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# MACHINE LEARNING MODELS FOR PREDICTING ROCK FRAGMENTATION IN GRANITE QUARRY BLASTING

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**Abstract:** Blasting operations in quarrying and mining require precise control over fragmentation to optimize downstream processes. Traditional fragmentation analysis methods often fail to capture all the variables impacting fragmentation. This study presents a soft-computing approach integrating Support Vector Regression (SVR), Random Forest (RF), Artificial Neural Networks (ANN), Linear Regression and the traditional Kuz-Ram models to predict characteristic particle size at D63, N, and fragmentation size-uniformity Index, Xc. Rock properties such as Uniaxial Compressive Strength (UCS), Young's Modulus, and Poisson's Ratio were utilized alongside blast design parameters like spacing, burden, drillhole diameter and drillhole length. Python, with libraries such as Pandas, Scikit-learn, Keras, and Numpy were used for the modelling, Model performances were evaluated using RMSE, RAE, and $R^2$, with RF demonstrating superior predictive capability in predicting both fragmentation index and characteristic particle sizes with $R^2$ score of 0.6 and 0.7, respectively. Whereas ANN performed the worst with $R^2$ score of -1549 and 142 for characteristic particle size and uniformity index, respectively, due to small dataset. The results highlight the potential of AI-driven models in optimizing blasting efficiency.

***Keywords: Blasting, granite, Fragmentation, Machine Learning, Predictive Modelling, Soft Computing.***

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## I. INTRODUCTION

In mining and quarrying activities, blasting operations play a pivotal role. It serves as the primary method for rock fragmentation. The efficiency of these operations influences downstream processes, including loading, hauling, and crushing, thereby affecting overall productivity and operational costs. A critical aspect of evaluating blasting performance is the fragmentation size-uniformity index, which quantifies the distribution uniformity of fragmented rock sizes [1]. Achieving optimal fragmentation enhances operational efficiency, while poor fragmentation can lead to increased costs and reduced productivity [2].
Traditionally, empirical models such as the Kuz-Ram model have been employed to predict rock fragmentation outcomes. The Kuz-Ram model integrates explosive properties, rock characteristics, and blast design parameters to estimate mean fragment size and size distribution [3]. However, this model has limitations, particularly in accounting for the inherent variability and complexity of geological formations, which can lead to inaccuracies in fragmentation predictions.
In recent years, advancements in soft computing techniques have provided alternative approaches to modelling complex, nonlinear systems like rock blasting. Soft computing encompasses methodologies such as artificial neural networks (ANNs), support vector machines (SVMs), and gene expression programming (GEP), which can handle uncertainties and learning from data patterns [4]. These techniques have been applied to predict rock fragmentation, offering improved accuracy over traditional empirical models.
For instance, [5] developed various novel soft computing models based on metaheuristic algorithms to predict rock size distribution in mine blasting. Their study demonstrated that these models could effectively capture the complex relationships between blasting parameters and fragmentation outcomes, leading to more reliable predictions.
Similarly, [2] explored the development of soft computing-based mathematical models for predicting mean fragment size, coupled with Monte Carlo simulations. Their findings indicated that ANN models exhibited high predictive accuracy, underscoring the potential of soft computing techniques in enhancing fragmentation prediction.

The application of these advanced modelling techniques addresses the limitations of traditional empirical models by incorporating a broader range of influential parameters and capturing the inherent variability in rock properties and blasting conditions
This study aims to develop and validate soft-computing models for predicting the fragmentation size-uniformity index in granite blasting. By leveraging the capabilities of soft computing techniques, the research seeks to enhance the accuracy of fragmentation predictions, thereby contributing to more efficient and cost-effective blasting practices in the mining industry.

