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Rock-Burst Occurrence Prediction Based on Optimized Naïve Bayes Models

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ABSTRACT Rock-burst is a common failure in hard rock related projects in civil and mining construction and therefore, proper classification and prediction of this phenomenon is of interest. This research presents the development of optimized naïve Bayes models, in predicting rock-burst failures in underground projects. The naïve Bayes models were optimized using four weight optimization techniques including forward, backward, particle swarm optimization, and evolutionary. An evolutionary random forest model was developed to identify the most significant input parameters. The maximum tangential stress, elastic energy index, and uniaxial tensile stress were then selected by the feature selection technique (i.e., evolutionary random forest) to develop the optimized naïve Bayes models. The performance of the models was assessed using various criteria as well as a simple ranking system. The results of this research showed that particle swarm optimization was the most effective technique in improving the accuracy of the naïve Bayes model for rock-burst prediction (cumulative ranking = 21), while the backward technique was the worst weight optimization technique (cumulative ranking = 11). All the optimized naïve Bayes models identified the maximum tangential stress as the most significant parameter in predicting rock-burst failures. The results of this research demonstrate that particle swarm optimization technique may improve the accuracy of naïve Bayes algorithms in predicting rock-burst occurrence.

INDEX TERMS Evolutionary random forest, naïve Bayes algorithm, particle swarm optimization, rock-burst occurrence, weight optimization.

I. INTRODUCTION

Rock-burst (RB) is an extreme and unexpected failure of rock caused by the intense release of elastic energy accrued in the rock mass during deep underground activities [1]–[4]. RB is typically associated with several destructive events, including slabbing and spalling. These can lead to severe injuries, damage to supporting systems and equipment, and significant delays in construction activities [5]–[7].

The location of rock burst (RB) is mostly near the newly excavated working face, and some of them are far away from the newly excavated working face. The common rock burst parts are arch or arch waist of tunnel in high stress concentration area. The RB cases can be occurred subsequently after excavation, mostly in 2-3 hours after blasting, or within 24 hours after blasting [1], [8], [9].

Rock-burst (RB) failures are typically classified into type I and II. The difference between these two RB types is in the damage mechanism and the location of the source mechanism. While type I occurs in the proximity of freshly excavated underground openings, type II occurs at a distance from excavation activities and involves the activation of geological discontinuities [10]. It is worth mentioning that type I is directly associated with the excavation process and is known as a ''strain burst'', as it is triggered due to the high stress concentration near the opening of the excavation. Type II failures incur damages of underground opening due to the rock mass displacements induced by the transmitted shock waves [10]. Typically, type II RB failures are more significant than type I failures, especially if more significant volumes of

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rock mass are involved, and more considerable stress arises far from the excavation [8].

It has been shown that RB failures are strongly influenced by seismic activities and it is therefore important to identify and localize seismic events in the assessment of the likelihood of occurrence of RB [11], [12]. During the past years, a number of experimental and theoretical studies were conducted on several aspects of RB, including control, mechanism, and prediction [13], [14]. However, according to He *et al.* [15], RB is still considered a complicated and unresolved issue in deep mining. Several classifications of RB are available based on the potential severity, potential damage, failure pattern, as well as scale. The severity of RB failures are typically assessed based on the failure depth [16], [17]. Damage assessment, is typically performed using four classifications including none, light, moderate, and strong. RB failures may be classified as cave collapse, slabby spalling, collapse, bending failure, as well as dome failure. Finally, the scale is classified as sparse, for RB lengths <10 m, large for RB lengths in the range of (10-20 m) and continuous, for RB lengths >20 mm.

Sousa and Einstein [18] identified several factors that influence the occurrence of RB i.e., the stress state, geological conditions, mechanical properties of the rock, and construction techniques. Considering the large number of influential factors and the complicated character of the RB, its control and prediction are extremely challenging tasks [8]. Both short-term and long-term predictions of the occurrence of RB are possible. For example, for short-term predictions, the precise location and occurrence of RB can be predicted using a micro-seismic monitoring system and acoustic emission, which are the main in situ measurements/techniques. Despite their extensive use, both of these techniques suffer from serious drawbacks in terms of high costs and time [1], [8]. Concerning the long-term prediction of rock-burst, several techniques can be used, including the conventional criteria, data mining techniques, as well as numerical models. Several studies [2], [5] have suggested that the long-term prediction techniques perform better than the short-term, especially for the initial stage of a project. These techniques allow engineers to select the most suitable excavation method.

In general the definition of RB prediction varies significantly [19]. The first term is "rock-burst liability", which is also known as "rock-burst proneness". This term refers to the activeness and intensity of the occurrence of RB. The second term is "rock-burst hazard", which refers to an initial evaluation of the probability of occurrence of an RB and the probable hazards of RB in the engineering context. Finally, the term "rock-burst severity" denotes a primary observation of a previously occurred RB, which is also considered as the intensity/classification/ranking of the RB. According to Zhou *et al.* [1] and Pu *et al.* [20], several well-known RB indices have been established utilizing different strength parameters, as shown in Table 1. This table shows that a limited number of input parameters were considered using the usual criteria, and several parameters that may influence the RB were overlooked by these criteria. Table 1 shows the RB evaluation indices using both the rock-burst liability and the rock-burst hazard terminologies. The rock-burst severity, can be typically classified using various indices e.g., failure modes, mechanical aspects, level of damage, etc. Some researchers have proposed different classifications for the rock-burst severity. For example, Yian [21] presented four grades of RB classification ranging between weak, moderate, strong, and violent, Petukhov *et al.* [22] classified the RB into 3 or 5 different types and Russenes [23] introduced types 0 to 3 for rock-burst severity, with class 0 corresponding to the weakest RB and class 3 corresponding to the most serious failure. Different RB levels of minor, moderate, strong and severe were proposed by Zhou *et al.* [24].

