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Potential of Repurposing Recycled Concrete for Road Paving: Flexural Strength (FS) Modeling by a Novel Systematic and Evolved RF-FA Model

Shuwei Gu [1], Hao Shen [2,*], Chuming Pang [3,*], Zhiping Li [1], Long Liu [1], Huan Liu [1], Shuai Wang [1], Yaxin Song [1] and Jiandong Huang [4]

1 Lijiahao Coal Mine, Baotou Energy Co., Ltd., China Energy Investment Corporation, Hantai Town, Dongsheng District, Erdos 017008, China
2 College of Resources, Shandong University of Technology, Taian 271000, China
3 College of Energy and Mining Engineering, Shandong University of Technology, Qiangangwan Road, Huangdao District, Qingdao 100027, China
4 School of Civil Engineering, Guangzhou University, Guangzhou 510006, China
* Correspondence: 15546368519@163.com (H.S.); 201981010010@sdust.edu.cn (C.P.)

Abstract: Concrete can be recycled after certain processing technologies for use in pavement engineering but the flexural strength (FS) is difficult to predict accurately in the design process. This study proposes a novel systematic and evolved approach to estimate the FS of recycled concrete. The proposed methods are conducted based on the random forest (RF) model as well as the firefly algorithm (FA), where the latter is employed to tune the hyperparameters of the RF model. For this purpose, data sets were collected from previously published literature for the training and verification of the model, and the accuracy of the model was verified by the fitting effect of the predicted and actual values. The results showed that the proposed hybrid machine learning model has a good fitting effect on the predicted and actual values; the calculation and evaluation process demonstrated fast convergence and significantly lower values of RMSE for the proposed model to determine the FS of the recycling concrete. In addition, the study analyzed the sensitivity of the FS of recycled concrete to input variables, and the results showed that effective water-cement ratio (WC), water absorption of recycling concrete (WAR), and water absorption of natural aggregate (WAN) show more obvious influences on FS, so these factors should be paid more attention in future pavement design using the recycling of concrete.

Keywords: hybrid machine learning; flexural strength; recycled concrete; hyperparameters

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1. Introduction

The development and renewal of technology in the field of construction engineering bring about an earth-shattering change in the appearance of the city, but they also bring about a huge amount of construction waste generated after the demolition of old buildings [1–3]. Construction waste refers to the waste generated by construction units in the process of construction, reconstruction, new construction, expansion, and demolition of various buildings, structures, and decorations, mainly including engineering slag, engineering mud, engineering waste, demolition waste, and decoration waste [4–7]. A huge amount of construction waste not only occupies land but also causes various environmental pollution problems due to the quantity and composition of construction waste. Therefore, relevant departments have invested a large amount of manpower, and financial and material resources to eliminate all kinds of pollution brought by construction waste to the environment, but the results are not good [8–10]. It is an important challenge for the sustainable development of the construction industry to use construction waste scientifically and rationally to reduce the impact of construction waste on the environment [11]. The application of waste in concrete can not only overcome environmental problems but also improve the performance of concrete [12,13]. Ke et al. [14] found that adding waste glass to concrete instead of part of the aggregate was conducive to enhancing the high temperature resistance of concrete. Mushunje et al. [15] evaluated the technology and feasibility of using different forms (fibers, particles) of waste tires in coagulation. Celik et al. [16] investigated the effect of lathe scrap fibers generated from Computer Numerical Control (CNC) lathe machine tools on concrete performance and found that the FS of fiber-reinforced concrete increases with increasing content of waste lathe. Civil engineering researchers have proposed to prepare recycled aggregate from construction waste through certain processing techniques and technical methods, which can be used in the preparation of recycled aggregate concrete to reduce the impact of construction waste on the environment and improve the performance of concrete [17,18]. Using construction waste to prepare recycled aggregate is not only conducive to reducing the environmental pollution caused by construction waste but also due to the low cost of recycled aggregate, the cost of recycled aggregate concrete is low, while achieving the same performance as ordinary concrete [19,20]. At the same time, the use of waste concrete to produce recycled concrete is conducive to reducing the production of cement, stone mining, and carbon dioxide emissions, to ensure the balance of the ecological environment [21,22]. Therefore, it is of great practical significance to use recycled concrete as material for pavements [23–25].

Due to the theme of green environmental protection, more and more civil engineers pay attention to the research on recycled concrete [26,27]. Mohamad et al. [28] studied the performance of sustainable polyester concrete (SPC) by replacing natural aggregate (NA) with recycled asphalt pavement (RAP), recycled concrete aggregate (RCA), and broken brick aggregate (CBA) with different weight percentages (0%, 25%, 75%, and 100%), The results showed that the recycled concrete had the best flexural strength (FS). Duy et al. [29] studied the impact of replacing natural fine aggregate with recycled aggregate in different proportions (10%, 20%, and 30%) on the compressive strength and FS of concrete. It has been confirmed that recycled aggregate has a certain impact on the mechanical properties of concrete, that is, with the increase of recycled aggregate proportion, the strength of concrete has a certain downward trend. Zhang et al. [30] evaluated the strength of the recycled aggregate concrete pavement.

With the development of artificial intelligence, machine learning models have attracted more and more attention from civil engineers because of their high prediction accuracy and high prediction efficiency [31,32], and have been successfully applied to the prediction of concrete strength [33–37]. Hoang et al. [38] proposed using Gaussian Process Regression (GPR) to simulate the mechanical properties of high-performance concrete (HPC) and compared the prediction effect of GPR with the prediction models of least squares support vector machines and artificial neural networks. This research indicated that GPR is the optimized model giving the highest predictive accuracy for HPC. Cook et al. [39] employed the FA and RF hybrid machine learning model to estimate compressive strength. Al-Shamiri et al. [40] proposed a predictive model for the mechanical property of HPC based on the Regularized Extreme Learning Machine (RELM) and used k-fold cross validation and various error measures to determine the results. The research results showed that the proposed RELM has high predictive accuracy for the mechanical properties of concrete. Yuan et al. [41] proposed to use the integrated learning method to analyze the strength of recycled concrete and proved that the proposed method has a high predictive accuracy for the strength of recycled concrete through error analysis. Yu et al. [42] analyzed the importance of variables affecting the shear strength of reclaimed concrete by using grey correlation analysis and simulated the shear strength of reclaimed concrete by using an artificial neural network and random forest. However, it should be noted that although the various ML techniques mentioned above were used in the previous studies, there were still some problems that need to be solved: (1) only a limited number of advanced ML algorithms have been employed for the prediction, and the reliability and computational efficiency of other advanced machine learning algorithms, such as the random forest (RF) model, have not been deeply studied; (2) the application of machine learning algorithm always requires proper selection of the hyperparameters, but the optimization ability of firefly algorithm (FA) for the hyperparameters has not been fully studied in the prediction process.

