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RESEARCH ARTICLE

A Tunnel Squeezing Prediction Model Based on the Hierarchical Belief Rule Base

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ABSTRACT Tunnel squeezing is a time-dependent significant deformation problem often occurring in weak rock masses and areas with high horizontal in situ stress. This phenomenon can cause construction delays, increased budgets, tunnel collapse, and additional problems. Therefore, accurately predicting tunnel squeezing is crucial. The surrounding rock of the tunnel is uneven in hardness and softness, and changes frequently due to the influence of geological structure, thereby rendering the prediction of extrusion deformation highly uncertain. The belief rule base (BRB) is a rule-based modeling approach capable of handling uncertain information. However, the performance of the BRB model is not only affected by the combinatorial rule explosion caused by too many input attributes but also by the limitations of expert knowledge. First, to solve the problem of the combinatorial rule explosion, a novel tunnel squeezing prediction model using a hierarchical BRB structure based on the Random Forest (RF) attribute selection method (H-RF-BRB) is proposed. Second, to avoid the limitations of expert knowledge, parameters of the tunnel squeezing prediction model are determined by combining the expert knowledge and the information gain ratio (IGR). The model effectively integrates qualitative knowledge with quantitative information, addressing the issue of limitations in expert knowledge. Additionally, it overcomes the challenge of limited datasets due to the difficulties in collecting tunnel squeezing samples, which enhances the accuracy of the model's predictions. Finally, the model's effectiveness and superiority are validated through five-fold cross-validation and several comparative experiments.

INDEX TERMS Belief rule base, tunnel squeezing, random forest, evidence reasoning.

I. INTRODUCTION

Tunnel squeezing is defined by the International Society for Rock Mechanics (ISRM) as the time-dependent, large deformation that occurs around the tunnel and is primarily associated with creep due to exceeding limiting shear stress [1]. Squeezing frequently occurs in weak rock masses and tectonically active regions [2], [3]. Due to the substantial deformation induced by squeezing, which can lead to significant support damage, considerable economic losses, and delays during tunnel construction, predicting tunnel squeezing remains a critical issue for ensuring tunneling safety [4], [5]. Therefore, investigating the squeezing potential of tunnels is crucial.

Since the 1980s, extensive research has been conducted on tunnel squeezing. Prediction models are typically categorized into two types: based on quantitative information and based on qualitative knowledge. Prediction models based on quantitative information are developed through data-driven approaches utilizing observed data. For instance, Sun et al. presented a multiclass SVM model for predicting tunnel squeezing [6]. Huang et al. developed a combined SVM-BP approach for classifying tunnel-surrounding rock squeezing [7]. Ghasemi and Gholizadeh used k-nearest

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neighbors (KNN) and C5.0 classifiers to predict ground status, i.e., (nonsqueezing or squeezing) in tunneling projects [8]. Chen et al. utilized the decision tree (DT) method to develop a multi-classification model that can predict the intensity of tunnel squeezing [9]. Feng and Jimenez presented a Naïve Bayes (NB) classifier to predict tunnel squeezing [4]. Jimenez and Recio used a logistic regression method to predict the occurrence of tunnel squeezing [5]. Zhang et al. employed a weighted collection of seven classifiers, which include DT, NB, back propagation neural network (BPNN), SVM, multiple linear regression, KNN, and logistic regression to predict whether tunnel squeezing occurs [10]. Bo et al. adopted and aggregated four typically various-structured algorithms (LR, ET, Ada, and GBC) to form a robust ensemble classifier to predict tunnel squeezing [11]. Geng et al. employed a combination of the Bayesian Optimization (BO) algorithm with the Entropy Weight Method (EWM) to enhance the Extreme Gradient Boosting (XGBoost) model, improving the accuracy of tunnel squeezing intensity predictions [12]. The prediction models based on quantitative information do not require complex mechanism analysis. They only require analyzing a large amount of data for modeling. However, a challenge in the tunnel squeezing prediction field is that training data is difficult to obtain because different researchers use different parameters to predict tunnel squeezing [10].

Unlike the model based on quantitative information, the model based on qualitative knowledge is constructed on the squeezing mechanism. For instance, Fritz evaluated the time-dependent strain and stress (for excavated tunnels) based on an axisymmetric assumption [13]. Pan and Dong calculated the time-dependent deformations of viscoelastic rocks, considering the advancement rate [14]. Debernardi and Barla evaluated the triaxial creep deformations using a stress-hardening constitutive law [15]. Jiao et al. used evidence theory to predict the tunnel squeezing intensity [16]. The prediction model based on qualitative knowledge relies on expert knowledge, which makes their accuracy be affected by the limitations of expert knowledge.

Compared to models based on quantitative information, semi-quantitative information models maintain accuracy while reducing dependence on data samples. In contrast to qualitative knowledge models, semi-quantitative information models simplify the internal structure, enhance resistance to interference, and improve the capacity to handle uncertain information.

The BRB is a typical semi-quantitative information model proposed by Yang et al. [17]. The model can effectively combine qualitative knowledge with quantitative information and handle the uncertainty in qualitative knowledge. Currently, the BRB model has been widely used for bridge risk assessment [18], security assessment [19], slope stability evaluation [20], and various other fields. Therefore, this paper proposes a tunnel squeezing prediction model based on BRB.

The complexity of the BRB model is related to the number of rules. The number of rules in BRB is determined by the Cartesian product algorithm. For instance, in the BRB model with M attributes, where the number of referential points for the i_{th} attribute is A_i, the total number of rules is $\prod_{i=1}^{M} A_i$. As the number of attributes increases, the number of rules grows exponentially, resulting in combinatorial rule explosion. This not only complicates the model but also significantly affects its performance. Thus, a hierarchical BRB structure based on the Random Forests (RF) attributes selection method is proposed to predict tunnel squeezing. The model is structured into two layers: the first layer has a main BRB, and the second layer has several sub-BRBs.The output of the main BRB represents the approximated classification between confusable classes. Then, these samples were transmitted to a certain sub-BRB for binary classification to make a precise prediction. The RF is used for attribute selection in the modeling process of each abovementioned BRB model.

Furthermore, the hierarchical BRB model's accuracy is significantly influenced by the main BRB in the first layer. Only when the main BRB assigns samples to the correct sub-BRB. The sub-BRB in the second layer can then further classify the samples accurately. The accuracy of the BRB model is influenced by its parameters. Currently, these parameters are usually determined by experts. However, due to the limitations of expert knowledge and the complexity of tunnel squeezing mechanisms, accurately determining these parameters remains challenging. Additionally, the number of model parameters impacts both the accuracy and performance of the model. For instance, When a BRB model has only two attributes, each with four reference points, 16 rules (4×4) will be generated; when each attribute has eight reference points, 64 rules will be generated. While fewer referential points make the rule base more concise, they reduce the model's accuracy. Conversely, an excessive number of referential points can lead to overly large rule base and over-fitting. Therefore, the BRB model should be designed with a reasonable number of referential points. This paper integrates expert knowledge with the information gain ratio (IGR) to determine the number of rules and the range of attributes, providing a reasonable reference for rule origination.

