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Sustainable Rock Fragmentation Improvement Using Artificial Intelligence: Minimizing Blast Toe Volume for Safer and Cleaner Operations

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Abstract

This study developed and assessed several artificial intelligence (AI) models for predicting blast-induced toe volume in small-scale dolomite mines located in the Akoko Edo Local Government Area, Edo State, Nigeria. Seven predictive models were constructed: Adaptive Boosting (AdaBoost), Random Forest (RF), Gaussian Process Regression (GPR), Support Vector Regression (SVR), a conventional Artificial Neural Network (ANN), and two Imperialist Competitive Algorithm-optimized ANNs (ICA-ANNs). The models were trained using eight input parameters including uniaxial compressive strength (UCS), spacing (S), burden (B), sub-drill (SB), drill hole length (DHL), stiffness ratio (SR), maximum instantaneous charge (MIC), and powder factor (K) with blast toe volume (TV) as the target output. Input data were collected through a combination of field measurements and laboratory analyses. Among all the models evaluated, the ICA-ANN with an 8-7-1 architecture achieved the highest predictive accuracy. It outperformed AdaBoost by 9.17%, SVR by 7.20%, GPR by 5.56%, RF by 4.75%, a standard ANN (8-5-1) by 0.78%, and a standard ANN (8-7-1) by 0.28%, based on mean squared error (MSE) and coefficient of determination (R^2) metrics. Furthermore, the ICA-ANN model was applied to optimize blast design parameters. The optimal values obtained were: spacing = 1.0 m, burden = 0.8 m, sub-drill = 0.6 m, MIC = 0.72 kg, and powder factor = 0.65 kg/m³. These optimized parameters reduced the blast toe volume by 20.05%, from 209.50 m³ to 154.87 m³. The results highlight the robustness and efficiency of the ICA-ANN model for blast design optimization. By improving fragmentation quality and minimizing residual toe volume, the approach offers a practical pathway for enhancing both productivity and cost-effectiveness in small-scale mining operations.

1. Introduction

Blasting is one of the most critical operations in mining, directly influencing both production efficiency and occupational safety [1]. Poorly designed blasts can result in the inefficient use of explosives and compromise mine safety [2–4]. For example, [5] identified insufficient subdrilling as a primary cause of excessive toes and uneven pit floors after blasting. Conducting a thorough pre-blast assessment is therefore

essential for achieving both safety and productivity goals. A toe-free, well-leveled floor not only improves operational safety but also facilitates the smooth movement of loading and excavation equipment, reducing machinery wear and tear. Moreover, maintaining a clean post-blast floor minimizes accident risks and supports safer access across the quarry. As highlighted by Leng et al. [5], reducing blast toe volume enhances

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productivity by limiting overbreak and material wastage, thereby improving fragmentation, material handling, and overall hauling efficiency [6].

Blast toe volume refers to the unfragmented material left at the base of a blast pattern, a common challenge in mining and construction [7]. Proper fragmentation and flyrock control are crucial to ensure both efficiency and safety. While geological conditions play a role in toe formation, factors such as explosive type, blast design, and drilling inaccuracies are often decisive [8]. Effective blasting practices, according to [9], can significantly reduce the downstream burdens associated with mucking, loading, crushing, and mineral processing. Conversely, inadequately designed blasts or misapplied explosive energy often lead to oversized fragments, persistent toes, and excessive fines [10–12]. A properly executed blast, however, creates a smooth and level pit floor, eliminates the need for costly secondary blasting, and ensures continuity in drilling cycles. Oversized fragments within the muckpile negatively affect downstream efficiency, raising costs linked to hauling, transportation, and processing [13–15].

The condition of the pit floor after blasting is therefore a key determinant of both cost and cycle effectiveness in subsequent drilling and blasting operations. Although blasting remains the most effective method for fragmenting in-situ rock, challenges such as toe formation, humps, and irregular pit floors as illustrated in Figure 1. These irregularities reduce production efficiency, lower tonnage output, and drive-up operating costs, often necessitating secondary blasting. In highly mechanized mining systems where operations are interdependent, each stage must perform reliably to achieve production targets. Thus, careful blast design is essential, as toe formation can significantly disrupt downstream processes and escalate operational expenses.

Recent advances in Artificial Intelligence (AI) provide promising solutions to these challenges by uncovering complex relationships between blasting parameters and rock mass characteristics, enabling the prediction and mitigation of blast-induced toe formation.

This study focuses on predicting and minimizing blast-induced toe volume while improving pit floor smoothness. To achieve this,

five AI models including Artificial Neural Networks (ANN), AdaBoost, Support Vector Regression (SVR), Random Forest (RF), and Gaussian Process Regression (GPR) were developed for small-scale mining applications. The research is structured into three parts: (i) data collection involving fragmentation analysis, explosive properties, blast design, and uniaxial compressive strength of rock samples; (ii) assessment of toe volume impacts on fragmentation size distribution using WipFrag 4; and (iii) AI modeling, performance evaluation, and optimization of operations through the Imperialist Competitive Algorithm (ICA), with the best-performing model adopted as the predictive tool.

2. Literature Review

2.1. Review of blasting and factors affecting blasting efficiency

Explosives are strategically applied in mining and construction to fracture rock, thereby facilitating easier extraction, handling, and processing across various industrial applications [16]. Detonation releases energy rapidly, generating stress waves and cracks that fragment the rock mass [17, 18]. The use of explosives for rock breakage dates back to ancient times, with industrial applications evolving from early black powder to more advanced and safer formulations. These innovations have significantly improved efficiency in mining, construction, and demolition while ensuring greater control over outcomes [19, 20].

Blast design parameters play a central role in controlling fragmentation, mitigating environmental impacts, ensuring safety, and maximizing efficiency in rock excavation [13]. The results of rock fragmentation are governed by both controllable and uncontrollable factors. Unlike engineered materials such as concrete, rocks exhibit heterogeneity and anisotropy, making their response to blasting highly variable. The diversity of rock characteristics plays a crucial role in blasting operations as it enables accurate prediction of the dispersion of fragmentation inside the blasted material [21, 22]. The strength, deformability, and strain wave propagation within a rock mass are largely dependent on the type, orientation, and spatial

distribution of these structural features. Previous studies have shown that such geological characteristics often exert a stronger influence on blast outcomes than explosive properties or blast geometry alone [23].

Among uncontrollable factors, rock density significantly affects energy transmission and stress distribution, with denser rocks requiring greater energy input for effective breakage [24]. Rock strength and physical qualities have a considerable impact on blasting efficacy, as

weaker rocks require less explosive energy to fracture, whereas harder rocks require more energy [25]. Porosity also plays a role. Hook [26] defines porosity as the volume fraction of voids within a rock mass, while Mulenga [27] demonstrated that porosity influences blasting by altering energy absorption and transfer. Rocks with lower porosity generally demand more explosive energy to achieve satisfactory fragmentation.



Figure 1. Evidence of toes after loading operation at Fanalou Quarry Pits

To address the challenges posed by these uncontrollable parameters, blast designers must carefully select controllable factors. Bench height, for instance, is a crucial parameter influencing fragmentation, ore recovery, energy consumption, and overall mining efficiency. Properly chosen bench heights promote uniform breakage and optimal fragment size distribution [28]. Likewise, burden, the distance from the fire hole to the nearest free face has a strong effect on confinement and energy release. Excessive burden can cause over-confinement, elevated ground vibrations, larger fragments, and even persistent toes [29, 30]. Sub-drilling, defined as the depth drilled below the intended floor level, is also essential for breaking rock at

the base of blast holes, where confinement is greatest [31].

Over the past two decades, the integration of artificial intelligence (AI), soft computing, and meta-heuristic optimization algorithms has revolutionized the prediction and optimization of blasting outcomes. These tools have proven highly effective in modeling the nonlinear and multivariable relationships that characterize blasting operations, thereby improving both accuracy and decision-making in practice.

Monjezi et al. [32] pioneered the application of fuzzy logic to predict rock fragmentation at the Gol-E-Gohar iron mine, achieving better performance than traditional regression models by addressing uncertainty inherent in blasting data. Building on this, Saeidi et al. [33]

demonstrated that hybrid ANN–fuzzy models outperform deterministic methods in predicting blast-induced backbreak. Similarly, Zhang and Luo [34] applied neural networks for real-time fragmentation forecasting in limestone quarries, highlighting AI's potential for mine-to-mill optimization.

Recent advances extend beyond fragmentation prediction. Davoodi et al. [35] employed a genetic algorithm-enhanced tree regression model to link rock mass rating (RMR) with seismic velocities, showcasing the promise of hybrid meta-heuristic approaches in characterizing rock behavior. Wang et al. [36] introduced a Grey Wolf Optimization–Random Forest (GWO-RF) hybrid model for predicting D80 fragmentation, combining high accuracy with interpretability through SHAP analysis, thereby improving transparency in blast design decisions. Likewise, Feng et al. [37] leveraged ensemble learning with geospatial data to predict excavation-induced risks, underscoring parallels to fragmentation modeling.

Other studies have expanded AI applications to related geotechnical and structural domains.

Collectively, these contributions illustrate the increasing reliability and practicality of AI, soft computing, and hybrid meta-heuristic methods in blasting research. From early fuzzy logic models to advanced hybrid frameworks such as ICA-ANN, GWO-RF, and GA-enhanced regressions, the literature demonstrates a clear trajectory toward data-driven blast optimization. These approaches not only improve predictive accuracy but also enhance safety, cost efficiency, and productivity by minimizing adverse outcomes such as excessive toe formation, overbreak, and energy inefficiency.

2.2. Review of artificial intelligence application to blast fragmentation

Analyzing fragmentation has proven useful in the mining, construction and aggregate industries to help understand the efficiency of blasting and to optimize energy costs [38-42]. The effect of other blasting drawbacks such as poor toe fracturing on fragmentation had not been considered according to reviewed literature. Several measures need to be taken to minimize the impact of these non-controllable parameters

to achieve a good rock fragmentation. The existing empirical models have not yet achieved a substantial equilibrium between the several variables and their interconnections. To address this limitation, the utilization of artificial intelligence models has proven beneficial in recent years [43-49]. In recent decades, numerous research studies have been conducted in the field of rock fragmentation. Prior scholars have constructed empirical models to forecast rock fragmentation [50]. Ouchterlony mentioned the development of a correlation between the average size of fragments and the specific charge, which aligns with the Rosin-Rammler theory [51]. Despite their widespread usage, these empirical approaches did not consider issues such as toe volume and also lacked other significant input parameters that are necessary for achieving better results. Several modern researchers have employed artificial intelligence techniques, such as artificial neural networks (ANN), to effectively address the limitations posed by these empirical prediction methods. Khajooei Sirjani et al. explained that artificial neural networks (ANNs) are regarded as intelligent engineering problem-solving tools in the mining industry [52]. They explained that ANNs are computational models that draw inspiration from the neuronal structure of the human brain. They are composed of interconnected nodes, sometimes known as artificial neurons, organized in layers [52]. Artificial neural networks (ANNs) are employed in the field of machine learning to perform tasks such as pattern recognition, classification, regression, and other similar activities. The algorithm learns from data in order to produce accurate predictions and informed judgments using input, hidden, and output layers that form the ANN architecture, as explained by [46].

