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# An Intelligent Hybrid System for Slope Stability Prediction: Integration of Random Forest with WOA, ACO and GWO Algorithms

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## Abstract
This study aims to develop and evaluate hybridised models combining Random Forest (RF) with metaheuristic algorithms, Whale Optimisation Algorithm (WOA), Ant Colony Optimisation (ACO), and Grey Wolf Optimisation (GWO), to predict the Factor of Safety (FS) in slope stability analysis. The study used a dataset of 281 data points from the AngloGold Ashanti Iduapriem Mine, comprising seven input parameters and FS as the output. Three hybrid models (RF-WOA, RF-ACO and RF-GWO) were developed and compared using performance indicators including mean absolute error (MAE), mean squared error (MSE), and coefficient of determination ($R^2$). A sensitivity analysis was conducted to determine the most influential parameters affecting the prediction of FS. The RF-WOA model outperformed the other hybrid models, achieving the lowest MAE (0.0416), MSE (0.0086) and highest $R^2$ (0.9656). Sensitivity analysis revealed that cohesion is the most critical factor influencing slope stability, followed by the slope height and pore water pressure. The rock mass rating had minimal impact on the prediction of the FS. This study presents a novel approach by integrating metaheuristic algorithms with Random Forest for slope stability analysis, offering improved predictive performance compared to traditional methods. The developed RF-WOA model provides mining engineers with a reliable tool for predicting slope stability, enabling more effective risk management and operational planning in open-pit mines. The identified key influencing factors can guide prioritisation in geotechnical assessments and slope design considerations.

## Keywords
Slope Stability, Factor of Safety, Random Forest, Metaheuristic Algorithms, Mining Optimisation, Machine Learning

## 1. Introduction
A slope is defined as a surface on which one end or side is at a higher level than another; a rising or falling surface (Digvijay et al., 2017). Slopes are commonly encountered in mines and other civil engineering structures. Unexpected movement on the ground can create dangerous conditions that could put people in danger, destroy equipment, and cause property loss (Girard & McHugh, 2000). Slope stability analysis is a crucial task in geotechnical engineering, because it helps determine the likelihood of slope failure or landslide. The Factor of Safety (FS) is a common method used to assess slope stability (Liu et al., 2014). It is influenced by factors such as the slope height (H), slope angle (β), cohesion (c), friction angle (φ), unit weight (γ), and pore water pressure (R) (Feng et al., 2018). A slope is considered safe when its safety factor exceeds a certain threshold. In contrast, a safety factor below 1.0 indicates an unstable and unsafe slope condition (Pourkhosravani & Kalantari, 2011). Engineers can design structures more intelligently and increase slope stability by using reliable and precise Factor of Safety (FS).

Various methods have been used to analyse slope stability, including Limit Equilibrium Methods (LEM)(Verma et al., 2013), Numerical approaches (Griffiths & Lane, 2000; Liu et al., 2014), and limit analysis methods based on lower- and upper-bound theorems (Chen, 2013).

The limit equilibrium method is the oldest method used for soil stability analysis. These methods are based on the calculation of the mobilised strength and the stresses applied on a sliding surface for a trial on the slope of the soil. The Factor of Safety is then calculated by taking these two values into account (Ullah et al., 2020). The advantage of this method is its simplicity, while the deficiency of this method is the difficulty of calculating the stability coefficient to accurately reflect the true properties of the slope, because it does not take the effect of stress and strain into account (Bolton et al., 2003). In addition, this approach does not satisfy the compatibility of displacement because it does not mention displacement (Mafi et al., 2020).

The numerical method of slope stability involves modelling the slope as a continuum accounting for soil deformation behaviour and utilising numerical techniques such as finite element or finite difference analysis to calculate the stress and strain distribution within the slope (Abbas, 2014). In particular, the numerical method can produce more accurate results for complex geometries and uneven soil qualities than the limit equilibrium method. Slope stability analysis using numerical methods has several drawbacks, such as oversimplifying assumptions, difficulties in calibrating the model, computational complexity, and the requirement for specialist knowledge (Bobet, 2010; Griffiths & Lane, 2000).

When using the limit analysis method, soil is modelled as a completely plastic substance that follows a related flow rule (Leshchinsky & Ambauen, 2015). This idealisation of soil behaviour allows for the proof of two plastic bounding theorems (lower and upper bounds). The results obtained using this method is highly sensitive to small changes in inputs or assumptions, leading to significant variations in the results analysed. Additionally, the method requires specialised knowledge and expertise in geotechnical engineering, which limits its widespread use and applicability.

Recently, artificial intelligence (AI) and machine learning algorithms have gained popularity in slope stability analysis, particularly in predicting the Factor of Safety. Artificial Intelligence (AI) refers to the development of computer systems capable of performing tasks that typically require human intelligence. These tasks include learning, problem-solving, understanding natural language, and perception. AI encompasses various subfields such as machine learning, natural language processing, computer vision, and robotics. One of the fundamental concepts in AI is machine learning, where algorithms learn from data to make predictions or decisions. These AI models estimate FS with high precision and low error rates, outperforming traditional stability analysis methods (Nanehkaran et al., 2022). Some machine learning methods applied in slope stability analysis include Multilayer Perceptron Neural Network (MLPNN) (Alzakkar et al., 2022), decision tree (DT) (Chen & Yang, 2023), support vector machines (SVM) (Samui, 2008), Random Forest (RF) (Maxwell et al., 2020) and k-Nearest Neighbour Prediction (k-NN) where Liu et al. (2023) applied the machine learning technique in predicting slope stability.