The primary contributions of this paper are as follows:

1) This paper presents the H-RF-BRB tunnel squeezing prediction model.
2) The hierarchical BRB structure based on RF attribute selection method is used to address the problem of combinatorial rule explosion.
3) Expert knowledge and IGR were introduced to determine model referential points so that more samples could be sent to the correct sub-BRB in the first layer. It can enhance the accuracy of the H-RF-BRB tunnel squeezing prediction model.

II. PROBLEM FORMULATION

When developing a tunnel squeezing prediction model, the following problems need to be considered to ensure the model's effectiveness and reliability:

Problem 1: Given the large number of attributes affecting tunnel squeezing, it is crucial to use an appropriate model structure, select relevant input attributes, and determine model parameters in the early stages of establishing the tunnel squeezing prediction model to avoid the problem of high complexity resulting from too many input attributes.

The first question is constructing a reasonable model structure. The developed tunnel squeezing prediction model can be represented as follows:

$$\tau = \varphi[x_1, x_2, \ldots, x_M] \tag{1}$$

where $x_i = (i = 1, 2, \ldots, M)$ represents the input attributes for the tunnel squeezing prediction model. The model structure is represented by the τ. The construction process of the model is denoted by φ, which encompasses the methods and steps involved in constructing the model.

The next question is how to reduce the size of the tunnel squeezing prediction model without compromising its accuracy by selecting appropriate input attributes. The selection of attributes can be represented as follows:

$$\{x_1, x_2, \ldots, x_M\} = f(x_1, x_2, \ldots, x_C) \quad (M < C) \tag{2}$$

where $\{x_1, x_2, \ldots, x_M\}$ is selected input attribute set.

The final problem is to determine the parameters of the tunnel squeezing prediction model while maintaining its accuracy without losing interpretability. The parameters of the model can be determined as follows:

$$\{\{r_1^1, r_1^2, \ldots, r_1^m, \}\ldots, \{r_M^1, r_M^2, \ldots, r_M^m\}\} = e(h(D)) \tag{3}$$

where $\{r_N^1, \ldots, r_N^m\}$ represents the set of referential points to be determined of the N_{th} attribute. D represents samples. $h(.)$ represents parameters obtain algorithm. $e(.)$ represents the adjustments to referential points by experts.

Problem 2: How can the inference process of the tunnel squeezing prediction model be designed reasonably? The inference process is represented as follows:

$$y = g(x_1, x_2, \ldots, x_M, \Phi) \tag{4}$$

where y denotes the output results of the model, and Φ represents the set of parameters of the inference process.

Problem 3: How can the tunnel squeezing prediction model be optimized to reduce the impact of limitations in expert knowledge? The optimization process can be illustrated as follows:

$$\Phi_{\text{best}} = \text{op}(\Phi) \tag{5}$$

where Φ represents parameters during the optimization process. Φ_{best} represents the optimized parameters.

III. H-RF-BRB TUNNEL SQUEEZING PREDICTION MODEL

This section defines the modeling approach for the H-RF-BRB tunnel squeezing prediction model, by analyzing the problems discussed above. Section III-A describes the model's basic structure. Section III-B utilizes the RF algorithm to select suitable attributes for the H-RF-BRB tunnel squeezing prediction model. Section III-C determines referential points of the tunnel squeezing prediction model. Section III-D explains the inference process of the model. Section III-E details the model optimization process. Section III-F summarizes Sections III-A to III-E and outlines the entire process of constructing the H-RF-BRB tunnel squeezing prediction model.

A. THE BASIC STRUCTURE OF THE H-RF-BRB TUNNEL SQUEEZING PREDICTION MODEL

BRB is composed of a series of belief rules, and the k_{th} IF-THEN belief rule is expressed as follows:

$$\begin{aligned} R_k: \quad & \text{IF } x_1 \text{ is } A_1^k \wedge x_2 \text{ is } A_2^k \wedge \ldots \wedge x_M \text{ is } A_M^k \\ & \text{Then } y \text{ is } \{(D_1, \beta_{1,k}), \ldots, (D_N, \beta_{N,k})\} \\ & \text{with rule weight } \theta_k \\ & \text{with attribute weights } \delta_1, \delta_2, \ldots, \delta_M \end{aligned} \tag{6}$$

where x_i represents the i_{th} input attribute of samples, A_i^k refers to the referential points of i_{th} attribute, and $\beta_{j,k}$ represents the belief degree of the j_{th} result D_j for the k_{th} rule.

Based on BRB, the hierarchical BRB structure is composed of several sub-BRBs. Each BBR uses different attributes based on the different tasks. This structure can well address the rule explosion issue when excessive input attributes are used in BRB model [21]. The H-RF-BRB tunnel squeezing prediction model is structured into two distinct layers. The main BRB in the first layer is used for approximate classification. It is designed to send samples to the appropriate sub-BRB based on their utility outputs. In the second layer, each sub-BRB distinguishes between two adjacent categories, further accurately classifying the samples received from the main BRB. By decomposing the complex task into simpler binary decisions, the model achieves greater accuracy and reliability. The comprehensive structure of the H-RF-BRB tunnel squeezing prediction model is depicted in Figure 1.

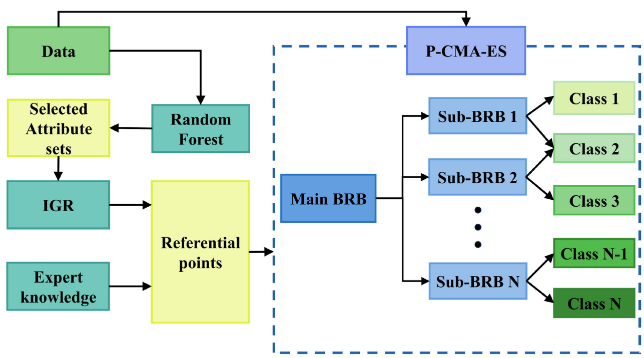

FIGURE 1. Structure of the H-RF-BRB tunnel squeezing prediction model.

B. ATTRIBUTE SELECTION FOR THE H-RF-BRB TUNNEL SQUEEZING PREDICTION MODEL

The RF attributes importance analysis method is used for attribute selection in this paper. RF, an ensemble learning technique, operates by constructing multiple decision trees and combining their outputs to generate the final estimation value. This method offers reasonable computational costs and ease of interpretation. If there are C attributes $X_1, X_2, \ldots, X_C$, the detailed steps to calculate the importance of each attribute X_j are as follows:

Step 1: Using the bootstrap method, K samples are randomly extracted from the dataset and selected as the decision tree's root nodes.