Recent advancements in artificial intelligence and soft computing have significantly improved the predictive capabilities in mining operations, especially in blasting performance analysis, vibration control, and material flow optimization. A critical contribution in this field is the study by Khajooei Sirjani et al. [53], which utilized Artificial Neural Networks (ANN) alongside statistical models to predict backbreak in open-pit blasting at the Gol-e-Gohar Iron Ore Mine. The study demonstrated that ANN models outperformed traditional statistical approaches in

accuracy, offering reliable predictions based on multiple input parameters including blast geometry and rock properties

Complementing this, Ataei and Sereshki [54] improved blast-induced vibration prediction in limestone mines using a Genetic Algorithm, highlighting the importance of optimizing explosive parameters to minimize environmental and structural impacts. Similarly, Ghasemi et al. [55] applied AI models to predict flyrock distances, achieving robust estimations critical for safe and efficient blasting practices in proximity to infrastructure. Optimization algorithms such as the Imperialist Competitive Algorithm (ICA) have also seen wide application. Mohammadi et al. [56] and Rafiee et al. [57] applied ICA and golden section search to optimize cutoff grades in open-pit mines, maximizing economic returns through strategic production scheduling. These approaches were further extended by Mohammadi et al. [58], who addressed multi-product mining scenarios to determine optimal extraction strategies. Soft computing models have also enhanced equipment performance and design decisions. Mikaeil et al. [59] combined ICA with fuzzy clustering to predict the performance of circular saw machines, a technique adaptable to drilling and excavation equipment selection. Saeidi et al. [60] applied ANN, fuzzy clustering, and regression to predict rock mass diggability, aiding in equipment matching and cost control. In terms of image processing applications, Hoseini et al. [61] utilized digital image analysis to measure blast fragmentation, underscoring the utility of computer vision in mine-to-mill optimization. Meanwhile, Sari et al. [62] and Motahedi et al. [63] developed stochastic and soft computing models to forecast backbreak and overbreak, contributing significantly to tunnel and pit wall control. The growing body of work by Ataei and collaborators culminates in Davarzani et al. [64], who introduced a hybrid FFTA-FDAHP method for assessing flyrock risk in road construction blasting, reflecting a trend toward multi-criteria and integrated risk assessment frameworks in hard rock environments. Together, these studies illustrate the transformative impact of machine learning, optimization algorithms, and digital technologies in predicting, monitoring, and

optimizing key aspects of blasting and overall mining operations.

The research conducted by Hosseini et al. determined that the optimal approach for predicting blast caused ground vibration is to develop an ensemble learning model using the Artificial Neural Network (ANN) and XGBoost algorithm [49]. Fissaha et al. utilized a Bayesian algorithm-based Neural Network and Gaussian Process Regression (GPR) Approach to forecast the blast-induced peak particle velocity in Mikurahana quarry [50-51]. Moreover, to reduce the formation of blast toe, we will employ a global optimization technique known as the Imperialist Competitive Algorithm (ICA), which draws inspiration from imperialistic competition. The Imperialist competitive algorithm (ICA) begins by creating an initial population, as is the case with other evolutionary algorithms [52]. To enhance the predictive accuracy of the suggested model, the Imperialist Competitive Algorithm (ICA) was employed to determine the optimal combination of scores and weights for the model. Atashpaz-Gargari explains that ICA is an evolutionary method used for optimizing models. It draws inspiration from imperialistic competition. To commence the competition, the initial step involves determining the likelihood of possession for each empire, which is determined by its overall power. The normalized total cost is calculated using Equation (1).

$$K \times Z \times G_n = Z \times G_n - \text{Max} \{Z \times G_i\} \quad (1)$$

where, $Z \times G_n$ and $\dots K \times Z \times G_i$ are respectively total cost and normalized total cost of n th empire. Having the normalized total cost, the possession probability of each empire is computed using Equation (2) [52].

$$W_{w_n} = \left| \frac{K \times Z \times G_n}{\sum_{i=1}^{K_{imp}} K \times Z \times G_i} \right| \quad (2)$$

Equation (3) Vector (G) was used to divide the colonies among empires based on the possession probability.

$$G = [W_{w_1}, W_{w_2}, W_{w_3}, \dots, W_{w_{N_{imp}}}] \quad (3)$$

Then a vector with the same size as W whose elements are uniformly distributed random numbers are created using Equation (4-5).

$$R = [r_1, r_2, r_3, r_4, \dots, r_{N_{imp}}] \tag{4}$$

$$P = G - R = [F_1, F_2, F_3, F_4, \dots, F_{N_{imp}}] \tag{5}$$

Solving Equation 5, a new equation was obtained Equation (6).

$$P = [W_{w_1} - r_1, W_{w_2} - r_2, W_{w_3} - r_3, \dots, W_{w_{N_{imp}}} - r_{N_{imp}}] \tag{6}$$

Referring to vector P, the identified colonies is added to an empire whose relevant index in P is maximum. Vector P was formed by simply subtracting R from Is present in Equation (6).

3. Case Study and Data Description

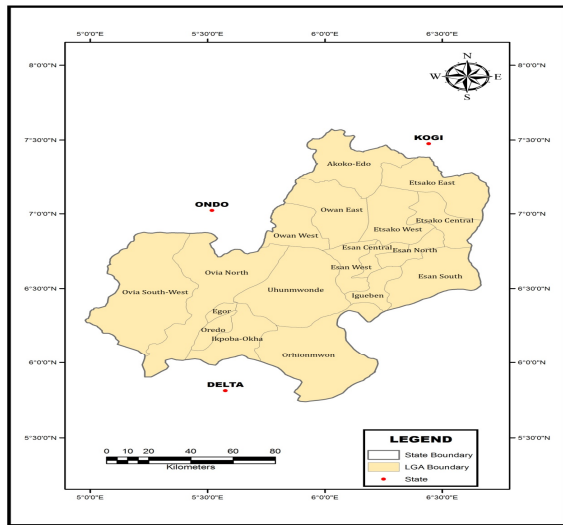
3.1. Description of case study area

To create a database for this research, four quarries were selected as the case study. The chosen quarries are Golden Girl Quarry (Q1) in Ikpeshi, HNF Global Resources Quarry (Q2) in Bekuma, Makana Limited Quarry in Atte (Q3), and Fanalou (Q4) in Enwan. These quarries are all situated in Akoko Edo, South-South Nigeria and the coordinates are presented Table 1. The case study region is a subset of the primary lithology component that constitutes the geological composition of Nigeria. Within this area, the basement rocks can be categorized into four distinct major groupings. The geological

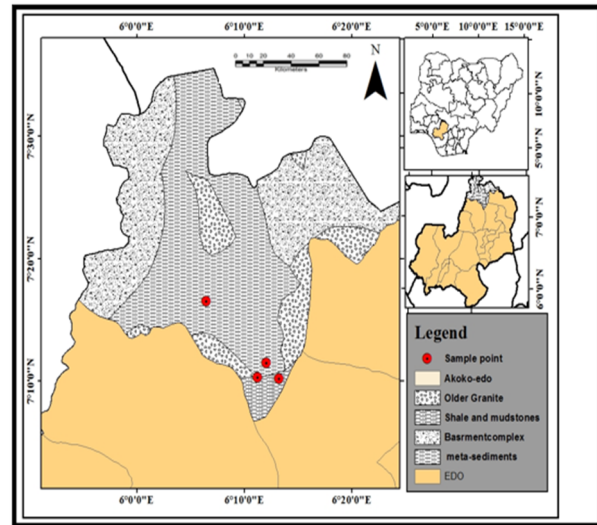
map depicting the formations of the case study is presented in Figure 2. The mine is currently facing issues with toe volume due to unblasted material on the floor. The deposits in the study area consist mainly of three distinct formations: white dolomite, grayish dolomitic marble, and grayish limestone, all primarily composed of calcium carbonate. The strength of these formations has been observed to influence the toe volume, as seen on-site, this was accounted for in this study model by including the deposit strength.

Table 1. Location of the Study Area

Quarries	Geographical co-ordinates of locations	
	Latitude	Longitude
Q1	7° 10' 04" N	6° 09' 54" E
Q2	07° 25' 15" N	006° 08' 50" E
Q3	07° 17' 15" N	06° 11' 30" E
Q4	7° 13' 20" N	06° 12' 15" E



(a)



(b)

Figure 2. Map of Edo State showing the location of Akoko Edo Local Government Area

3.2. Collected Data Visualization and Interpretation

The blast design parameters such as burden, spacing, drill hole length, hole diameter, and sub-drill depth were obtained from blast plans and operational reports from four quarry sites selected for this case study. These sites are in the Akoko region of Edo State. Geometric data were collected from each quarry to support the analysis. To determine the volume of the blast-induced toe, the pit floor at each site was inspected after a successful loading operation and before the commencement of the next drilling cycle. The volume of intact rock remaining above the lower boundary of the excavation floor, representing the blast toe, was measured and recorded for each explosive round configuration.

The datasets used in this study comprise numerous data points organized across multiple rows and columns, making them complex to interpret without statistical summarization. Descriptive statistics, as shown in Table 2, indicate that the Uniaxial Compressive Strength (UCS), spacing, Maximum Instantaneous Charge (MIC), and toe volume varied between 167.75–186.25 MPa, 0.7–1.3 m, 0.51–1.06 kg, and 107.67–443.29 m³, respectively. The powder factor ranged from

0.44 to 1.8 kg/m³ across the blasting operations. The maximum recorded stemming length, which was filled using fine gravel, reached 0.66 m.

Figures (3–6) show that histogram, Pearson, Spearman, violine, scatter plots of input and output data.

The target variable in the data set, Toe Volume, has large skewness value. An extended right tail and possible outliers are indicated by a large positive skewness in the distribution. The presence of skewed data can have an impact on statistical studies and interpretations, as it may influence central tendency measures. So, it was determined to have a left-skewed and different distribution than normal distribution (See Table 4.1). In addition, it was concluded that other input variables did not show a normal distribution. The correlation matrix showing the relationship among all variables of the data set is given in Figure 5. The Pearson correlation coefficient is a crucial measure for evaluating the connection between two variables [46]. It is a numerical value that runs from -1 to 1. A correlation coefficient of 0 signifies the absence of a link between the variables. Conversely, a positive correlation coefficient shows a positive relationship between the variables, while a negative correlation coefficient signifies a negative relationship between the variables [45].

Table 2. Dataset statistical analysis result

	UCS (MPa)	S (m)	B (m)	SB (m)	DHL (m)	SR	MIC (kg)	K (kg/ m ³)	(TV) (m ³)
Max	186.25	1.30	1.20	0.90	1.45	2.00	1.06	1.80	443.29
Min	167.75	0.70	0.60	0.29	0.70	1.07	0.51	0.44	107.67
Average	170.92	1.05	0.83	0.66	1.30	1.59	0.85	0.77	191.28
Mode	167.75	1.20	0.80	0.66	1.30	1.63	0.87	0.70	172.27
Skewness	1.97	-0.12	0.79	-0.82	-4.79	0.15	-1.12	2.80	2.52
Kurtosis	3.13	-0.16	2.41	3.52	36.33	0.22	3.04	13.31	11.33
Stdev	5.25	0.11	0.10	0.09	0.08	0.19	0.10	0.20	51.20

Moreover, the extent of correlation may be discovered by analyzing the magnitude of the correlation coefficient, wherein a greater absolute value signifies a stronger association between the variables. Based on the data shown in Figure 5a, a statistically significant positive association was discovered between variables powder factor and blast toe volume, with a correlation coefficient of 0.97 which is a good fitting. Conversely, a negative correlation was identified among variables DHL, S, B, MIC, and Blast toe volume. It is vital to comprehend that the Pearson coefficient just provides insight into the linear relationship between two variables. However, when it comes to nonlinear

connections, the use of Pearson correlation is not considered to be suitable or useful. In this research, a Spearman correlation coefficient, which is a method that doesn't suppose a linear relationship between variables, was used to obtain a nonlinear relationship among the variables. In addition, the Spearman correlation is suitable for capturing nonlinear and linear relationships. Figure 5b showed that the variable K exhibits the highest values of interaction for the variable blast toe volume. This case pointed to the fact that K and TV variables have a stronger relationship than that of other variables in the dataset.