## II. STATEMENT OF THE PROBLEM

Blasting in mines and quarries contribute significantly to the cost of operation. The key performance indicators of good blasting are good fragmentation that enhances good loading, haulage, and crushing operations [6]. In pre soft computing age, fragmentation analysis was often calculated by mining engineers using various traditional methods like the Kuz-Ram, Rosin-Rammler distribution curve, Swebrec function etc [7], [8]. However, these traditional methods fail to model the fragmentation analysis accurately due to the many variables involved in blasting.
With the advent of AI models, engineers have modelled fragmentation analysis using various models such as ANN, Artificial Bee Colony, Support Vector Machine, and Gene Expression Programming [9], [10], [11]. However, most of the models failed to predict fragmentation outcome accurately. This is due to the various geological factors affecting fragmentation. Geological factors vary greatly over different places. This study addressed these gaps by using geological parameters within the study areas along with drill and blasting parameters to model fragmentation outcomes using ANN, SVR, RF, LR and Kuz-Ram.

## III. RESEARCH METHODOLOGY

The study employs a data-driven approach, using Python-based machine learning techniques to model the complex relationships between blasting inputs and fragmentation outcomes.

### 3.1 Research Design

The study adopts a quantitative research design integrating computational modelling and empirical data analysis. The core aim is to train, validate, and compare the predictive performance of three machine learning models—SVR, RF, ANN—using rock and blast parameter datasets. Traditional models like linear regression and Kuz-Ram were also used to evaluate fragmentation index and rock size characteristics. analysis.

### 3.2 Data Source

Data used in this study were collected from documented blast events in three granite sites in Ogun State Nigeria. The dataset comprises both geological and blast design parameters, including: UCS, tensile strength, young's modulus, rock density, poison's ratio, joint spacing and dip, drill hole diameter, burden and spacing, charge length and weight, explosive density, nature of rock mass. The target variable is the Fragmentation Uniformity Index, N, and Characteristics Particle size, Xc, which is the Size at which 63.2 % of the material pass through the sieve. These are obtained by image processing and fragmentation analysis workflow which was custom-built in Python using OpenCV and scikit-image.

### 3.3 Image-Based Fragmentation Analysis

Blasted muck pile images were analysed using OpenCV and scikit-image libraries in Python. Standard image preprocessing techniques such as grayscale conversion, Gaussian filtering, edge detection (Canny algorithm), and morphological operations were employed [12]. Fragment contours were extracted and evaluated for area and shape. This method has also been used by [13]. The data were used to estimate fragment size distributions, which served to validate the machine learning models. The advantage of using Python over traditional fragmentation software like WipFrag and Slip-Desktop is that Python is free

### 3.4 Model Development

All the total 15 blast rounds – 5 from each site – were combined to form the training dataset. The input variables were analysed for multicollinearity and correlation using Pearson correlation coefficients. All modelling was implemented in Python 3.10 using libraries such as Panda, scikit-learn, Joblib, TensorFlow, Keras, and NumPy. SVR was developed using the SVR() function from scikit-learn. The radial basis function (RBF) kernel was used due to its capability to model nonlinear relationships. Grid search with 5-fold cross-validation was conducted to optimize hyperparameters such as C, epsilon, and gamma [14]. The Random Forest (RF) model was implemented using the RandomForestRegressor() class from scikit-learn. This ensemble technique builds multiple decision trees on random subsets of the dataset and aggregates the results to reduce overfitting and enhance prediction accuracy. Important hyperparameters tuned include n_estimators, max_depth, and min_samples_split [15]. The ANN model was developed using the Keras API within TensorFlow. A feedforward multilayer perceptron (MLP) structure was adopted, consisting of an input layer equal to the number of input features, two hidden layers with ReLU activation and an output layer with a linear activation for regression. The model was trained using the Adam optimizer, with Mean Squared Error (MSE) as the loss function. The models were evaluated using the Root Mean Squared Error (RMSE), Coefficient of Determination ($R^2$) and Mean Absolute Error (MAE).