This study aims to employ advanced artificial intelligence techniques to predict Factor of Safety using the Random Forest algorithm (RF) hybridised with the Grey Wolf Optimiser (GWO), Ant Colony Optimiser (ACO), and Whale Optimisation Algorithm (WOA) to improve the performance of RF in predicting FS. The Random Forest algorithm is a versatile and widely applicable technique that performs excellently on numerous datasets. Its strengths include robustness against statistical assumptions, preprocessing requirements, and handling large, high-dimensional datasets with missing values. However, RF faces challenges with categorical variables of high cardiac intensity, unbalanced data, time series prediction, and the interpretation of individual variable contributions (Zhu, 2020). In mining engineering, Random Forest has been used for blast design in surface mines. The experimental results indicated that the Random Forest tree network system possesses the ability to optimise the design parameters of the explosion, resulting in scenario-specific solutions that deviate from conventional one-size-fits-all approaches (Mishra et al., 2018).

Metaheuristic Algorithms inspired by natural phenomena, offer a promising alternative for solving complex optimisation problems. They improve on the predictive performance of the machine learning algorithms. These optimisations have proved worthwhile in some areas of study. In the investigation, Mirjalili et al. (2014) successfully applied the Grey Wolf Optimiser in slope stability analysis to optimise the design of slope reinforcement measures. It offered a robust and efficient approach to optimising slope stability designs, providing valuable insight for engineers in geotechnical applications. According to Kahatadeniya et al. (2009), Ant Colony Optimisation was employed to identify slip surfaces with the lowest Factor of Safety, ensuring that the search process avoided getting stuck in local points and instead explored the entire solution space to find the global optimum. Wei et al. (2021) researched to predict the Factor of Safety for circular failure slope. Support Vector Regression (SVR) was first applied and the results were further optimised with the Whale Optimisation Algorithm. Results showed that the SVR-WOA hybrid produced more accurate performance than the SVR.

The objectives of this research are to develop and train the RF model for the prediction of Factor of Safety, hybridise the RF model with the three optimisers to improve its performance in predicting FS. The hybridised versions (RF-GWO, RF-ACO and RF-WOA) will be evaluated and compared using various indicators, including the coefficient of determination, mean squared error and mean absolute error, to determine the most accurate model for predicting the safety factor.

## 2. Materials and Methods

### 2.1 Description of the Study Area

The Iduapriem Mine, located in the Western Region of Ghana, has been operational since 1992. Initially owned by Golden Shamrock Limited, it was later acquired by Ashanti Goldfields Company Limited in 1996 and subsequently by AngloGold Ashanti in 2004. The mine has undergone expansions and upgrades, increasing its capacity to 5.2 Mtpa. Fig. 1 shows the location of the Iduapriem mine on the map of Ghana. Currently, a three-year investment plan aims to extend the mine's life through accelerated waste stripping and expand the capacity of the Iduapriem Tailings Storage Facility. The mine is located near the town of Tarkwa, approximately 70 km north of Takoradi, and is accessible via a 6 km unsealed road (Boateng, 2009). The area features undulating landscapes with prominent ridges, and the mine is divided into eight blocks, with gold mineralisation confined to four specific zones or reefs. Gold is fine-grained, particulate, and able to be used freely. The geology of the mine is characterised by the Birimian formation, with gold-bearing rock found in the Banket series and Kawere rocks within the Tarkwaian group. The deposits are classified as fossil placers, where gold was deposited along with the sediments (Kesse, 1985). Climate is equatorial, with high temperatures and humidity contributing to a deep residual soil profile (Acheampong, 2009). Mining operations are carried out by AMAX, a joint venture between Maxmass and the African Mining Service, using conventional drill and blast methods. The mine operates three pits, with rock fragmentation achieved through drilling and blasting. The loading and hauling are handled by AMAX using excavators and dump trucks. Gold-bearing ore is processed using a refractory gold process, including crushing, milling, aggressive leaching of cyanide, and adsorption through carbon-in-pulp (CIP). The processing plant features a two-stage crushing circuit, semi-autogenous grinding (SAG) mills, and ball mills, achieving gold recoveries of approximately 95 to 99%. The mine has undergone significant development since its inception, with a focus on extending its life and increasing production capacity. The current investment plan aims to ensure the continued operation and profitability of the mine.