Machine learning (ML) and soft computing (SC) are advanced computational methods, which identify complex correlations between numerous input and output variables [1], [9], [25]. These techniques are a branch of computational intelligence that employ a variety of statistical and optimization tools to learn from past examples and to then utilize that prior training to estimate novel trends. ML and SC methods have been widely employed in several research areas [26], [27], [36]–[45], [28], [46]–[55], [29], [56]–[65], [30], [66], [67], [31]–[35].

In terms of the applications of ML and SC in RB classification and prediction, the initial attempts were made by Feng and Wang [68], who established artificial neural networks (ANNs) for controlling and predicting the likelihood of RB. Several other studies [69]–[72] applied ML and SC techniques in the assessment of RB after the study by Feng and Wang [68]. Zhou *et al.* [1] introduced three hybrid support vector machine (SVM) models which were optimized using heuristic algorithms i.e., genetic algorithm, grid search method, and particle swarm optimization (PSO) for determining the RB. Another hybrid model of least squares SVM-PSO was developed by Wu *et al.* [73] to determine a non-linear relationship between the model input parameters and RB and to evaluate the risk associated with the RB. The risk level of RB was evaluated and predicted in the study conducted by Zhou *et al.* [74] using another model, which was a combination of the firefly algorithm and ANN. Zhou *et al.* [74] showed that their model could evaluate the risk level of the RB with a high degree of accuracy. In another research Pu *et al.* [75] investigated the likelihood of occurrence of RB in an igneous rock type (i.e., kimberlite) using a combination of principal component analysis and a fuzzy model and concluded that their proposed model could perform well in the field of RB occurrence.

All these researchers used some well-known ML techniques for predicting and classifying the likelihood of rock-burst, the researchers neglected some of effective ML techniques, such as Naïve Bayes (NB). The underlying assumption of the Naïve Bayes (NB) technique is that under a given set of classification characteristics, the attributes are independent of each other. In practice however, this independence assumption is not always satisfied [76]. Consequently, for NB classification deficiency, researchers improve

TABLE 1. Some of the indices to evaluate the RB together with their classifications.

Terminology	Index	Reference	Symbol	Description	Criterion /Classification
RBL	Strain energy storage index	Kidybiński [24]	W_{et}	It was developed for coal burst liability. Ratio of the elastic energy stored and the elastic energy dissipated in a uniaxial cyclic loading.	W_{et} less than 2: no RBL, $2 \leq W_{et} < 3.5$: weak RBL, $3.5 \leq W_{et} < 5$: moderate RBL, $W_{et} \geq 5$: strong RBL
	Strain energy density	Jaeger and Cook [25]	SED	$SED = \frac{\sigma_c^2}{E_s}$, where, σ_c is the uniaxial compressive strength of the rock sample and E_s is Young's modulus.	Miao et al. [26] proposed the following classifications: SED less than 40: low RBL, $40 \leq SED < 100$: moderate RBL, $100 \leq SED < 200$: strong RBL, $SED \geq 200$: violent RBL
	Rock brittleness index modified	Aubertin et al. [27]	BIM	It is referred to a ratio between the energy given by the entire area below the stress-strain curve and the elastic energy stored in rock sample.	BIM equal and more than 1.5: low RBL, $1.2 \leq BIM < 1.5$: moderate RBL, $1 \leq BIM < 1.2$: high RBL.
	Failure duration	Wu and Zhang [28]	D_t	After development for coal burst liability, it was generalized for different rock types. It is an index referring to dynamic rock failure time.	For coal: D_t more than 500 ms: no RBL, 50 ms $< D_t \leq$ 500 ms: moderate RBL, $D_t \leq$ 50 ms: strong RBL.
	Rock brittleness	Zhang et al. [29]	B	B is a ratio between uniaxial compressive strength and uniaxial tensile strength of rock sample.	B less than 15: no RBL, $15 \leq B < 18$: weak RBL, $18 \leq B < 22$: moderate RBL, B equal or more than 22: strong RBL.
	Rock failure energy	Richard [30]	B_{er}	B_{er} refers a ratio between the kinetic energy of a bursting rock fragment (when the rock sample is loading) and the stored maximum elastic strain energy (during the loading).	B_{er} less than 3.5: no RBL, $3.5 \leq B_{er} < 4.2$: weak RBL, $4.2 \leq B_{er} < 4.7$: moderate RBL, B_{er} equal and more than 4.7: strong RBL.
	Impact energy	Ran and Run-cang [31]	W_{ef}	This index is defined as a ratio between stored elastic strain energy at pre-peak and dissipated strain energy in the failure procedure.	W_{ef} less than 2: no RBL, $2 \leq W_{ef} < 3$: weak RBL, W_{ef} equal and more than 3: strong RBL.
RBH	Tangential stress	Russenes [22] and Wang and Park [32]	T_s	$T_s = \frac{\sigma_\theta}{\sigma_c}$, where, σ_θ is the tangential stress around the underground opening and σ_c is the uniaxial compressive strength of the rock sample.	T_s less than 0.3: no RBH, $0.3 \leq T_s < 0.5$: weak RBH, $0.5 \leq T_s < 0.7$: moderate RBH, T_s more than 0.7: violent RBH.
	Energy-based burst potential	Mitri et al. [33]	BPI	$BPI = \frac{ESR}{e_c} \times 100\%$, where, e_c refers to the area under the stress-strain curve up to the point of peak stress and ESR is defined as the total mining-induced strain energy stored in rock Mass.	There is no specific classification/ criterion for this index in literature.
	Strength-stress ratio	Turchaninov [34]	T_1	$T_1 = \frac{\sigma_{\theta max}+\sigma_L}{\sigma_c}$, where, σ_L represents the radial stress in disturbed zone, σ_c refers to the uniaxial compressive strength of the rock sample, and $\sigma_{\theta max}$ is the maximum tangential stress around an underground opening.	T_1 less than 0.3: no RBH, $0.3 \leq T_1 < 0.5$: weak RBH, $0.5 \leq T_1 < 0.8$: moderate RBH, T_1 more than 0.8: violent RBH.
	Strength-stress ratio	Barton et al. [35]	T_2	$T_2 = \frac{\sigma_c}{\sigma_1}$, where, σ_1 represents the maximum principal stress of in-situ stress and σ_c refers to the uniaxial compressive strength of the rock sample.	T_2 less than 2.5: intensive RBH, $2.5 \leq T_2 < 5$: moderate RBH, $5 \leq T_2 < 10$: weak RBH, T_2 equal and more than 10: no RBH.
	Rock burst proneness	Ma et al. [36]	RPI	$RPI = \frac{\sigma'_{rm}}{\sigma_{max}}$, where, σ_{max} refers to the maximum horizontal stress perpendicular to the tunnel, and σ'_{rm} presents as the triaxial rock-mass strength determined by the Hoek-Brown strength criterion.	$1 \leq RPI < 2$: intensive RBH, $2 \leq RPI < 4$: moderate RBH, $4 \leq RPI < 7$: weak RBH, RPI equal and more than 7: no RBH.