Step 2: From the C attributes, m attributes ($m \ll C$) are randomly extracted. One of these m attributes is chosen as the split attribute of the node using the Gini-coefficient gain method. The Gini-coefficient gain method can be represented as follows:

$$\Delta I^G = I^G(n_q) - q_l * I^G(n_l) - q_r \times I^G(n_r) \tag{7}$$

where $I^G(n) = 1 - \sum_{s=1}^{|s|} \cdot q_c$ is the proportion of class c samples in node N, and q_s^2 is the Gini index o f node N. These steps are repeated to build K decision trees to form a random forest.

Step 3: Currently, the out-of-bag (OOB) data error method is commonly employed to calculate attribute importance. The OOB data error is obtained using the corresponding OOB data and is denoted as err_r^{OOB1}. The OOB data error is recalculated after randomly introducing noise interference to attribute X_i in all the OOB data samples, which is represented as $err_{r,i}^{OOB2}$. The importance of attribute X_i for the K trees is shown as:

$$V_i = \frac{1}{K} \sum_{r=1}^{R} \left(err_r^{OOB1} - err_{r,i}^{OOB2} \right) \tag{8}$$

If noise is randomly added to an attribute. In that case, the accuracy of the OOB data is greatly reduced, indicating that this attribute significantly influences the classification results of the sample and is of high importance. The top two most important attributes are used to construct each BRB classifier.

C. REFERENTIAL POINTS DETERMINATION FOR THE H-RF-BRB TUNNEL SQUEEZING PREDICTION MODEL

Referential points are the foundation of constructing the H-RF-BRB tunnel squeezing prediction model [22], [23]. Generally, these points are provided by experts. However, due to the complex mechanism involved in tunnel squeezing, the referential points provided by experts are limited. The quantity and quality of these points significantly influence the model's accuracy. Consequently, this paper integrates expert knowledge and the IGR to determine the referential points.

It is well known that, by using the IGR, several decision variables are sequentially selected in C4.5 for decision tree building, effectively mitigating the influence of sample size across different categories. However, the referential points generated by the IGR do not include boundary points. Lack of boundary points can disrupt the completeness of the BRB [24]. This lack of boundary points may result in the input data not belonging to any referential points, making it impossible to activate any rules. To address this issue, this paper integrates the IGR algorithm and expert knowledge to determine referential points. First, the referential point set is determined using the IGR. Then, experts add boundary points and significant points to this referential point set. The detailed steps of this integrated approach are outlined below:

Step 1: Discretize each attribute to obtain the corresponding discrete values [25], denoted as $S = \{a_i^n \mid 1 \le i \le m_n,\ 1 \le n \le N\}$. N represents the quantity of attributes and m_n represents the quantity of discrete values for the n_{th} attribute.

Step 2: Divide the sample set into subsets, using the discrete value a_j^l in S, denoted as $\{D^v \mid v \in \{1, 2\}\}$. D^1 includes only data where the l_{th} attribute value is less than a_j^l, while D^2 contains the residual data. The corresponding IGR is calculated as follows:

$$\begin{aligned}
IGR(D, a_j^l) &= \frac{IG(D, a_j^l)}{H(a_j^l)} \\
H(a_j^l) &= -\sum_{v=1}^{2} \frac{|D^v| \log_2 \left(\frac{|D^v|}{|D|} \right)}{|D|} \\
IG(D, a_j^l) &= Ent(D) - \sum_{v=1}^{2} \frac{|D^v|\, Ent(D^v)}{|D|} \\
Ent(D) &= \sum_{n=1}^{N} \frac{|C_n|}{|D|} \log_2(p_n)
\end{aligned} \tag{9}$$

where $H(a_j^l)$ represents the information entropy computed with the value a_j^l, $IG(D, a_j^l)$ denotes the information gain, $|\cdot|$ indicates the number of sample sets.

Step 3: The referential point is determined by the highest IGR value.

Step 4: Replacing D with subset D^v that is obtained with a_j^l and repeating Steps 2 and 3, until it is no longer possible to divide D into two nonempty subsets.

Step 5: Reduced-error pruning technology [26] is employed to eliminate the over-subdivided branches to improve the generalization ability of referential points. This is achieved by systematically evaluating the impact of each branch on the model's overall accuracy. Branches that do not contribute significantly to improving accuracy are pruned. As such, a group of referential points is generated.

Step 6: Based on expert knowledge, boundary points and other significant points are added to the set of referential points. These points are derived from empirical data and expert observations to ensure they are accurate and meaningful. For example, the IGR provides an initial set of referential points: {a1, a2}. Experts then add boundary points and significant points to this set, resulting in the final referential point set of {b1, a1, c1, a2, b2}. Here, {b1, b2} are boundary points, and {c1} is regarded as a significant point by experts.

D. THE INFERENCE PROCESS OF THE TUNNEL SQUEEZING PREDICTION MODEL

The evidential reasoning approach is used to implement evidence fusion, which is proposed based on the decision theory and the Dempster-Shafer(D-S) theory of evidence [27], [28]. This approach is particularly powerful for handling and fusing uncertain and nonlinear information, which is often encountered in complex predictive models. The following steps are utilized for the model inference:

Step 1: The degree to which the input attributes match the belief rule can be determined as follows:

$$\alpha_i^t = \begin{cases} \dfrac{H_i^{j+1} - x_i}{H_i^{j+1} - H_i^j}, & t = j, H_i^j \le x_i \le H_i^{j+1} \\ 1 - \alpha_i^t, & t = j+1 \\ 0, & t = 1, 2, \ldots, L, t \ne j, j+1 \end{cases} \tag{10}$$

where α_i^t is the matching degree of the i_{th} attribute to the t_{th} rule, x_i denotes the input value of the i_{th}, and H_i^j is the referential point of the i_{th} attribute.

Step 2: The rule activation weight can be calculated using the following formula:

$$\omega_t = \frac{\theta_t \prod_{i=1}^{M} (\alpha_i^t)^{\overline{\delta_i}}}{\sum_{j=1}^{P} \theta_j \prod_{i=1}^{M} (\alpha_i^j)^{\overline{\delta_i}}} \tag{11}$$

where ω_i is the activation weight for the t_{th} rule.

