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Original Article

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Abstract: The safety factor is a crucial quantitative index for evaluating slope stability. However, the traditional calculation methods suffer from unreasonable assumptions, complex soil composition, and inadequate consideration of the influencing factors, leading to large errors in their calculations. Therefore, a stacking ensemble learning model (stacking-SSAOP) based on multi-layer regression algorithm fusion and optimized by the sparrow search algorithm is proposed for predicting the slope safety factor. In this method, the density, cohesion, friction angle, slope angle, slope height, and pore pressure ratio are selected as characteristic parameters from the 210 sets of established slope sample data. Random Forest, Extra Trees, AdaBoost, Bagging, and Support Vector regression are used as the base model (inner loop) to construct the first-level regression algorithm layer, and XGBoost is used as the meta-model (outer loop) to construct the second-level regression algorithm layer and complete the construction of the stacked learning model for improving the model prediction accuracy. The sparrow search algorithm is used to optimize the hyperparameters of the above six regression models and correct the over- and under-fitting problems of the single regression model to further improve the prediction accuracy. The mean square error (MSE) of the predicted and true values and the fitting of the data are compared and analyzed. The MSE of the stacking-SSAOP model was found to be smaller than that of the single regression model (MSE = 0.03917). Therefore, the former has a higher prediction accuracy and better data fitting. This study innovatively applies the sparrow search algorithm to predict the slope safety factor, showcasing its advantages over traditional methods. Additionally, our proposed stacking-SSAOP model integrates multiple regression algorithms to enhance prediction accuracy. This model not only refines the prediction accuracy of the slope safety factor but also offers a fresh approach to handling the intricate soil composition and other influencing factors, making it a

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precise and reliable method for slope stability evaluation. This research holds importance for the modernization and digitalization of slope safety assessments.

Keywords: Multi-layer regression algorithm fusion; Stacking ensemble learning; Sparrow search algorithm; Slope safety factor; Data prediction

1 Introduction

With the rapid and global development of slope engineering, ensuring slope stability has grown increasingly important. A slope is a complex geological body that is influenced by many factors. Accordingly, slope engineering is a complex nonlinear, uncertain, and dynamic system (Lin et al. 2022b). Accurately evaluating slope stability is one of the most difficult problems in rock mechanics. However, it is essential to preventing and dealing with landslide disasters (He et al. 2019; Nie et al. 2019; Pandit et al. 2018). In tandem with developments in computer technology, machine learning techniques are increasingly being applied in slope engineering (Ahmed et al. 2020; Cai et al. 2020; Himanshu et al. 2021), making slope stability analysis more efficient, accurate, and intelligent. By combining the latest research methods with actual slope cases, researchers (Zhang et al. 2023; Zhang et al. 2022a; Zhang et al. 2022b) have innovated and made significant progress in the field of slope stability analysis.

Various traditional (Li et al. 2022; Li et al. 2019; Liu et al. 2015) and numerical analysis methods(Dong et al. 2019; Peng et al. 2020; Zhao et al. 2020) have been widely used in numerous large slope projects to evaluate slope stability, and good results have been achieved. However, the traditional analysis method has high time and labor costs, and the numerical analysis method requires establishing a constitutive model and providing accurate parameters, which is neither time-saving nor economical in some slope stability evaluation projects. Meanwhile, with continuous developments in mining technology, the latest computer technology is being applied to slope stability analysis. Moreover, machine learning and deep learning technologies, which are widely utilized in various fields, are gradually being applied to slope problems (Pandey et al. 2022; Qin et al. 2022). Slope problems have diverse solutions with efficient, intelligent, and accurate prospects. Machine learning facilitates learning the complex relationship between the key characteristic parameters of different types of slopes and their safety. However, unlike the deep learning method, which demands numerous samples and has high equipment requirements and a long training period, the former is applicable to few samples. Its high speed, high precision, and low cost mean the slope safety factor can be rapidly evaluated and predicted (He et al. 2020). Many researchers have utilized machine learning methods to classify and predict slope stability. For instance, Feng et al. (2018), Zhou et al. (2019), Samui et al. (2013), Huang et al. (2020), and Haghshenas et al. (2021) used the naive Bayes classifier (NBC), gradient boosting machine, support vector classifier, improved K-nearest neighbor, algorithm for harmony search and K-means aggregation to determine whether the slope is stable. However, the above methods can only qualitatively describe the stability of the slope; they cannot predict the slope safety factor or be used for quantitative analysis. The safety factor is an important indicator of slope stability. Moreover, the slope stability can be directly quantified. Therefore, predicting the slope safety factor using the regression algorithm is comparable to classification in the stability analysis. Notably, the former has engineering significance and reference value. Marrapu et al. (2021) used an artificial neural network (ANN) model to predict the safety factor of the slope and compared it with the results obtained via the limit equilibrium method and measured field data. The ANN model was found to be efficient and accurate in predicting the slope safety factor. Erzin et al. (2013, 2014) and Chakraborty et al. (2017) used ANN and multiple linear regression (MLR) to predict the slope safety factor. Comparisons of the prediction results with the calculation results obtained via the Bishop method and finite element method (FEM) revealed that the ANN model has higher reliability than the MLR model. In applying the heuristic algorithm to slope stability analysis, Kang et al. (2013), Hang et al. (2014), Chu et al. (2015), Khajehzadeh et al. (2012), and Wang et al. (2022a) proposed using the artificial bee colony algorithm, particle swarm optimization, firefly algorithm, gravitational search algorithm, and grey wolf algorithm to improve the model for predicting the slope safety factor. The accuracy and generalization ability of the model were improved to varying degrees. Additional, optimization algorithms have been continuously improving. Some researchers improved their accuracy by combining improved optimization algorithms with machine learning. Wang et al. (2022b) proposed an improved their particle swarm optimization support vector machine (IPSO-SVM) algorithm model. It was then compared with the original particle swarm optimization support vector machine (PSO-SVM) and single SVM model. The IPSO-SVM model had more realistic predictions and higher accuracy. Lin et al. (2022a) predicted the slope safety factor via a Bayesian optimization of convolutional neural networks. Although the accuracy of the models of predicting the slope safety factor as well as that of various optimization algorithms has been improved, their single-model characteristics result in instability errors in the prediction results when the sample data volume is small.

To further improve the prediction accuracy of the safety factor in slope stability analysis and reduce instability error, a stacking ensemble learning algorithm (stacking-SSAOP) based on the sparrow search algorithm (SSA) (Xue et al. 2020) optimization multi-layer regression algorithm fusion is proposed in this study. In the stacking-SSAOP ensemble learning model, 210 sets of slope data consisting of six slope parameters as eigenvalues and slope safety factors as target values are selected as sample data sets, which are divided into 180 training data sets and 30 test data sets. For the ensemble learning algorithm model, Random Forest regression (RFR), Extra Trees regression (ETR), AdaBoost regression (ADAR), Bagging regression (BGR), and Support Vector regression (SVR) were selected as the base model (inner loop) to construct the first-level regression algorithm layer. XGBoost regression (XGBR) was used as the meta-model (outer loop) to build a secondary regression algorithm layer. Meanwhile, to reduce the instability error caused by subjectively setting hyperparameter values in the regression model and improve the prediction accuracy of the slope safety factor, the SSA, which has better performance, is introduced to optimize the hyperparameter values of all regression algorithm models in the model. The stacking-SSAOP ensemble learning model proposed in this study not only reduces the instability error during prediction, which is associated with the single model but also improves the accuracy of the prediction model. The predicted specific slope safety factor is used as a quantitative index to intuitively express the slope stability state.

2 Ensemble Learning and Optimization Algorithms

2.1 Stacking ensemble learning model

The stacking ensemble learning method involves aggregating various classification or regression algorithms in machine learning algorithms (Costache et al. 2022; Guo et al. 2020; Shi et al. 2019; Yin et al. 2021) This method utilizes one- and two-stage models. The one-stage model is a single model with a divided training set as the input, which is called the base model (inner loop). Notably, different single regression models can be selected as base models for construction and training. The two-stage model utilizes the predicted output value of the original training set in the base model as a new training set and inputs it into the meta model (outer loop). The final prediction result of the stacking ensemble learning model is the output from the meta -model. In this study, the base model (level-1) of the stacking ensemble learning model consisted of RFR, ETR, ADAR, BGR, and SVR. In contrast, XGBR is used as the meta-model (level-2). The stacking learning model is mainly used for regression prediction of the slope safety factor, and its model architecture is shown in Fig. 1. Due to the small sample size of the data set, a large test error was utilized in the training process to avoid the overfitting resulting from the training set error being too small. Accordingly, K-Fold cross-validation was applied to the base model to reduce model overfitting (Moayedi et al. 2021) . In this study, a 7-fold cross-validation (Fig. 2) was used to verify the effectiveness of this method in reducing model overfitting.