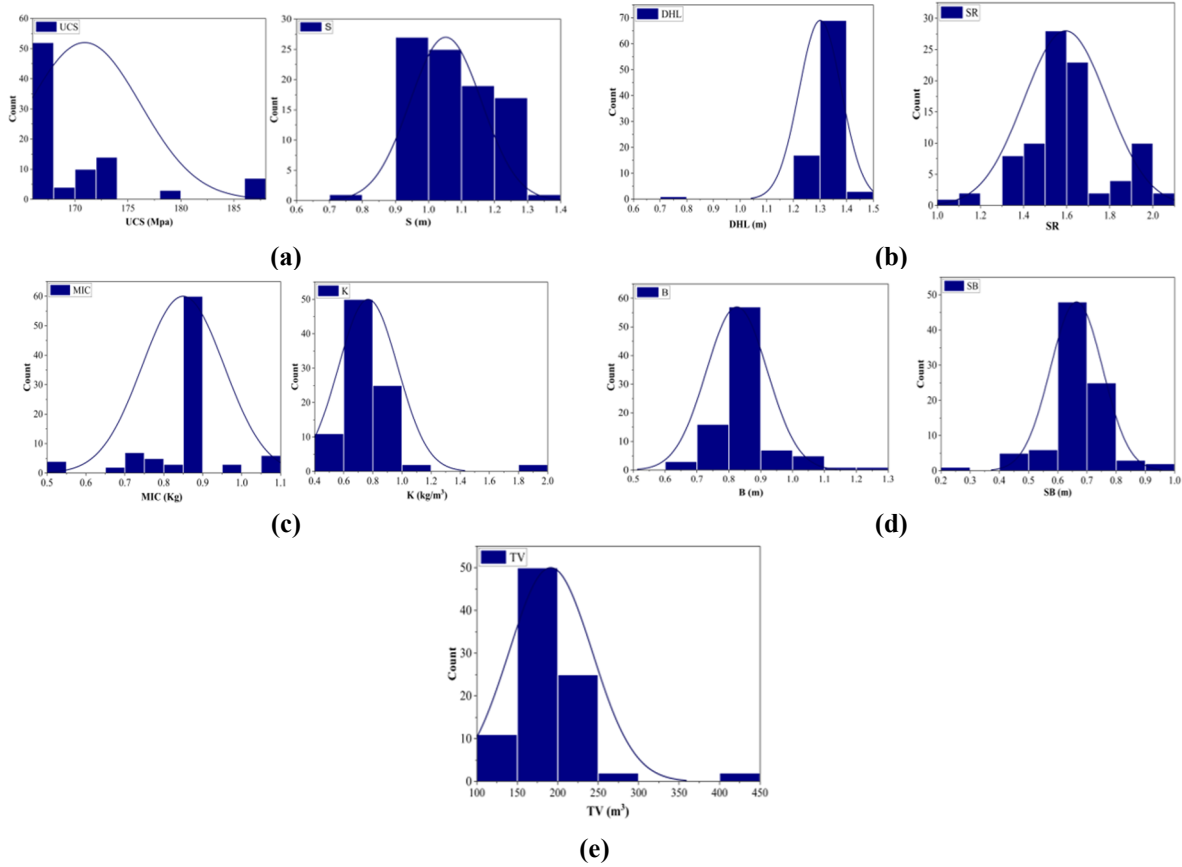


Figure 3. Distribution graph and Ridgeline of the input and output variables

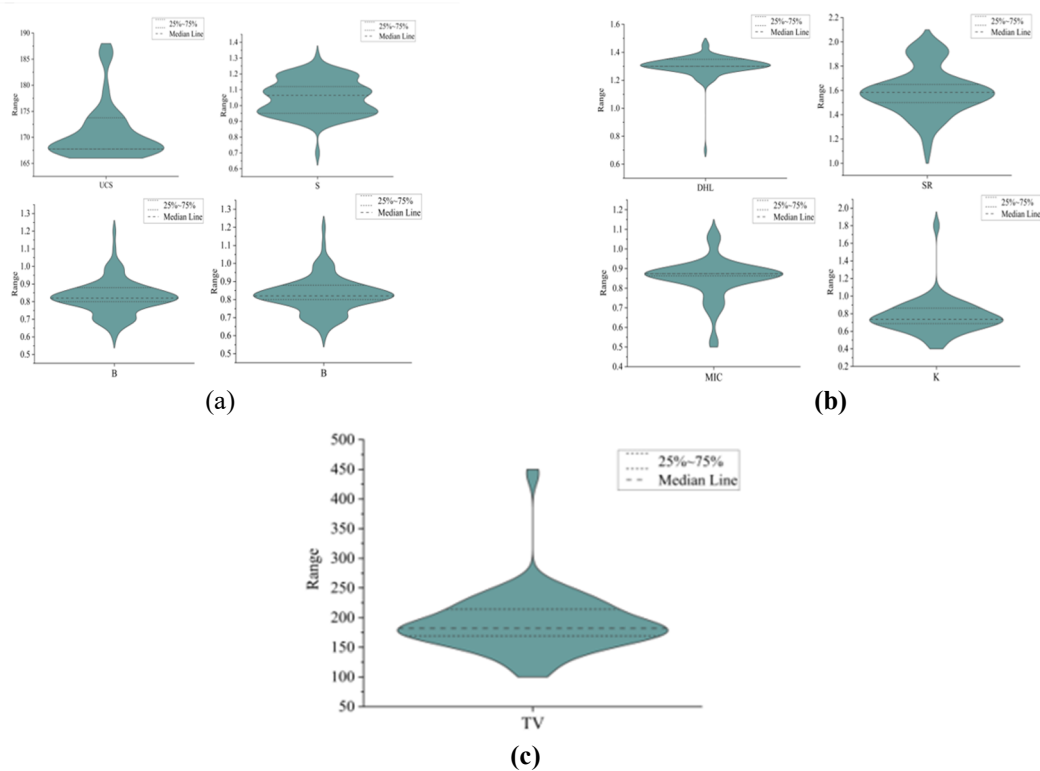
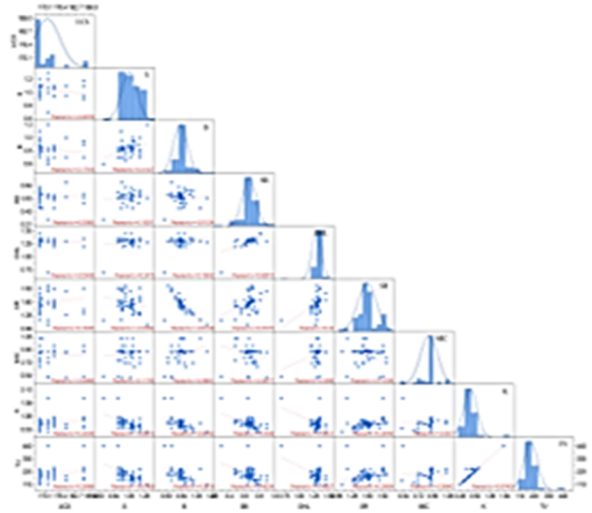
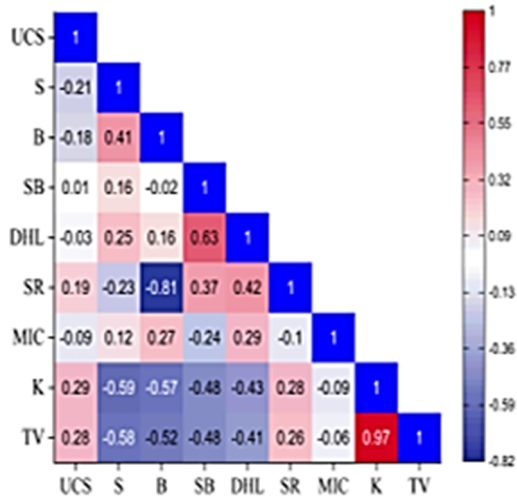


Figure 4. Violin plot of each input variables, and output variable



(a) (b)
Figure 5. a) Pearson and b) Scatter matrix plot

3.3. Relationship Between Input Parameters and Blast Toe Volume

When independent variables in a regression model are highly correlated, multicollinearity occurs, leading to difficulty in assessing their individual effects on the dependent variable. This can distort statistical results, making it challenging to isolate the true relationship between the dependent variable and each independent variable. High levels of correlation or multicollinearity can undermine the reliability of statistical judgments for independent variables. Different studies have suggested different amounts of multicollinearity based on the Variance Inflation Factor (VIF). The VIF has been calculated for the input parameters specified as shown in Figure 6.

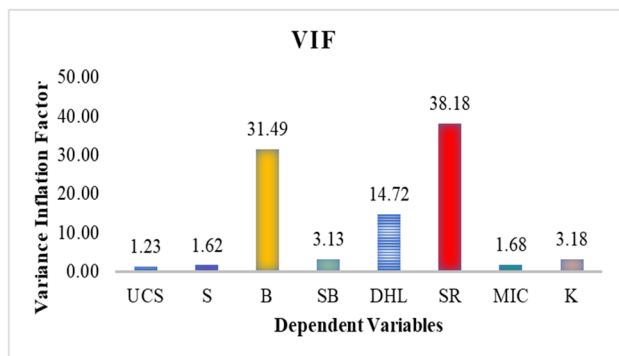


Figure 6. Variance Inflation Factor for all model Variables

Figure 6 shows that the rock strength, spacing, and maximum instantaneous charge have a low level of multicollinearity ($0 < VIF \leq 2$); burden, powder Factor, and the drill hole length have a moderate level of multicollinearity ($5.0 < VIF \leq 15.0$); and the burden and stiffness ratio have a problematic level of multicollinearity ($VIF > 15.0$). The VIF value as shown in Figure 6 revealed that the selected prediction parameters are well correlated with the dependent parameter.

4. Toe Volume Model Development

The proposed models will be developed using artificial neural networks (ANN), AdaBoost, Support vector regression, random forest, and Gaussian Process Regression (GPR) algorithms (See Figure 7). The techniques are discussed in the following subsections.