Step 3: The activated rules are integrated using the ER parsing algorithm to produce the result. The detailed process is shown below:

$$\beta_k = \frac{\prod_{t=1}^{l} (\omega_t \beta_{k,t} + (1 - \omega_t) \sum_{k=1}^{N} \beta_{k,t})}{\mu - \prod_{t=1}^{L} (1 - \omega_t)} - \frac{\prod_{t=1}^{L} \left(1 - \omega_t \sum_{k=1}^{N} \beta_{k,t}\right)}{\mu - \prod_{t=1}^{L} (1 - \omega_t)} \tag{12}$$

$$\mu = \sum_{k=1}^{N} \prod_{t=1}^{L} \left(\omega_t \beta_{k,t} + (1 - \omega_t) \sum_{k=1}^{N} \beta_{k,t} \right) - (N-1) \prod_{t=1}^{L} \left(1 - \omega_t \sum_{k=1}^{N} \beta_{k,t} \right) \tag{13}$$

where β_k represents the belief degree of the k_{th} squeezing degree.

Step 4: The final output of the model is as follows:

$$Z = \sum_{i=1}^{N} u(D_n) \beta_i \tag{14}$$

where $u(D_n)$ denotes the utility of D_n, and Z represents the actual output results.

E. THE OPTIMIZATION PROCESS OF THE H-RF-BRB TUNNEL SQUEEZING PREDICTION MODEL

Due to its advantages of high convergence speed and high accuracy, the projection covariance matrix adaptive evolution strategy (P-CMA-ES) algorithm is employed to optimize the H-RF-BRB tunnel squeezing prediction model [24]. The P-CMA-ES algorithm generates solutions within the scope of the allowable region and conforms to the specified equality constraints. Adherence to these constraints is essential for maintaining the validity and applicability of the results. The optimization objectives and constraints for the H-RF-BRB tunnel squeezing prediction model are represented as follows:

$$Loss_{\mathrm{main}} = \frac{1}{N} \sum_i (y_i' - y_i)^2 \times Z \tag{15}$$

$$Z = \begin{cases} 0, & |y_i' - y_i| \le 1 \\ 1, & |y_i' - y_i| > 1 \end{cases} \tag{16}$$

$$Loss_{sub} = \frac{1}{N} \sum_i (y_i' - y_i)^2 \tag{17}$$

$$\begin{aligned} &\min Loss(\theta_k, \beta_{k,t}, \delta_i) \\ &s.t. \quad \sum_{k=1}^{N} \beta_{k,t} = 1 \quad t = 1, 2, \ldots, W \\ &\quad 0 \le \theta_t \le 1 \quad t = 1, 2, \ldots, L \\ &\quad 0 \le \delta_i \le 1 \quad i = 1, 2, \ldots, T \\ &\quad 0 \le \beta_{k,t} \le 1 \quad n = 1, 2, \ldots, N \quad k = 1, 2, \ldots, L \end{aligned} \tag{18}$$

where y_i represents the actual result, y_i' represents the predictive result, θ_t represents the weight of the t_{th} rule is between 0 and 1.

The procedure of the P-CMA-ES algorithm is illustrated in Figure 2, and the detailed steps are outlined below:

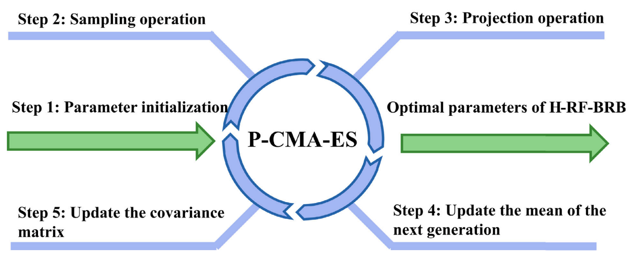

FIGURE 2. Optimization process of the P-CMA-ES algorithm.

Step 1: Parameters initialization. The set of parameters needed to be optimized can be expressed as follows:

$$\Omega^0 = \{\theta_1, \ldots, \theta_L, \delta_1, \ldots, \delta_T, \beta_{1,1}, \ldots, \beta_{N,L}\} \tag{19}$$

Step 2: Sampling operation. The output of each generation can be generated through the sampling operation shown by the following formula:

$$\Omega_i^{(d+1)} \sim \omega^d + \epsilon^d N(0, C^d), \quad i = 1, 2, \ldots, \lambda \tag{20}$$

where Ω_i^{d+1} denotes the solution of the i_{th} individual in the $d+1_{th}$ generation, while ω^d represents the mean of the d_{th} generation search distribution, and ϵ^d represents the step size of the d_{th} generation, respectively.

Step 3: Projection operation. Project the potential solution into the allowable region to adhere to the specified equality constraints. This process can be described as follows:

$$\Omega_i^{(d+1)}(1 + n_e \times (k-1) : n_e \times k)$$
$$= \Omega_i^{(d+1)}(1 + n_e \times (k-1) : n_e \times k)$$
$$- A_e^T \times (A_e \times A_e^T)^{-1}$$
$$\times \Omega_i^{(d+1)}(1 + n_e \times (k-1) : n_e \times k) \times A_e \quad (21)$$
$$A_e \Omega_i^d (1 + n_e \times (k-1) : n_e \times k) = 1 \quad (22)$$

where equation (22) is the hyperplane expression, n_e represents the number of variables of the equality constraint in the solution, A_e represents the parameter vector, and k denotes the number of equality constraints.

Step 4: Update the mean of the next generation. The mean of the next generation can be calculated by the below formula:

$$\omega^{d+1} = \sum_{i=1}^{\tau} h_i \Omega_{i:\lambda}^{d+1} \quad (23)$$

where h_i represents the weighting factor. τ represents the progeny population size.

Step 5: Update the covariance matrix. The covariance matrix is described as follows:

$$C^{(d+1)} = (1 - c_1 - c_2)C^d + c_1 P_c^{d+1} (P_c^{d+1})^T$$
$$+ c_2 \sum_{i=1}^{s} h_i \left(\frac{B_{i:\lambda}^{d+1} - \varphi^d}{\rho^d} \right) \left(\frac{B_{i:\lambda}^{d+1} - \varphi^d}{\rho^d} \right)^T \quad (24)$$

where $K_{i:\lambda}^{d+1}$ represents the i_{th} parameter vector of vector λ in the $(d+1)_{th}$ generation, c_1 and c_2 represent the learning rate.

F. THE DEVELOPMENT PROCESS OF THE H-RF-BRB TUNNEL SQUEEZING PREDICTION MODEL

Based on Section III-A to Section III-E, the modeling process of the H-RF-BRB tunnel squeezing prediction model is illustrated in Figure 3. The process is outlined in detail below:

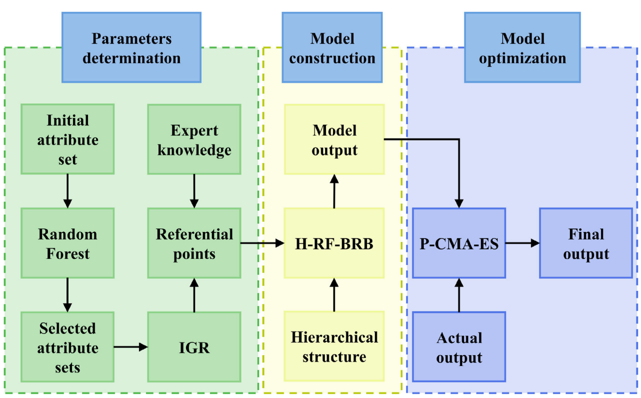

FIGURE 3. Flowchart of the modeling process.