2.2 Sparrow search algorithm

For a prediction model constructed using a machine learning algorithm, the value of the hyperparameters is one of the main factors affecting the overall accuracy. Slight differences in the hyperparameters often result in different prediction results. Each regression model usually contains multiple hyperparameters, which together affect the prediction accuracy of the model. Therefore, subjective adjustments cannot produce the best results in terms of efficiency and accuracy. Thus, the SSA is introduced to optimize the hyperparameters of the regression model (RMHP-SSAOP), and the

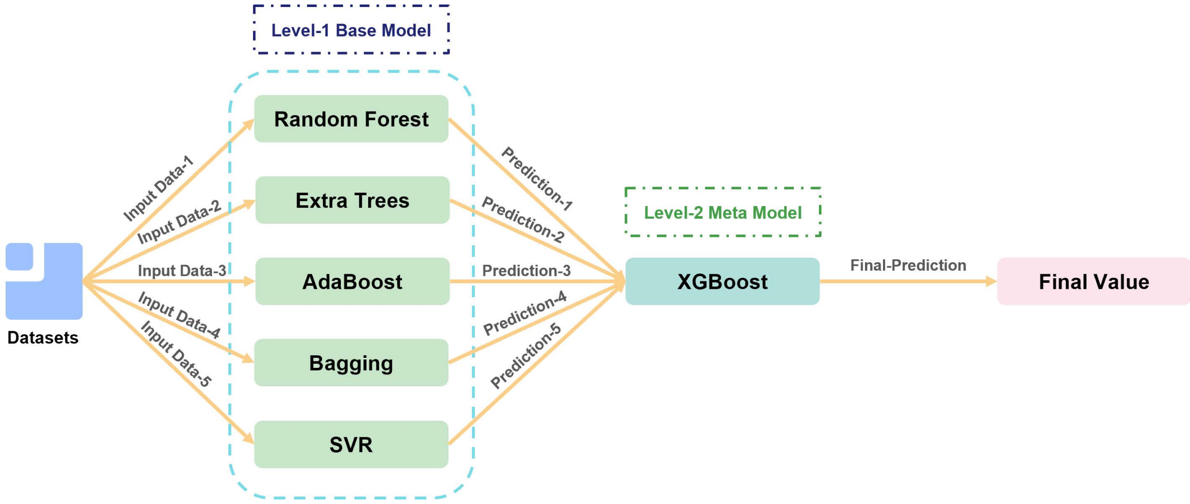


Fig. 1 Stacking ensemble learning model implementation process.

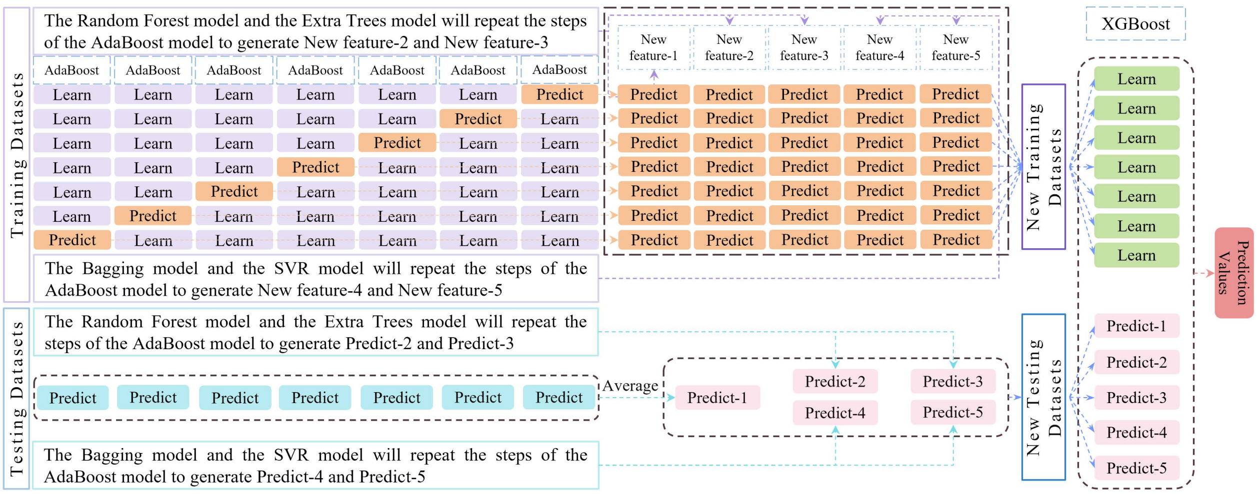


Fig. 2 7-fold cross-validation implementation process.

optimal parameter values are obtained in the iterative operation by leveraging the automatic optimization ability of the algorithm to complete the parameter adjustment process efficiently and accurately.

Fundamentally, SSA optimization simulates the foraging and anti-predating behavior of sparrows by using a heuristic search based on biological behavior. It utilizes an explorer–follower–warner model with a reconnaissance and warning mechanism to find the optimal solution. The manual search method (Wang et al. 2021) cannot handle multiple hyperparameters: for instance, finding the optimal parameters using the grid search method (Wicaksono et al. 2018) takes too long. In contrast, the random search method (Mantovani et al. 2015) takes less time than the grid search method but has lower reliability and applicability. Moreover, although the Bayesian optimization method (Cui et al. 2021; De et al. 2003; Mihaljević et al. 2021) utilizes previous search information, it easily falls into the local optimal solution. However, SSA has better global exploration and local-development abilities. By considering all factors in the population, the sparrow in the population moves to the global optimal value and quickly converges near the optimal value while avoiding falling into the local optimal solution.

In SSA, individuals in the population can be divided into explorers, followers, and warners. Explorers mainly identify foraging areas and direct followers. The followers go after the explorer with the best fitness value to find food, thus establishing their own energy reserves while increasing their fitness value. Warners are attentive to their surroundings and alert sparrow populations to move quickly to a safe area when they sense danger. Before using the mathematical model to describe the sparrows' feeding behavior, the following abstract rules are defined:

(1) In the entire population, the fitness value and energy reserve of explorers are higher than those of followers, and the larger the fitness value is, the higher the energy reserve. Explorers are mainly responsible for searching for food-rich areas and defining foraging areas and directions to all followers.

(2) Warners will immediately raise an alarm when they detect a threat. When the alarm value exceeds the security value, the explorer will guide the population to safer foraging areas.

(3) The algorithm defines the sparrow's identity according to its ability to find food: that is, the sparrow's identity can change at any time, but the proportion of explorers to followers in the population is constant.

(4) To gain more energy, followers with low energy may fly to other places to find food.

(5) Followers usually follow explorers with higher energy reserves when foraging, but a competitive relationship also exists among them. Some followers compete for food to boost their energy by monitoring explorers.

(6) When the enemy threatens a population, the warner at the edge of the group moves quickly to a safe area, whereas the sparrow in the middle of the group moves randomly, thus reducing the probability of predation.

Mathematical formulas for expressing the SSA are established from the above abstract criteria. The entire sparrow population X can be expressed as follows:

$$X = \begin{bmatrix} x_1^1 & x_1^2 & \cdots & x_1^d & \cdots & x_1^D \\ x_2^1 & x_2^2 & \cdots & x_2^d & \cdots & x_2^D \\ \cdots & \cdots & \cdots & \vdots & \ddots & \vdots \\ x_N^1 & x_N^2 & \cdots & x_N^d & \cdots & x_N^D \end{bmatrix} \tag{1}$$

In Eq. (1), N represents the number of sparrow populations and d and D represent the dimension of the problem (the number of hyperparameters) to be optimized.

The fitness value of all sparrows can be expressed as follows:

$$F_x = \begin{bmatrix} f(x_1^1 & x_1^2 & \cdots & x_1^d & \cdots & x_1^D) \\ f(x_2^1 & x_2^2 & \cdots & x_2^d & \cdots & x_2^D) \\ \cdots & \cdots & \cdots & \vdots & \ddots & \vdots \\ f(x_N^1 & x_N^2 & \cdots & x_N^d & \cdots & x_N^D) \end{bmatrix} \tag{2}$$

In Eq. (2), f is the fitness value. F contains the fitness values of all individuals in the entire population.

$R_2 < ST$ indicates that the warning value (R_2) is less than the safety value (ST). This means that the explorer has not found a threat, and the foraging environment is safe. Accordingly, it can guide the population toward extensive search operations. $R_2 \geq ST$ indicates that some sparrows in the population have detected predators and warned other sparrows in the population. All sparrows need to fly to safe areas for foraging. The explorer location update is described as follows:

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^t \cdot \exp\left(-\frac{i}{\alpha \cdot \mathrm{MaxIter}}\right), & if\ R_2 < ST \\ X_{i,j}^t + Q \cdot L, & if\ R_2 \geq ST \end{cases} \tag{3}$$

In Eq. (3), t represents the current iteration number, $X_{i,j}^t$ represents the j-dimension position information of the i-th sparrow in the t-th iteration, $MaxIter$ is a constant representing the maximum number of iterations, α is a random [0,1] number, Q is a random number subject to a normal distribution, L is a $1 \times d$ with all elements being 1, $R_2 \in [0,1]$ represents the early warning value, and $\mathrm{ST} \in [0.5,1]$ represents the security threshold for the current environment.