Rock burst liability: RBL; Rock burst hazard: RBH.

its performance using the weighted naive Bayes, in which inputs have different weights [76]–[78]. To achieve the best attributes' weight, which improves the overall performance of NB, studies in other disciplines, employed some optimization techniques, including forward, backward, PSO, and evolutionary [76], [79]. However, to the authors' best knowledge, no study employed NB method and its optimized variants for predicting the likelihood of rock-burst. This research investigates the suitability of optimization techniques for improving the NB model performance for rock-burst prediction.

II. METHODS AND MATERIAL

This research employed four weight optimization techniques to improve the accuracy of the NB model to predict the likelihood of rock-burst. These optimization techniques include forward, backward, PSO, and evolutionary (i.e., genetic algorithm). Before development of these optimized models, the most important input parameters should be selected. The suitable input selection was performed using evolutionary random forest (RF) modelling. The input variables selected in this step were used to develop the optimized NB models and the best optimized NB model will be selected based on the performance prediction results and the ranking system. Figure 1 shows the steps performed in assessing the most suitable NB technique in predicting RB occurrence.

A. INPUT SELECTION TECHNIQUE

Random Forest (RF) is one the most frequently used technique for input selection. RF combines a huge number of decision trees to produce results that are more accurate. RF uses bagging techniques to create bagged trees by generating "x" number of decision trees that are trained using "n" bootstrapped training sets. While this technique is known as an efficient technique for solving regression and classification problems as well as input selection, it can tend to overfit, thus its hyper-parameters should be tuned. To this end, this study combined the optimized the RF model using the evolutionary algorithm. the RF algorithm was used for non-linear relationship modeling while evolutionary was used for RF hyper-parameters tuning. Figure 2 shows the evolutionary RF modelling flowchart.

B. NAÏVE BAYES

Naive Bayes (NB) classifier is a kind of simple "probabilistic classifier" which applies the Bayes theory with influential (naïve) independence assumptions among the input variables. This technique is the most suitable and easy to implement for Bayesian network models and when applied in combination with kernel density approximations, the prediction accuracies may increase significantly [80], [81]. NB classifier is extremely scalable, requiring some linear input parameters in the number of predictors in a learning problem. NB trains the dataset using the maximum-likelihood technique and assesses a closed-form formulation, which uses linear time, rather than an expensive iterative calculation, which utilizes numerous other kinds of classifiers.

The NB classifier integrates the NB probability model into a decision rule. The NB classifier employs the maximum a posteriori or MAP decision rule as a common rule for selecting the most feasible hypothesis. A similar classifier, the Bayes classifier, is the function that allocates a class label $y = C_k$, (kv{1,..., K}) for some k as follows:

$$y = argmax\ p\left(C_k\right) \prod_{i=1}^{n} p\left(\left(x_i \mid C_k\right)\right) \tag{1}$$

C. OPTIMIZATION TECHNIQUES

The performance of NB may be affected by initial weight assignment. Optimizing the inputs' weight is important in developing NB models. Weighting the inputs aims when defining the optimal level of an input's power by adopting a training dataset. If the application of this technique is successful, the related inputs are assigned a high weight value and unrelated inputs are assigned a zero or near-zero weight value. This study applied four weight optimization techniques, including forward, evolutionary, backward, and PSO to optimize the inputs' weight of the NB model.

The forward weight optimization technique assumes that the inputs are independent and if the inputs are not strongly correlated, this method may provide exceptional outcomes. This technique defines the weight of each input based on the naive theory. In this technique, inputs are assigned weights using a linear search. The forward optimization technique chooses a subset of inputs for the final model. Contrary to the forward optimization technique, the backward method commences with the complete least squares model comprising all inputs. This technique then repetitiously eliminates the most insignificant inputs, one after another. Both forward and backward techniques designate 1's and 0's as the primary weights.

The evolutionary weight optimization technique estimates the inputs' weight using the genetic algorithm (GA). Inputs with higher weights are consider to be more suitable inputs. The GA is an efficient exploratory method, which mimics the natural evolution's procedure. This method provides an efficient solution to optimization and search queries [55], [82]. GA belongs to the more general classification of evolutionary algorithms (EA) that provide answers to optimization queries by implementing methods stimulated via natural evolution, including inheritance, mutation, selection, and crossover (Figure 3). In GA, mutation points to shifting inputs on and off and crossover includes swapping employed inputs [83].

The PSO technique learns the process by making a series of arbitrary particles and every particle implies a single set of weights and biases in the model. Later, the model is trained by employing the initial weights and biases [84]. Eventually, the PSO updates the model's weights and biases in each replication. PSO determines the system errors among the actual and forecasted values in each repetition. These errors further are depreciated by modifying the particles' positions. This process is maintained to produce excellent weights and biases to minimize the error function.