The application of recycled concrete is conducive to the development of a green and sustainable construction industry, and the FS of concrete refers to the ultimate breaking stress of concrete under load per unit volume, which reflects the parameter shape of concrete. It is one of the important parameters to determine the quality of recycled concrete. However, there are few types of research on the FS of recycled concrete, and most of them use laboratory test methods [43,44], which have the disadvantages of high cost and time consumption. The machine learning model can effectively address the shortcomings of the laboratory test methods. Therefore, this study proposed to use FA and RF hybrid machine learning models to predict the FS of recycled concrete.

2. Research Objective

Figure 1 presents the research objective of the present study. In this study, four specific processes will be carried out to achieve the prediction of the FS of the road surface materials when recycled concrete is used for paving. First, a data mining process will be established and a dataset will be collected from recycled concrete to paving concrete. Among them, the input variables involved (i.e., those derived from recycled concrete) include the water-to-cement ratio (WC), aggregate concentration ratio (AC), recycled concrete aggregate (RCA) replacement ratio, nominal maximum RCA size (NMR), nominal maximum natural aggregate (NA) size, bulk density of RCA (BDR), bulk density of Na (BDN), water absorption of RCA (WAR), water absorption of NA (WAN). After that, a data filtering process is initiated to determine whether the FS meets the requirements of the paving: if so, it is entered into the machine learning dataset. If not, the data is discarded. After that, the machine learning process will be carried out, where 80% of the dataset will be used for training and the other 20% will be used for testing. In this study, a so-called RF-FA evolutionary model will be used in the machine learning process. It is based on the RF model as well as the FA, where the latter is employed to tune the hyperparameters of the RF model. Finally, the 10-fold cross-validation process will be used in the machine learning training process to evaluate the prediction effect and determine a reliable prediction model for the FS of recycled concrete.

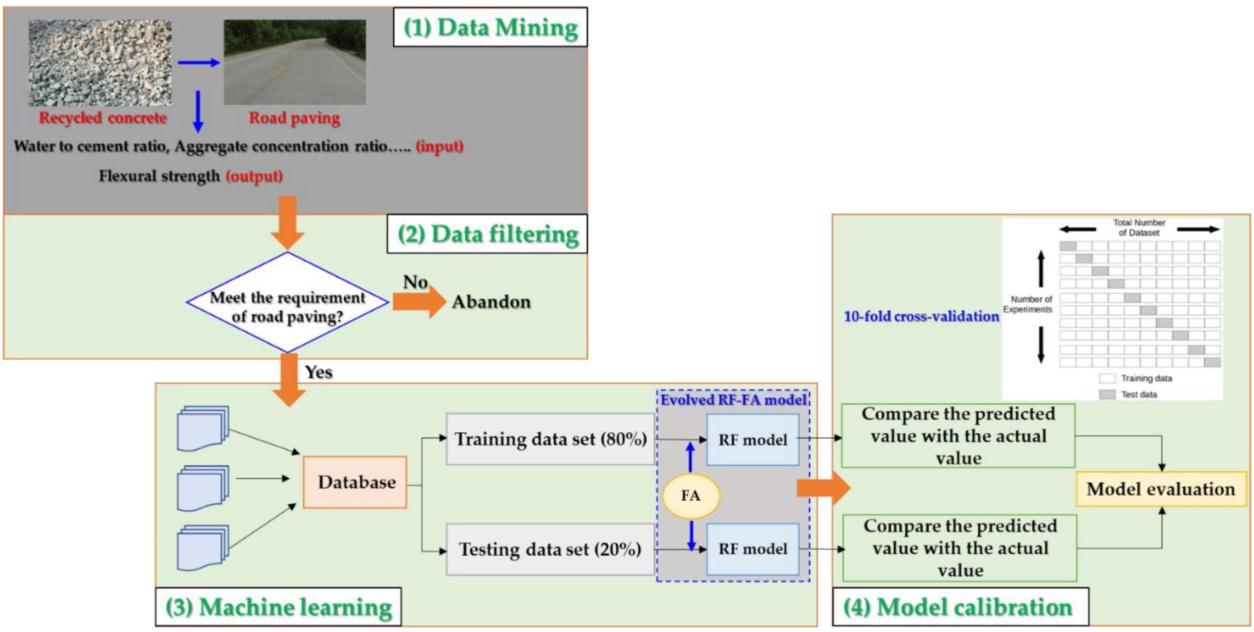


Figure 1. Research overview.

3. Methods

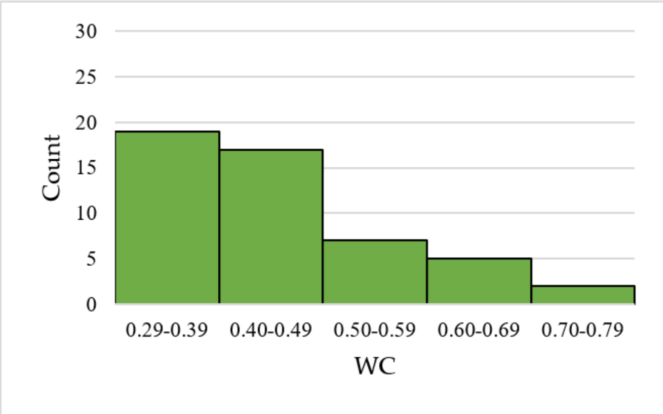
3.1. Dataset Description

There are many factors affecting the FS of concrete and researchers usually analyze the influence of raw material quality, composition design, and construction on the FS. The research into raw material composition design mainly focuses on unit water consumption, water-cement ratio, coarse aggregate grading and maximum particle size, fine aggregate grading and maximum particle size, etc. Compared with ordinary concrete, the difference in the FS of recycled concrete is mainly affected by the residual mortar on the surface of recycled aggregate, and the residual mortar on the surface is mainly affected by the replacement rate of recycled aggregate and the properties of recycled aggregate. To further analyze the influence of the composition design of recycled concrete on its FS, this study collected data sets with WC, AC, RCA, NMR, NMN, BDR, BDN, WAR, and WAN as input variables and flexural FS as output variable, drawing on the previously published literature. The FS was measured in the laboratory as follows. The tripartite-point-loading method was employed to determine the FS of the samples. After the specimen is removed from the curing box, it is covered with a wet towel and tested in time to keep the dry and wet state of the specimen unchanged. The width and height in the middle of the specimen should be measured. The maximum load and the location of the fracture at the lower edge of the specimen were recorded.