$i > \frac{n}{2}$ means that the i-th follower has a low fitness and is not qualified to compete with the explorer for food, and needs to fly to other areas for food. When $i \leq \frac{n}{2}$, the follower will forage near the optimal explorer. The location update of the followers is as follows:

$$X_{i,j}^{t+1} = \begin{cases} Q \cdot \exp\left(\frac{X_{\mathrm{worst}}^t - X_{i,j}^t}{\mathrm{i}^2}\right), & if\ i > \frac{\mathrm{n}}{2} \\ X_P^{t+1} + \left|X_{i,j}^t - X_P^{t+1}\right| \cdot \boldsymbol{A}^+ \cdot L, & if\ i \leq \frac{\mathrm{n}}{2} \end{cases} \tag{4}$$

In Eq. (4), X_{worst}^t represents the position of the individual with the worst fitness in the t-th iteration, and X_P^{t+1} represents the individual position with the best fitness in the t+1th iteration. A is a $1 \times d$ -dimensional matrix, and each element in the matrix is preset to -1 or 1, and $A^+ = A^T(AA^T)^{-1}$.

The locations of the warners are randomly generated, and they comprise 10%–20% of the total sparrow population. When warners sense danger, the sparrow populations will adopt anti-predation behavior. $f_i \neq f_g$ means that the individual is at the periphery of the population and needs to adopt anti-predation behavior, which involves constantly changing positions to obtain a higher fitness value. $f_i = f_g$ means that the individual is in the center of the population, and it approaches nearby peers to stay away from the danger zone. The location update of the warners is as follows:

$$X_{\mathrm{i,j}}^{t+1} = \begin{cases} X_{\mathrm{best}}^t + \beta \cdot \left|X_{i,j}^t - X_{\mathrm{best}}^t\right|, & \text{if } f_i \neq f_g \\ xX_{\mathrm{best}}^t + k \cdot \left(\frac{X_{i,j}^t - X_{best}^t}{|f_i - f_w| + \varepsilon}\right), & \text{if } f_i = f_g \end{cases} \tag{5}$$

In Eq. (5), X_{best}^t represents the global optimal position in the t-th iteration; β is the control step size, which is a random number that obeys a normal

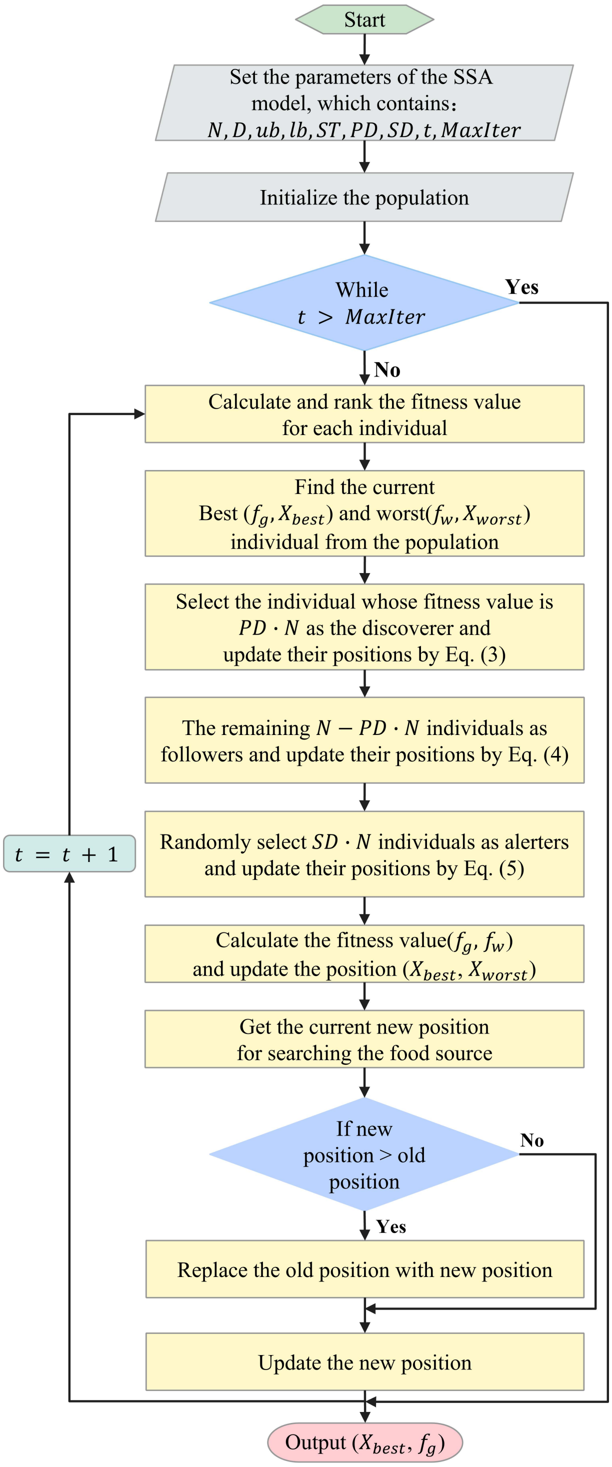


Fig. 3 Flowchart of the sparrow search algorithm.

distribution with mean 0 and variance 1; $k \in [-1,1]$; ε is set to a constant to avoid a denominator of 0; f_i represents the fitness value of the current individual, and f_g and f_w represent the fitness values of the current global best and worst individuals, respectively.

According to the above description and analysis, the implementation steps of SSA are as follows:

Step 1: Set the initial parameters of the SSA model, including population size N, objective function dimension D, dimension upper boundary ub and lower boundary lb of each variable, maximum number of iterations $MaxIter$, safety threshold ST, explorer ratio PD, and warner ratio SD.

Step 2: Initialize the population.

Step 3: When $t < MaxIter$, calculate and rank individual fitness values and corresponding positions, identifying the individual with the best fitness value f_g and its corresponding position X_{best} and marking the individual with the worst fitness value f_{w} and its corresponding position X_{worst}.

Step 4: Select the individual with fitness value $PD \cdot N$ as the explorer, update the position of the discoverer according to Eq. (3), and record the optimal position X_{op} occupied by the current discoverer.

Step 5: After identifying the explorer, the remaining sparrows in the population are regarded as followers, and the positions of the followers are updated according to Eq. (4).

Step 6: Select individuals with fitness values $SD \cdot N$ randomly as warners, and update the location of the warner according to Eq. (5).

Step 7: Calculate and update the sparrow's fitness value; its own position; and the value of f_g, f_w, X_{best}, X_{worst}.

Step 8: Obtain the latest position and its fitness value and judge whether it is better than the old position and its fitness value. If it is better than the old one, replace the original position, and update the data and output; otherwise do not replace.

Step 9: When $t >$ MaxIter, output the result and stop running; otherwise repeat steps 3–8.

The SSA workflow is shown in Fig. 3.

2.3 Stacking-SSAOP ensemble model

A stacking-SSAOP ensemble learning model is proposed in this study. By using the SSA (Section 2.2), the six single regression models, namely RFR, ETR, ADAR, BGR, SVR, and XGBR, are optimized for hyperparameters. These models are then integrated using the stacking algorithm (Section 2.1) to form a new machine-learning regression model to predict the slope safety factor. The implementation process from model building to data prediction is detailed in the following sections.

3 Stacking-SSAOP Ensemble Model Application and Analysis

3.1 Dataset and feature parameter analysis

The main factors affecting slope stability are soil weight, cohesion, friction angle, slope angle, and pore pressure ratio (Guo et al. 2017; Niu et al. 2011; Wen et al. 2012; Ye et al. 2020). The size and quality of the data set directly affect the reliability of the prediction model. Therefore, to obtain precise and reliable model prediction results from the slope stability prediction analysis and reduce the impact of data differences and data inaccuracy on the algorithm accuracy, the geological conditions and stability evaluation index differences are considered. Accordingly, 210 sets of non-repeating slope data were selected from the literature (Fu et al. 2003; Li et al. 2015; Qiao et al. 2010; Sun et al. 2022), and the sample data set was randomly arranged and combined. The first 180 sets of data were used for training, whereas the remaining 30 sets were used for testing. The specific values are listed in Table 1.

The correlation between the different parameters, their importance, and the correlation coefficient R were obtained by determining the sample attribute information of the characteristic parameters in the 210 sets of sample data, as shown in Fig. 4. The aim was to clarify the implicit relationship between the six characteristic parameters and the slope safety factor as well as their respective importance in the prediction of the slope safety factor. Fig. 4a shows the univariate kernel probability density distribution and multivariate scatter distribution. Noticeably, compared with the slope with a safety factor of less than 1, the slope with a safety factor greater than 1 has a higher density, cohesion, friction angle, slope angle, and slope height because good rock and soil compactness and large shear strength parameters are the necessary conditions for maintaining slope. Specifically, these conditions ensure that the gravity of the soil and the shear stress generated under external loads are less than the shear strength of the soil. Fig. 4b shows the average importance of each characteristic parameter in all single regression prediction models, revealing the importance of the friction angle, slope angle, and slope height in the regression model prediction. In addition, as shown in Fig. 4c, most of the characteristic parameters have poor correlation (R<0.5), and only the internal friction angle and slope height (R = 0.595) are highly correlated. Therefore, no direct causal relationship between the characteristic parameters exists, implying that it is unnecessary to reduce the data dimension. Simultaneously, the correlation suggests that as the slope height increases, the internal state of the soil changes. These include alterations in soil stress distribution, enhanced compaction effects, and shifts in particle interactions. In the context of stress distribution, the base of the slope was subjected to heightened stress, leading to increased inter-particle friction and a subsequent rise in the internal friction angle. As for compaction, the added self-weight pressure from the increased slope height compacts the soil particles further, intensifying friction and elevating the internal friction angle. It is also essential to recognize that the link between slope height and internal friction angle can be affected by geological characteristics and soil type. Different geological and soil compositions might yield varied responses regarding the internal friction angle.