D. CASE STUDY AND DATA

Rock-burst events were compiled from various works in the published literature [1], [5], [6], [68], [85], [86] in order to propose several optimized NB models in estimating rock-burst occurrence. A total of 134 rock-burst incidents were employed in this research. These compiled RB events were taken from different projects, such as hydropower plants, underground coal and metalliferous mines, and powerhouse stations. In the data used, the elastic energy index (EEI), the uniaxial tensile strength (UTS), the uniaxial compressive strength (UCS), and the maximum tangential stress (MTS) were considered as model inputs while the RB's occurrence was set as model output. In the database, the EEI values refer to the ratio of elastic energy saved to the dissipated energy in one cycle of a cycling compression test. Actually, EEI which was proposed by Kidybiński [87], is considered as a classification index of the likelihood of RB. In this research the average value of MTS was 51.3MPa and ranged between (2.6–108.4 MPa), the average value of the UCS was 128MPa and ranged between (20–306.6 MPa), the average value of UTS was 7.5MPa and ranged between

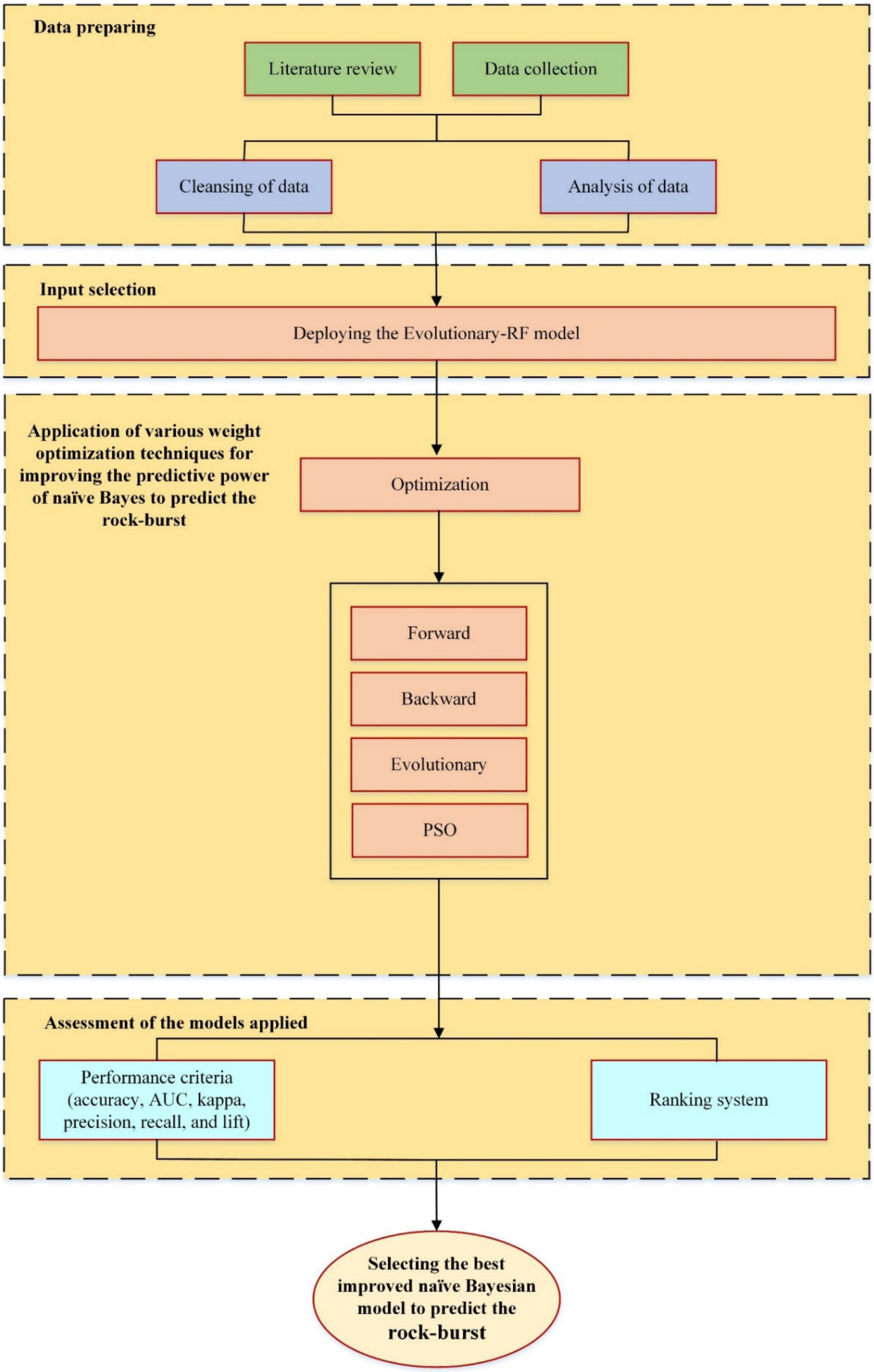

FIGURE 1. Process of this present study in predicting RB occurrence.