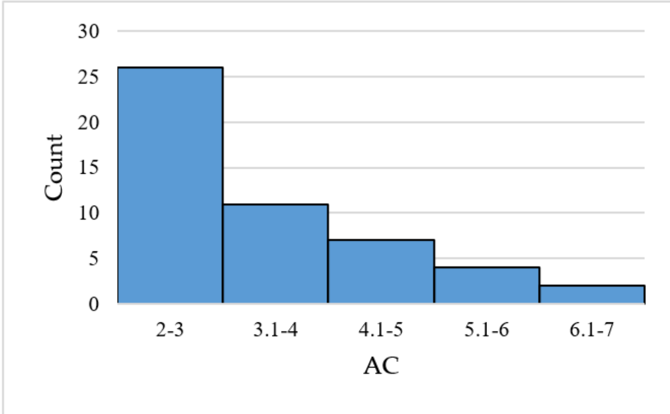
Researchers usually focus only on developing models with high efficiency and prediction accuracy, while ignoring the importance of reliable databases for model verification. To verify the rationality of the data distribution in the database, we made the frequency distribution histogram of each parameter, as shown in Figure 2. The figure shows the distribution density of the variable in the corresponding interval. To further understand the data distribution of each parameter, the data analysis table of the parameters is shown in Table 1. It is shown that the data sets of nine input variables distribute in a centralized manner, cover a wide range, and the frequency distribution histogram of FS of recycled concrete is the unimodal shape which is a reasonably distributed type of data defined in the histogram. Therefore, the data sets distribution of input variables selected in this study to predict the FS of recycled concrete is reasonable.

Table 1. Descriptive statistics of the database used for the prediction.

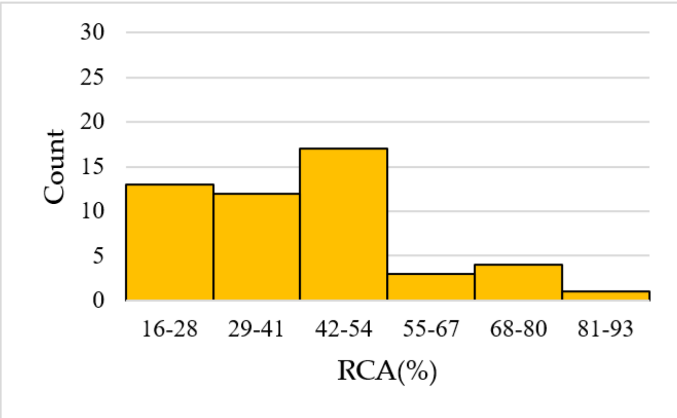
Parameters	Minimum	Maximum	Median	STD	Variance	Number of Data
WC	0.29	0.72	0.45	0.11	0.01	50
AC	2	6.4	2.95	1.24	1.53	50
RCA (%)	16	90	45	17.05	290.73	50
NMR (mm)	10	32	20	7.22	52.18	50
NMN (mm)	10	32	20	6.81	46.35	50
BDR (Kg/m^3)	2200	2661	2400	104.7	10961.47	50
BDN (Kg/m^3)	2570	2810	2680	71.83	5159.5	50
WAR (%)	1.5	7	6	1.75	3.07	50
WAN (%)	0.2	2.5	1.4	0.78	0.6	50
FS (MPa)	1.9	9.7	4.95	1.8	3.25	50



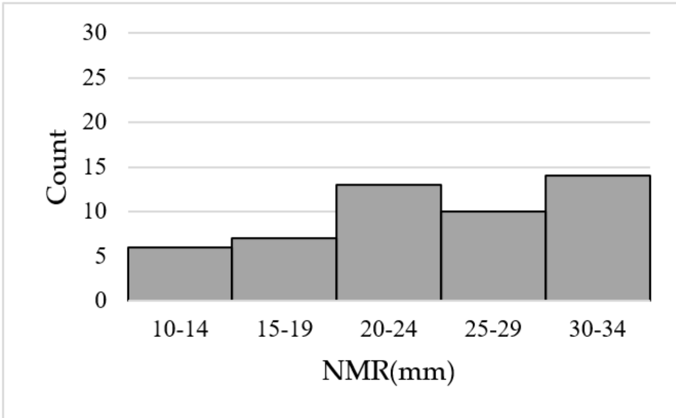
(**a**) Frequency analysis histogram of WC



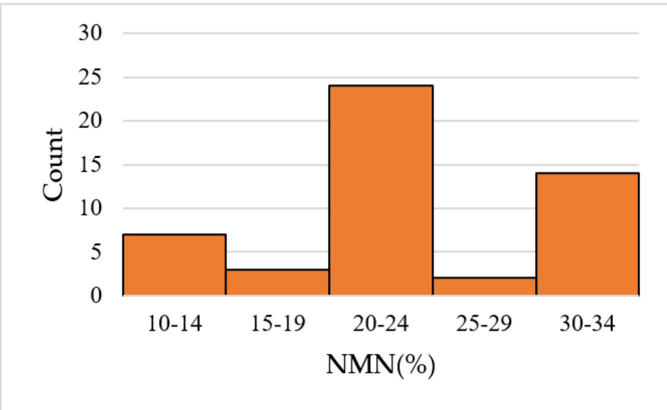
(**b**) Frequency analysis histogram of AC