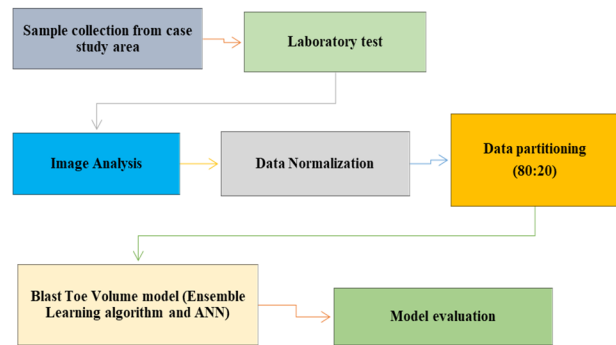


Figure 7. Flow Chart of the Study

4.1. Artificial Neural Networks (ANNs) for the Predictions of Blast Toe Volume

In this study, the collected datasets were utilized to link and connect neurons, determine the parametric function, and train the algorithm for blast-toe volume forecast. The weights were changed many times until the desired outcome was obtained to decrease the margin of toe volume prediction error. The input and output variables were normalized between -1 and 1 using Equation (7) to achieve dimensional consistency in the variable elements and to eliminate over-fitting.

$$Xi = \frac{2(Yi - Y_{min})}{(Y_{max} - Y_{min})} - 1 \quad (7)$$

Where X_i is the Scaled elements, Y_i is the actual data to be scaled; Y_{max} and Y_{min} are the maximum and minimum values of the actual data, respectively. The optimum model hyper parameters were de-normalized using Equation (8) [60].

$$Yi = \left(\frac{Y_{max} - Y_{min}}{2} \right) Xp + \left(\frac{Y_{max} + Y_{min}}{2} \right) \quad (8)$$

Where X_p is the predicted elements, Y_i is the actual predicted data de-normalized; Y_{max} and Y_{min} are the maximum and minimum values of the actual data, respectively.

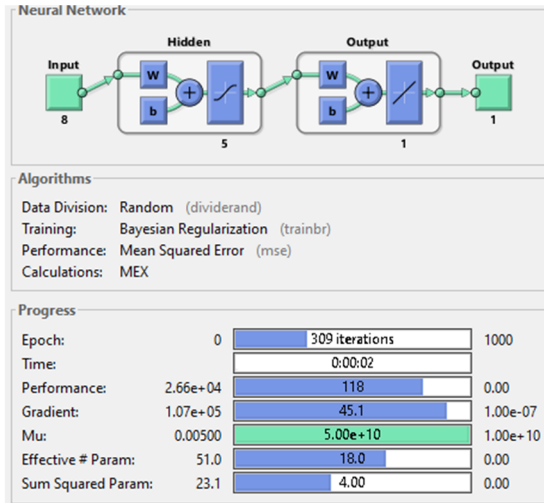
Table 3. Model Parameters

Model parameters	Symbols
Uniaxial Compressive strength (MPa)	UCS
Spacing (m)	S
drill hole depth (m)	DHL
Sub-drill (m)	SB
Burden (m)	B
stiffness ratio (m)	SR
Maximum Instantaneous charge (kg)	MIC
powder factor (kg/m ³)	K
Toe volume (m ³) (Output)	TV

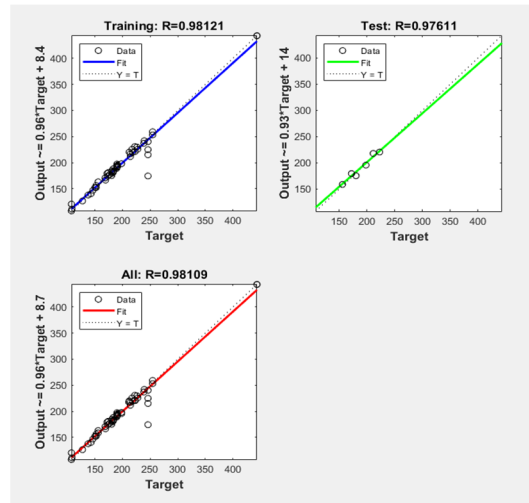
Using 90 datasets, 80% of the data was used for training and 20% for testing the proposed ANN model for blast toe volume prediction. The model was developed using MATLAB software. The input and output parameters are presented as shown in Table 3. The proposed model was developed using the MATLAB 2018a© version.

Two model architectures (MD 1= 8:5:1, and MD 2 = 8:7:1) were developed; the hyperbolic tangent function was used as the transfer function for the hidden and output layers in the cases for each of the proposed ANN models. The Bayesian regularization algorithm was preferred for training MD 1 and MD 2 architecture due to its ability to improve generalization performance and prevent overfitting. This choice was supported by the findings of Baghirli, who compared various backpropagation algorithms for multistep ahead wind speed forecasting using a multilayer perceptron feedforward neural network [44]. In the study, Bayesian regularization demonstrated superior performance over the Levenberg-Marquardt and Scaled Conjugate Gradient algorithms, particularly in reducing the impact of noise and enhancing the predictive accuracy. The use of a Bayesian framework helps in optimizing the network's weight distribution, leading to more reliable and efficient model training in complex systems. The model training performance and structure is present in Figure8, and the model with MD 2 performed best for the forecasting of blast toe volume as indicated by the error assessment indices.

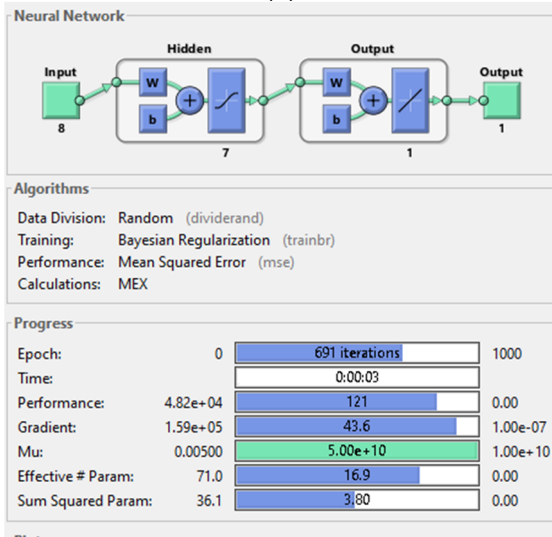
Figures9 illustrates the relationship between the 8-5-1 (training dataset, $R^2 = 0.9625$ and the testing dataset, $R^2 = 0.9825$) and 8-7-1 (training dataset, $R^2 = 0.961$ and the testing dataset, $R^2 = 0.9863$) ANN model predicted toe blast volume, respectively.



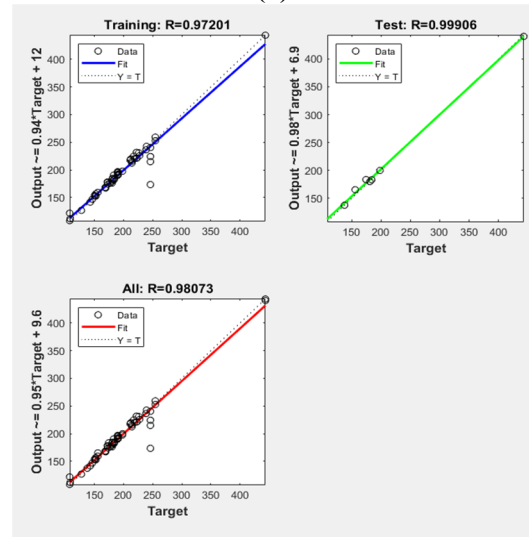
(a)



(b)



(c)



(d)

Figure 8. ANN model Training output for blast Toe Volume a) 8-5-1 Architecture, b) 8-5-1 Training Regression, c) 8-7-1 Architecture, d) 8-7-1 Training Regression

The optimum model with architecture 8-7-1 (MD 2) was extracted into the mathematical expression using Equation (9) which shows the general form of the principle of operation of the ANN model as noted by Taiwo [45-46].

$$P_j = f_{sig} \left\{ b_0 + \sum_{k=1}^n [f_{sig}(b_{nk} + \sum_{i=1}^m w_{ik} \Gamma_i)^{w_{k \times \dots}}] \right\} \quad (9)$$

where, n is the number of neurons in the hidden layer; b_{nk} is the bias in the k th neuron of

the hidden layer; b_0 is the bias in the output layer; w_k is the weight of the connection between the k th of the hidden layer and the single output neuron; w_{ik} is the weight of the connection between the

i th input parameter and the hidden layer; Γ_i is the input variable i ; p_j is the output variable; f_{purlin} and f_{sig} are the linear and nonlinear transfer functions respectively.

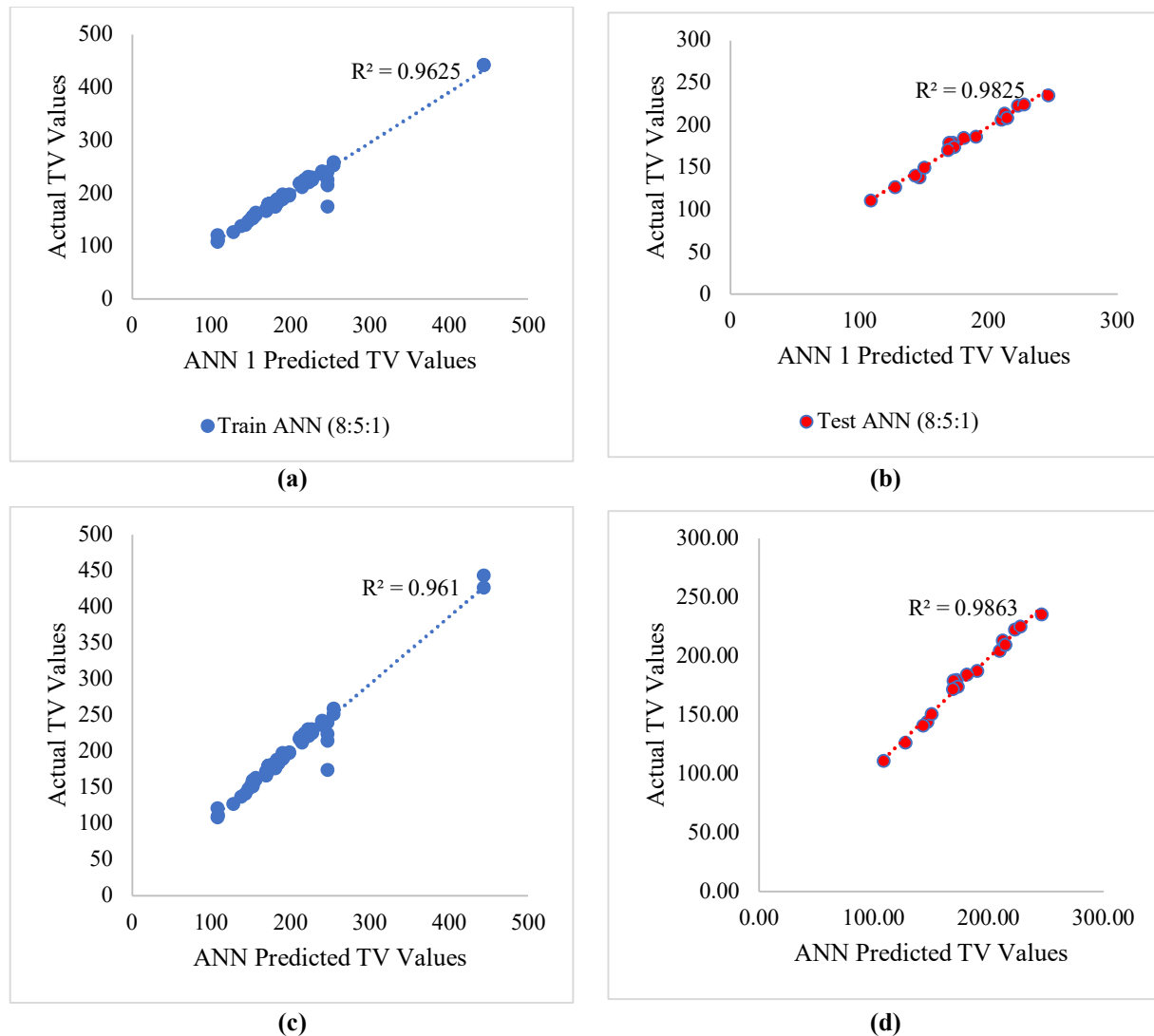


Figure 9. Relationship between the ANN predicted and actual Toe Volume, a&c Training dataset, b&d Testing dataset