## IV. RESULTS AND DISCUSSION

### 4.1 **Blast and Rock properties**

Figure 1 is drilling, blasting and rock property data set obtained from three granite quarries: Obanta, CNBM, and Richjo. The data is for 5 blast rounds for each site. The burden is the same for all the rounds in the three quarries. However, spacing varies between 2.0 m and 3.0 m. The bench height for the three sites is between 12.4 m to 9.6 m. The bench height is constant in all the rounds at CNBM but varied at Obanta and Richjo. Drill patterns at Obanta and Richjo are rectangular with CNBM having a square pattern. Drill hole diameter is constant at 112 mm in all the rounds at Richjo, and 90 mm for all the rounds at CNBM. However, it varied from 125 mm to 90 mm in all the five rounds at CNBM. Drill hole depth in all the quarries for the five rounds are all varied. It varied from 12.9 m to 14.9 m at Obanta, 10 m to 9.8 m at CNBM, and 11.8 m to 10.5 m at Richjo. CNBM has a constant stemming length of 1.5 m for all blast rounds. Stemming varied from 3.5 m to 4.5 m at Obanta, and between 4.0 m to 4.5 m at Richjo. The charge length followed the same pattern as the stemming, with CNBM having constant charge length of 8.1 m for all the blast rounds. Obanta has a varied charge length between 10 m and 7.9 m, while Richjo has charge length between 6.2 m and 7.0 m. Numbers of drill holes for each round at Richjo is 164, except round 3 that is 156. At CNBM, number of drill holes is 120 for the first two rounds, 100 for the third and last round, and 98 for second to the last. Number of holes at Obanta is 164 for all the rounds, except round 3 that is 156. The main explosive type used at CNBM and Richjo is ANFO with little gelatine for priming. The ANFO density for CNBM is 920 kg/m$^3$ and that of Richjo is 850 kg/m$^3$, while emulsion with 1250 kg/m$^3$ density was solely used at Obanta. The drill and blasting data were slightly varied across the sites between the 5 rounds to obtain diverse data suitable for modelling.

| Quarry | Obanta | | | | | CNBM | | | | | Richjo | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Blast Round | 1 | 2 | 3 | 4 | 5 | 1 | 2 | 3 | 4 | 5 | 1 | 2 | 3 | 4 | 5 |
| Burden (m) | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
| Spacing (m) | 2 | 2 | 2 | 2 | 2 | 3 | 3 | 3 | 3 | 3 | 2 | 2 | 2 | 2 | 2 |
| Bench Height (m) | 12.4 | 12.4 | 12.4 | 12.4 | 14.5 | 9.6 | 9.6 | 9.6 | 9.6 | 9.6 | 11.5 | 11.5 | 11.5 | 10.2 | 10.2 |
| Drill Pattern | Rec | Re | Rec | Rec | Rec | Squ | Squ | Squ | Squ | Squ | Rec | Rec | Rec | Rec | Rec |
| Hole Diameter (mm) | 125 | 125 | 125 | 90 | 90 | 90 | 90 | 90 | 90 | 90 | 112 | 112 | 112 | 112 | 112 |
| Drill Hole Depth (m) | 12.9 | 12.9 | 12.9 | 12.9 | 14.9 | 10 | 10 | 9.8 | 9.8 | 9.8 | 11.8 | 11.8 | 11.8 | 10.5 | 10.5 |
| Stemming (m) | 4.5 | 3.5 | 3.5 | 4.5 | 4.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 4.4 | 4.5 | 4 | 4 | 4 |
| Drilling Accuracy (%) | 87 | 90 | 93 | 93 | 95 | 82 | 86 | 85 | 84 | 83 | 98 | 98 | 99 | 98 | 97 |
| Sub Drill (m) | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.4 | 0.4 | 0.2 | 0.2 | 0.2 | 0.3 | 0.3 | 0.3 | 0.3 | 0.3 |
| Charge Length (m) | 7.9 | 8.9 | 8.9 | 7.9 | 10 | 8.1 | 8.1 | 8.1 | 8.1 | 8.1 | 7.1 | 7 | 7.5 | 6.2 | 6.2 |
| Charge Weight (Kg) | 121.1 | 136.4 | 136.4 | 62.8 | 79.5 | 47.4 | 47.4 | 47.4 | 47.4 | 47.4 | 59.4 | 58.6 | 62.8 | 51.9 | 51.9 |
| Total No of Drill Holes | 124 | 108 | 120 | 124 | 146 | 120 | 120 | 100 | 98 | 100 | 164 | 164 | 156 | 164 | 164 |
| Explosive Type | Emulsion | Emulsion | Emulsion | Emulsion | Emulsion | ANFO | ANFO | ANFO | ANFO | ANFO | ANFO | ANFO | ANFO | ANFO | ANFO |
| Explosive Density (kg/m$^3$) | 1250 | 1250 | 1250 | 1250 | 1250 | 920 | 920 | 920 | 920 | 920 | 850 | 850 | 850 | 850 | 850 |
| Rock Type | Granite | | | | | Granite | | | | | Granite | | | | |
| Average UCS (Mpa) | 178 | | | | | 136 | | | | | 215 | | | | |
| Average Tensile Strength (Mpa) | 12 | | | | | 8 | | | | | 17 | | | | |
| Average Density (kg/m$^3$) | 2786 | | | | | 2450 | | | | | 2838 | | | | |
| Average Young's Modulu (Gpa) | 0.744 | | | | | 0.5 | | | | | 0.915 | | | | |
| Average Poisson's Ratio | 0.22 | | | | | 0.227 | | | | | 0.214 | | | | |
| Average Nature of Rock Size | Fracture | | | | | Massive | | | | | Fracture | | | | |
| Average Joint Spacing | >1 m | | | | | >1 m | | | | | <1 m | | | | |
| Average Joint Dip | Horizontal | | | | | Horizontal | | | | | Out of Face | | | | |