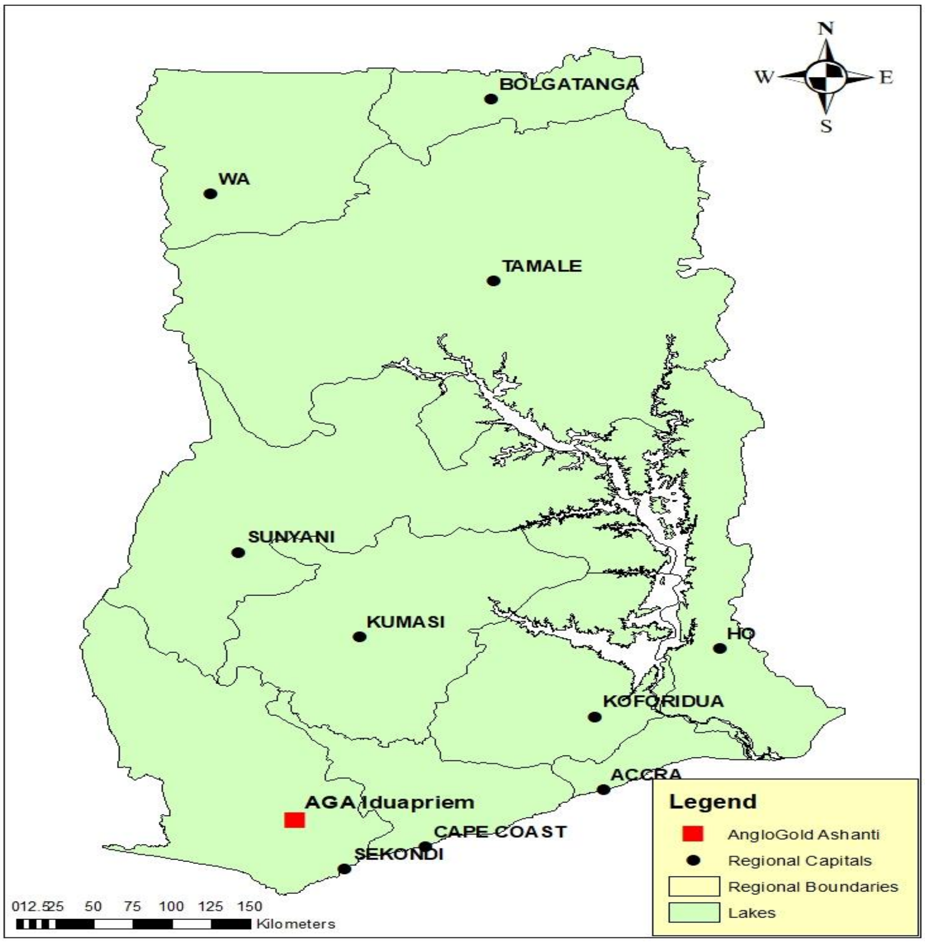


**Fig. 1** Location of Iduapriem Mine

### 2.2 Data Description

A secondary data collection exercise was carried out on site at AngloGold Ashanti Iduapriem Limited through a field visit. This exercise involved acquiring crucial information on slope stability analysis from the Geotechnical Engineering section. This project used a data set of 281 data points related to slope stability. It encompassed seven key input parameters: Slope Height (H), slope angle (β), cohesion (c), Friction Angle (φ), Unit Weight (γ), Rock Mass Rating (RMR) and pore water pressure (R). The FS served as the output parameter. The selection of these input parameters was informed by previous research, which established a strong correlation between these variables and FS. The statistical properties of the data set are represented in Table 1 and Fig. 2.

**Table 1** Statistical Description of the Data

| Statistics | RMR | γ | c | φ | β | H | R | FS |
|---|---|---|---|---|---|---|---|---|
| Mean | 0.86 | 19.93 | 25.54 | 24.85 | 32.13 | 45.46 | 0.26 | 1.34 |
| Median | 0.90 | 19.10 | 20.00 | 25.00 | 30.00 | 37.00 | 0.30 | 1.25 |
| Mode | 0.90 | 18.80 | 20.00 | 20.00 | 30.00 | 50.00 | 0.30 | 1.84 |
| Std Dev | 0.08 | 2.63 | 25.85 | 10.95 | 8.60 | 47.95 | 0.16 | 0.42 |
| Variance | 0.01 | 6.94 | 668.38 | 120.00 | 73.91 | 2299.2 | 0.03 | 0.18 |
| Kurtosis | -0.40 | 3.06 | 11.82 | -0.35 | -0.50 | 3.35 | -1.04 | -0.62 |
| Skewness | -0.93 | 0.64 | 3.13 | -0.29 | 0.47 | 1.94 | -0.26 | 0.44 |
| Range | 0.29 | 16.44 | 150.05 | 45.00 | 37.00 | 210.34 | 0.50 | 1.69 |
| Min | 0.69 | 12.00 | 0.00 | 0.00 | 16.00 | 3.66 | 0.00 | 0.63 |
| Max | 0.98 | 28.44 | 150.05 | 45.00 | 53.00 | 214.00 | 0.50 | 2.31 |