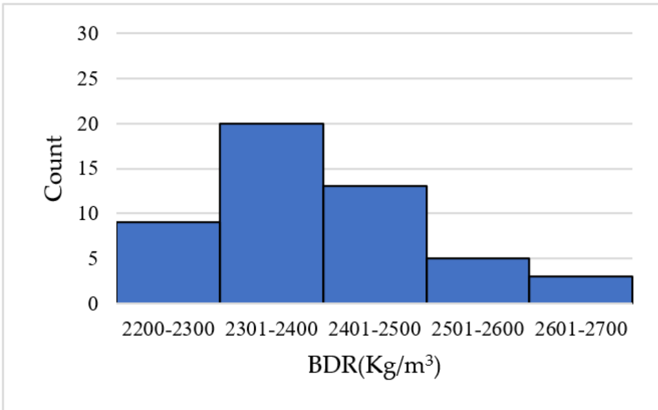
(**c**) Frequency analysis histogram of RCA



(**d**) Frequency analysis histogram of NMR

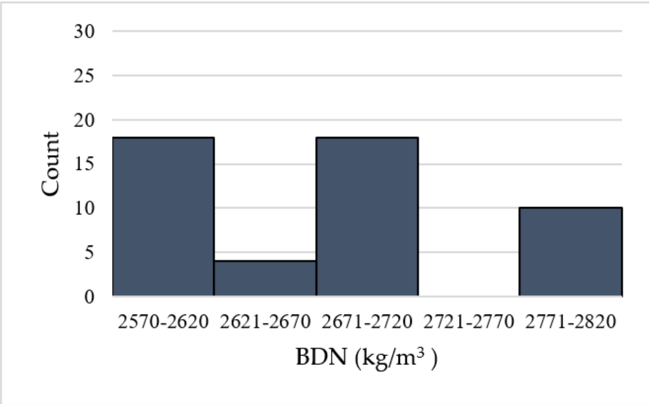


(**e**) Frequency analysis histogram of NMN

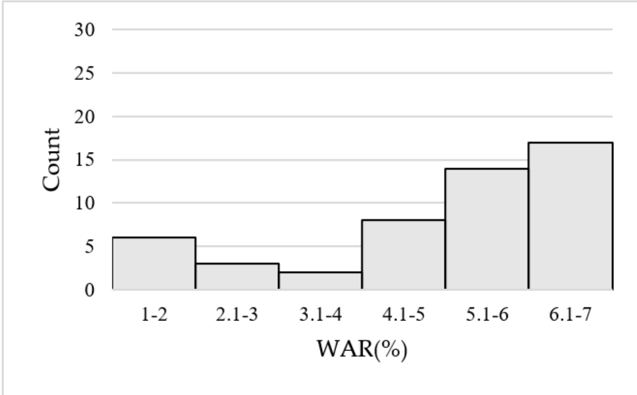


(**f**) Frequency analysis histogram of BDR

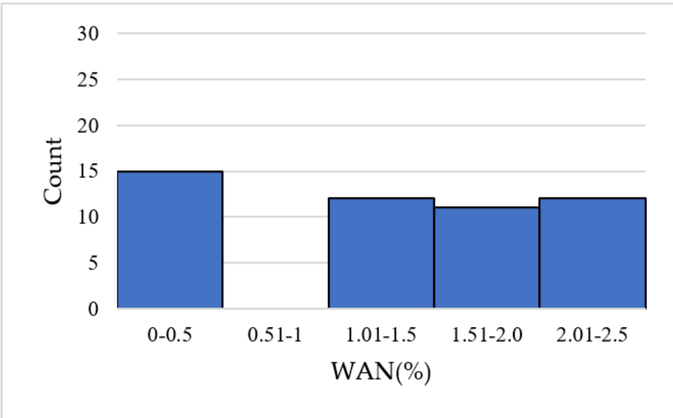
Figure 2. *Cont.*



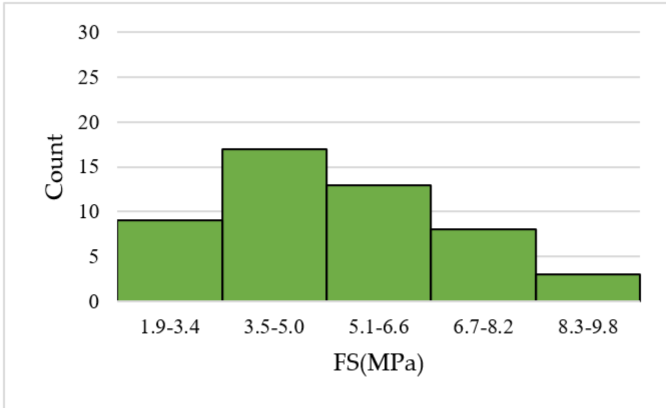
(**g**) Frequency analysis histogram of BDN



(**h**) Frequency analysis histogram of WAR



(**i**) Frequency analysis histogram of WAN



(**j**) Frequency analysis histogram of FS

Figure 2. Dataset description.

3.2. Correlation between the Input Parameters

Correlation analysis refers to measuring the correlation degree between the parameter elements. Since a high positive or negative correlation between input parameters will lead to multiple collinearities, which will affect the prediction effect of the model, it is very necessary to analyze the correlation of input parameters before model training. The correlation analysis results among the 9 input parameters are shown in Figure 3. It can be seen that the correlation coefficient on the diagonal is 1, while the correlation coefficients in other positions are all less than 0.6. Through the analysis of the above results, it is proved that the correlation between the 9 input parameters in this study is low, so considering them as input parameters will not affect the prediction effect of the model due to a high correlation between the input parameters.

3.3. Algorithm

3.3.1. Firefly Algorithm (FA)

As one type of heuristic algorithm, FA is designed to simulate the luminescence behavior of fireflies in nature. Since light intensity is inversely proportional to the square of the distance from the light source, the flash of fireflies can only be perceived by other fireflies within a certain range. The construction of FA should meet the following three idealization principles:

- In the algorithm, all fireflies do not distinguish between males and females, so the attraction between fireflies is only based on brightness information, without considering the effect of sex.

- The attraction between fireflies increases with brightness and decreases with distance. The low-light fireflies move toward the high-light fireflies.
- The brightness of the firefly is related to the value of the objective function to be optimized [45,46].