The ANN mathematical expression for blast toe volume is presented in Equation (10).

$$TV = 167.8118 \tanh \left(\sum_{i=1}^7 X_i - 0.142368 \right) + 275.48$$

$$X_1 = 0.1329 \tanh \left(0.0104UCS + 0.0303S + 0.0315B + 0.0098SB + 0.0146DHL - 0.0303SR + 0.0245MIC + 0.1150K - 0.01615 \right)$$

$$X_2 = -0.1169 \tanh \left(-0.0096UCS - 0.02669S - 0.0276B - 0.00827SB - 0.01221DHL - 0.02673SR - 0.02124MIC - 0.1016K + 0.01469 \right) \tag{10}$$

$$X_3 = 0.09195 \tanh \left(0.00813UCS + 0.02108S + 0.02158B + 0.00611SB + 0.08933DHL - 0.02110SR + 0.016363MIC - 0.08016K - 0.01209 \right)$$

$$X_4 = -0.8781 \tanh \left(-0.1494UCS + 0.5581S - 0.2684B + 0.1988SB + 0.04518DHL + 0.3533SR + 0.02177MIC - 0.5805K - 0.02429 \right)$$

$$X_5 = 0.6181 \operatorname{Tanh} (-0.2881\text{UCS}+0.1662\text{S}-0.1323\text{B}-0.07586\text{SB} +0.08126\text{DHL}-0.05144\text{SR} \\ +0.19845\text{MIC}+0.5433\text{K} +0.2345)$$

$$X_6 = 0.1073 \operatorname{Tanh} (0.0091\text{UCS}+0.02454\text{S}+0.0253\text{B}+0.0074\text{SB} +0.01089\text{DHL}-0.0246\text{SR} \\ +0.01934\text{MIC}+0.0933\text{K} -0.0137)$$

$$X_7 = -0.6560 \operatorname{Tanh} (-0.1299\text{UCS}-0.31974\text{S}+0.2606\text{B}-0.2899\text{SB} -0.1491\text{DHL}-0.2444\text{SR} +0.15559\text{MIC}- \\ 0.5192\text{K} -0.06364)$$

Where TV is the blast toe volume in m^3 , UCS is the uniaxial compressive strength in MPa, S is the spacing in m, B is the burden in m, SB is the sub-drill in m, DHL is the drill hole length in m, and SR is the stiffness ratio, MIC is the maximum instantaneous charge Kg/m^3 , K is the powder factor in Kg/m^3 , X_1, X_2, \dots, X_7 are total layer weight effect.

4.3. AdaBoost regression Algorithm for Prediction model development

4.3.1. AdaBoost regression Algorithm

Weidong et al. stated that AdaBoost regression is a machine learning approach utilized for developing regression models [67]. This modelling technique is a meta-estimator that initially fits a regressor on the original dataset. It then fits numerous copies of the regressors on the same dataset, but with updated weights for each instance based on the error of the current prediction [68]. AdaBoost comprises two primary components: a powerful classifier known as multi-model and a step-by-step algorithm. Adaboost algorithm yields a highly effective classifier, which is its primary benefit, and achieves this through a two-stage process [69]. To begin with, it utilizes a weight matrix to train numerous weak classifiers within the training dataset. Additionally, it combines many regression algorithms for tree boosting.

The prediction equation for the regression is present in Equation (11), where T is the number of weak classifiers, h_t is the t^{th} trained weak classifier, and α_t is the weight of h_t . The final category of the sample is H , the predictor [69].

$$H_x = \operatorname{sign}\left(\sum_{t=1}^T \alpha_t h_t(x)\right) \quad (11)$$

As explained by [70], the loss function that is used by the traditional AdaBoost algorithm is the exponential loss function. Therefore, the weight calculation formula for α_t is defined as Equation (12).

$$\alpha_t = \frac{1}{2} \ln\left(\frac{1-\varepsilon_t}{\varepsilon_t}\right) \quad (12)$$

Where ε_t is the classification error rate of the h_t .

Moreover, the distribution of the training samples is adjusted based on α_t , thus the formula is given as Equation (13).

$$\omega_{t+1} = \begin{cases} \frac{\omega_t e^{-\alpha_t}}{Z_t}, & \text{if } y = h_t(x) \\ \frac{\omega_t e^{\alpha_t}}{Z_t}, & \text{else} \end{cases} \quad (13)$$

Where ω_t represents the weights of training samples in the previous iteration, y represents the classification label, and z_t is the normalization factor.

4.3.2. AdaBoost regression Algorithm for the Prediction of Blast Toe Volume

The AdaBoost model developed in this study has one dependent variable (blast toe volume) and eight independent variables. The AdaBoost model was trained using 80% of the data set and tested on a 20% section of the entire normalized database. The implementation was done using the MATLAB© software. Figure 10 depicts the association between the actual blast toe volume and the projected outcomes of the AdaBoost model for both the training dataset ($R^2 = 0.8114$) and the testing dataset ($R^2 = 0.8705$).

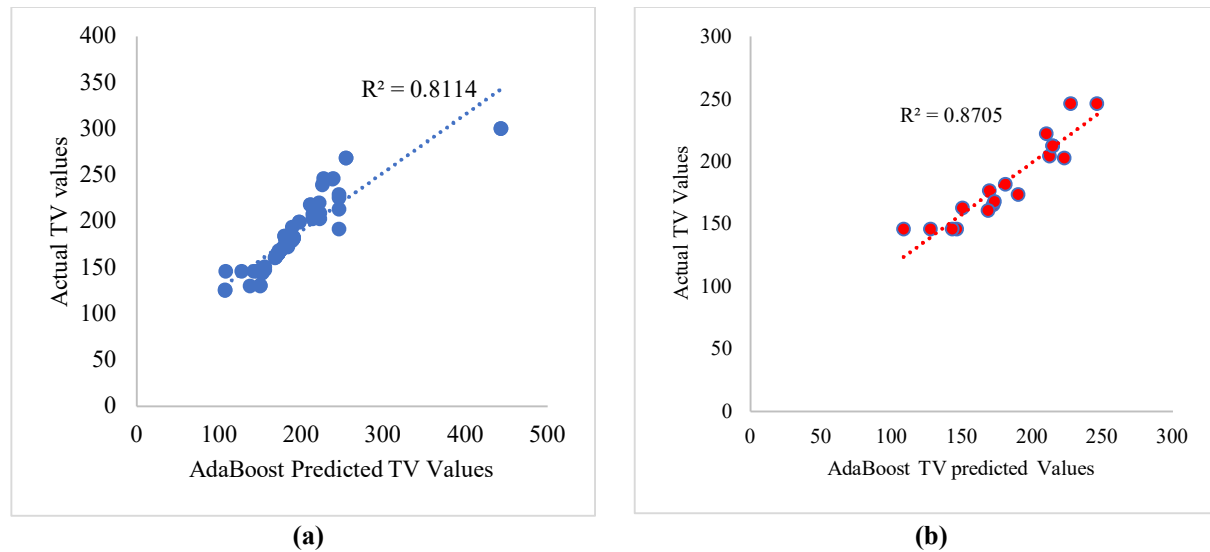


Figure 10. Relationship between the Adaboost predicted and actual Toe Volume; a. Training dataset, b. Testing dataset

4.4. Support Vector Regression for Prediction model development

4.4.1. Support Vector Regression Algorithm

Support Vector Regression (SVR) is a regression approach that utilizes Support Vector Machines to represent many types of situations. [71] stated that Support Vector Regression (SVR) is a method used to predict continuous variables. It achieves this by identifying a hyperplane that provides the greatest fit to the data, while allowing for a given margin of error [71]. Using the kernel method, SVR translates input features into a higher-dimensional space to capture complex relationships [72]. Support vectors, which are data points located near the hyperplane, play a vital role in determining the appropriate hyperplane. The technique aims to minimize a loss function by punishing any deviations that exceed a specified margin of epsilon. The crucial parameters for Support Vector Regression are C , which controls the balance between smoothness and accuracy, and epsilon (ϵ), which determines the width of the insensitive tube. In addition, Support Vector Regression (SVR) exhibits outstanding ability to generalize and achieves a high degree of accuracy in predicting outcomes. This machine learning technique employs a linear regression process, as outlined in Equation (14), to provide predictions. The SVR model produces an output denoted as $Z(q)$, where q_i represents the input variable, ϕ represents the non-linear

mapping, and w_i and b are the weight vector and bias of the regression function.

The non-negative slacker parameters ξ_i and ξ_i^- ($i = 1, 2, \dots, l$) is established to evaluate the divergence of train support vectors that arise outside the ϵ -insensitive zone. During the training process, SVR aims to minimize both the total permitted error and the squared weight vector. The SVR ϵ -insensitive for the model was determined by minimizing Equation (14). For kernel minimization, Equations (15-17) were utilized for all the kernel models.

$$z(q) = \sum_i^G \beta(q_i) \times w_i + b \quad (14)$$

$$C \sum_{n=1}^N (\xi_n + \xi_n^-) + \frac{1}{2} \|w\|^2 \quad (15)$$

$$\xi_n \geq 0 \quad \text{and} \quad t_n \leq f(x_n) + \epsilon + \xi_n \quad (16)$$

$$\xi_n^- \geq 0 \quad \text{and} \quad t_n \geq f(x_n) - \epsilon - \xi_n^- \quad (17)$$

4.4.2. Support Vector Regression for the Prediction of Blast Toe Volume

The proposed SVR model in this research consists of a single dependent variable (blast toe volume) and eight independent variables. The proposed SVR model was trained with 80% of the data set and tested with 20% portion of the whole

normalized database and was implemented using the MATLAB© software.

Figure 11 illustrates the degree of correlation that exists between the actual blast toe volume

and the outcomes that the SVR model predicted with regard to the training dataset ($R^2 = 0.9697$) and the testing dataset ($R^2 = 0.9127$), respectively.