In this study, the density, cohesion, friction angle, slope angle, slope height, and pressure ratio of these six factors were utilized as the model eigenvalues, whereas the slope safety factor was the target value of the model. The distribution of each eigenvalue and the corresponding safety factor of the sample is shown in Fig. 5.

3.2 Stacking-SSAOP Model parameters selection

In this study, RFR, ETR, ADAR, BGR, and SVR were selected as the base regressor model (inner loop), and XGBR was selected for the meta regressor model (outer loop). How these models are realized is described in detail in references(Abedi et al. 2022; Lin et al. 2021b; Rahman et al. 2021; Ramos et al. 2021; Sari et al. 2019; Xie et al. 2022) To further improve the prediction accuracy of the stacking ensemble learning model, the 7-fold cross-validation method was selected to disturb the sample data set and reduce over-fitting. In terms of the hyper-parameter setting of the regression model, because the six regression

Table 1 Datasets of slope samples (Fu et al. 2003; Li et al. 2015; Qiao et al. 2010; Sun et al. 2022)

No.	γ	c	φ	β	H	r_u	F_s	No.	γ	c	φ	β	H	r_u	F_s
1	18.50	25.00	0.00	30.00	6.00	0.15	1.09	52	26.80	60.00	28.80	59.00	108.00	0.25	1.25
2	25.00	46.00	35.00	47.00	443.00	0.25	1.28	53	27.30	14.00	31.00	41.00	110.00	0.25	1.25
3	25.00	55.00	36.00	45.50	299.00	0.25	1.52	54	100.00	20.00	23.00	0.00	20.00	0.30	1.15
4	27.00	40.00	35.00	47.10	292.00	0.25	1.15	55	23.00	24.00	19.80	23.00	380.00	0.00	1.25
5	27.00	35.00	35.00	42.00	359.00	0.25	1.27	56	27.30	26.00	31.00	50.00	92.00	0.25	1.00
6	25.00	63.00	32.00	46.00	300.00	0.25	1.45	57	18.80	20.00	20.00	30.00	50.00	0.30	1.30
7	10.00	39.81	20.36	0.98	32.50	0.70	1.01	58	25.00	120.00	45.00	53.00	120.00	0.00	1.12
8	50.00	45.00	20.00	0.00	36.00	0.25	0.79	59	20.15	22.00	20.00	20.00	20.00	0.50	1.37
9	26.89	150.00	33.00	52.00	120.00	0.25	1.80	60	25.00	46.00	35.00	44.00	435.00	0.25	1.20
10	20.00	0.00	36.00	45.00	50.00	0.25	0.79	61	31.30	68.00	37.00	49.00	200.50	0.25	0.97
11	19.00	30.00	35.00	35.00	11.00	0.20	2.00	62	18.80	20.00	10.00	25.00	50.00	0.30	0.81
12	19.63	11.97	20.00	22.00	12.19	0.41	1.35	63	7.00	26.57	18.80	1.00	20.00	0.10	0.90
13	22.40	10.00	35.00	30.00	10.00	0.15	2.00	64	22.40	10.00	35.00	45.00	10.00	0.40	0.96
14	10.00	45.00	22.40	10.00	35.00	0.40	0.90	65	20.00	20.00	36.00	45.00	50.00	0.25	1.53
15	12.80	28.00	21.82	8.62	32.00	0.49	1.03	66	21.00	45.00	25.00	49.00	12.00	0.30	0.67
16	21.00	20.00	40.00	40.00	12.00	0.00	1.84	67	50.00	45.00	20.00	0.00	36.00	0.50	2.05
17	22.40	10.00	35.00	30.00	10.00	0.00	2.00	68	18.00	5.00	30.00	20.00	8.00	0.30	1.70
18	22.00	0.00	40.00	33.00	8.00	0.35	1.45	69	21.40	10.00	30.34	30.00	20.00	0.25	1.25
19	27.00	50.00	40.00	42.00	407.00	0.25	1.44	70	27.30	31.50	29.70	41.00	135.00	0.15	1.01
20	13.70	26.57	18.71	0.00	14.00	0.00	1.28	71	21.51	6.94	30.00	31.00	76.81	0.38	1.03
21	12.00	0.00	30.00	45.00	8.00	0.25	0.80	72	9.50	25.50	18.61	10.42	10.14	0.31	1.02
22	18.80	30.00	20.00	30.00	50.00	0.10	1.46	73	22.00	10.00	36.00	45.00	50.00	0.25	1.80
23	23.50	10.00	27.00	26.00	190.00	0.00	1.02	74	15.00	45.00	22.40	100.00	45.00	0.25	0.83
24	27.00	32.00	33.00	42.20	289.00	0.25	1.30	75	50.00	45.00	20.00	20.00	36.00	0.50	0.78
25	18.84	15.32	30.00	25.00	10.67	0.38	1.63	76	18.50	12.00	0.00	30.00	6.00	0.15	1.01
26	21.00	20.00	24.00	21.00	565.00	0.00	1.26	77	76.81	31.00	21.51	6.94	30.00	0.38	1.49
27	31.30	68.00	37.00	46.00	366.00	0.15	1.34	78	25.00	48.00	40.00	49.00	330.00	0.25	0.97
28	27.00	40.00	35.00	43.00	420.00	0.25	1.15	79	10.04	15.24	18.80	0.00	20.00	0.33	1.25
29	20.00	20.00	36.00	45.00	50.00	0.50	0.83	80	27.30	16.80	28.00	50.00	90.50	0.25	0.80
30	27.30	16.80	28.00	50.00	90.50	0.15	1.25	81	12.00	0.00	30.00	45.00	8.00	0.15	1.49
31	25.00	46.00	35.00	46.00	432.00	0.15	1.23	82	21.00	30.00	35.00	40.00	12.00	0.40	1.20
32	12.20	17.10	18.80	1.50	20.00	0.32	0.98	83	26.78	300.00	38.70	54.00	155.00	0.25	1.12
33	6.20	16.72	18.80	0.00	20.00	0.30	0.75	84	18.00	24.00	30.15	45.00	20.00	0.12	1.25
34	27.00	32.00	33.00	42.60	301.00	0.25	1.16	85	20.60	16.28	26.50	30.00	40.00	0.00	1.20
35	7.62	20.00	18.84	0.00	20.00	0.45	1.05	86	26.00	150.05	45.00	50.00	200.00	0.00	0.67
36	44.10	19.98	22.80	16.50	37.50	0.30	0.68	87	20.00	0.00	36.00	45.00	50.00	0.50	1.05
37	20.41	24.90	13.00	22.00	10.67	0.35	1.40	88	15.00	12.99	20.00	21.00	17.00	1.00	1.50
38	28.44	39.23	38.00	35.00	100.00	0.00	1.99	89	44.00	19.98	22.80	16.80	37.50	0.40	1.15
39	24.00	0.00	40.00	33.00	8.00	0.30	1.58	90	27.00	40.00	35.00	43.00	420.00	0.15	1.20
40	31.30	58.80	35.50	47.50	438.50	0.25	1.20	91	31.30	68.60	37.00	47.50	262.50	0.25	0.62
41	20.00	0.10	36.00	45.00	50.00	0.25	0.79	92	5.10	25.25	18.05	5.75	18.00	0.64	1.30
42	22.00	20.00	36.00	45.00	50.00	0.00	1.02	93	27.00	32.00	33.00	42.40	289.00	0.25	1.42
43	18.84	57.46	20.00	20.00	30.50	0.00	2.05	94	27.30	10.00	39.00	40.00	470.00	0.25	0.65
44	18.68	26.34	15.00	35.00	8.23	0.00	1.11	95	19.10	10.00	20.00	30.00	50.00	0.40	1.43
45	25.00	48.00	40.00	45.00	330.00	0.25	1.62	96	27.30	10.00	39.00	41.00	511.00	0.25	1.24
46	27.30	10.00	39.00	40.00	480.00	0.25	1.45	97	27.00	37.50	35.00	37.80	320.00	0.15	1.43
47	25.00	55.00	36.00	44.50	299.00	0.25	1.55	98	27.30	10.00	39.00	40.00	470.00	0.25	0.90
48	31.30	68.00	37.00	47.00	213.00	0.25	1.20	97	27.00	37.50	35.00	37.80	320.00	0.15	1.43
49	10.67	25.00	18.84	15.32	30.00	0.38	1.63	98	27.30	10.00	39.00	40.00	470.00	0.25	0.90
50	25.00	63.00	32.00	44.50	239.00	0.25	1.49	99	22.40	10.00	35.00	45.00	10.00	0.35	0.99
51	16.00	70.00	20.00	40.00	115.00	0.00	1.11	100	9.10	26.60	18.31	5.16	15.12	0.10	1.05

Notes: γ, Density (kN/m^3); c, Cohesion (Mpa); φ, Friction angle (°); β, Slope angle (°); H, Slope height (m); r_u , Pressure ratio; F_s , Safety factor.