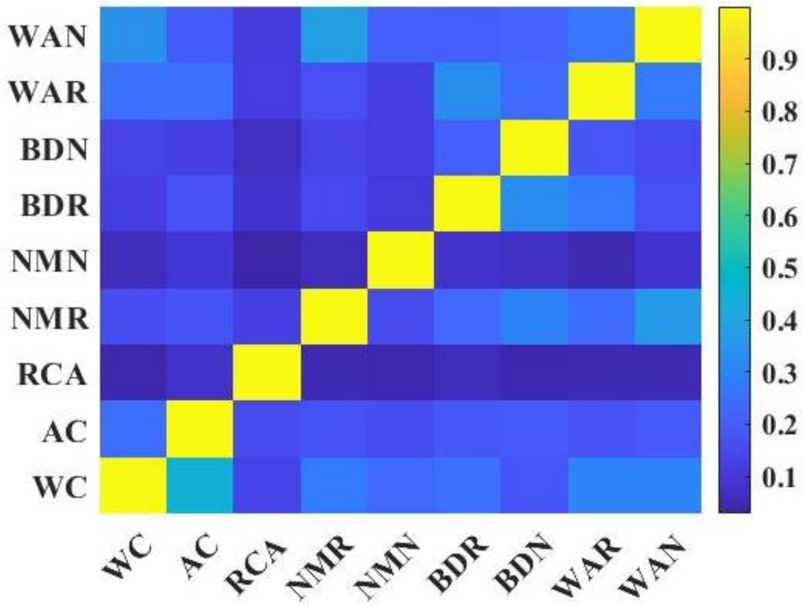


Figure 3. Relationship between the input parameters.

In the calculation process, the FA moves the firefly to all fireflies in the population whose absolute brightness is greater than it, updates the position based on the position update equation, and continues to update it iteratively until the set number of iterations or optimization accuracy is reached. The relative brightness of two fireflies can be defined by the following equation:

$$I_{ij}(r_{ij}) = I_i e^{-\gamma r_{ij}^2} \tag{1}$$

in which I_i and γ represent the absolute brightness and the light absorption coefficient, respectively; r_{ij} represents the cartesian distance between the firefly at the i_{th} position and the firefly at the j_{th} position. The calculation formula is:

$$r_{ij} = x_i - x_j = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \tag{2}$$

The firefly moves to the fireflies with higher absolute brightness. The attraction between two fireflies can be calculated by the relative brightness between fireflies. The greater the relative brightness, the greater the attraction. Assuming that the absolute brightness of the j_{th} firefly is greater than that of the i_{th} firefly, it can be seen from the definition of the relative brightness of firefly j that the attraction of firefly j to firefly i is defined as:

$$\beta_{ij}(r_{ij}) = \beta_0 e^{-\gamma r_{ij}^2} \tag{3}$$

in which $\beta_{ij}(r_{ij})$ and β_0 represent the attraction of the j_{th} firefly to the i_{th} firefly and maximum attraction, respectively. Firefly I is attracted by firefly J and moves to its position. The position update formula is as follows:

$$x_i(t+1) = x_i(t) + \beta_0 e^{-\gamma r_{ij}^2}(x_j(t) - x_i(t)) + \alpha \varepsilon_i \tag{4}$$

in which t, ε_i, α are the iteration number, random function, and random term coefficient, respectively. The FA needs two steps: algorithm initialization and algorithm iteration, and the algorithm iteration includes three stages: absolute brightness update, attraction update, and position update. Figure 4 gives the flow chart of FA.

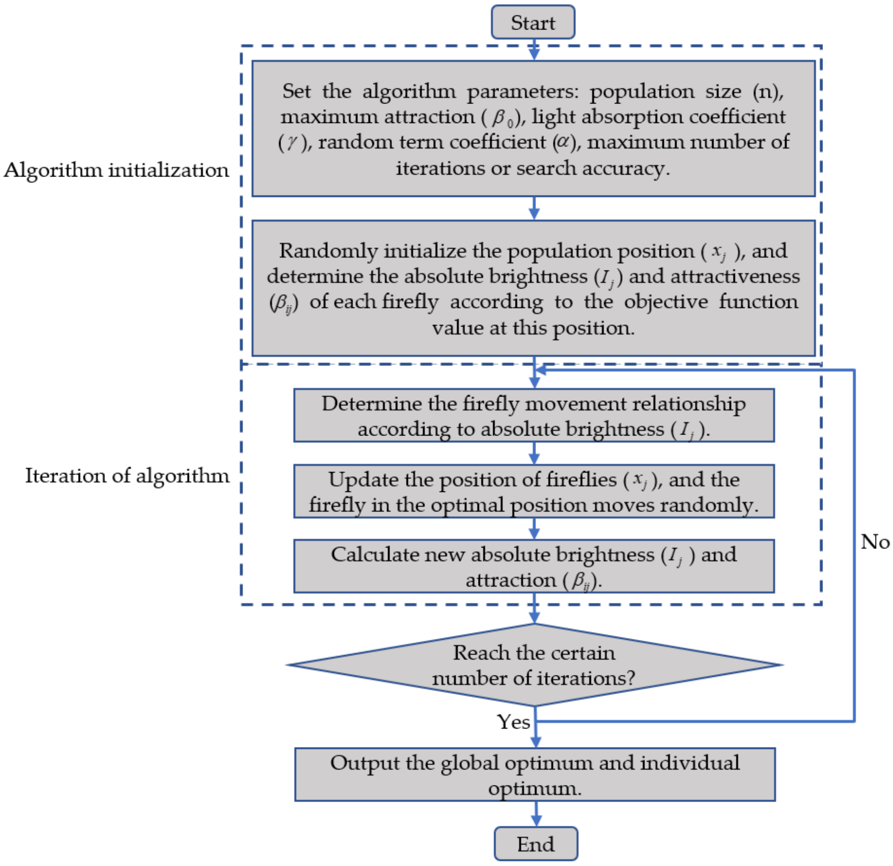


Figure 4. The flow chart of FA.

3.3.2. Random Forest (RF)

As a representative algorithm of the bagging integration method, the RF model uses the repeated sampling method of bootstrap to randomly select multiple samples from the original data, models each sample into a decision tree, and then combines them into multiple decision trees. The process diagram of the bagging integration method is shown in Figure 5.