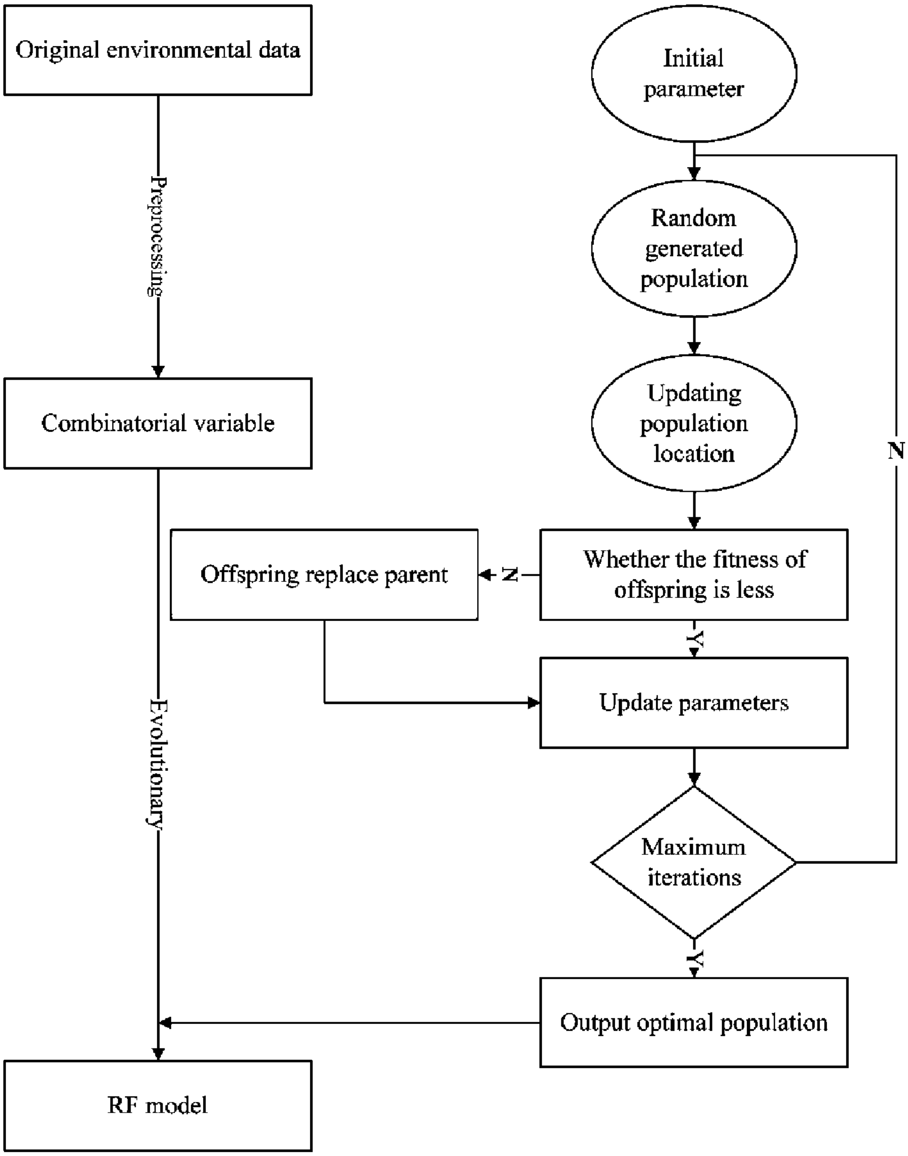

FIGURE 2. Evolutionary RF modelling flowchart.

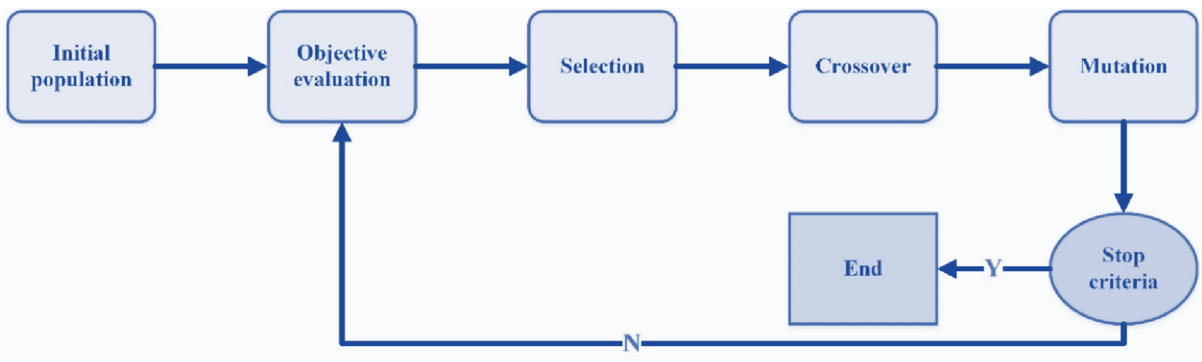

FIGURE 3. Important steps of GA for optimizing problems.

FIGURE 4. **Data visualization of 134 sets of the RB data.**

(1.3–22.6 MPa) and the average value of EEI was 4.7 and ranged between (0.85–10.6 MPa).

III. RESULTS AND DISCUSSION

A. INPUT SELECTION

In this research, RF was used for input selection. The RF employed an evolutionary algorithm (i.e., GA) for input selection. Fig. 5 shows some parameters and settings used to develop the RF model.

Once the parameters were defined, the model was applied and MTS, UTS, and EEI were selected as the most important and relevant factors for predicting the RB occurrence. The performance of the model is shown in Table 2. The overall accuracy of this model is 94.78%. A 10-fold cross validation technique for estimating the statistical performance of the model was used.

```
Evolutionary parameters
Maximal fitness = Infinity
Selection scheme = tournament
Tournament size = 0.25
P initialize = 0.5
P mutation = -0.1
P crossover = 0.5
Crossover type = uniform
Random forest parameters
Number of trees = 100
Criterion = gain_ratio
Maximal depth = 10
Voting strategy = confidence vote
```

FIGURE 5. **Parameters' used for applying input selection technique.**

B. OPTIMIZED NB MODELS

Four optimization techniques were used to improve the accuracy and performance of the NB model. These techniques included forward, backward, PSO, and evolutionary techniques. Before applying these techniques, a basic NB model was applied and used as a benchmark. This research used a 10-fold cross validation technique to evaluate the statistical performance of the models. Fig. 6 presents the parameters,

TABLE 2. Performance of the RF- evolutionary algorithm for input selection.

	True 1	True 2	Class Precision
Pred. 1	104	4	96.30%
Pred. 2	3	23	88.46%
Class Recall	97.20%	85.19%	

```
Evolutionary parameters
Maximal fitness = Infinity
Selection scheme = tournament
Tournament size = 0.25
P initialize = 0.5
P mutation = -0.1
P crossover = 0.5
Crossover type = uniform
Forward and backward parameters
Keep best = 1
Generations without improval = 1
Maximal fitness = infinity
PSO parameters
Population size = 5
Maximum number of generations = 30
Inertia weight = 1.0
Local best weight = 1.0
Global best weight = 1.0
Min weight = 0.0
Max weight = 1.0
```

FIGURE 6. Parameters employed for developing optimized NB models.

which were applied on each model. The accuracy of the NB model was 86.43% for the RB occurrence.