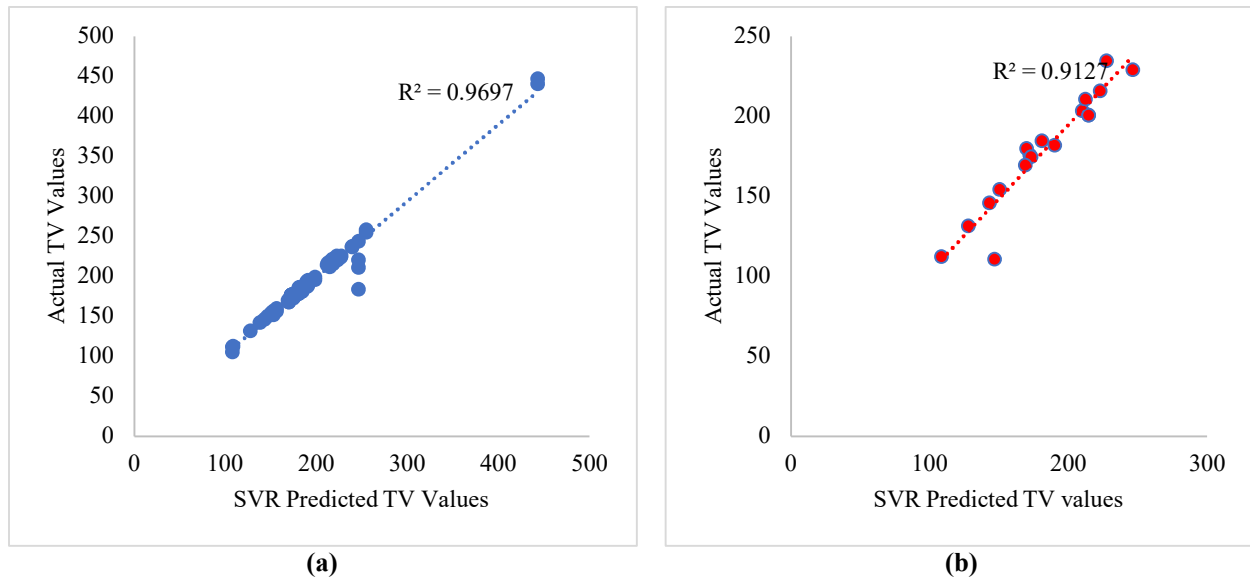


Figure 11. Relationship between the SVR predicted and actual Toe Volume; a. Training dataset, b. Testing dataset

4.5. Random Forest (RF) algorithm for Prediction model development

4.5.1. Random Forest (RF) algorithm

The Random Forest technique, renowned for its adaptability, is utilized for blast optimization by leveraging its capacity to manage intricate, non-linear associations [72]. Random Forest is capable of effectively representing the complex relationships between blast design factors in this scenario. Every individual tree inside the forest evaluates distinct combinations of characteristics, resulting in a varied range of forecasts [73]. This diversity is essential for capturing the intricate interactions that are vital for maximizing blast outcomes. The robustness of Random Forest in mitigating overfitting and its capacity to handle high-dimensional data make it highly suitable for enhancing the accuracy and efficiency of blast optimization procedures. This, in turn, contributes to safer and more effective blasting in mining or construction applications. Random Forest is an ensemble learning technique devised by Breiman in 2001, used to solve classification

and regression problems. The Random Forest algorithm is composed of a collection of decision trees, and its final output is obtained by combining the outputs of each individual tree [74]. The primary parameters for the RF model include identifying the square root of the number of components (mtry) and the number of trees to execute the model (ntree).

4.5.2 Random Forest (RF) algorithm for the Prediction of Blast Toe Volume

The RF model suggested in this work has one dependent variable, Blast Toe Volume, and eight independent factors. The RF model was trained using 80% of the data set and evaluated with a 20% section of the normalized database. The implementation was done using the MATLAB© software.

Figure 12 illustrates the degree of correlation that exists between the actual blast toe volume and the outcomes that the RF model predicted with regard to the training dataset ($R^2 = 0.8046$) and the testing dataset ($R^2 = 0.9493$), respectively.

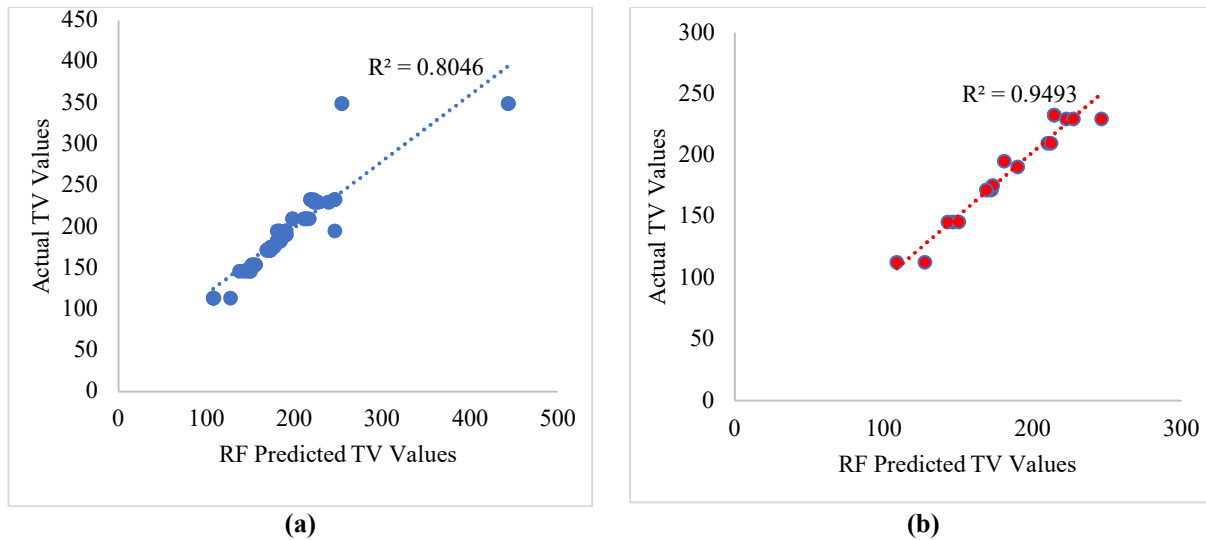


Figure 12. Relationship between the RF predicted and actual Toe Volume, a. Training dataset, b. Testing dataset

4.6. Gaussian Process Regression (GPR) for Prediction model development

4.6.1. Gaussian Process Regression

Gaussian Process Regression (GPR) is a useful method for estimating Blast Toe Volume. It provides a probabilistic way to estimate this important parameter in blasting optimization [75]. GPR has the capacity to represent the inherent uncertainty in blast outcomes, offering not only predictions but also confidence intervals. This is essential for evaluating the trustworthiness of blast toe volume estimation. The utilization of Ground Penetrating Radar (GPR) has gained widespread recognition across various disciplines. [76] employed Ground Penetrating Radar (GPR) and other ensemble learning techniques to forecast meteorological drought and standardized precipitation index. Gaussian Process Regression (GPR) is a powerful technique for forecasting blast toe volumes with high accuracy, considering the inherent variability of the data points. GPR achieves this by effectively utilizing the covariance structure of the data, making it an excellent choice for precision blasting and minimizing environmental impact.

4.6.2 Gaussian Process Regression (GPR) for the Prediction of Blast Toe Volume

The GPR model suggested in this work comprises one dependent variable, Blast Toe Volume, and eight independent factors. The GPR model was trained using 80% of the dataset and

evaluated with a 20% section of the normalized database. The implementation was done using the MATLAB© software. Figure 13 depicts the correlation between the actual blast toe volume and the projected results of the GPR model for both the training dataset ($R^2 = 0.9972$) and the testing dataset ($R^2 = 0.933$).

4.6. Model optimization with Imperialist Competitive algorithm (ICA)

The ICA technique was utilized to reduce the volume of the toe in the mines being studied, with the objective of improving the controllable parameters of the blast. The utilization of a fitness function is important to attain the most favorable cost while optimizing a model through the ICA method. The most accurate predictive model, the 8-7-1 Artificial Neural Network (ANN) model, was utilized as the fitness function to do this. A MATLAB software file was used to access the ANN model during the simulation of ICA. The key parameters used to assess the performance capacity of the ICA algorithm are the count of countries, the count of imperialists, and the count of decades. These enable us to get the most optimal model and optimize the parameters of the blast design. According to the optimal model, the best settings for the model's hyperparameters were determined using 25 imperialists, 86 countries, and 100 decades. The enhanced blast design parameters are visible in Table 4. The optimal blast design parameters have been

identified as follows: $S = 1$ m, $B = 0.65$, $H/B = 2$ m, $MIC = 0.72$ kg, and $K = 0.85$ kg/m³. By substituting these values, the volume of the toe can be decreased by 30.85% after the process of blasting. The results indicated that the ICA model

greatly decreases the amount of blast toe volume, thereby confirming its efficacy as an optimization method for optimizing blasting pattern parameters.

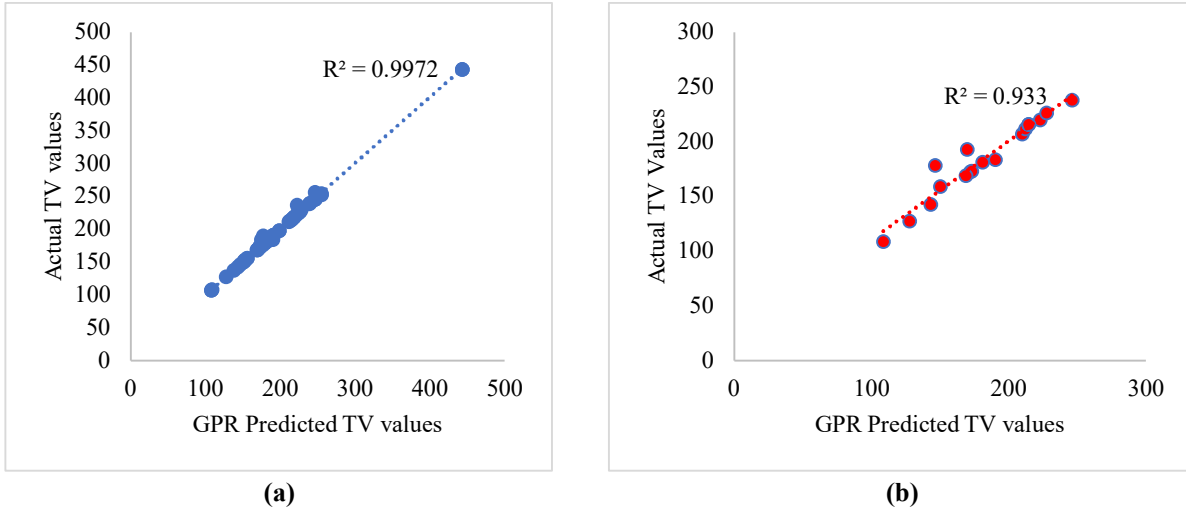


Figure 13 Relationship between the GPR predicted and actual Toe Volume; a. Training dataset, b. Testing dataset

Table 4. Optimized blast design parameters using ICA

Parameter state	S (m)	B (m)	H/B	MIC (kg)	K (kg/m ³)	Toe Volume (m ³)
Current	1.2	0.80	1.91	0.86	0.97	191.2802
Optimized	1.00	0.65	2.00	0.72	0.85	132.27
Difference (%)	16.67	18.75	4.48	16.64	12.10	30.85

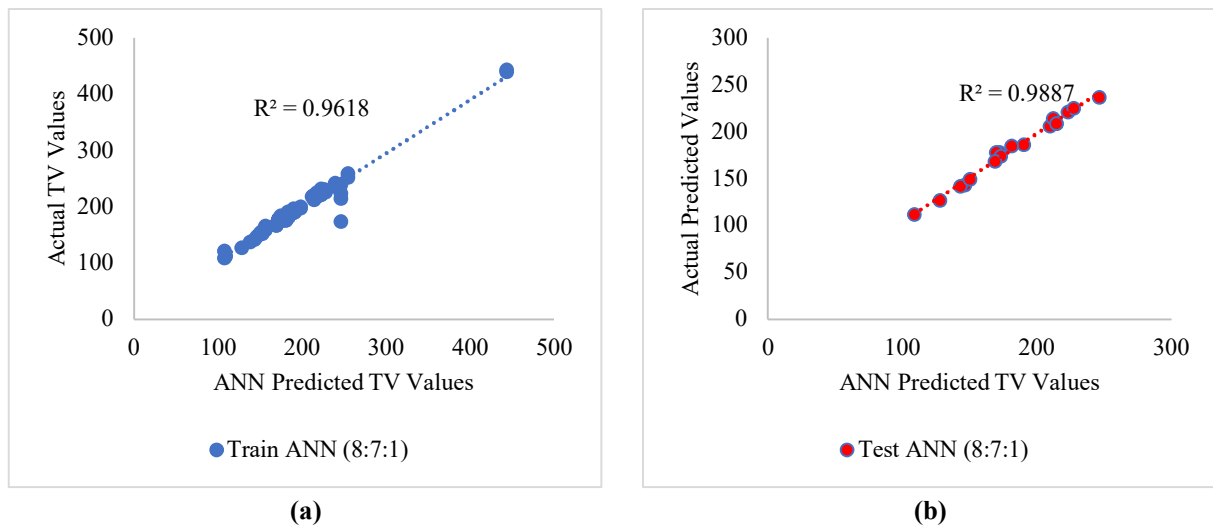


Figure 14. Relationship between the ICA-ANN predicted and actual Toe Volume

Furthermore, the ICA-ANN technique was employed to develop a predictive model for toe volume. During the training phase, 80% of the dataset was utilized, while the remaining 20% was

allocated for post-training model validation. The findings demonstrated that the ICA-ANN model exhibited enhancement over the conventional ANN model, employing an 8-7-1 configuration. As

shown in Figure 14, the ICA optimized model demonstrated high prediction accuracy, as evidenced by R^2 values of 0.962 and 0.9887 for the training and test phases, respectively. In the subsequent subsection, the performance of the ICA-ANN model was assessed by comparing it to other models, including Conventional ANN models. This assessment was conducted utilizing many error analysis indices.