°Rec=Rectangular; Squ=Square

**Figure 1: Blasting Parameters and Rock Properties from the Three Quarries: Obanta, CNBM and Richjo**

### 4.2 Muckpile Images, Edge Detection and Rosin-Ramla Distribution Curve

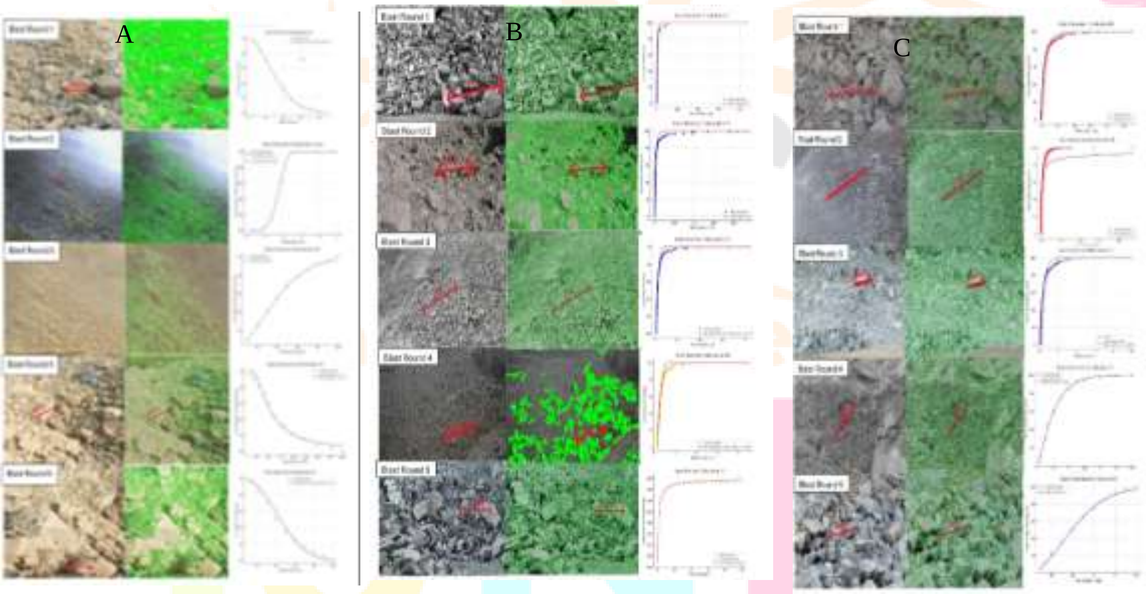


**Figure 2: Muckpile Images, Edge Detection Analysis and Rosin-Rammler Curve for: (A) Obanta, (B) CNBM, (C) Richjo**

At Obanta, See Figure 2a, Blast Round 1 produced coarse fragmentation with large blocks and high D63.2, indicating poor performance [16]. Rounds 2 and 3 showed finer, more uniform fragmentation with higher uniformity index (n) and steeper Rosin-Rammler curves, suggesting effective blast design. Round 4 showed mixed fragment sizes, possibly due to poor burden spacing or energy distribution. Round 5 had moderate results with some large slabs and elevated D63.2, reflecting reduced uniformity. Image segmentation supported these findings: Rounds 2 and 3 had the most even distribution, while Rounds 1, 4, and 5 showed larger retained fragments, impacting loading and hauling efficiency [17].