The performance of the models was assessed using the following six criteria; accuracy, kappa, area under the curve (AUC), precision, recall, and lift. The equations for each performance criterion are shown in Figure 7.

A simple ranking method was developed, which ranked each model based on each criterion. This ranking system also provides a cumulative ranking for each model, by summing each criterions' rankings. The formula for a models' cumulative ranking may be expressed as:

$$Model' scummulative\ ranking = R_1 + R_2 + R_3 + R_4 + R_5 + R_6 \quad (2)$$

where, the R_1 denotes the ranking of the model's accuracy, R_2 is the ranking of model's kappa, R_3 is the ranking of the model's AUC, R_4 is the ranking of the model's precision, R_5 is the ranking of model's recall, and R_6 is the ranking of the model's lift.

This study employed a wide range of indicators to assess the performance of the models developed in this study comprehensively and systematically. While accuracy is the corresponding number of precisely classified samples or namely the percentage of accurate forecasts, the kappa statistics consider the accurate prediction happening by accident. In addition, the AUC graph sorts the forecasts by score, from greatest to lowest, and the graph is plotted sample by sample. Precision and recall together examine how great the model is catching information. Lift represents the model's enhancement over arbitrary sampling.

Since four optimized models were developed in this study, the model that achieved the highest value of a certain criterion was ranked as four. On the other hand, the lowest ranking was assigned to a model, which achieved the lowest criterion value. The same value of the same criterions received the same ranking.

The correct predictions of the two RB classes by the four NB optimized models are shown in Figure 8. The NB models optimized using forward, PSO, and evolutionary techniques predicted a class 1 likelihood of RB failure, and whereas the NB model optimized using, the backward technique achieved the smallest prediction accuracy. For class 2, NB models optimized using forward and evolutionary techniques predicted a class 1 likelihood of RB failure. NB models optimized using the backward technique showed the best performance for correctly predicting class 2 of the RB.

The performance and the cumulative ranking of each NB optimized models are presented in Table 3. All optimization techniques improved the NB accuracy level. However, the improvement in prediction accuracy was the lowest for the backward technique. The PSO model achieved the highest cumulative ranking among the models developed in this study. Whereas the NB model optimized using the backward techniques performed poorly compared to other optimized models. In terms of accuracy, AUC, and kappa, the NB model optimized by the PSO technique achieved the highest ranking (four). In addition, regarding the precision, recall, and lift, the NBPSO technique achieved the second greatest ranking.

AUC and receiver operating characteristic (ROC) graphs/curves were used for each model to measure the prediction performance, rather than their absolute values. The true positive rate in ROC curve is highlighted as the vertical axis while the horizontal axis shows the false positive rate. A greater AUC indicates a more immeasurable classification accuracy. AUC and ROC are generally used to evaluate the prediction accuracy of classifiers in binary classification problems. In this study, the RB risk classification is a twofold problem, thus the AUC area and ROC curve can be helpful to show the performance of the models. Figure 9 shows the ROC curve and AUC values obtained by the four optimized NB models. It can be seen that the NB models optimized by PSO and evolutionary techniques achieved the highest AUC, followed by NB model optimized by forward technique; whereas NB model optimized by backward technique performed, the worst compared with other optimized NB models.

The PSO optimization technique possesses many advantages; the higher accuracy ranking of PSO than other optimization techniques was expected. Remarkable advantages of this technique are as follows: (1) the PSO technique requires a little number of input variables, (2) it possesses a flexible

Criterion	Description	Formula
Accuracy	Overall accuracy rate	(Correct predictions)/(Number of Examples)
kappa	The Kappa value examines how closely the samples classified by the model matched the samples labelled as ground truth.	Cohen's kappa = $(p_o - p_e)/(1 - p_e)$ where: p_o = observed accuracy p_e = expected accuracy
AUC	AUC is scale-invariant. It measures how well predictions are ranked, rather than their absolute values.	$AUC_{total} = \sum_{c_i \in C} AUC_{c_i}.p_{c_i}$ $P_i = c_i$ $N_i = U_{j \neq i} c_j \in C$ Where $AUC(c_i)$ is the area under the class reference ROC for c_i and $p(c_i)$ is the prevalence for c_i.
Precision	Precision and recall measure are used to quantify how much a process model over-approximates the behavior seen in an event log.	(True positive predictions)/(All positive predictions)
Recall		(True positive predictions)/(Number of positive Examples)
Lift	Lift is the ratio of two quantities, representing the improvement over random sampling.	1. The probability of choosing a positive Example from the group of all positive predictions: TP / (TP + FP) 2. The probability of choosing a positive Example from the group of all Examples: (TP + FN) / (TP + FP + FN + TN) Lift = [TP / (TP + FP)] / [(TP + FN) / (TP + FP + FN + TN)]

FIGURE 7. Performance criteria used in this study.

TABLE 3. Performance and cumulative ranking of the optimized NB models.

Performance Index	NB Forward		NB Backward		NB PSO		NB Evolutionary	
	Value	Ranking	Value	Ranking	Value	Ranking	Value	Ranking
Accuracy (%)	90.38	3	86.70	2	91.10	4	90.38	3
AUC	0.915	3	0.876	2	0.953	4	0.953	4
Kappa	0.71	3	0.64	1	0.727	4	0.696	2
Precession (%)	81.67	4	68.33	1	80.83	3	80.17	2
Recall (%)	75.83	2	83.33	4	81.67	3	75	1
Lift (%)	428.61	4	365	1	411.67	3	411.61	2
Cumulative ranking	19		11		21		14	

scaling of design search, (3) it can be applied straightforward, and (4) it has an effective s global optimum search.