RF usually consists of the following three steps [31,47,48]:

(1) The selection of training set. K training sets are randomly selected from the original data set (M attributes).

(2) The construction of RF. Create a classification tree for each selected training set in step (1), generate K decision trees, and form a forest. The tree constructed by the above method does not select the optimal feature as the internal node splitting condition, but randomly selects m ($m \leq M$) features to split. Choosing the best splitting method is the most important problem of splitting trees.

(3) The creation of simple voting. The training process of each decision tree is independent, so the training of random forest can be carried out at the same time, which greatly improves the efficiency. The classification results of input samples depend on the simple voting of the output of each decision tree.

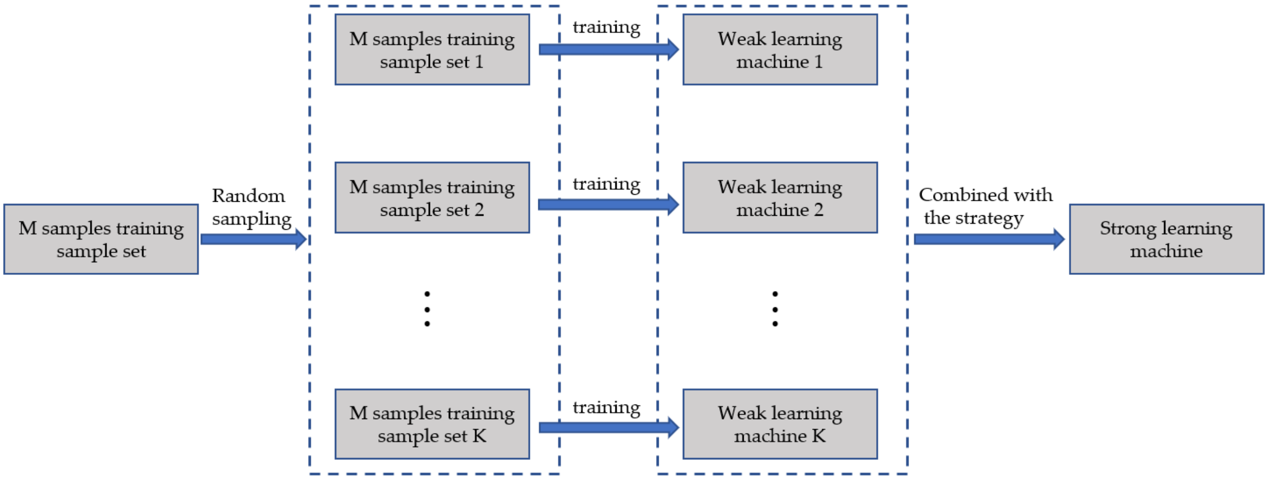


Figure 5. The process of bagging integration.

4. Results and Analysis

4.1. Hyperparameter Tuning

The optimization of the model is the most important step and one of the most difficult challenges in machine learning models. Hyperparameters are different from the general parameters in the model, which refer to the parameters set before model training. The purpose of the optimization of hyperparameters in machine learning is to find the hyperparameters with the best performance of the machine learning models on the test set. In the present research, FA is employed to optimize the hyperparameters of the RF model, and the relationship between the iteration times and RMSE values is presented in Figure 6. With the increase in the number of iterations, the changing trend of RMSE values is to decrease to a lower value at first and then stabilize. The above results prove that FA has a good effect on the optimization of hyperparameters of RF.

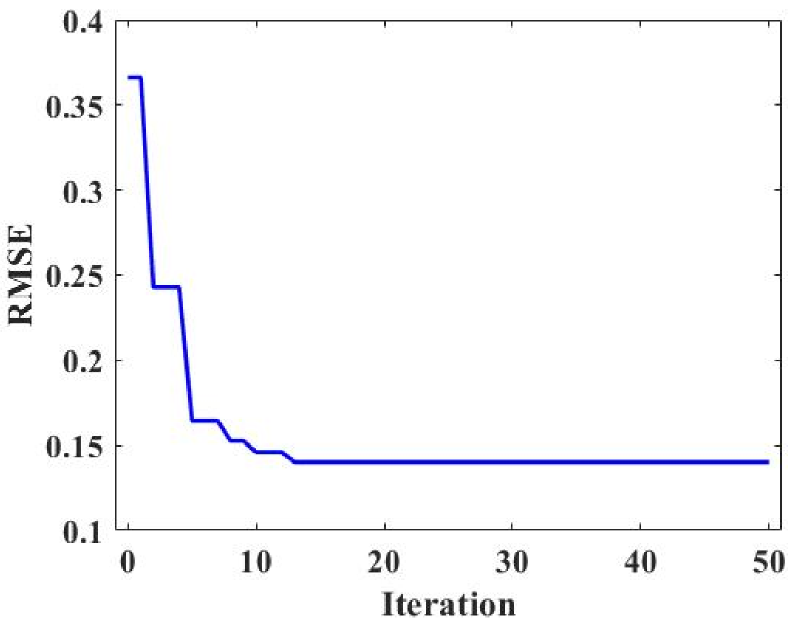


Figure 6. RSME values vs. iteration number.

A single partition of the training set and test set may lead to contingency. Cross-validation can make full use of the existing data sets for multiple partitions, thus reducing the contingency of the model and improving the generalization ability. The 10-fold cross-validation method is a cross-validation method with good effect, which has been validated by previous researchers. This study selects the 10-fold cross-validation method to optimize the hyperparameter of RF, and the results are shown in Figure 7. The minimum RMSE value can be observed at the seventh turn and this RMSE value can be represented as the optimized structure of the RF model.