At CBM, Figure 2b, round 1 also had coarse fragmentation and high D63.2. Rounds 2 and 3 showed improved and most uniform breakage. Round 4 showed variability and poor energy distribution. Round 5 had large slab-like fragments and flatter Rosin-Rammler curves, indicating suboptimal results. Round 3 had the highest fragmentation efficiency, followed by Round 2. Rounds 1 and 5 were least effective.

In Richjo, Figure 2c, round 1 had coarse fragmentation and high D63.2. Rounds 2 and 3 improved significantly, with round 3 showing the best fragmentation and highest uniformity. Rounds 4 and 5 had mixed or poor fragmentation, with larger blocks and flatter Rosin-Rammler curves. Overall, rounds 2 and 3 consistently delivered the best fragmentation across all sites, while Rounds 1 and 5 showed the poorest results.

### 4.4 Results of Model Development for Fragmentation Characteristic Particle Size


**Figure 3: Predicted Vs Actual Characteristic Particle Size for SVR, Linear Regression, Kuz-Ram, ANN, and RF**

Figure 3 shows the comparative performance of five models—Support Vector Regression (SVR), Linear Regression, Kuz-Ram, Artificial Neural Network (ANN), and Random Forest (RF)—for predicting fragmentation characteristic particle size (Xc) using actual vs. predicted scatter plots with both best-fit and ideal-fit lines.

From the graphs, the Random Forest model displays the best alignment between the predicted and actual values, as evidenced by a tight clustering of data points around the ideal fit line and a relatively high $R^2$ value (0.74). This confirms the earlier numerical results and reinforces Random Forest's effectiveness in capturing the nonlinear relationships typical in rock fragmentation prediction [9].

Linear Regression shows moderate performance, with data points more dispersed than in the RF model but still trending toward the ideal line. Its $R^2$ value of 0.42 suggests that the model may not fully capture the complex interactions among blasting parameters [2].

The SVR model demonstrates a poor fit, with data points widely scattered and an $R^2$ of just 0.085, indicating minimal predictive power. This poor performance may be due to suboptimal hyperparameter tuning or insufficient data, as SVR typically requires careful calibration to function effectively in high-variance datasets [18].

The Kuz-Ram model, while a widely cited empirical approach [19], also performed poorly with a negative $R^2$ of -0.091, confirming that it failed to generalize well to the given data. Its simplifying assumptions and lack of adaptability to different blasting environments likely contributed to its limited predictive accuracy.

The ANN model performed the worst, with extreme deviations from the ideal fit line and a highly negative $R^2$ of -1549.3, reflecting significant overfitting or poor model training. The predicted values remained nearly flat, regardless of changes in actual values, indicating that the network may have failed to learn meaningful patterns—likely due to the small dataset size, which is insufficient for training deep learning models [20].

In conclusion, the visual and statistical evidence supports the Random Forest model as the most reliable predictor for Xc. It effectively balances accuracy and generalization, while simpler models like Linear Regression offer moderate utility [24]. In contrast, SVR, Kuz-Ram, and ANN underperform significantly under the dataset's limitations.