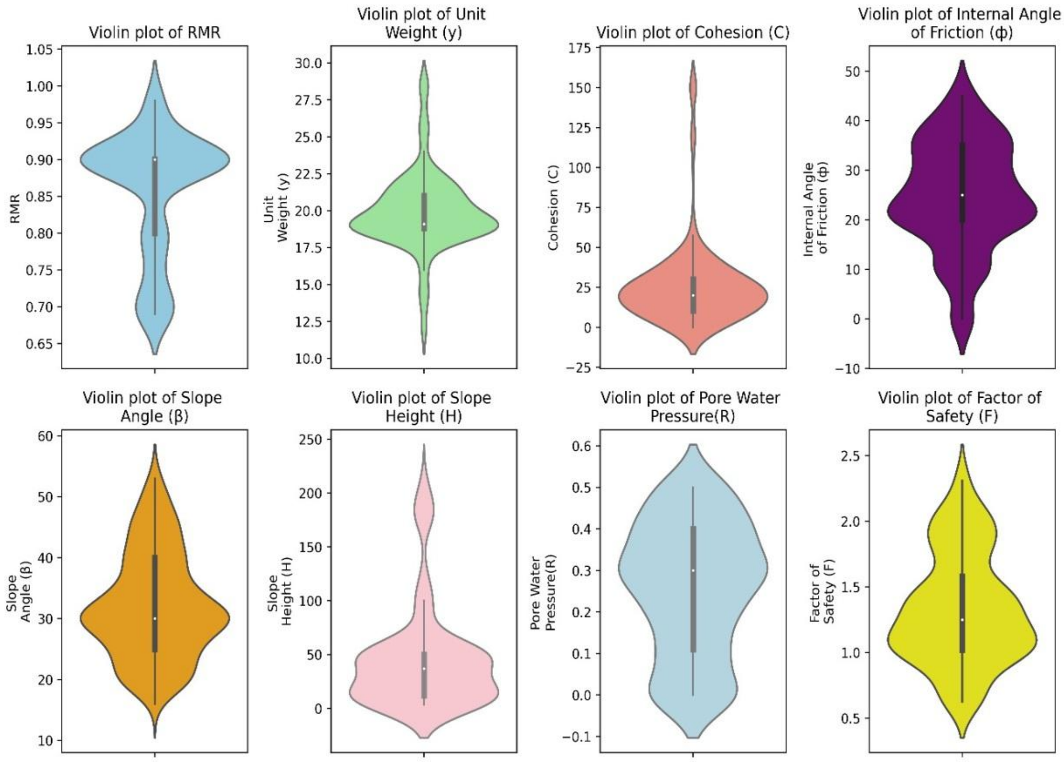


**Fig. 2** Violin plot showing the description of the data

## 2.3 Data Preparation

The data set was randomly partitioned into training and testing sets. It consisted of 195 data points (70%) for training and 86 data points (30%) for testing and validation. The split allowed the evaluation of the generalisability of the models and validated their performance on unseen data, ensuring the reliability and precision of the trained models.

## 2.4 Methods

In this study, three models were considered. These were developed by hybridising a machine learning algorithm with three metaheuristic algorithms, namely: hybridised Random Forest with Ant Colony Optimisation (RF-ACO), hybridised Random Forest with Whale Optimisation Algorithm (RF-WOA), and hybridised Random Forest with Grey Wolf Optimisation (RF-GWO). The models were developed using a supervised machine learning technique. This involves training the model on the labelled data set to allow it to learn and understand the relationships between input and output parameters, allowing accurate predictions and classifications. All these developments were accomplished using the Python Programming Language, which offered extensive libraries and frameworks for efficient algorithm implementation.

### *2.4.1 Random Forest Algorithm*

The Random Forest algorithm was created by Breiman (Breiman, 2001) and is a highly acclaimed machine learning method that unites the predictions of multiple decision trees to generate a single result. Its accessibility and versatility have led to its widespread use, allowing it to handle both classification and regression tasks with ease. Using randomisation, the algorithm generates a diverse set of decision trees, combining their outputs through voting (classification) or averaging (regression). This process known as bagging involves resampling the data set and randomly selecting characteristics at each node, ultimately increasing the precision and reliability of the model (Rigatti, 2017). Fig. 3 shows a diagram representing a Random Forest algorithm.