(-To be continued-)

Table 1 Datasets of slope samples (Fu et al. 2003; Li et al. 2015; Qiao et al. 2010; Sun et al. 2022)(-Continued-)

No.	γ	c	φ	β	H	r_u	F_s	No.	γ	c	φ	β	H	r_u	F_s
101	22.50	18.00	20.00	20.00	290.00	0.00	0.97	156	12.00	0.00	30.00	35.00	4.00	0.25	1.46
102	14.30	27.00	19.60	9.60	25.00	0.32	1.09	157	20.00	22.00	20.00	0.00	20.00	0.50	0.90
103	19.06	11.71	28.00	35.00	21.00	0.11	1.02	158	17.00	33.69	18.80	1.00	20.00	0.43	0.97
104	14.00	11.97	26.00	30.00	88.00	0.00	1.24	159	20.00	45.00	18.00	24.00	30.15	0.12	1.12
105	27.00	37.50	35.00	37.80	320.00	0.25	1.15	160	4.90	18.43	18.80	1.20	20.00	0.27	1.10
106	27.00	40.00	35.00	47.10	292.00	0.25	1.80	161	31.30	68.00	37.00	47.00	360.50	0.25	1.20
107	26.70	150.00	33.00	50.00	130.00	0.25	1.80	162	18.50	12.00	0.00	30.00	6.00	0.25	0.78
108	25.00	22.00	18.80	30.00	20.00	0.25	1.36	163	25.00	46.00	35.00	47.00	443.00	0.15	1.28
109	18.80	30.00	10.00	25.00	50.00	0.10	1.40	164	18.85	10.34	21.30	34.00	37.00	0.30	1.29
110	10.00	26.57	19.61	31.70	13.00	0.90	1.61	165	26.57	300.00	38.70	45.30	80.00	0.15	1.18
111	20.00	0.00	24.50	20.00	8.00	0.35	1.37	166	20.00	20.00	19.72	30.00	30.00	0.50	1.54
112	31.30	68.60	37.00	47.00	270.00	0.25	1.20	167	26.00	150.00	45.00	30.00	200.00	0.15	1.20
113	22.40	100.00	45.00	45.00	15.00	0.25	1.80	168	27.30	10.00	39.00	40.00	480.00	0.15	1.55
114	26.00	150.00	45.00	30.00	200.00	0.25	1.20	169	22.00	29.00	15.00	18.00	400.00	0.00	1.04
115	26.43	50.00	26.60	40.00	92.20	0.15	1.25	170	22.40	10.00	35.00	30.00	10.00	0.25	2.00
116	44.20	20.00	22.00	16.80	37.50	0.50	1.25	171	30.50	20.00	18.84	14.36	25.00	0.45	1.11
117	27.30	10.00	39.00	40.00	470.00	0.15	1.42	172	18.50	25.00	0.00	30.00	6.00	0.25	1.09
118	18.84	14.36	25.00	20.00	30.50	0.00	1.88	173	11.50	27.60	17.71	9.09	20.35	0.00	1.25
119	25.00	55.00	36.00	45.00	239.00	0.25	1.71	174	26.70	50.00	26.60	50.00	170.00	0.25	1.25
120	12.00	0.00	30.00	45.00	4.00	0.15	1.46	175	27.30	26.00	1.00	50.00	92.00	0.25	1.25
121	8.00	45.00	18.45	18.06	10.10	0.14	0.97	176	25.00	46.00	35.00	50.00	284.00	0.15	1.15
122	7.62	26.57	17.61	7.66	26.00	0.20	1.13	177	27.43	26.40	17.29	44.54	12.00	0.00	1.52
123	26.49	150.00	33.00	45.00	73.00	0.15	1.23	178	18.80	25.00	20.00	30.00	50.00	0.20	1.21
124	22.00	20.00	22.00	20.00	180.00	0.10	0.99	179	28.44	29.42	35.00	35.00	100.00	0.00	1.78
125	110.00	41.00	27.30	14.00	31.00	0.25	1.25	180	27.30	10.00	39.00	41.00	511.00	0.15	1.43
126	19.10	10.00	10.00	25.00	50.00	0.40	0.65	181	10.00	33.69	17.66	7.85	25.00	0.25	1.07
127	30.00	20.56	19.61	14.71	20.00	0.00	1.75	182	31.30	58.80	35.50	47.50	502.70	0.25	1.20
128	26.81	200.00	35.00	58.00	138.00	0.25	1.20	183	25.00	46.00	35.00	50.00	284.00	0.25	1.34
129	27.30	31.50	29.70	41.00	135.00	0.25	1.25	184	20.00	40.00	40.00	40.00	10.00	0.20	2.31
130	27.00	40.00	35.00	43.00	420.00	0.20	1.15	185	27.30	26.00	31.00	50.00	92.00	0.15	1.25
131	22.40	10.00	35.00	45.00	10.00	0.30	0.90	186	31.30	68.00	37.00	49.00	200.50	0.25	1.20
132	22.54	29.40	20.00	24.00	210.00	0.00	1.06	187	22.00	20.00	22.00	20.00	180.00	0.00	1.12
133	21.40	10.00	30.34	30.00	20.00	0.15	1.70	188	25.00	46.00	36.00	44.50	299.00	0.15	1.20
134	22.50	20.00	16.00	25.00	220.00	0.00	1.36	189	22.00	40.00	30.00	30.00	196.00	0.00	1.11
135	27.30	10.00	39.00	40.00	480.00	0.25	1.45	190	27.30	10.00	39.00	41.00	511.00	0.25	1.47
136	18.80	25.00	10.00	25.00	50.00	0.20	1.18	191	25.00	46.00	35.00	44.00	435.00	0.15	1.37
137	31.30	68.60	37.00	47.00	305.00	0.25	1.20	192	18.84	14.36	25.00	20.00	30.50	0.45	1.11
138	22.00	0.00	36.00	45.00	50.00	0.15	0.89	193	20.00	40.00	30.00	30.00	15.00	0.30	1.84
139	20.00	0.10	36.00	45.00	50.00	0.50	0.67	194	31.30	68.00	37.00	47.00	213.00	0.25	1.20
140	32.80	18.16	17.00	12.00	16.30	1.00	0.94	195	20.00	20.00	36.00	45.00	50.00	0.25	0.96
141	18.85	24.80	21.30	29.20	37.00	0.50	1.07	196	20.00	20.00	36.00	45.00	50.00	0.20	0.96
142	12.00	0.00	30.00	45.00	4.00	0.15	1.44	197	24.00	0.00	40.00	33.00	8.00	0.30	1.58
143	25.00	46.00	35.00	46.00	432.00	0.25	1.23	198	27.00	40.00	35.00	47.10	292.00	0.15	0.96
144	25.00	46.00	35.00	46.00	393.00	0.25	1.31	199	12.00	0.00	30.00	35.00	4.00	0.25	1.44
145	22.00	20.00	36.00	45.00	50.00	0.25	0.89	200	50.00	45.00	22.00	20.00	36.00	0.25	1.02
146	21.40	10.00	30.34	30.00	20.00	0.00	1.70	201	61.00	20.00	21.43	0.00	20.00	0.50	1.03
147	22.00	20.00	36.00	45.00	50.00	0.15	1.02	202	20.00	0.00	24.50	20.00	8.00	0.35	1.37
148	21.82	8.62	32.00	28.00	12.80	0.49	1.03	203	25.00	46.00	35.00	46.00	432.00	0.25	1.23
149	10.67	22.00	20.41	24.91	13.00	0.35	1.40	204	20.00	0.00	24.50	20.00	8.00	0.30	1.37
150	25.00	46.00	35.00	46.00	393.00	0.15	1.45	205	18.00	45.00	25.00	25.00	14.00	0.30	2.09
151	31.30	68.00	37.00	46.00	366.00	0.25	1.20	206	22.40	10.00	35.00	45.00	10.00	0.40	0.90
152	22.00	21.00	23.00	30.00	257.00	0.00	1.10	207	45.72	16.00	20.41	33.52	11.00	0.20	1.28
153	8.56	44.50	18.50	20.00	10.00	0.00	1.15	208	21.00	35.00	28.00	40.00	12.00	0.50	1.43
154	12.19	22.00	19.63	11.97	20.00	0.41	1.35	209	27.30	14.00	31.00	41.00	110.00	0.25	1.25
155	88.00	30.00	14.00	11.97	26.00	0.45	0.66	210	18.00	0.00	30.00	20.00	8.00	0.30	2.05

Notes: γ, Density (kN/m^3); c, Cohesion (Mpa); φ, Friction angle (°); β, Slope angle (°); H, Slope height (m); r_u , Pressure ratio; F_s , Safety factor.