As mentioned before, there is a high level of RB possibility immediately after excavation and blasting in underground mines and spaces. Therefore, the prediction of the RB occurrence is of interest and importance in any underground project. With the introduced models in this study, a mining or geotechnical engineer can know about the possibility of the RB occurrence. In fact, the developed models in this study can be efficiently utilized/implemented in the same mentioned condition for minimizing the associated risk with a high level of accuracy.

IV. IMPORTANCE OF INFLUENTIAL FACTORS

In mining construction, the prediction of the RB under particular rock mass conditions is of interest. To accurately predict the RB occurrence and reduce the cost and risk of tunneling, the impact of the factors must be assessed. In summary,

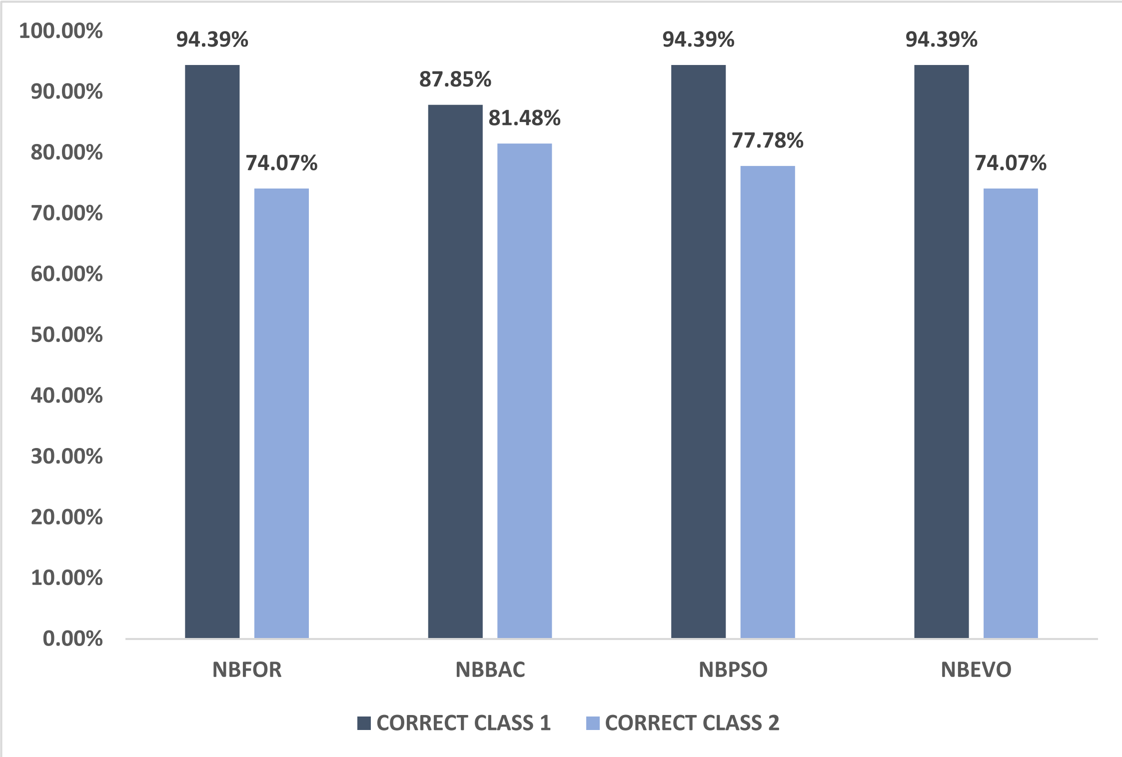

FIGURE 8. Correct predictions of the two RB classes by various optimized NB models.

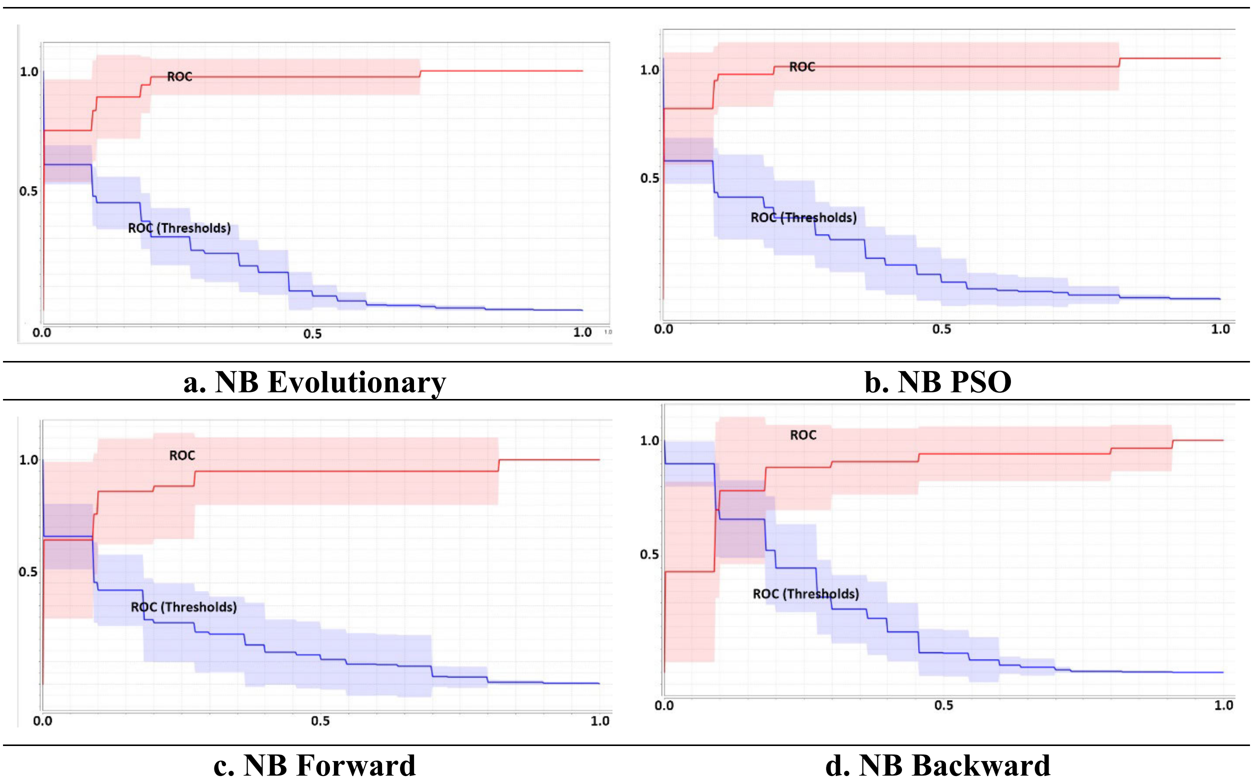

FIGURE 9. AUC graphs of the optimized models in this study.