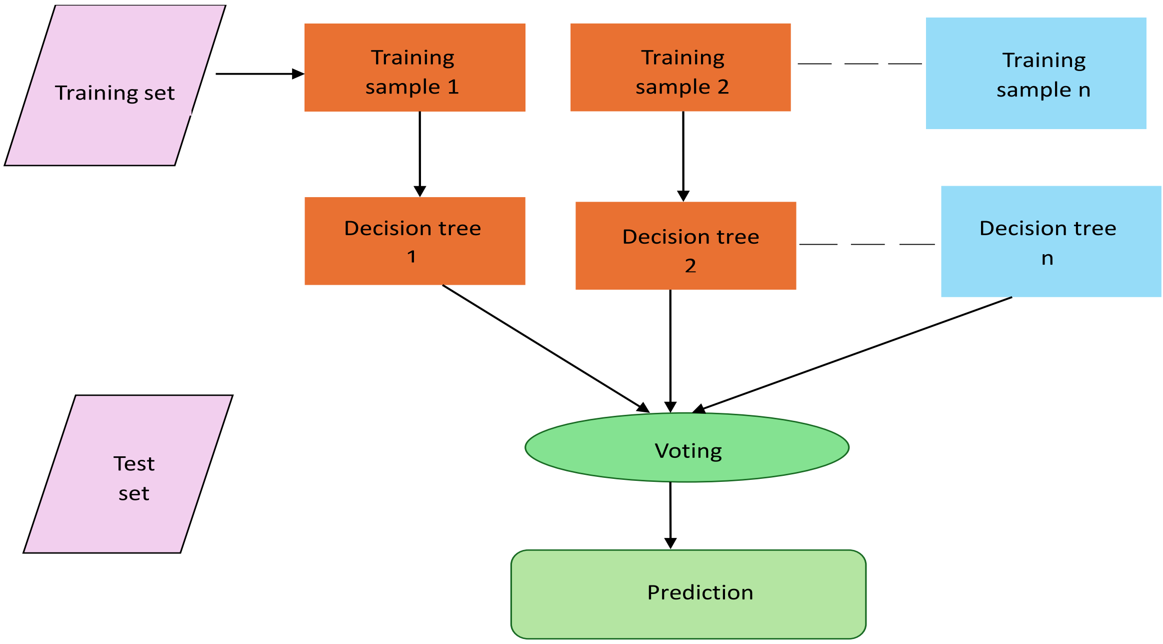


**Fig. 3** Random Forest Algorithm

### *2.4.2 Grey Wolf Optimisation (GWO)*

The GWO algorithm is designed to replicate the social structure and hunting behaviour of grey wolves in the wild. It involves four classes of wolves, alpha (α), beta (β), delta (δ), and omega (ω), which represents the leadership hierarchy within a wolf pack. The hunting process, which includes the search for prey, encircling it and attacking it, is also modelled in the algorithm (Muro et al., 2011). In nature, grey wolves live in packs with a clear social order, led by an alpha male and female. The alphas make decisions that the rest of the pack follows, whereas beta wolves support the alphas and reinforce their commands. Omega wolves are at the lowest level of the hierarchy and are subject to dominant wolves. The GWO algorithm has been used effectively in various engineering, computer science, and operations research problems. Its mathematical model is based on the leadership hierarchy of wolves, where the best solution is considered the alpha, followed by the beta and delta solutions (Mirjalili et al., 2014). The remaining solutions are represented as omega wolves that follow the three best solutions. Fig. 4 is a representation of the grey wolf algorithm.