**4.6**: **Results of Model Development for Uniformity Index**

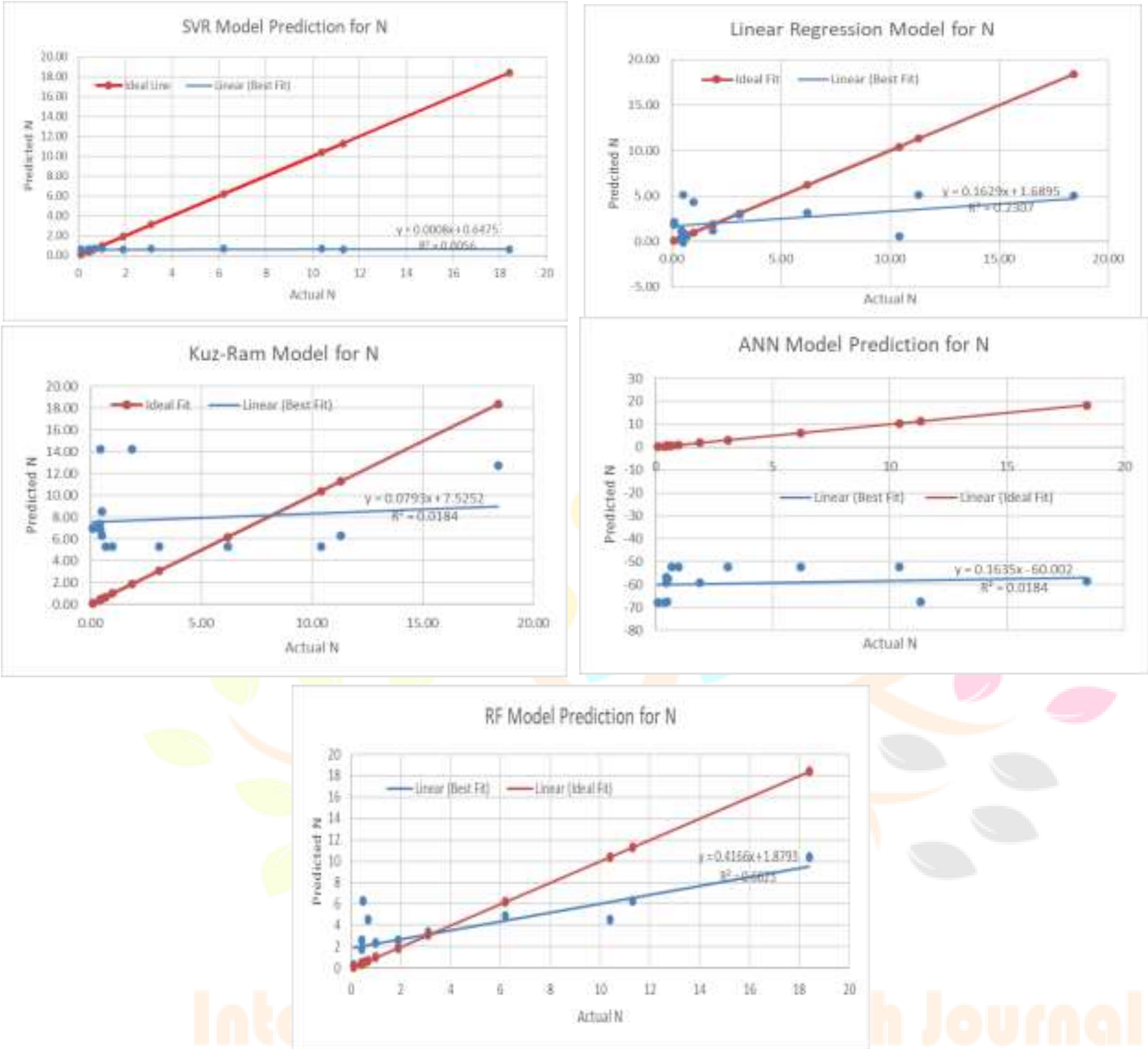


**Figure 4: Predicted Vs Actual Characteristic Fragmentation Index for SVR, Linear Regression, Kuz-Ram, ANN, and RF**

The plots in Figure 4 compare the predicted and actual values of uniformity index (N) across five models. The Random Forest (RF) model again demonstrates the best performance, with predicted values closely following the ideal fit line and a strong $R^2$ of 0.62, indicating good predictive accuracy and generalization, consistent with its known robustness in handling nonlinear data [21]

In contrast, Linear Regression shows moderate performance ($R^2$ = 0.50), reflecting a linear trend but limited ability to capture complex relationships in blasting data [23]. The Kuz-Ram and SVR models exhibit weak predictive power, with $R^2$ values of -0.1 and -0.3, respectively, suggesting poor model fit and underperformance.