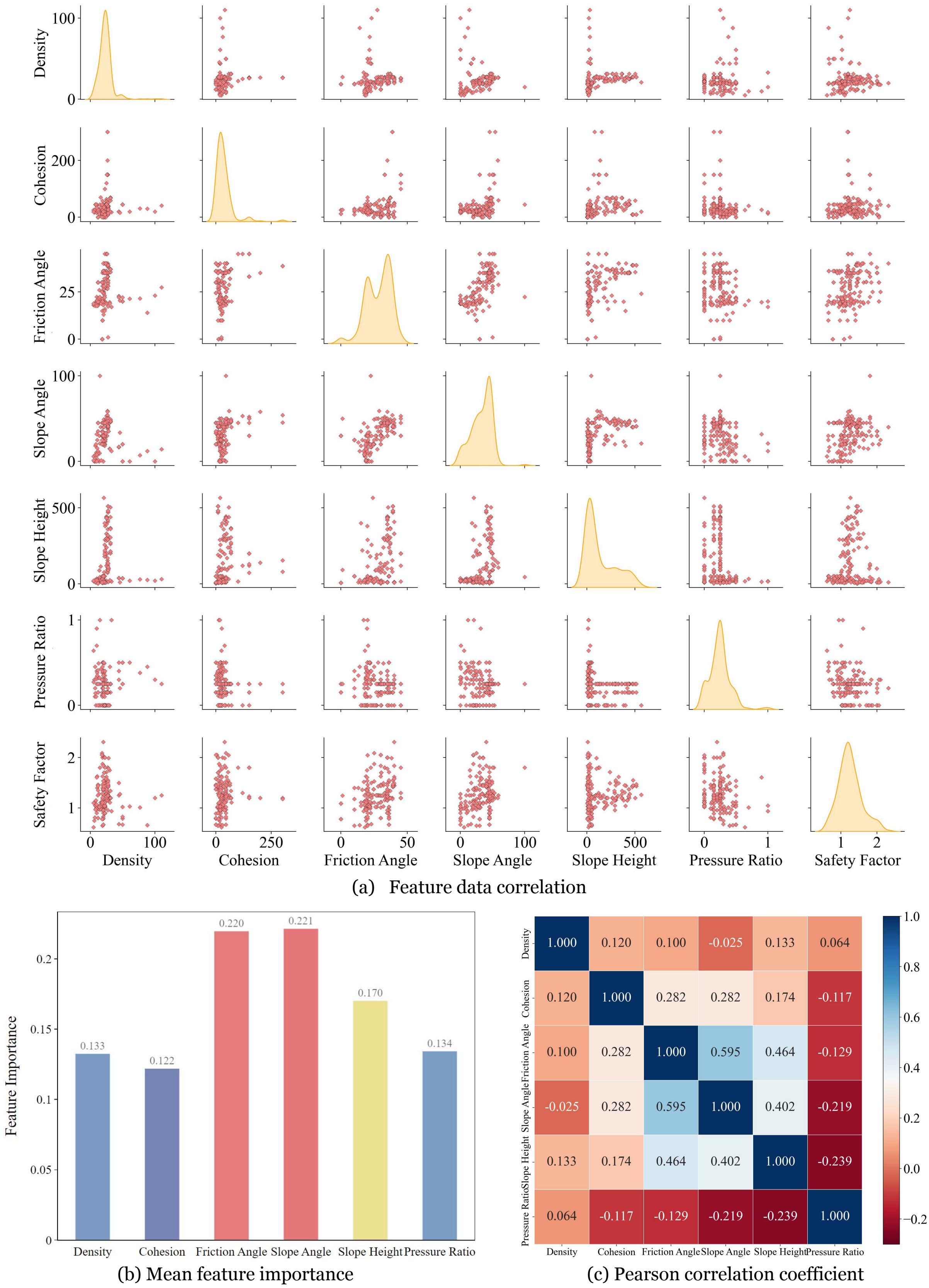


Fig. 4 Analysis of feature relationships and importance. (a) Feature correlation; (b) Mean feature importance; (c) Pearson correlation coefficient of the data (R).

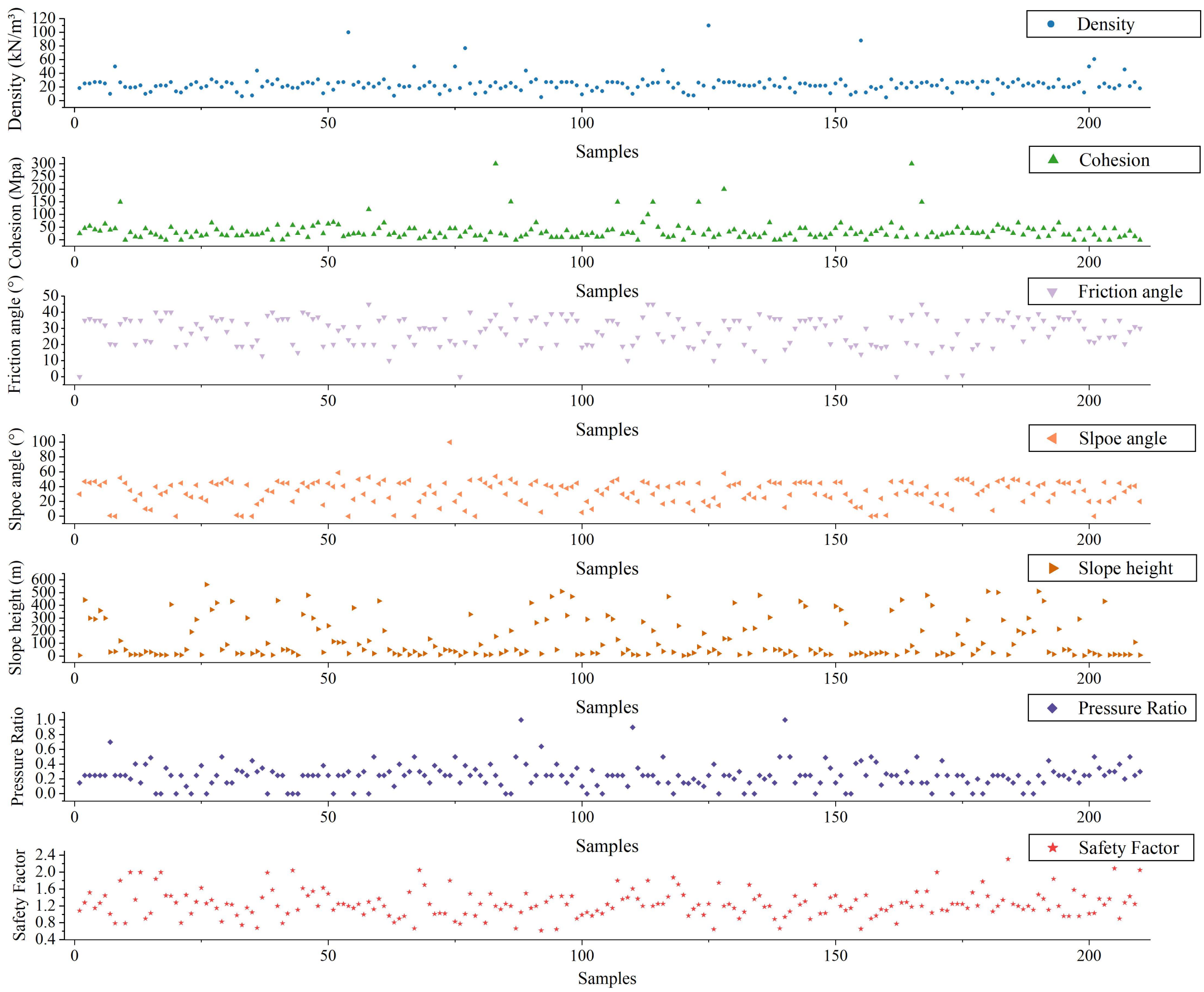


Fig. 5 Distribution of eigenvalues and safety factors of samples.

Table 2 Hyperparameter optimization

Algorithm	Default hyperparameters	Optimal hyperparameters
Random Forest	max_depth=None, min_samples_leaf=1.0, min_samples_split=2.0	max_depth=11, min_samples_leaf=0.1, min_samples_split=0.1
Extra Trees	n_estimators=10, max_depth= None, min_samples_leaf=1.0	n_estimators=78, max_depth=5.0, min_samples_leaf=0.1
AdaBoost	n_estimators=50, learning_rate=1.0	n_estimators=59, learning_rate=1.608
Bagging	n_estimators=10, max_samples=1.0	n_estimators=98, max_samples=0.28
SVR	C=1.0	C=20
XGBoost	learning_rate=0.3, min_child_weight=1.0, gamma=0, subsample=1.0, colsample_bytree=1.0, reg_lambda=1.0	learning_rate=0.57, min_child_weight=0.759, gamma=0.4, subsample=0.82, colsample_bytree=0.94, reg_lambda=0.1

algorithm models contain one or more important hyper-parameters, the automatic optimization ability of the SSA was leveraged to obtain the optimal solution of the parameters in the iterative operation, thus optimizing the prediction accuracy of the model. Table 2 lists the default and optimized hyperparameter values of the five base regression models and the meta-regression model.