5. Performance Evaluation

The performance and accuracy of the proposed soft computing models was evaluated using the following metrics: (1) root mean square error, (2) coefficient of determination, (3) weighted mean absolute percentage error (4) variance accounted for, (5) the index of scatter and (6) product index, (7) mean absolute error, and (8) Mean square Error. The mathematical formulation of the performance indicators is as follows [77].

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\alpha - \omega)^2} \quad (18)$$

$$R^2 = \frac{\sum_{i=1}^r (\alpha - \beta)^2 - \sum_{i=1}^r (\alpha - \omega)^2}{\sum_{i=1}^r (\alpha - \beta)^2} \quad (19)$$

$$WMAPE = \frac{\sum_{i=1}^n \left| \frac{\alpha - \omega}{\alpha} \right| * \alpha}{\sum_{i=1}^n \alpha} \quad (20)$$

$$VAF = \left(1 - \frac{var(\alpha - \omega)}{var(\alpha)} \right) * 100 \quad (21)$$

$$IOS = \frac{RMSE}{Avg. \text{ of Actual Values}} \quad (22)$$

$$PI = R^2 + (VAF/100) - RMSE \quad (23)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |(P - O)| \quad (24)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (\alpha - \omega)^2 \quad (25)$$

where α and ω are the actual and predicted i^{th} value, n presents the total number of data, β is the mean of the actual values, $\bar{\omega}$ is the mean of the predicted value, k is the number of independent variables, and N is the total number of data samples.

The error analysis findings for each model developed in this study to estimate the volume of blast toe are presented in Table 5 for the training dataset and Table 6 for the testing dataset, respectively. The results demonstrate the superior effectiveness of two artificial neural network (ANN) models in comparison to random forest, Gaussian process regression (GPR), support vector regression (SVR), and gradient boosting models. Upon comparing the two distinct artificial neural network (ANN) models developed in this study, the error analysis revealed that the 8-7-1 version had superior predictive capabilities compared to the 8-5-1 model. Furthermore, the acquired data clearly indicated that the two artificial neural networks (ANN) yield the smallest values for root mean square error (RMSE), mean absolute error (MAE), and weight mean absolute percentage error (WMAPE). Moreover, the results clearly demonstrated that the ICA-based ANN model significantly improves the prediction of root mean square error compared to the AdaBoost, SVR, GPR, RF, 8-5-1, and 8-7-1 ANN models. The ICA-based model outperforms the AdaBoost model by 9.17%, the SVR model by 7.2%, the GPR model by 5.56%, the RF model by 4.75%, the ANN (8-5-1) model by 0.78%, and the ANN (8-7-1) model by 0.28%. The ICA-ANN model is proposed to have a much higher predicting correlation coefficient compared to the AdaBoost, SVR, GPR, RF, ANN (8-5-1), and 8-7-1 ANN models. An exceptionally effective artificial neural network (ANN) equation was particularly devised to precisely predict the volume of the toe resulting from an explosion. The mathematical equation of the artificial neural network (ANN) demonstrated exceptional accuracy in computing the volume of the blast-generated toe. The R^2 values obtained from the training and testing datasets are 0.962 and 0.9887, respectively. This study is the initial endeavor to develop a mathematically based artificial neural network (ANN) equation for accurate forecasting the volume of blast toe. The objective is to enhance the effectiveness of post-blast operations and the efficiency of fragmentation. The artificial neural network (ANN) model, based on independent component analysis (ICA), developed in this study, has the capability to accurately forecast the magnitude of blast toe in mining operations. Implementing the methods as suggested in this study can enhance the efficiency of blasting operations and mining procedures in realistic scenarios.

Table 5. Model Error Analysis Result for Training Dataset

	Training						
	AdaBoost	SVR	GPR	RF	ANN (8:5:1)	ANN (8:7:1)	ICA-ANN (8:7:1)
RSME	27.07	9.56	2.95	23.86	10.75	10.76	10.56
R ²	0.81	0.97	0.98	0.82	0.96	0.96	0.96
MSE	732.71	91.44	8.69	569.37	119.27	115.89	111.56
WMAPE	0.07	0.02	0.001	0.05	0.03	0.03	0.03
VAF	77.16	96.95	99.71	80.46	96.25	96.02	96.17
IOS	0.14	0.05	0.02	0.12	0.06	0.06	0.05
PI	-25.49	-7.62	-0.96	-22.24	-8.82	-8.84	-8.64

Table 6. Model Error Analysis Result for Testing Dataset

	Testing						
	AdaBoost	SVR	GPR	RF	ANN (8:5:1)	ANN (8:7:1)	ICA-ANN (8:7:1)
RSME	13.52	11.55	9.91	9.10	5.13	4.63	4.35
R ²	0.87	0.91	0.93	0.95	0.98	0.987	0.996
MSE	182.66	133.55	98.21	82.81	26.32	21.44	18.92
WMAPE	0.05	0.04	0.03	0.04	0.02	0.02	0.02
VAF	86.86	91.25	93.18	94.12	98.12	98.42	98.64
IOS	0.07	0.06	0.05	0.05	0.03	0.03	0.02
PI	-11.78	-9.72	-8.05	-7.21	-3.17	-2.66	-2.37

5.2. Model score analysis results

The superiority of the proposed models was evaluated with Equation (26) [78], using a

combination of train and test performance measures.

$$Ra = \sum_{i=1}^2 r_i^{RSME} + r_i^{WMAPE} + r_i^{R^2} + r_i^{MSE} + r_i^{PI} + r_i^{VAF} + r_i^{EI} + r_i^{ISO} \tag{26}$$

Where r_i is the rate of evaluation criteria, $i = 1$ designates the train rates of evaluation indicators, $i = 2$ represents the test rates of evaluation indices, Ra is the final rating value for each model, and r_i is the rate of evaluation criteria.

As indicated in Table 7, the score result demonstrated that the ICA-ANN model has the highest rank, while adaptive Boost Ensemble learning model has the lowest rank.

5.3 Assessing the model and effect of blast Toe on Fragmentation

Figures 15 and 16 present the comparative results of blast fragmentation analysis conducted at the mine site, illustrating the performance before and after the refinement of blast design parameters. The analysis encompasses key fragmentation metrics, including the average fragment size (X50), uniformity index, and blast toe volume across three independent blast events, providing a clear view of the impact of optimization efforts.

Following the simulation of input blast parameters using the Improved Cuckoo Algorithm–Artificial Neural Network (ICA-ANN) model, a significant improvement in blast performance was observed, particularly in terms of toe fragmentation. By predicting and optimizing the blast

configuration before field implementation, the operation achieved a marked reduction in toe volume, which is a critical indicator of effective energy distribution and rock breakage at the base of the bench.

Specifically, the toe volume decreased from 472.87 mm to 369.97 mm, and in volumetric terms, from 209.5 m³ to 140.5 m³, representing an approximate 30% reduction, as summarized in Table 8. This outcome demonstrates the efficacy of the predictive model and the subsequent optimization strategies adopted by the firm to enhance blasting outcomes and operational efficiency. The X50 values for rock fragments remained within the acceptable limits, confirming that the fragment size distribution met the desired specifications for downstream processes.

The same optimized parameters were subsequently applied at a nearby quarry site, as detailed in Figures 15 and 16. The implementation yielded similar improvements, validating the general applicability and robustness of the optimized design across different geological settings. This resulted in enhanced blast results, reduced oversized generation, and improved overall productivity in both mining and quarrying operations.

Table 7. Model Ranking Result

		RSME	R ²	MSE	WMAPE	VAF	IOS	PI	EI	Total	Rating	Rank
AdaBoost	Train	7	7	7	7	7	7	7	7	56	112	7
	Test	7	7	7	7	7	7	7	7	56		
SVR	Train	2	2	2	2	2	2	2	2	16	72	5
	Test	6	6	6	6	6	6	6	6	48		
GPR	Train	1	1	1	1	1	1	1	1	8	47	2
	Test	5	5	5	4	5	5	5	5	39		
RF	Train	6	6	6	6	6	6	6	6	48	81	6
	Test	4	4	4	5	4	4	4	4	33		
ANN (8:5:1)	Train	4	3	5	4	3	4	4	5	32	56	4
	Test	3	3	3	3	3	3	3	3	24		
ANN (8:7:1)	Train	5	5	4	5	5	5	5	4	38	54	3
	Test	2	2	2	2	2	2	2	2	16		
ICA-ANN (8:7:1)	Train	3	4	3	3	4	3	3	3	26	34	1
	Test	1	1	1	1	1	1	1	1	8		