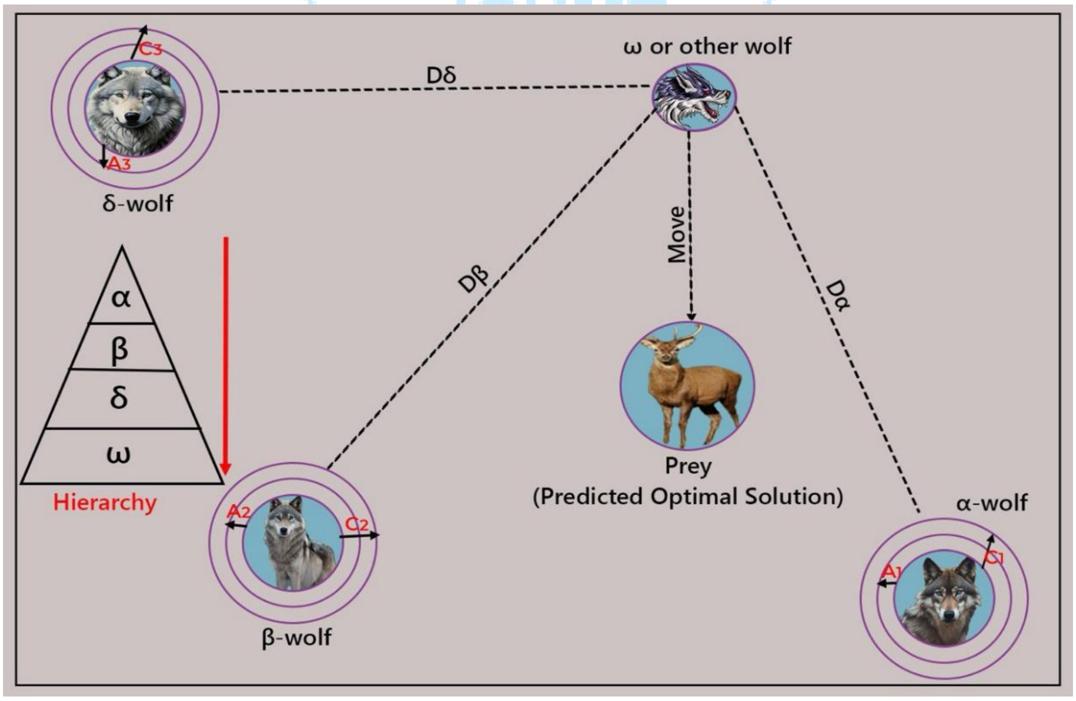


**Fig. 4** Grey wolf optimisation

### *2.4.3 Ant Colony Optimiser (ACO)*

ACO is inspired by the foraging behaviour of ants in search of food. Ants leave trailing pheromones as they move, which serve as a means of communication with other ants (Dorigo & Gambardella, 1997). These trails gradually evaporate over time, and the rate of evaporation is inversely related to the distance from the food source (Dorigo & Stützle, 2019). The algorithm employs a group of artificial ants that establishes pheromone trails as they explore the search space, guiding other ants to the best solution (Hou et al., 2022). The process involves three key steps: initialisation, construction, and update. During initialisation, pheromone levels are set low and the ants are randomly placed in the search area. In the construction phase, each ant navigates the search space, leaving pheromone trails based on both trail intensity and problem-specific heuristic information. In the update stage, the pheromone levels are adjusted according to the quality of the solutions discovered by the ants. ACO has been effectively used in a variety of optimisation challenges, such as the travel salesman problem (TSP), knapsack problems, and scheduling dilemmas (Dorigo & Gambardella, 1997). The operation of the Ant Colony Algorithm is illustrated in Fig. 5.

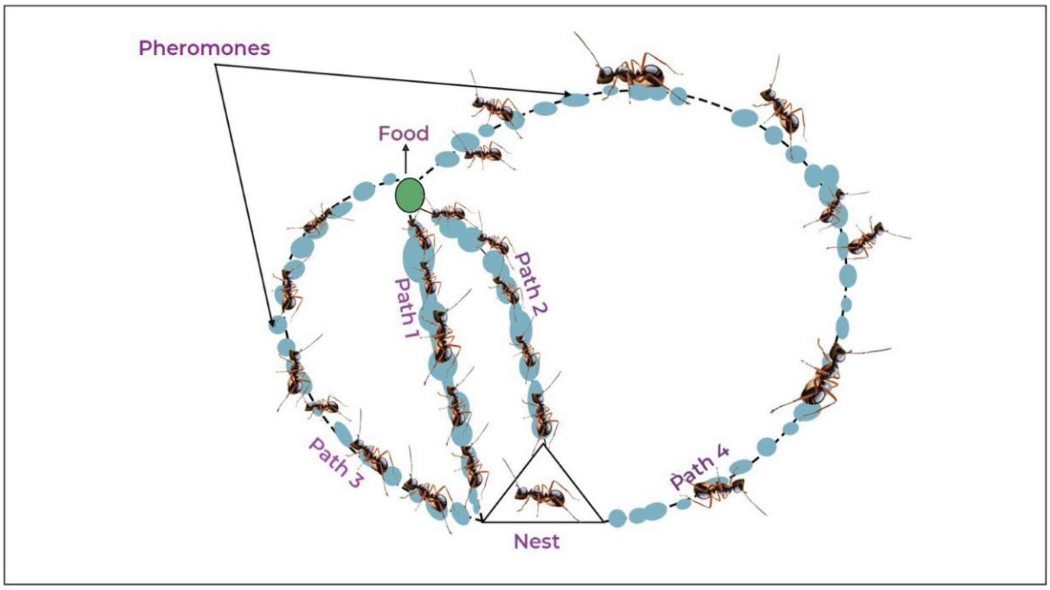


**Fig. 5** Operation of the Ant Colony Algorithm

### *2.4.4 Whale Optimisation Algorithm (WOA)*

WOA is a new metaheuristic approach based on swarm behaviour, drawing inspiration from the hunting tactics of humpback whales. Proposed by Mirjalili and Lewis (Mirjalili & Lewis, 2016), this algorithm has gained widespread recognition in various engineering disciplines due to its simplicity, minimal operator requirements, fast convergence, and effective balance between exploration and exploitation phases. Consequently, WOA has been widely used in various fields, using its optimal performance and efficiency to address complex optimisation problems (Rana et al., 2020). Humpback whales employ a distinctive hunting strategy called the bubble net feeding method, as shown in Fig. 6. which involves creating spiral-shaped bubbles to surround and capture prey (Mirjalili & Lewis, 2016). This behaviour is mirrored in the WOA algorithm, where search agents adjust their positions based on the best solution found so far, simulating the encircling and attacking phases of whale hunting. The mathematical model of WOA comprises three phases: exploration, encircling, and exploitation. The exploration phase involves random search, while the encircling phase updates positions towards the best solution using a shrinking encircling mechanism and a spiral updating position mechanism.

