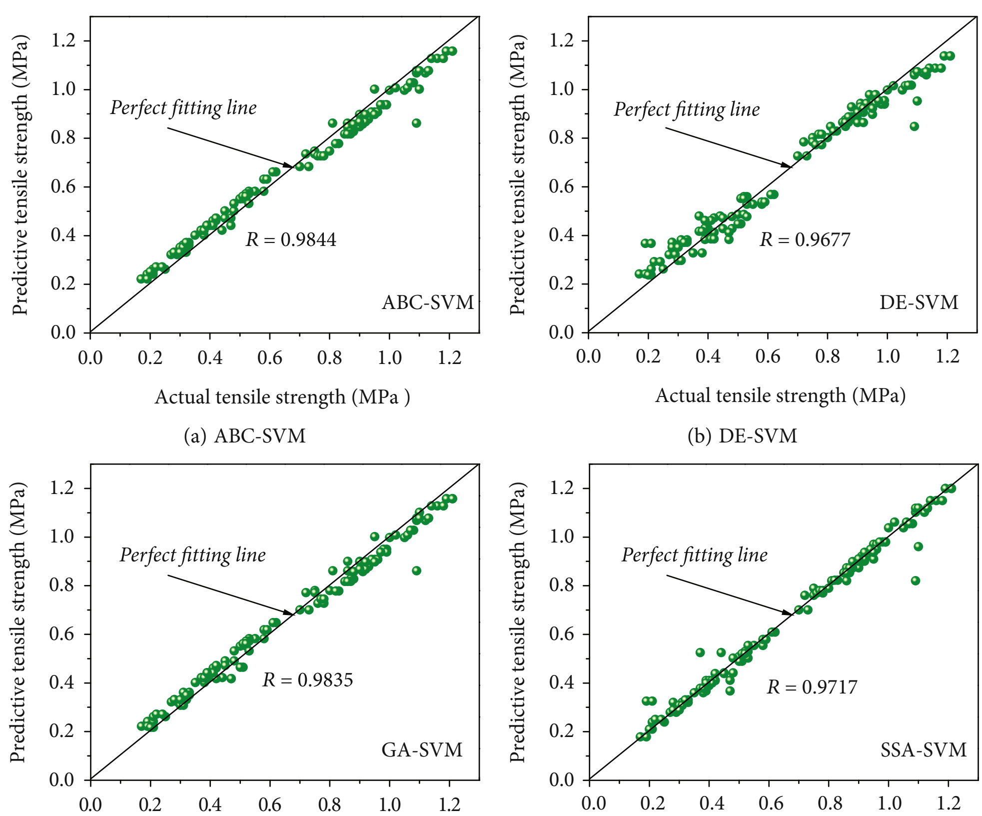


Figure 4: Overall analysis process.

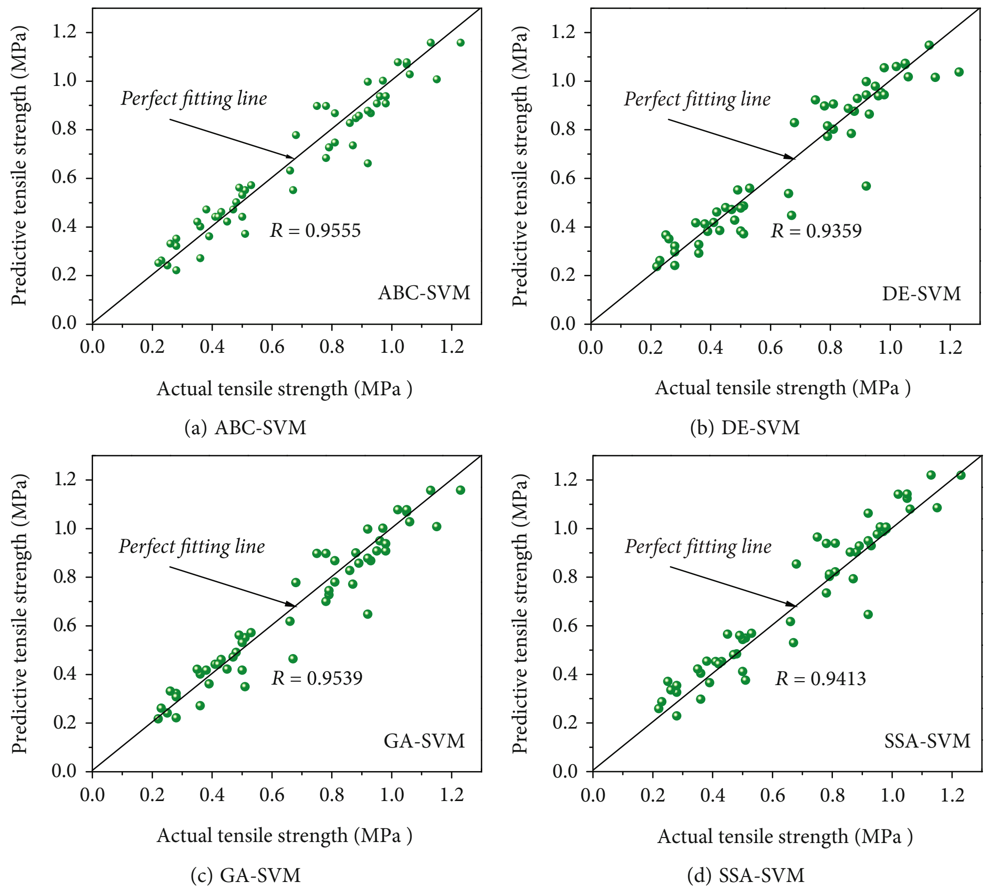


(a) ABC-SVM
(b) DE-SVM
(c) GA-SVM
(d) SSA-SVM

Figure 5: The training effects of different prediction model for training set.