3.3 Stacking-SSAOP Model prediction effect and analysis

In this study, MSE (Xiao et al. 2022) was used to measure the prediction accuracy of the model. First, the parameter optimization comparison experiment of the base model was conducted. The five single regression models in the base model were divided into the default hyperparameter numerical group and SSAOP hyperparameter numerical group. The specific hyperparameter values of each model are listed in Table 2. For each group, training and prediction were sequentially conducted using the 180 training sets and 30 test sets, and their respective MSEs were obtained. Thereafter, the stacking comparison test was conducted. The XGBoost regression model was used as the meta-model, and the outputs of the five single regression models in the base model after SSAOP were used as the input for the meta-model. The stacking ensemble learning method was used to integrate the above models. Finally, the slope safety factor was predicted. The MSE results of each model are listed in Table 3. The specific flow chart of the SSA for optimizing the superimposed ensemble learning prediction model is shown in Fig. 6. The predicted values of each single regression model before and after the SSA optimization and the predicted values of the stacking model are compared with the real values.

Table 2 and Table 3 list the hyperparameters of each model and the default values before the SSA was optimized. Noticeably, the MSEs between the training and test data sets for all the models except ADAR are not ideal. The MSEs of the Random Forest training and test sets were 0.00652 and 0.03597, respectively, and the maximum difference was 0.02945; overfitting occurred. The MSE of the Extra Trees and XGBoost training data sets even drops too, indicating that each model had different degrees of overfitting and underfitting when the hyperparameters of the default values were used. However, the MSE of the training and test data sets optimized using the SSA was more acceptable. For Random Forest, the maximum MSE difference was reduced to 0.02131, and over-fitting was eliminated. The MSEs of the Extra Trees training and test data sets were improved from 0.00000 and 0.04408 to 0.07543 and 0.11135, respectively, and those of XGBoost were improved from 0.00001 and 0.02412 to 0.03279 and 0.05930, respectively. The MSEs of the training and test data sets of SVR and Bagging decreased by 0.01656 and 0.02935, and 0.06038 and 0.05849, respectively, indicating that the single regression model optimized using SSA has a better (lower) MSE. More importantly, when the stacking-SSAOP method proposed in this study was used for data prediction, the MSE of the training data set was 0.03234, that for the test data set was 0.03917, and the maximum difference was only 0.00683 less than that for all other regression models (RFR: 0.02131, ETR: 0.03592, ADAR: 0.01956, BGR: 0.02740, SVR: 0.01245, XGBR: 0.02651). A comparison of the prediction results of the Stacking-SSAOP ensemble learning model and the single regression model reveals that the Stacking-SSAOP ensemble learning model had the best data fitting degree. Moreover, it had a smaller mean square error

Table 3 MSE comparison before and after sparrow search algorithm optimization

Algorithm	MSE before SSAOP		MSE after SSAOP	
	Training datasets	Testing datasets	Training datasets	Testing datasets
Random Forest	0.00652	0.03597	0.06012	0.08143
Extra Trees	0.00000	0.04408	0.07543	0.11135
AdaBoost	0.03732	0.06123	0.03464	0.05420
Bagging	0.09703	0.12254	0.03665	0.06405
SVR	0.07956	0.10480	0.06300	0.07545
XGBoost	0.00001	0.02412	0.03279	0.05930
Stacking	——	——	0.03234	0.03917

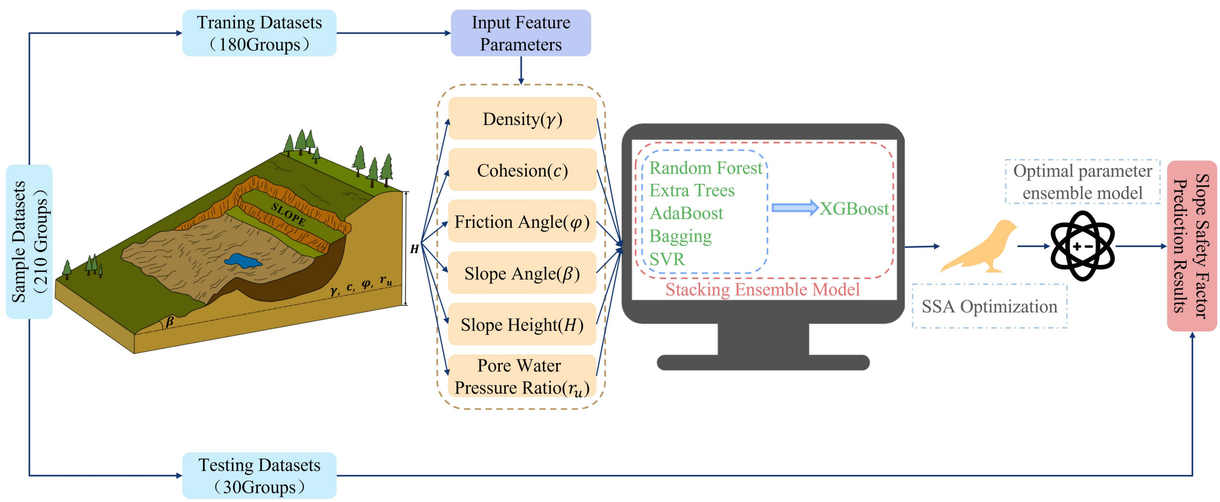


Fig. 6 Flow chart of slope safety factor prediction.

(MSE) between the predicted and real values for the slope safety factor (0.03917).

As shown in Fig. 7, the predicted value of the single regression model optimized via the SSA is closer to the true value than that predicted using the default parameter values. Moreover, the stacked learning model optimized by the SSA had better prediction than any single regression model after the same optimization.

As presented in Table 2, Table 3, and Fig. 7, the stacking-SSAOP ensemble learning model proposed in this study has higher prediction accuracy and better data learning and model generalization ability than the single regression model. Therefore, the stacking-SSAOP ensemble learning model can better predict the slope safety factor and has relatively greater reference value in the field of slope stability evaluation than the other prediction models. With slope engineering in different countries gradually developing toward slope stability analysis, the stacking-SSAOP ensemble learning model method not only has great reference value for slope stability evaluation but also provides some technical reference for intelligent prediction and analysis to establish an early warning platform for slope stability.

4 Discussions

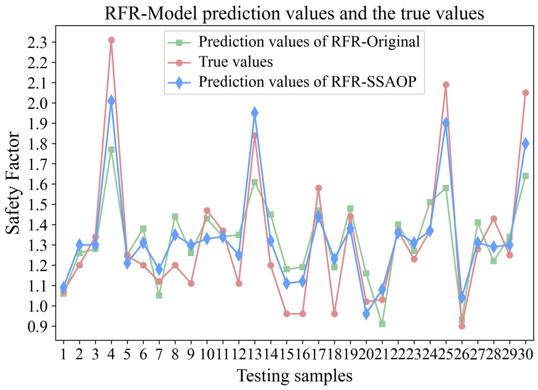
4.1 Stacking-SSAOP model superiority

The machine learning regression models selected in this study have many advantages over other technical methods. First, the Random Forest algorithm can quickly process high-dimensional data without data scaling(Ao et al. 2019). The Extra Tree algorithm has good performance in regression problems because of its high random splitting and low variance (Yarveicy et al. 2017). The AdaBoost algorithm can generally fully consider the weight of each weak regressor and is not prone to overfitting. It has high accuracy in regression prediction problems(Ra et al. 2022). With good accuracy and stability, the bagging algorithm avoids overfitting and is robust to noise because it reduces variance in the results, thus reflecting the real distribution of the samples (Lin et al. 2021a). SVR is robust to outliers, suitable for small-sample learning, and has high prediction accuracy and excellent generalization ability(Babangida et al. 2016). SSA, which was proposed in 2020, has prominent advantages in terms of convergence speed, search accuracy, stability, and optimization ability over other swarm intelligence optimization algorithms(Yan et al. 2021). Thus, it was selected for building and optimizing the stacked learning model in this study. Second, the stacking ensemble learning model was constructed by cross-constructing different types of ensemble algorithms and a single algorithm. While reducing the model correlation, it combines the advantages of high precision, high randomness, and anti-overfitting of the different algorithms. Moreover, it possesses the random learning ability and generalization ability of the stacking model and, thus, improved prediction accuracy. As shown in Fig. 8, the regression models between the base and meta-model in stacking are arranged and combined, and the 70% correlation of the combined models is less than 0.8

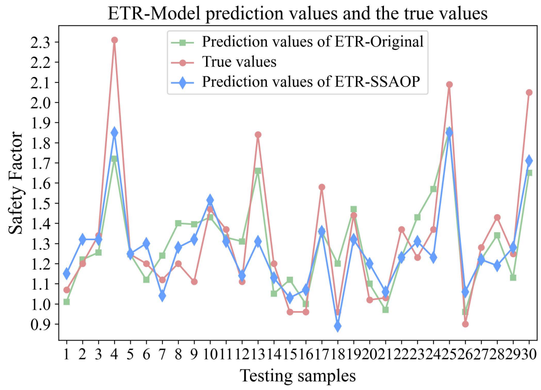
To verify the superiority of the stacking-SSAOP method in predicting the slope safety factor, the AdaBoost, Bagging, and XGBoost algorithms, which are also integrated algorithms, were first compared. Table 3 indicates that although the above three integrated algorithms have better prediction results and their MSEs are lower than those of other algorithms, stacking-SSAOP has the lowest MSE (0.03917). Second, (Bui et al. 2019)revealed that the multilayer perceptron had the lowest MSE (0.49548) for slope safety factor prediction, whereas simple linear regression had the highest MSE. The MSE of the stacking-SSAOP method decreased by 92.09% and 99.24% for the training and test data sets, respectively, compared to that of those other models, which verifies its superiority.