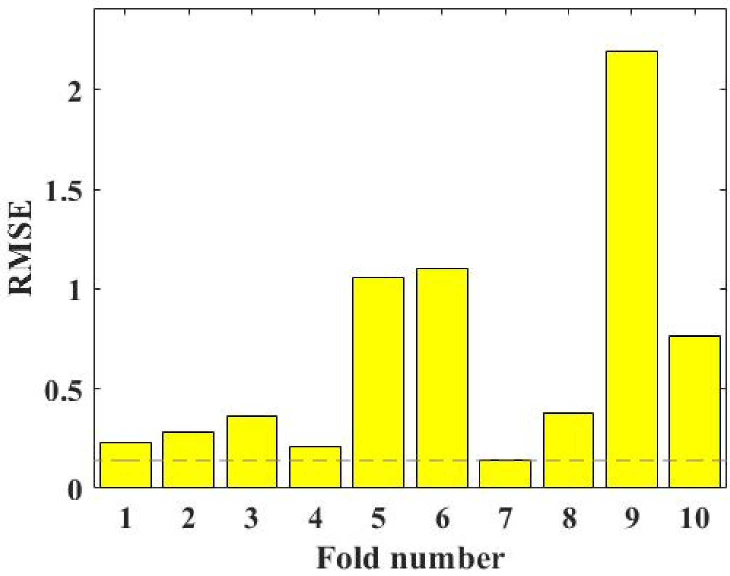
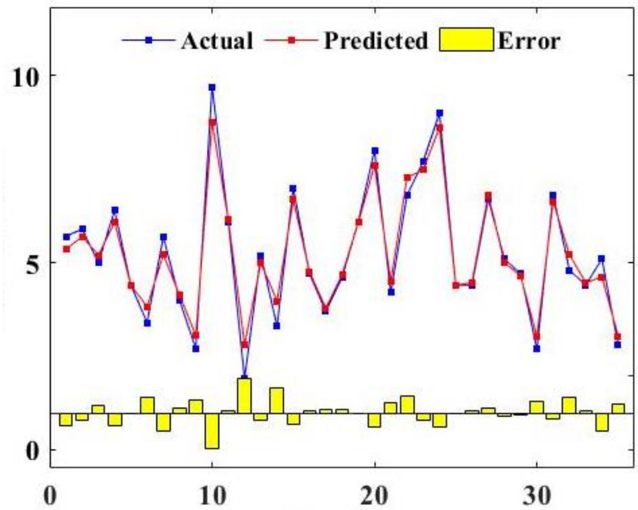


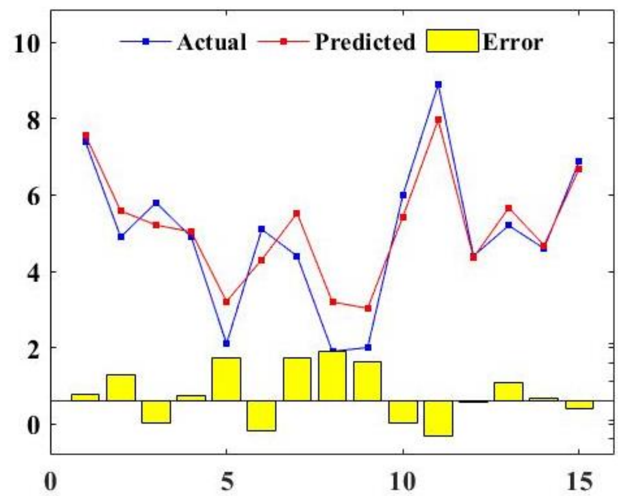
Figure 7. RMSE values vs. fold number.

4.2. Evaluation of Predictive Results

In this study, the accuracy of the model is verified by comparing the predicted and measured values regarding the training and testing datasets. The results are shown in Figure 8a,b, respectively. The horizontal line represents the error between the predicted value and the measured value. The predicted FS value of recycled concrete in the training set and testing set fits the measured value well, and only a few points have a slight difference, which basically will not affect the predicted results of the proposed model.



(**a**) Error analysis of the training set



(**b**) Error analysis of test set

Figure 8. Predicted values vs. the actual values in the training and testing dataset.

Figure 9 gives the predicted FS vs. actual FS regarding the training and testing dataset. As can be observed, the RMSE values of the training set and testing set were 0.3574 and

0.7377, respectively; the R values of the training set and testing set were 0.9875 and 0.9482, respectively; both the training and testing dataset have high R values and low RMSE values. It is once again proved that the proposed model combining the FA algorithm and RF model indicates a high prediction accuracy for the FS of recycled concrete.

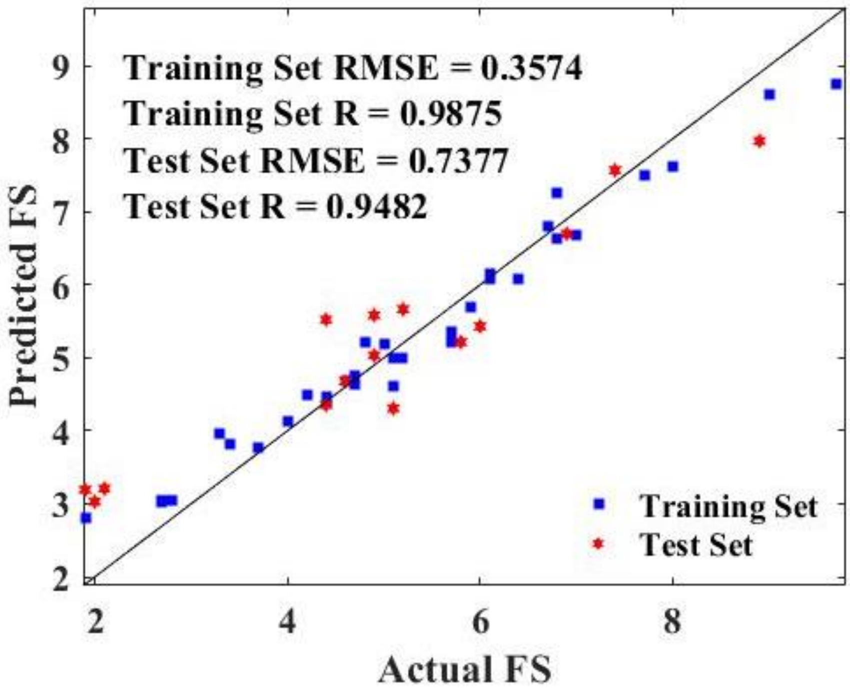


Figure 9. Predicted FS vs. actual FS.