Step 1: Parameters determination.

The main BRB and sub-BRBs utilize the RF algorithm to select two attributes for each BRB in Section III-B. The appropriate referential points are determined by using expert knowledge and the IGR, as proposed in Section III-C.

Step 2: Model construction.

The H-RF-BRB tunnel squeezing prediction model is constructed using the referential point set. The modeling process follows the overall structure defined in Section III-A. The inference process is described in Section III-D.

Step 3: Model optimization.

The P-CMA-ES algorithm is used to improve the accuracy of the H-RF-BRB tunnel squeezing prediction model. The details and steps are shown in Section III-E.

IV. CASE STUDY

A. DATASET

Through literature research and data collection, the paper collected 139 samples about tunnel squeezing [9], [16]. Among the 139 samples, 20% were tunnels with nonsqueezing deformation, 27% were slightly squeezing, 23% were moderately squeezing, 19% were severely squeezing, and 11% were extremely heavily squeezing. In this paper, four key attributes were used as input attributes to predict tunnel squeezing. These attributes are Strength Stress Ratio (SSR), Rock Mass Quality Index in the BQ system ([BQ]), Tunnel diameter (D), and Support Stiffness (K). The selection of these attributes was based on their relevance and impact on tunnel squeezing. The experimental development environment includes Windows 11 and a 7_{th} Gen Intel (R) Core (TM) i7-8750H processor, and the experiment was conducted using Matlab.

B. H-RF-BRB TUNNEL SQUEEZING PREDICTION MODEL CONSTRUCTION

First, the H-RF-BRB tunnel squeezing prediction model is structured into two layers, comprising five belief rule bases. The first layer comprises a main BRB. The second layer comprises four sub-BRBs. The specific structure of the model is illustrated in Figure 4.

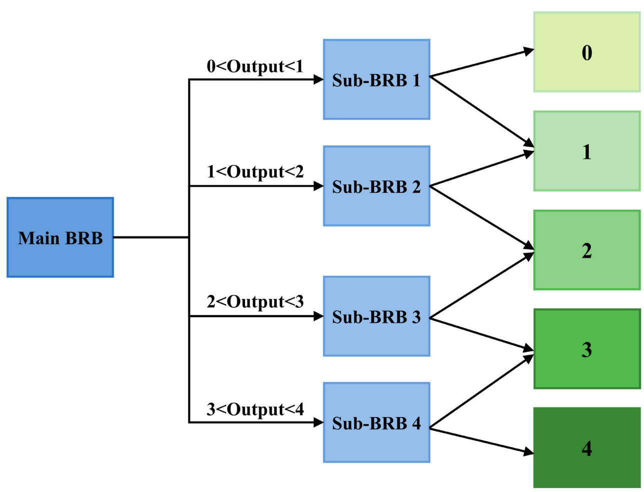

FIGURE 4. The herarchical structure of tunnel squeezing prediction model.

TABLE 1. Selected attributes of each BRB model.

BRB model	Selected attribute 1	Selected attribute 2
Main BRB	SSR	[BQ]
sub-BRB 1	SSR	D
sub-BRB 2	SSR	[BQ]
sub-BRB 3	SSR	[BQ]
sub-BRB 4	[BQ]	K

TABLE 2. Main BRB referential points for input attributes.

Attribute	L	M	H	VH
SSR	0.008	0.21	0.43	1.55
$[BQ]$	70	111	205	441

TABLE 3. Sub-BRB 1 referential points for input attributes.

Attribute	L	M	H
SSR	0.008	0.43	1.55
D	4	8	14

TABLE 4. Sub-BRB 2 referential points for input attributes.

Attribute	L	M	H
SSR	0.008	0.23	1.55
$[BQ]$	70	205	441

TABLE 5. Sub-BRB 3 referential points for input attributes.

Attribute	L	M	H
SSR	0.008	0.18	1.55
$[BQ]$	70	205	441

TABLE 6. Sub-BRB 4 referential points for input attributes.

Attribute	L	M	H
$[BQ]$	70	106	441
K	2.98	1000	1980

The RF attribute selection method selects two critical attributes for each BRB, which can effectively reduce the number of rules. Table 1 shows the selected attributes for each BRB model. The referential points determined by combining expert knowledge and the IGR are shown in Tables 2 to 6. Due to the distinct tasks of each sub-BRB, the referential points for each sub-BRB are different. In Tables 2 to 6, L, M, H, and VH represent low, medium, high, and very high, respectively. The referential points of the output results are shown in Table 7. In the table, N, SI, M, SE, and E represent no squeezing, slight squeezing, moderate squeezing, severe squeezing, and extremely heavy squeezing, respectively.

TABLE 7. Referential points for output results.

squeezing degree	N	SI	M	SE	E
Referential point	0	1	2	3	4

TABLE 8. Main BRB optimized parameters.

$x_1 \wedge x_2$	Rule weights	Distribution of output
	θ_k	$\{\beta_1^k, \beta_2^k, \beta_3^k, \beta_4^k, \beta_5^k\}$
L ∧ L	0.5201	{0.1143,0.1268,0.0699,0.05,0.639}
L ∧ M	0.8404	{0.158,0.0029,0.1067,0.1389,0.5935}
L ∧ H	0.3881	{0.2506,0.0303,0.2127,0.1821,0.3243}
L ∧ VH	0.2955	{0.0636,0.058,0.042,0.3624,0.474}
M ∧ L	0.4713	{0.0426,0.061,0.0597,0.205,0.6326}
M ∧ M	0.6205	{0.1595,0.0219,0.0558,0.2082,0.5546}
M ∧ H	0.4563	{0.0735,0.0299,0.1729,0.4668,0.2569}
M ∧ VH	0.4711	{0.5457,0.0475,0.1721,0.1238,0.1109}
H ∧ L	0.9503	{0.2377,0.1052,0.1335,0.4942,0.0294}
H ∧ M	0.4209	{0.0889,0.1786,0.1629,0.2168,0.3528}
H ∧ H	0.9245	{0.7667,0.0523,0.0733,0.0848,0.0229}
H ∧ VH	0.2393	{0.269,0.2033,0.173,0.0103,0.3444}
VH ∧ L	0.2763	{0.1294,0.1258,0.3466,0.1181,0.2801}
VH ∧ M	0.8882	{0.0519,0.2619,0.3104,0.3391,0.0367}
VH ∧ H	0.0105	{0.2544,0.0702,0.2299,0.4238,0.0217}
VH ∧ VH	0.1615	{0.3232,0.1784,0.0078,0.3532,0.1374}

C. EXPERIMENTAL CASE ANALYSIS

The H-RF-BRB tunnel squeezing prediction model was optimized using the P-CMA-ES algorithm, as detailed in Section III-E. The main BRB was used as a representative example to illustrate the optimization process. The optimized parameters for the main BRB are shown in Table 8.