4.2 Limitations and future work

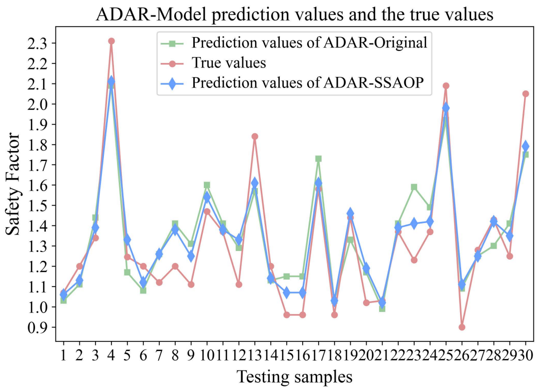
In this study, the first attempt was made to apply the stacking-SSAOP model to predict slope safety factors. The model sensitivity of the selected characteristic parameters and the sample size of the constructed data set are important factors affecting the model's prediction accuracy. However, they were not of primary interest in this study. Therefore, in the follow-up research, the model sensitivity of existing and non-added different feature parameters and their impact on prediction accuracy will be analyzed, and the latest engineering data will be collected to expand the sample data set to further validate the generalization performance of the model, as well as improve the prediction accuracy and training



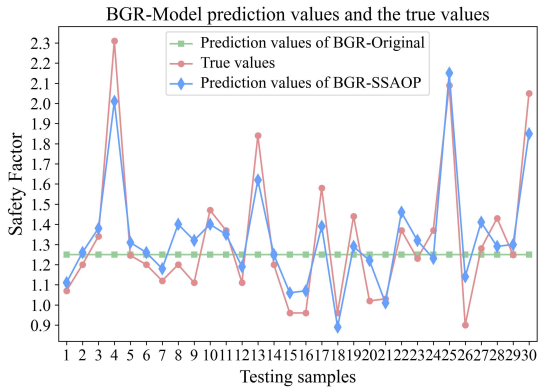
(a) Result of RFR



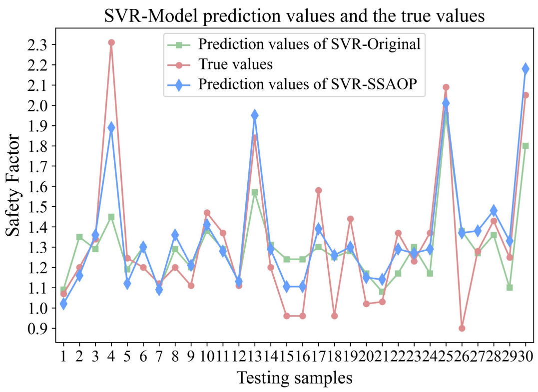
(b) Result of ETR



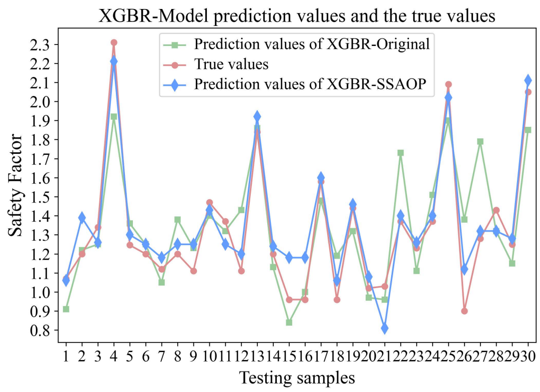
(c) Result of ADAR



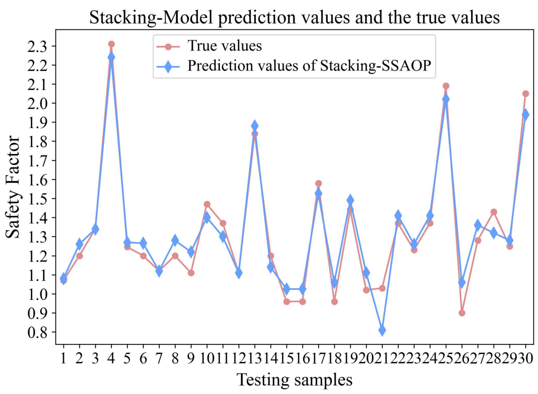
(d) Result of BGR



(e) Result of SVR



(f) Result of XGBR



(g) Result of Stacking

Fig. 7 Prediction results before and after optimization of six single regression models and stacking ensemble learning model (a) Result of RFR (b) Result of ETR (c) Result of ADAR (d) Result of BGR (e) Result of SVR (f) Result of XGBR (g) Result of stacking.

efficiency of the stacking-SSAOP model.

5 Conclusions

In this study, an integrated learning prediction model based on the stacking of multilayer regression algorithms that are optimized by SSA is established. The model learns the implicit relationship between the characteristic parameters of the slope sample data set and the safety factor to predict the slope safety factor. In addition, comparisons of the prediction effects of the single model before and after SSA optimization with the stacked ensemble learning prediction model reveal that the stacking-SSAOP model has marked advantages in the regression prediction of the slope safety factor. The main conclusions are as follows:

(1) Compared with other heuristic algorithms, the SSA has better global exploration and local automatic optimization ability. The hyperparameters of the machine learning regression model proposed in this study are automatically optimized and the optimal parameter values are obtained. Thus, the tendency of the regression prediction model to overfit or underfit when the parameter setting is unreasonable is overcome.

(2) Comparing the predictive performance of individual regression models, including RFR, ETR, ADAR, BGR, SVR and XGBR, with that of the Stacking ensemble learning model confirms the superior data learning and predictive capabilities, higher prediction accuracy, and better fitting characteristics of the latter compared individual regression models.

(3) The application of the Stacking ensemble learning model combined with the Sparrow Search Algorithm Optimization Process (Stacking-SSAOP) further enhances the accuracy and reduces the prediction errors of the Stacking ensemble learning model. When conducting predictions on the test dataset, the Stacking-SSAOP model achieves a significantly lower MSE of 0.03917 than any of the individual regression models mentioned earlier. Moreover, compared to the MLP and SLR regression algorithms in other studies, the Stacking-SSAOP approach exhibits a substantial decrease in MSE ranging from 92.09% to 99.24%. This indicates that the proposed method can accurately and effectively predict the slope safety factor, thereby providing valuable technical insights for the analysis and

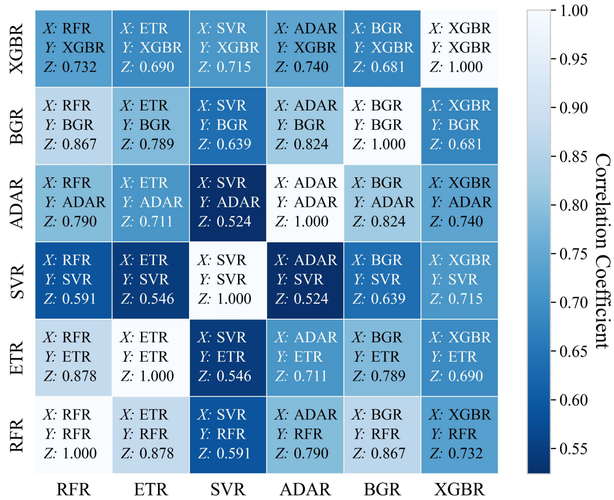


Fig. 8 Correlation amongst individual models.

warning platform of slope stability prediction. Furthermore, it serves as a supportive tool for slope reinforcement and early warning activities.

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Author Contribution

All authors participated in the relevant work of this study, with specific contributions as follows. SHUI Kuan: Conceptualization, Data curation, Software, Methodology, Writing–original draft. HOU Ke-peng: Supervision, Writing–review & editing. HOU Wen-wen: Investigation, Visualization. SUN Jun-long: Validation, Resources. SUN Hua-fen: Funding acquisition. All authors have read and approved the final manuscript.

Ethics Declaration

Data Availability: The data sets supporting this study are available from the corresponding author upon reasonable inquiry, within collaboration agreements and scientific research initiatives.

Conflict of Interest: The authors declare no conflicts of interest.

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