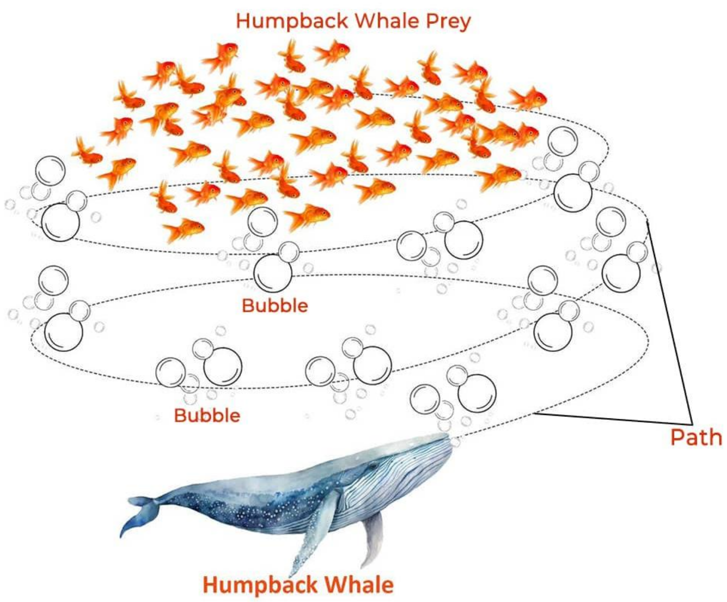


**Fig. 6** Feeding behaviour of humpback whales

## 2.5 Model Development Process

In this research, three models were considered. These were developed by hybridising a machine learning algorithm (RF) with three optimisation algorithms, namely: Grey Wolf Optimiser, Ant Colony Optimiser and Whale Optimiser. The models were developed using supervised machine learning techniques using PyCharm 2024.2.2 on a Lenovo 81YT laptop with Intel(R) Core(TM) i7-10750H CPU @ 2.60GHz processor (12 CPUs) and 64GB RAM, running Windows 11 Pro 64-bit operating system. This computational setup ensured adequate processing power for model training and optimisation of the 281 data points collected from AngloGold Ashanti Iduapriem Mine. This involves training the model on the labelled data set to allow it to learn and understand the relationships between the inputs and output parameters, allowing accurate predictions. Implementing the algorithms involved several stages including data preparation, model instantiation, and hyperparameter tuning. All these developments were accomplished using the Python programming language, which offered extensive libraries and frameworks for efficient algorithm implementation. All models, namely RF, RF-WOA, RF-GWO, and RF-ACO were developed using the Scikit-learn library. The machine learning algorithm, Random Forest (RF), was trained on a dataset to learn relationships between input and output parameters. Metaheuristic algorithms, namely Whale Optimisation Algorithm (WOA), Grey Wolf Optimisation (GWO), and Ant Colony Optimisation (ACO), were integrated to enhance performance. The models were then evaluated on a testing set to assess accuracy and generalisation capabilities. Fig. 7 shows a flow chart illustrating the development of the models.