To validate the effective improvement of Section III-C on the accuracy of the main BRB, this paper designed a comparative experiment using two different sets of referential points. A is the set of referential points generated by the method described in Section III-C. The specific points of A are listed in Table 2. B is the other set of referential points in the comparative experiment, defined as follows:

$$B : [0.008, 0.525, 1.043, 1.55], [70, 193.8, 317.6, 441]$$

Figure 5 shows the misclassification rate of the main BRB using two different sets of referential points, A and B. The lower misclassification rate indicates that the referential points are better at guiding the main BRB to send samples to the correct sub-BRB, thus improving the overall model accuracy. In 20 comparative experiments, A consistently achieved a lower misclassification rate, indicating that the main BRB using A was able to direct more samples to the correct sub-BRB. Figure 6 presents the detailed classification results of the main BRB using A and B in the 15th experiment.

Each circle in Figure 6 represents a sample. The circles below the red line indicate samples sent from the main

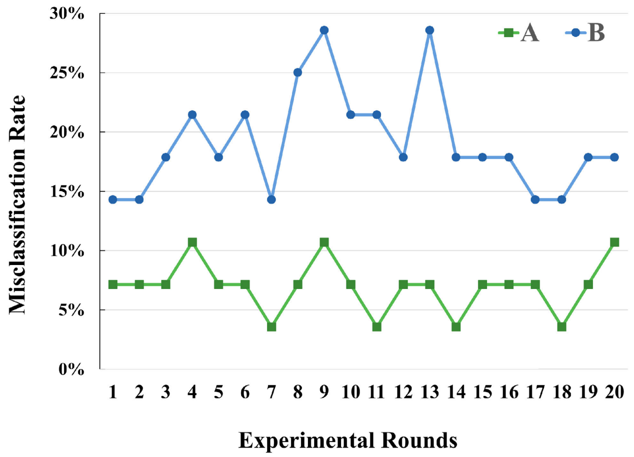

FIGURE 5. Misclassification rate obtained by different referential points on 20 repeats.

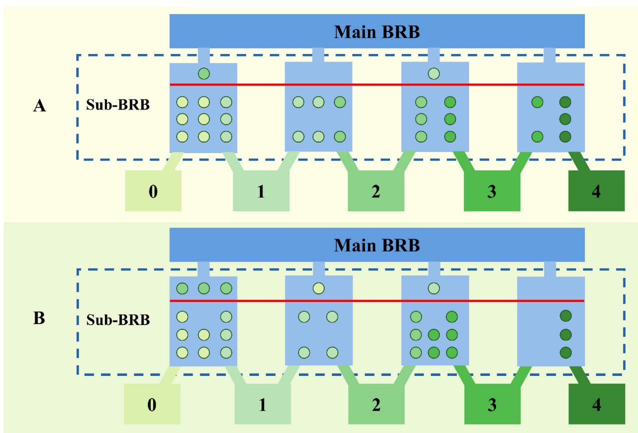

FIGURE 6. Classification results of the main BRB based on different referential points.

BRB to the correct sub-BRB, where they have the potential to be classified correctly. In contrast, the circles above the red line represent samples sent to the wrong sub-BRB by the main BRB, which will never be correctly classified in that sub-BRB. Figure 6 shows that the main BRB using A has only two misclassified samples, while the main BRB using B has five misclassified samples. Combining the results from Figure 5 and Figure 6, using referential points determined by combining expert knowledge and IGR effectively improves the classification accuracy of the main BRB, thereby enhancing the overall model accuracy.

In this paper, the five-fold cross-validation approach was employed to assess the H-RF-BRB tunnel squeezing prediction model performance. First, the original dataset of 139 samples was split into five groups. Second, four of the five groups were utilized to train the model, while the remaining group was used to test the model. The training and testing processes were repeated five times, ensuring that each sample in the dataset was predicted once. Cross-validation accuracy was defined as the proportion of correctly classified samples. The confusion matrix is shown in Figure 7. After five-fold cross-validation, the model's average accuracy is 87.77%. This rigorous cross-validation process ensures the robustness and reliability of the model.

Figure 8 presents the experimental results of the Group No.1 test set. The accuracy achieved was approximately 92.9%. Notably, the model achieved a prediction accuracy of 100% for samples categorized as no squeezing, slight squeezing, and severe squeezing.

D. ABLATION EXPERIMENT

To validate the effectiveness of each module in the proposed H-RF-BRB model for tunnel squeezing prediction, an ablation experiment was conducted using the same training and testing datasets. The basic BRB model was established as the baseline. Subsequently, three modules were added sequentially: a hierarchical structure module, an attribute selection module based on RF, and a referential points determination module based on expert knowledge and the IGR.

The hierarchical structure module employs a divide-and-conquer strategy to decompose the complex multi-class classification task into several simpler binary classification tasks. By reducing the problem size, this approach simplifies the model training process, thereby enhancing the overall efficiency and accuracy of the model. In the attribute selection module, the RF algorithm is employed to assess the importance of attributes and select the two most relevant attributes for each BRB. This method reduces the number of rules and avoids performance degradation caused by an excessively large rule base. The referential points determination module combines expert knowledge and the IGR to overcome the limitations of relying on single expert knowledge. Referential points can be determined more accurately, significantly enhancing the model's accuracy.

Subsequently, four models are designed to analyze the effectiveness of each module. The specific settings of these models were as follows:

- Model 1: This model served as the baseline, which was the basic BRB model.
- Model 2: This model added the hierarchical structure module into Model 1.
- Model 3: This model incorporated the attribute selection module into Model 2.
- Model 4: This model introduced the referential points determination module into Model 3. It also represents the H-RF-BRB tunnel squeezing prediction model proposed in this paper.