The ANN model performs the worst, with widely scattered predictions and a highly negative $R^2$ of -142.2, indicating model instability likely caused by insufficient training data or overfitting [20]. Overall, Random Forest remains the most reliable model for predicting N in this study.

**Table 1: Performance Metrics on Characteristic Size Modelling**

| Model | Target | RMSE | MAE | $R^2$ |
|---|---|---|---|---|
| SVR | Xc | 1.6 | 1.1 | 0.0 |
| Linear Regression | Xc | 1.2 | 1.0 | 0.4 |
| Kuz-Ram | Xc | 2.2 | 1.9 | -0.7 |
| ANN | Xc | 64.7 | 64.4 | -1549.3 |
| Random Forest | Xc | 0.9 | 0.6 | 0.7 |

Table 1 presents a comparative evaluation of five different models used to predict the characteristic size (Xc) in rock fragmentation studies. The models include Support Vector Regression (SVR), Linear Regression, the empirical Kuz-Ram model, Artificial Neural

Network (ANN), and Random Forest. The performance of each model was assessed using three standard metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination ($R^2$).

Among the five models, Random Forest emerged as the best performer, recording the lowest RMSE (0.9) and MAE (0.6), along with the highest $R^2$ value of 0.7. This indicates that the model not only predicted values that were close to the actual measurements but also explained 70% of the variability in the target variable. Such performance highlights the model's robustness and suitability for modelling non-linear relationships in rock fragmentation, aligning with previous research that demonstrates the effectiveness of Random Forest in geotechnical and mining engineering applications [13], [22].

Linear Regression also showed a fair performance, with an RMSE of 1.2 and MAE of 1.0. It achieved an $R^2$ of 0.4, which suggests that it was able to capture about 40% of the variation in the dataset. Although its performance was not as strong as Random Forest, Linear Regression offers advantages in simplicity and interpretability, making it a viable option in early modelling stages or for quick assessments.

Support Vector Regression (SVR) produced moderate results with an RMSE of 1.6 and MAE of 1.1. However, its $R^2$ value was 0.0, indicating that it did not explain any variance in the data. This suggests that although SVR's predictions were not far from actual values on average, the model failed to generalize well across different samples. It's possible that the model requires better tuning of kernel parameters or further preprocessing such as normalization, as recommended in related machine learning literature [14].

The Kuz-Ram model, an empirical model widely used in blast design, underperformed in this context. It recorded higher error values (RMSE = 2.2, MAE = 1.9) and a negative $R^2$ of -0.7, indicating it was less effective than simply predicting the mean value. While the Kuz-Ram model has been instrumental in providing baseline fragmentation estimates in the field [19], its assumptions may not be compatible with the variability in the study dataset, demonstrating the limitations of empirical models when applied outside their original calibration conditions.

The Artificial Neural Network (ANN) showed the worst performance across all metrics, with an RMSE of 64.7, MAE of 64.4, and a significantly negative $R^2$ of -1549.3. Such results strongly indicate issues related to overfitting, poor model design, or insufficient training. Given that ANN models typically require large volumes of data and are sensitive to input scaling and hyperparameters [20], using only 15 data samples is likely inadequate.

The results strongly support the use of Random Forest for predicting the characteristic size in fragmentation studies, due to its superior accuracy and variance explanation. Linear Regression and SVR can serve as supplementary models, particularly if computational simplicity or explainability is a priority [24]. The Kuz-Ram model, while useful for preliminary estimations, does not appear adequate for precise prediction in this case. The ANN model requires significant refinement and should only be adopted after addressing its current limitations.

**Table 2: Performance Metrics on Size Uniformity Index Modelling**

| Model | Target | RMSE | MAE | $R^2$ |
|---|---|---|---|---|
| SVR | N | 6.1 | 3.3 | -0.3 |
| Linear Regression | N | 3.9 | 3.4 | 0.5 |
| Kuz-Ram | N | 5.7 | 3.6 | -0.1 |
| ANN | N | 63.6 | 63.1 | -142.2 |
| Random Forest | N | 3.5 | 2.4 | 0.6 |

The table summarizes the performance of five predictive models—Support Vector Regression (SVR), Linear Regression, Kuz-Ram, Artificial Neural Network (ANN), and Random Forest—in estimating the Size Uniformity Index (N), a key indicator of fragmentation consistency in blasting operations. The models were evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination ($R^2$).