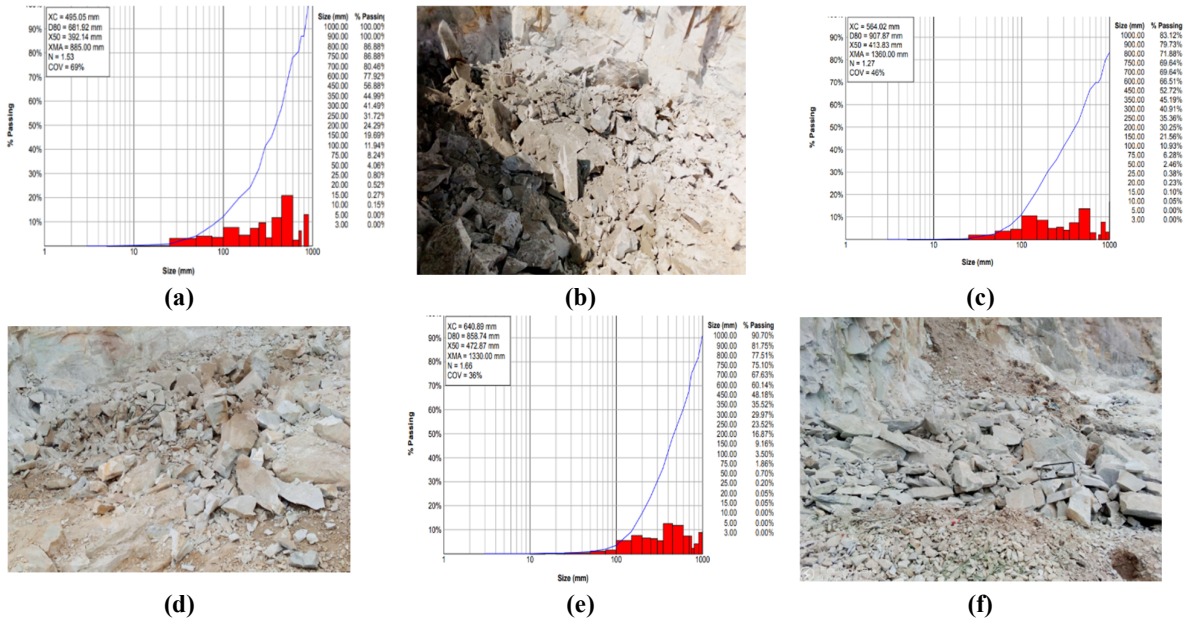


Figure 15. Blast Fragmentation Results before Optimization

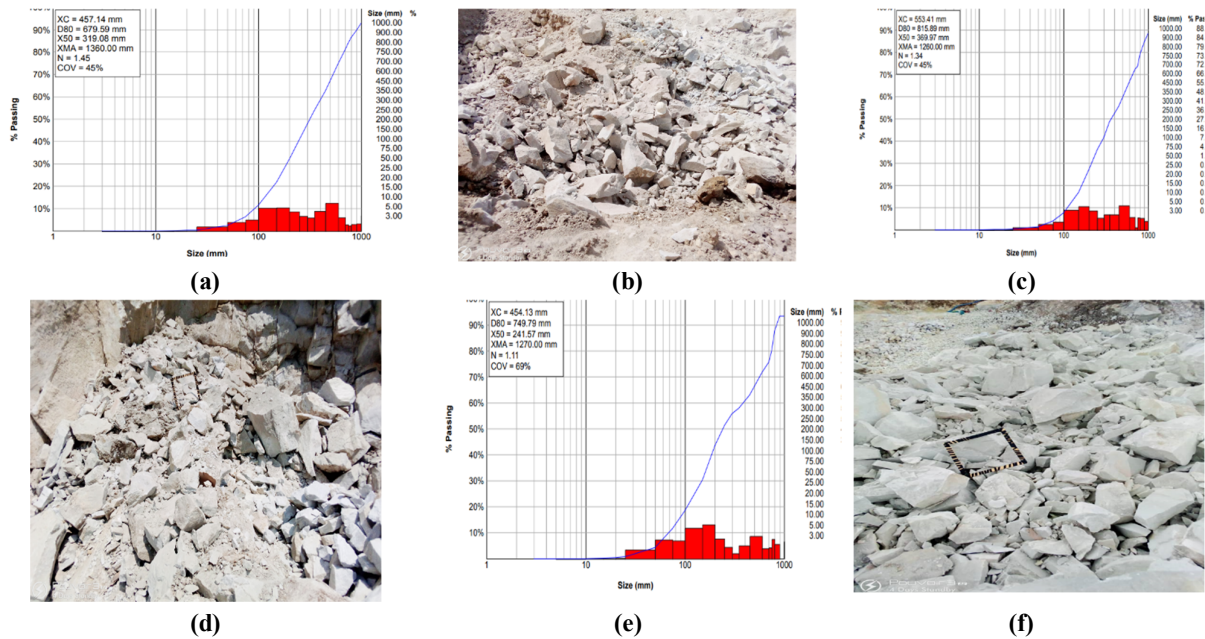


Figure 16. Blast fragmentation result After optimization

Table 8. Comparison of equipment stats before and after ICA-ANN application

	Before			After			
	X50	N	TV	X50	N	TV	
A1	392.14	1.53	209.5	B1	319.08	1.45	128.6
A2	413.83	1.27	240.6	B2	369.97	1.34	134.8
A3	472.87	1.66	238.2	B3	241.57	1.11	140.5

6. Conclusions

Minimizing the blast radius is crucial for mitigating damage to buildings and enhancing safety during rock blasting. Effective strategies involve optimizing the placement of explosives, controlling detonation

parameters, and utilizing advanced techniques such as confinement approaches. Decreasing the blast toe volume reduces the likelihood of ground displacement and collateral damage. All these will ensure mitigation of environmental, structural consequences, promotion of effective and controlled explosive outcomes. This study

involved the development of machine learning models to predict the toe volume. The models utilized artificial neural networks (ANN), AdaBoost, support vector regression, random forest, and Gaussian Process Regression (GPR) approaches. The results revealed that toe was reduced by implementing the Imperialist Competitive Algorithm (ICA). The ICA was used to optimize the blast parameters, considering the 8-7-1 structured Artificial Neural Network (ANN) model as the function for fitting.

The findings of the research are as follows:

1. The blast parameters and rock strength dataset for the development of the proposed model was gathered from four quarries (Q1, Q2, Q3, Q4). The data collected from the case study quarries show that the current blast design including spacing, burden, sub-drill, and charge length for Q1, Q2, Q3, Q4 are (0.85 m, 0.96 m, 1.1 m), (0.7 m, 0.8 m, 0.8 m, 0.9 m), and (0.65 m, 0.7 m, 0.66 m) respectively.
2. The blast toe volume left on the pit floor was assessed after each blast round. The results show that the blast toe volume ranged from 107.67-443.29 m³. The findings show that the blast toe volume reduces as the explosive charge quantity increases. Furthermore, the multicollinearity analysis result shows that rock strength, spacing, maximum instantaneous charge has a low level of multicollinearity ($0 < VIF \leq 2$); burden and powder Factor have a significant level of multicollinearity ($2 < VIF \leq 4.0$); the drill hole length has a moderate level of multicollinearity ($5.0 < VIF \leq 15.0$); and the burden and stiffness ratio have a problematic level of multicollinearity ($VIF > 15.0$).
3. The study also employed various machine learning techniques to develop prediction models for blast toe volume forecasting. In the study, 90 blasting operations were monitored and a database was created using 8 important blasting parameters. For this aim, six base models which are AdaBoost, SVR, GPR, RF, 8-5-1 ANN, and 8-7-1ANN and ICA hybrid were developed. The statistical parameters of RSME, MSE, MAE, R², IOS, PI, and VAF were used to evaluate the performance of developed base and hybrid models. The base model results indicated that the GPR with RSME (2.95 and 9.91), R² of (0.98 and 0.93), MSE of (8.69 and 98.21), WMAPE of (0.01 and 0.03), VAF of (99.71 and 93.18), and IOS of (0.02 and 0.05) for training and testing datasets, respectively. The hybrid model results indicated that the ICA-ANN with RSME (10.56 and 4.35), R² of (0.96 and 0.996), MSE of (111.56 and 18.92), WMAPE of (0.05 and 0.02), VAF of (96.17 and 98.64), and IOS of (0.05 and 0.02) for training and testing datasets, respectively. Hybrid models developed with ICA contributed to the development of basic models and enabled more reliable prediction results to be obtained for blast toe volume estimation.
4. Considering results of all models in predicting toe volume, ANN model with 8-7-1 architecture can provide higher performance capacity compared to other developed models. Therefore, it was selected as the best model to predict toe volume induced by blasting and then used as the objective function in optimizing the blast design parameters.
5. The results of ICA optimization technique showed that the new proposed blast parameters are S = 1 m, B = 0.8 m, SB = -0.6m, MIC = 0.72 kg, and K = 0.65 kg/m³, minimizing the blast toe volume by 20.05% (reducing from 209.5 m³ to 154.87 m³).

Future work will focus on scaling and validating the model's application across large-scale mining and quarry operations to assess its robustness and adaptability in diverse geological and operational conditions.

Conflicts of interest

The authors declare no conflict of interest.

Ethical statement

The authors state that the research was conducted according to ethical standards.

Data Availability

Data will be made available on request

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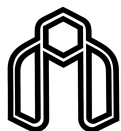
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بهبود پایدار خردایش سنگ با استفاده از هوش مصنوعی: به حداقل رساندن حجم پنجه انفجار برای عملیات ایمن تر و پاک تر

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چکیده	اطلاعات مقاله
این مطالعه چندین مدل هوش مصنوعی (AI) را برای پیش‌بینی حجم پنجه ناشی از انفجار در معادن دولومیت کوچک‌مقیاس واقع در منطقه دولتی محلی آکوکو ادو، ایالت ادو، نیجریه توسعه داده و ارزیابی کرد. هفت مدل پیش‌بینی ساخته شد: تقویت تطبیقی (AdaBoost)، جنگل تصادفی (RF)، رگرسیون فرآیند گاوسی (GPR)، رگرسیون بردار پشتیبان (SVR)، یک شبکه عصبی مصنوعی (ANN) معمولی و دو شبکه عصبی مصنوعی بهینه شده با الگوریتم رقابت استعماری (ICA-ANNs). مدل‌ها با استفاده از هشت پارامتر ورودی شامل مقاومت فشاری تک‌محوری (UCS)، فاصله‌گذاری (S)، بار (B)، زیر مته (SB)، طول سوراخ مته (DHL)، نسبت سختی (SR)، حداکثر بار لحظه‌ای (MIC) و ضریب پودر (K) با حجم پنجه انفجار (TV) به عنوان خروجی هدف آموزش داده شدند. داده‌های ورودی از طریق ترکیبی از اندازه‌گیری‌های میدانی و تجزیه و تحلیل‌های آزمایشگاهی جمع‌آوری شدند. در میان تمام مدل‌های ارزیابی شده، ICA-ANN با معماری ۸-۷-۱ بالاترین دقت پیش‌بینی را به دست آورد. این مدل بر اساس معیارهای میانگین مربعات خطا (MSE) و ضریب تعیین (R^2)، ۹.۱۷ درصد بهتر از AdaBoost، ۷.۲۰ درصد بهتر از SVR، ۵.۵۶ درصد بهتر از GPR، ۴.۷۵ درصد بهتر از RF، ۰.۷۸ درصد بهتر از ANN استاندارد (۸-۵-۱) و ۰.۲۸ درصد بهتر از ANN استاندارد (۸-۷-۱) عمل کرد. علاوه بر این، مدل ICA-ANN برای بهینه‌سازی پارامترهای طراحی انفجار به کار گرفته شد. مقادیر بهینه به‌دست‌آمده عبارت بودند از: فاصله = ۱.۰ متر، بار = ۰.۸ متر، زیر مته = ۰.۶ متر، $MIC = 0.72$ کیلوگرم و ضریب پودر = ۰.۶۵ کیلوگرم بر متر مکعب. این پارامترهای بهینه‌شده، حجم پنجه انفجار را ۲۰.۰۵ درصد کاهش دادند، از ۲۰۹.۵۰ متر مکعب به ۱۵۴.۸۷ متر مکعب. نتایج، استحکام و کارایی مدل ICA-ANN را برای بهینه‌سازی طراحی انفجار برجسته می‌کند. با بهبود کیفیت خردایش و به حداقل رساندن حجم باقیمانده سنگ، این رویکرد مسیری عملی برای افزایش بهره‌وری و مقرون‌به‌صرفه بودن در عملیات معدنکاری در مقیاس کوچک ارائه می‌دهد.	تاریخ ارسال: ۲۰۲۵/۰۴/۲۱ تاریخ داوری: ۲۰۲۵/۰۸/۲۲ تاریخ پذیرش: ۲۰۲۵/۰۹/۰۷ DOI: 10.22044/jme.2025.16088.3102 کلمات کلیدی انفجار حجم پنجه پا تقویت تطبیقی شبکه‌های عصبی مصنوعی الگوریتم رقابت استعماری