In Figure 9, it is evident that each added module contributes effectively to model performance. Model 2, compared to Model 1, achieves higher accuracy and fewer rules by adding a hierarchical structure module. Model 3, compared to Model 2, not only achieves higher accuracy but also significantly reduces the number of rules by adding the attribute selection module. Model 4, compared to Model 3, achieves higher accuracy by adding the referential points selection

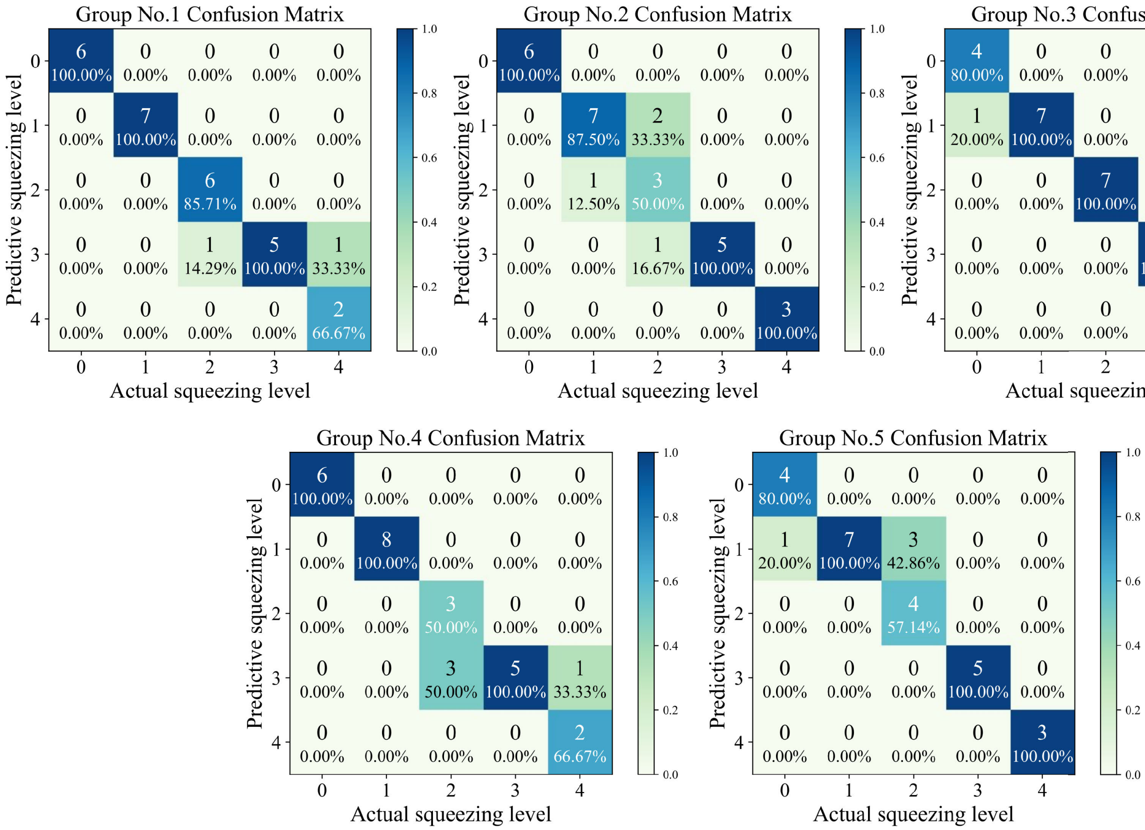

FIGURE 7. Five-fold cross-validation experiment results.

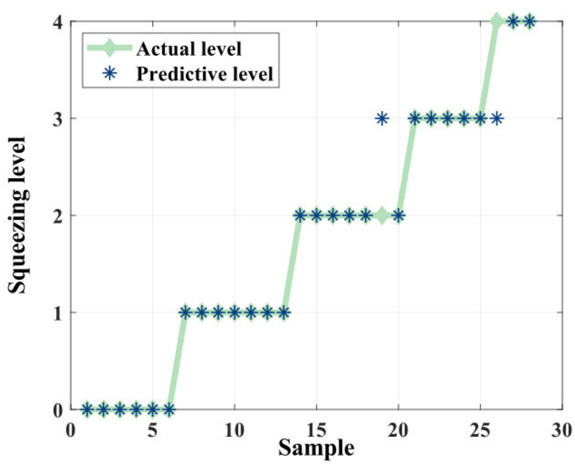

FIGURE 8. Predictive outcomes for Group No.1 of the H-RF-BRB tunnel squeezing prediction model.

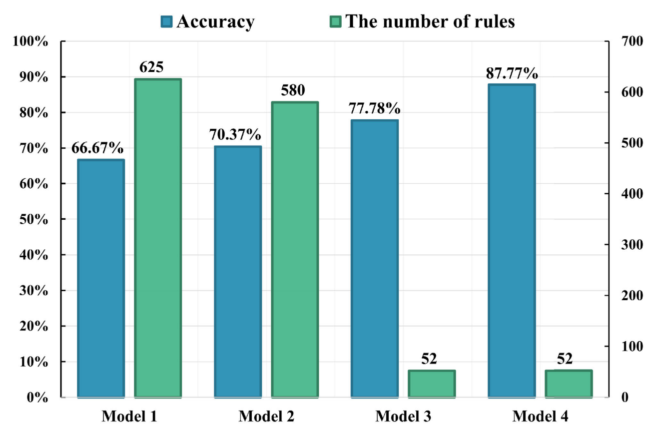

FIGURE 9. Ablation experiment results.

module. Overall, each module added to the model improves its performance without redundancy or deterioration in model performance.

E. COMPARISON TEST

To prove the superiority of the proposed H-RF-BRB tunnel squeezing prediction model, Interval BRB [29], BPNN [30], BO-XGBoost [31], KNN [32], and RF [33] were selected for comparison. All models were validated using the five-fold cross-validation approach to ensure a comprehensive evaluation. The experimental results are presented in Figure 10. To provide a clearer visual representation of the data in Figure 10, a bar chart comparing the average accuracy of each model based on five-fold cross-validation is shown in Figure 11.

As illustrated in Figure 11, the average accuracy of the H-RF-BRB tunnel squeezing prediction model is 87.77%, which is significantly higher than that of the other models.