square error (RMSE), respectively, [26]. The closer the value of R is to 1, the better correlation between predicted value and measured value; the smaller the MAE and RMSE, the smaller the error between the predicted value and the measured value. The calculation formula of the three evaluation indexes is as follows:

$$R = \frac{\sum_{i=1}^{n}\left(y_i^* - \overline{y^*}\right)\left(y_i - \bar{y}\right)}{\sqrt{\sum_{i=1}^{n}\left(y_i^* - \overline{y^*}\right)^2}\sqrt{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2}}, \tag{1}$$



(a) ABC-SVM (b) DE-SVM (c) GA-SVM (d) SSA-SVM

Figure 6: The prediction effects of different prediction model for testing set.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i^* - y_i\right|, \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_i^*\right)^2}, \tag{3}$$

where n refers to the number of datasets, $y_i{}^*$ refers to the predicted value, y_i refers to the measured value, $\overline{y^*}$ refers to the average of the predicted value, and $\bar{y}$ refers to the average of the measured value.

5. Results and Discussion

5.1. Comparative Analysis of Different Prediction Models. This study mainly analyzes and compares the forecast performance of the above four hybrid artificial intelligence models in the tensile strength of GFCBM from two parts of training set and testing set.

Figure 5 shows the training effects of different prediction model for training set. It can be demonstrated that the four hybrid artificial intelligence models have obtained good training effects, and the sample data are essentially near the ideal fitting line (measured value = predicted value), and only a few sample points deviate from the fitting line. From the perspective of the R value, the training effect of ABC-SVM is the best, its R value is 0.9844, followed by GA-SVM, SSA-SVM, and DE-SVM, and its R values are 0.9835, 0.9717, and 0.9677, respectively. In general, the training effects of the four hybrid artificial intelligence prediction models have reached high accuracy.

When completing the model training, the trained model is used for prediction. Figure 6 shows the prediction effects of different prediction model for testing set. By analyzing the data distribution, it is clear that the sample data of testing set is also essentially near the ideal fitting line (measured value = predicted value). According to the order from high to low, the prediction ability of the four prediction models is as follows: ABC-SVM, GA-SVM, SSA-SVM, and DE-SVM, and the corresponding R values are 0.9555, 0.9539, 0.9413, and 0.9359, respectively. Consequently, ABC-SVM has the best predictive ability in terms of the tensile strength of GFCBM.

To better analyze and compare different forecast model performance, the performance indicators of different prediction models are summarized, as shown in Table 3, and it can be drawn that compared with the other three models, the prediction accuracy of ABC-SVM hybrid model is higher in training set and testing set. Its R value is the largest, and its RMSE and MAE values are also very small. This shows that the ABC-SVM intelligent model not only gives full play to the superiority of SVM in handling problems with few samples but also gives full play to the characteristics of ABC in hyperparameter optimization. Considering

Table 3: The performance indicators of different prediction models.

	Training set			Testing set		
	R	RMSE	MAE	R	RMSE	MAE
ABC-SVM	0.9844	0.0474	0.0413	0.9555	0.0749	0.0605
DE-SVM	0.9677	0.0541	0.0515	0.9359	0.0967	0.0707
GA-SVM	0.9835	0.0453	0.0384	0.9539	0.0769	0.0626
SSA-SVM	0.9717	0.0501	0.0507	0.9413	0.0860	0.0661

comprehensively, the ABC-SVM intelligent model has better learning and predictive capabilities. Consequently, this study suggests using the ABC-SVM intelligent model to forecast the tensile strength of GFCBM.

5.2. Contributions and Shortcomings. The innovations and main contributions of this research are as follows: (1) it is proposed to use artificial intelligence technology to predict the tensile strength of GFCBM, which effectively avoids the disadvantages of complex laboratory testing process, long time-consuming, and high cost; (2) considering that SVM has many unique advantages in solving small sample and nonlinear and high-dimensional pattern recognition, it is proposed to use support vector machine to construct the prediction model, which solves the defect of small sample data; (3) systematic comparative research on intelligent optimization algorithms to optimize the performance of SVM has been carried out.

This study is the initial exploration of artificial intelligence technology to forecast the GFCBM mechanical properties. In the future, it is necessary to use artificial intelligence model to forecast the compressive strength and shear strength of GFCBM. Meanwhile, the dataset of artificial intelligence prediction model needs to be continuously enriched, so as to make the better predictive ability.

6. Conclusions

In this research, there are four hybrid artificial intelligence models to be proposed and compared for predicting the tensile strength of GFCBM, that is, ABC-SVM, DE-SVM, GA-SVM, and SSA-SVM. The dataset of the model is built through laboratory tests on tensile properties of GFCBM. The input variables are aeolian sand content, cement content, glass fiber length, and glass fiber content, and the output variable is the tensile strength of GFCBM. The R, RMSE, and MAE are selected to assess the estimated performance of the hybrid intelligent model. The main findings are as follows:

(1) Through laboratory tests of different fly ash content, aeolian sand content, cement content, quicklime content, glass fiber length, and glass fiber content on the tensile strength of GFCBM, it is found that the glass fiber can effectively change the tensile strength of cemented backfill materials

(2) The four hybrid artificial intelligence models proposed in this study show a latent capacity for forecasting the tensile strength of GFCBM, and ABC, DE, GA, and SSA have good effects on SVM hyperparameter optimization

(3) According to the order from high to low, the prediction ability of the four prediction models is as follows: ABC-SVM, GA-SVM, SSA-SVM, and DE-SVM, and the corresponding R values are 0.9555, 0.9539, 0.9413, and 0.9359, respectively. In this study, ABC-SVM intelligent model is suggested to forecast the tensile strength of GFCBM

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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