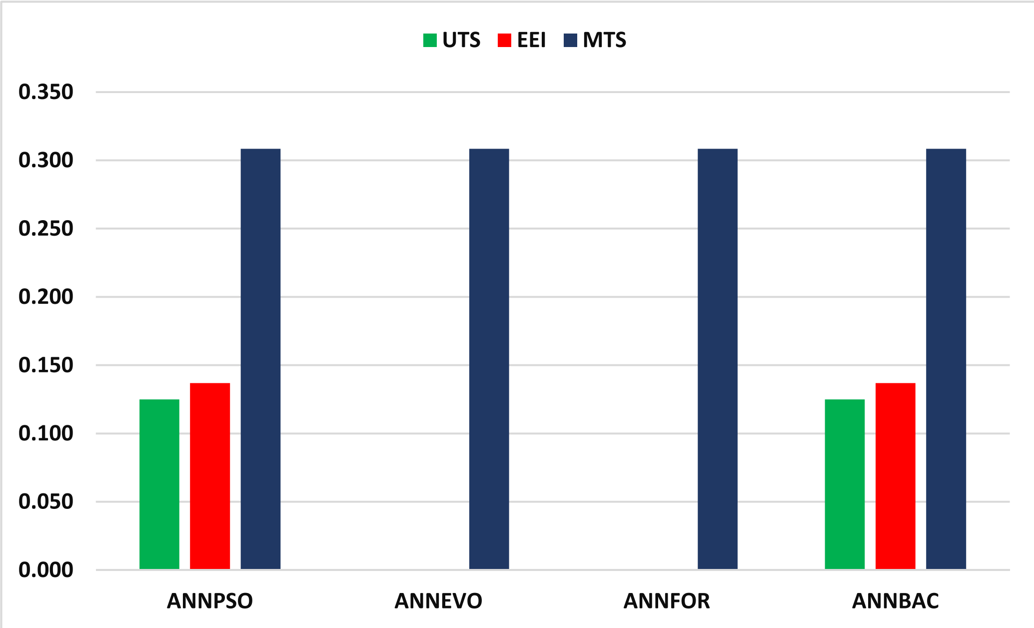

FIGURE 10. Importance score of influencing variables on rock-burst for each model developed in this study.

those input variables that were selected using the RFEVO method i.e. MTS, UTS, and EEI have an impact level on rock-burst; however, the sensitivity of each input is uncertain and requests further investigation. To this end, this research investigated the significance of the input variables on each model output using the test of mutual information (MI). MI is a filtering system employed to capture the random association among various features and the label. MI identifies how the variables are associated. The information gain is employed to estimate the magnitude of the mutual information among variables.

$$Gain\,(A, B) = Ent\,(A) - \sum\nolimits_{v-1}^{v} \frac{|A^v|}{|A|} Ent\left(A^v\right) \tag{3}$$

where, v signifies the number of all probable values of B, Av denotes the set of A corresponding to when B takes Bv, and Ent(A) denotes the information entropy. The greater the value of Gain (A, B), the greater the association between B and A. Ultimately, according to the variable score in the mutual information test, the significance levels of the input variables in calculating rock-burst for each model, were estimated. As shown in Figure 10, MTS was identified by all models. In addition, this input variable achieved the highest importance score. ANNEVO and ANNFOR models identified only MTS as the influential factor for predicting the rock-burst. ANNPSO and ANNBAC, on the other hand, ANNEVO and ANNFOR showed similar behavior for determining the importance score of the variables for predicting the rock-burst.

Determining the MTS as the most important factor for rock-burst prediction in all four models was in line with the findings of those studies that previously confirmed the importance of this factor for predicting the rock-burst [72]. However, other studies also identified different factors, including the properties and stress of surrounding rock for rock-burst prediction [6], [68], [85], [86].

V. SUMMARY AND CONCLUSION

The aim of this research was to employ an NB algorithm for predicting the rock-burst hazard and to improve the NB model performance using weight optimization techniques. To this end, an evolutionary random forest technique was employed for input selection. This technique identified MTS, EEI, and UTS as the most suitable input variables for rock-burst prediction. These variables were then used to develop the optimized NB models using forward, backward, PSO, and evolutionary optimization techniques. The performance of these optimized models was assessed using six criteria. A simple ranking system was also developed to evaluate the models systematically. The results of this research show that PSO is the most suitable optimizer for improving the predictive accuracy of the NB model to predict the likelihood of rock-burst failure. The developed NBPSO model, which achieved a cumulative rank of 21, attained the highest prediction accuracy, whereas the developed NB forward, NB backward, and NB evolutionary models achieved cumulative rankings of 19, 11 and 14 respectively. MTS was the most influential factor for predicting rock-bust failures in all optimized models. Future research may explore the suitability of other optimized NB models such as NB artificial bee colony, NB ant colony optimization and NB whale optimization algorithm in increasing the prediction accuracy of rock-burst failures.

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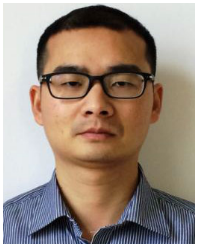

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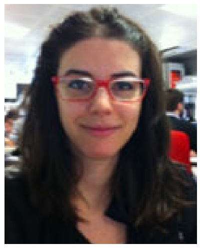

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