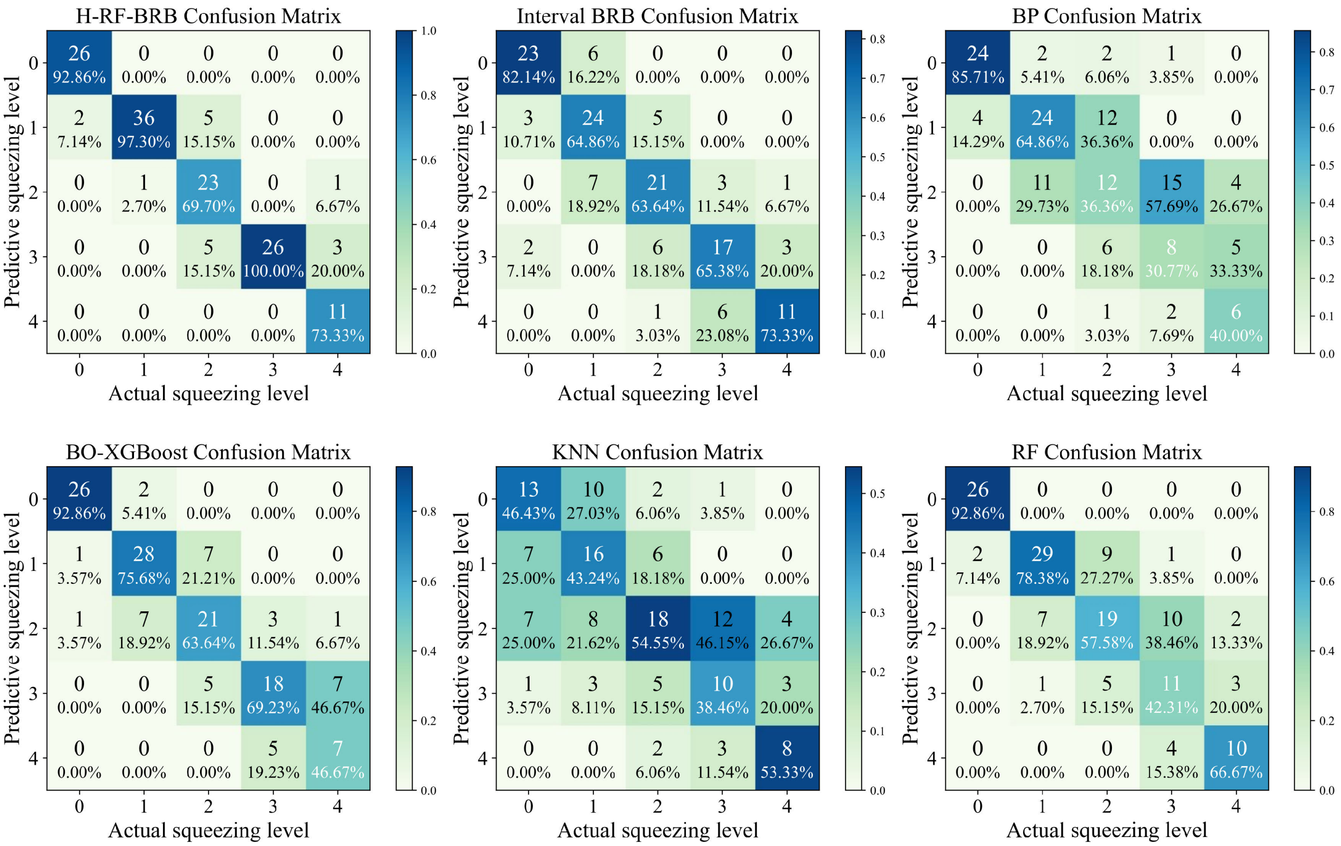

FIGURE 10. Comparative results of different models.

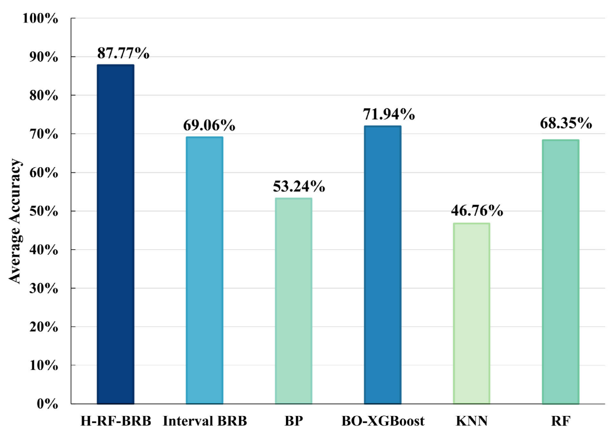

FIGURE 11. Model performance comparison.

This indicates that the H-RF-BRB tunnel squeezing prediction model has a significant advantage. In contrast, the KNN model performs poorly. The average accuracy of the KNN model is only 46.76%. Although these models show some predictive capability, none match the accuracy of the H-RF-BRB tunnel squeezing prediction model. This indicates its superior performance in predicting tunnel squeezing.

Although the H-RF-BRB tunnel squeezing model has demonstrated excellent performance in experiments, deploying it in the field may encounter issues such as inaccurate data collection, delays in real-time predictions, and incompatibility with existing construction monitoring systems. To address these challenges, we recommend establishing a data validation mechanism to ensure data accuracy, developing efficient data processing algorithms to enable rapid response to real-time data, and using standardized data exchange formats and interface protocols to achieve effective integration with current construction monitoring systems.

Furthermore, when developing the tunnel squeezing prediction model, it is essential to analyze its complexity to ensure efficiency and practicality. This paper compares the complexity of six different models used in the experiment. The complexity analysis focuses on two main aspects: training complexity and spatial complexity. Training complexity is defined as a measure of the algorithm's performance speed relative to the input scale. It evaluates how quickly an algorithm can process data and converge to an optimal solution as the input data size increases. The memory needed to perform a machine learning algorithm is referred to as spatial complexity. The analysis results are shown in Table 9. In this table, d represents the number of parameters that need to be optimized, λ represents the population size, and T represents the number of iterations. a signifies the number of training samples in the experiment. *rule* denotes the number

TABLE 9. Computation complexity analysis.

Model	Complexity of training	Complexity of space
H-RF-BRB	$O(d^2 \cdot \lambda \cdot T)$	$O(rule)$
Interval BRB	$O(d^2 \cdot \lambda \cdot T)$	$O(rule)$
BPNN	$O(a \cdot p)$	$O(p)$
BO-XGBoost	$O(T \cdot a \cdot p \cdot \log(a)$	$O(q \cdot s)$
KNN	$O(k \cdot n \cdot p)$	$O(a \cdot p)$
RF	$O(a \cdot \log(a) \cdot p \cdot s)$	$O(q \cdot s)$

of rules in the model. q denotes the number of nodes in the decision tree for models that use a decision tree. p indicates the data dimension. s represents the quantity of decision trees used in the RF. k refers to the quantity of nearest neighbors.

V. CONCLUSION

In this paper, a H-RF-BRB tunnel squeezing prediction model is proposed. One significant problem addressed by the model is the combinatorial rule explosion, which is effectively simplified through a hierarchical structure and RF attribute selection method. Another problem is that to overcome the limitations of single expert knowledge. By integrating expert knowledge with the IGR to determine referential points, the main BRB can send samples to the correct sub-BRB, thereby improving the accuracy of the tunnel squeezing prediction model. The five fold cross validation experiment with other models further verify the superiority of the model.

The H-RF-BRB tunnel squeezing prediction model discussed in this paper demonstrates exceptional performance. It benefits from the integration of expert knowledge and quantitative information achieving superior results with small sample datasets. Therefore, this method can be widely used in fields with small sample datasets. In the future, we will also explore the potential applications of this model in other fields. As the current dataset we used is small-scale, we plan to collect more tunnel squeezing samples to train the model to improve its accuracy.

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