4.3. Importance of Parameters

The importance of the nine input parameters (WC, WAR, WAN, AC, NMR, BDR, BDN, NMN, RCA) on the FS of recycled concrete was also analyzed in this study. Due to the particularity of recycled concrete admixtures and the complexity of FS, different parameters have different degrees of influence on FS. To provide some practical suggestions for civil engineers in designing recycled concrete with high FS, this study analyzes the importance scores of the above nine input parameters on the FS of recycled concrete, and the results are given in Figure 10. The importance scores of WC, WAR, WAN, AC, NMR, BDR, BDN, NMN, and RCA on the FS of recycled concrete are all positive and decrease in turn. Although the FS of recycled concrete is proportional to the above nine input parameters, WC, WAR, and WAN have a greater impact on the FS of recycled concrete, while NMN and RCA have a smaller impact. Therefore, civil engineers need to focus on WC, WAR, and WAN when designing recycled concrete with high FS for the road pavements. Moreover, in the practical application, it can be predicted whether concrete specimens meet the FS requirements for the pavement and can be used in the actual pavement paving process. It should be noted that if the FS of recycled concrete is below 3 MPa, the actual bearing requirements of the pavement and the importance scores of the input materials should be reassessed.

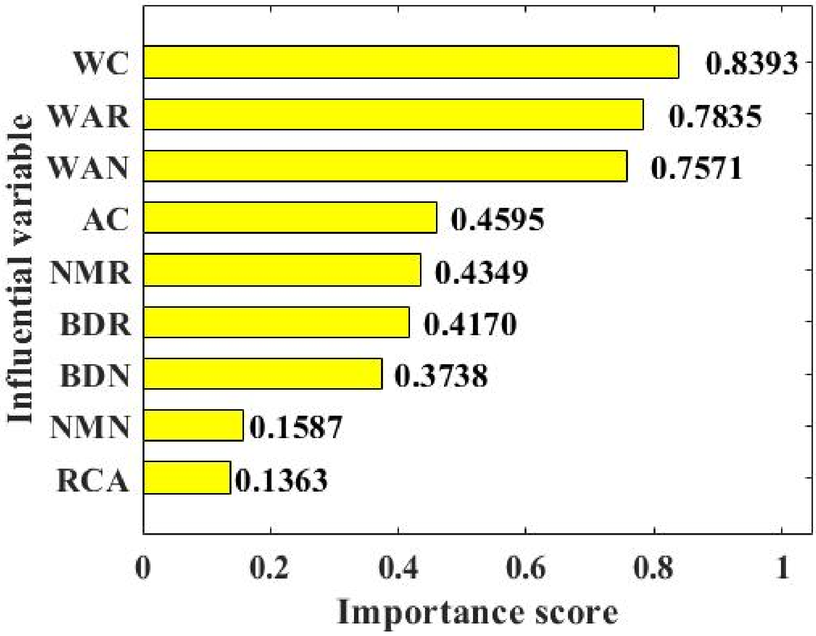


Figure 10. Importance scores of different input parameters on the FS of recycled concrete.

5. Conclusions

With the continuous development of the civil engineering industry, the construction of public facilities such as roads and bridges is increasing. Therefore, the demand for concrete materials to meet the requirements of the road is increasing. At the same time, old buildings are also being demolished, resulting in a large amount of construction waste, which undoubtedly aggravates the exploitation and destruction of the natural environment. The application of recycled concrete made from construction waste in road materials through a series of processing technologies is an important solution to deal with the increasing tension between the demand for natural building materials and the increasingly serious demand for environmental protection. To provide some feasible suggestions for civil engineers to prepare recycled concrete with high FS, this study researched the predictive results of the proposed hybrid machine learning method based on the FA algorithm and RF model as well as the importance scores of different input parameters. The following conclusions can be drawn from the research process.

(1) By analyzing the factors influencing the FS of recycled concrete, this study analyzed the influence of WC, WAR, WAN, AC, NMR, BDR, BDN, NMN, and RCA on the FS of recycled concrete. The data sets used for model training and testing were collected from the published literature, and the reliability of the data sets for the evaluation of the model effect was verified by mathematical statistical analysis and correlation analysis.

(2) The model for the FS of recycled concrete was evaluated by the fitting effect between the predicted values and the actual values, and the evaluation of the R values and RMSE values for training sets and test sets. The results showed that the fitting effect between the predicted values and the actual values is close to the perfect fitting curve of R = 1, and the training set and the test set both have high R values (0.9875, 0.9482) and low RMSE values (0.3574, 0.7377), which proves the FA and RF hybrid machine learning model proposed in this study has high accuracy in predicting the FS of recycled concrete.

(3) This study further analyzed the importance score of the input variables to the FS of recycled concrete, and the results showed that the sensitivity of recycled concrete to the input variables decreased in the order of WC, WAR, WAN, AC, NMR, BDR, BDN, NMN, and RCA, and their importance scores are 0.8393, 0.7835, 0.7571, 0.4595, 0.4349,

0.4170, 0.3738, 0.1587, 0.1363, respectively. Therefore, civil engineers should pay more attention to the WC, WAR, and WAN of recycled concrete to design recycled concrete with high FS; the actual bearing requirements of the pavement and the importance scores of the input materials should be reassessed if the FS of recycled concrete is below 3 MPa.

The study of recycled concrete is of great significance for the sustainable development of the concrete industry. In this study, a hybrid machine learning model of FA and RF was developed to evaluate the FS of recycled concrete, the model can effectively overcome the disadvantages of low efficiency and high cost existing in the traditional laboratory test methods. In the future, researchers can develop more machine-learning models to study the FS of recycled concrete, and compare the prediction efficiency and accuracy of different machine-learning models, to select the model with the best prediction effect. For the convenience of civil engineers in assessing the FS of recycled concrete, it is also necessary to develop visual predictive tools for them to use.

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Abbreviations

WC	Effective water-cement ratio (weff/c)
WAR	Water absorption of RCA (%)
WAN	Water absorption of NA (%)
AC	Aggregate-cement ratio (a/c)
NMR	Nominal maximum RCA size (mm)
BDR	Bulk density of RCA (kg/m3)
BDN	Bulk density of NA (kg/m3)
NMN	Nominal maximum NA size (mm)
RCA	RCA replacement ratio (RCA %)
FS	Flexural strength (MPa)
FA	Firefly algorithm
RF	Random forest
R	Correlation coefficient
RMSE	Root mean square error

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