Among the evaluated models, the Random Forest algorithm outperformed the others, registering the lowest RMSE (3.5) and MAE (2.4), along with the highest $R^2$ value (0.6). This result demonstrates the model's strong predictive capability and its ability to capture complex, non-linear relationships inherent in fragmentation data. Random Forest's ensemble learning approach enables it to reduce overfitting while maintaining high accuracy [23], making it well-suited for predicting blasting outcomes where multiple interacting parameters are involved.

Linear Regression followed closely with an RMSE of 3.9, MAE of 3.4, and an $R^2$ of 0.5, suggesting that it explained around 50% of the variation in the Size Uniformity Index. Although not as precise as Random Forest, Linear Regression remains a reliable and interpretable method, especially when the relationship between variables is approximately linear [23].

The Kuz-Ram model, which is empirical in nature and widely used for estimating fragmentation based on explosive energy and rock properties, achieved an RMSE of 5.7 and MAE of 3.6 with a negative $R^2$ of -0.1. This negative $R^2$ indicates that the Kuz-Ram predictions were worse than simply using the mean of the observed values. Such poor performance may stem from the model's inherent simplifications and assumptions that do not generalize well across all datasets [19].

The Support Vector Regression (SVR) model produced similar underwhelming results with an RMSE of 6.1, MAE of 3.3, and an $R^2$ of -0.3. Despite its robustness in handling non-linear data [14}, SVR may require more careful hyperparameter tuning and normalization to perform well, particularly when data size is small or noisy.

Once again, the Artificial Neural Network (ANN) performed very poorly, yielding an RMSE of 63.6, MAE of 63.1, and an $R^2$ of -142.2. This drastically negative $R^2$ value highlights severe overfitting or poor training—likely due to a combination of limited data of only 15 samples, and possibly inadequate model architecture or parameter optimization. Neural networks generally require a substantial amount of data and rigorous training to produce reliable outputs [20], and their performance deteriorates when such conditions are not met.

In summary, Random Forest stands out as the most effective model for predicting the Size Uniformity Index (N), followed by Linear Regression. SVR and the Kuz-Ram model provided limited utility in this context, while the ANN model was not viable under the current conditions. The results underline the importance of choosing models that balance flexibility, interpretability, and suitability for the available data size and structure.

**4.7 Conclusion**

The use of machine learning techniques to predict rock fragmentation outcomes in granite quarries was explored in this study. Support Vector Regression (SVR), Random Forest (RF), Artificial Neural Networks (ANN), Linear Regression, and the traditional Kuz-Ram model, were used to predict two key blasting outcomes: the characteristic particle size (Xc) and the fragmentation uniformity index (N). Data were collected from 15 blast rounds across three granite sites in Ogun State, Nigeria, and image analysis techniques using Python libraries were employed to estimate fragment size distributions. Among the models evaluated, Random Forest outperformed others with the $R^2$, MAE and RMSE values of 0.6, 2.4 and 3.5 respectively for fragmentation index; 0.7, 0.6 and 0.9 for characteristics particle size respectively. RF showed strong predictive accuracy and robustness to data complexity compared to the others. In contrast, ANN and Kuz-Ram models performed poorly, with ANN exhibiting extreme overfitting due to limited data. ANN has an $R^2$, MAE and RMSE score of -147, 63, and 63 for uniformity index respectively; and -1549, 64 and 64 for characteristic particle size respectively. The study shows that Random Forest is the most reliable tool for predicting blast outcomes and improving efficiency in rock fragmentation, supporting the broader adoption of AI driven approaches in mining operations. ANN model prediction performed worst due to limited dataset leading lead to error and overfitting as the results in this study showed.

More research on analysis of blast outcome should be conducted with other AI models and with large dataset.

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