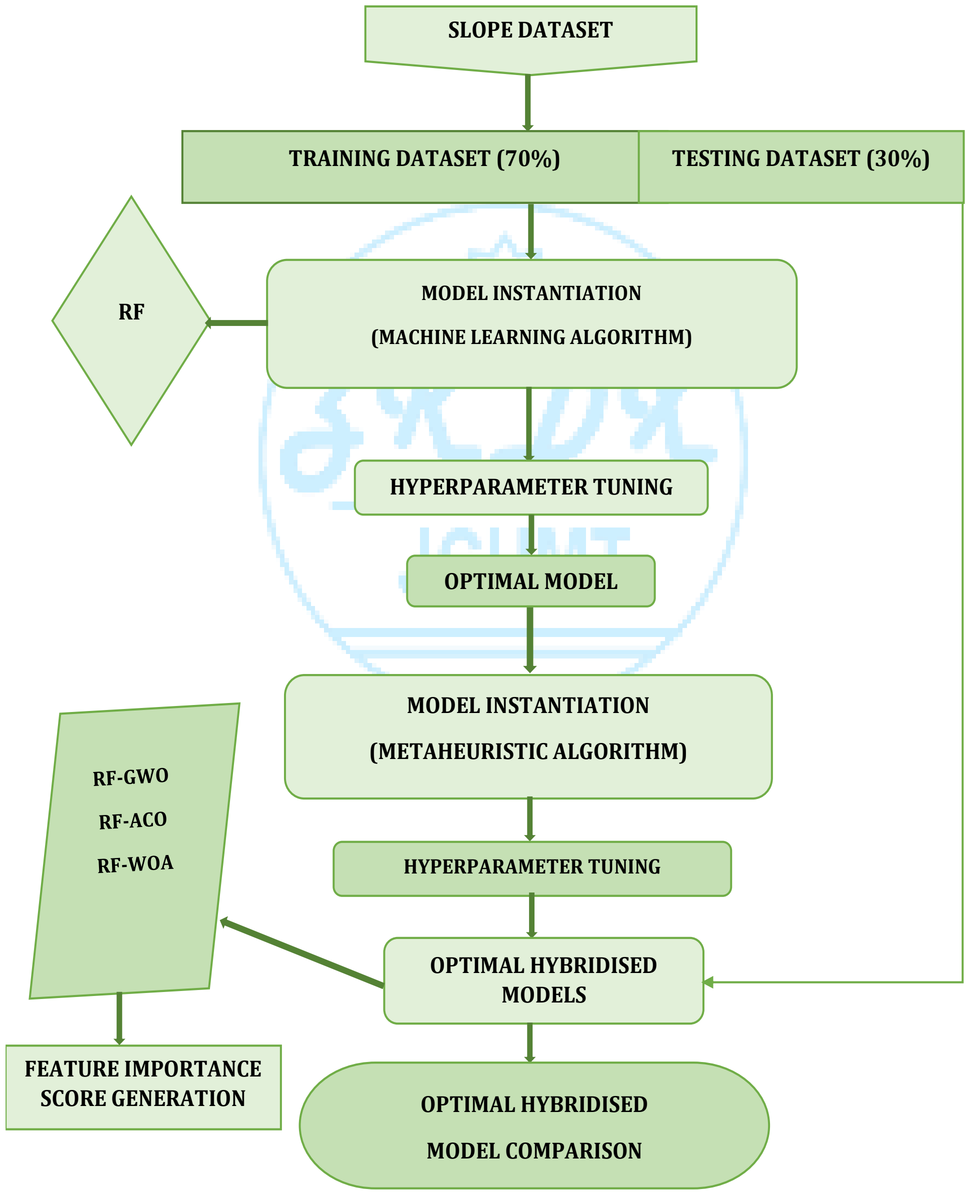


**Fig. 7** Flow chart of model development

### *2.5.1 Hyperparameter Tuning*

The optimal hyperparameters for each algorithm and model, namely, RF, RF-ACO, RF-GWO and RF-WOA were determined using the GridSearchCV function from Scikit-learn. This involved an exhaustive search through all possible combinations of hyperparameters, iterating until the optimal values were identified. By systematically sweeping through the hyperparameter space, the best performing combinations were pointed out, yielding the range and optimal results for each algorithm. Table 2 shows the hyperparameters, their range and their optimal values.

**Table 2** Hyperparameters, their Range, and Optimal Values

| Model | Parameter | Range | Optimal Value |
|---|---|---|---|
| RF | n_estimators | [50, 100, 200] | 71 |
| | max_depth | [None, 10, 20, 30] | None |
| | min_samples_split | [2, 5, 10] | 2 |
| | min_samples_leaf | [1, 2, 4] | 1 |
| | max_features | ["auto, "sqrt", "log2"] | "auto" |
| RF-ACO | n_estimators | [10, 100] | 52 |
| | max_depth | [1, 20] | 10 |
| | min_samples_split | [2, 10] | 2 |
| | min_samples_leaf | [1, 10] | 1 |
| RF-GWO | n_estimators | [10, 100] | 14 |
| | max_depth | [1, 20] | 16 |
| | min_samples_split | [2, 10] | 2 |
| | min_samples_leaf | [1, 10] | 1 |
| RF-WOA | n_estimators | [10, 100] | 71 |
| | max_depth | [1, 20] | 11 |
| | min_samples_split | [2, 10] | 2 |
| | min_samples_leaf | [1, 10] | 1 |

### *2.5.2 Performance indicators*

To evaluate the performance of these algorithms, various indicators were used, including the Coefficient of Determination ($R^2$), the Mean Squared Error (MSE) and the Mean Absolute Error (MAE).

*Coefficient of determination ($R^2$)*

The coefficient of determination ($R^2$) is an important performance indicator that shows the proportion of variance in the dependent variable that is predictable from the independent variable(s) (Sinha et al., 2019). This is illustrated in equation (1). $R^2$ values range from no predictability (0) to perfect predictability (1), with higher values indicating better predictability (Pham et al., 2017). However, $R^2$ is sensitive to the number of predictors and can be inflated by adding more predictors, even if they do not improve the model's performance.

$$R^2 = \frac{\sum_{i=i}^{n}(y_i - \bar{y}_i)(x_i - \bar{x}_i)}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y}_i)\sum_{i=1}^{n}(x_i - \bar{x}_i)}} \quad (1)$$

*The Mean Square Error (MSE)*

The mean square error (MSE) is similar to the RMSE but more sensitive to outliers (Pham et al., 2017). MSE is used to evaluate the average magnitude of squared errors in the predictions, with lower values indicating better accuracy. The formula for MSE is shown in equation (2).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2 \quad (2)$$

*The Mean Absolute Error (MAE)*

The mean absolute error (MAE) is a measure of the average magnitude of the errors in the predictions without squaring. MAE is less sensitive to outliers compared to RMSE and MSE and is widely used to evaluate the accuracy of predictions (Sinha et al., 2019). Equation (3) shows the equation to calculate MAE.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - x_i}{y_i}\right| \quad (3)$$

where n represents the total number of samples utilised for training or testing the model, $y_i$ represents the measured value, $x_i$ represents the predicted value, $\bar{y}_i$ represents the sample mean of the measured values and $\bar{x}$ represents the sample mean of the predicted values.

### 2.6 Sensitivity Analysis

The feature importance score method was used to conduct the sensitivity analysis. Feature importance scores were calculated for the best model to quantify the impact of each input feature on the predicted Factor of Safety. This analysis revealed the relative contributions of each feature to the output parameter, allowing the identification of the most influential feature that drove the predictions.

## 3. Results and Discussion

### 3.1 Performance Evaluation

The performance of the models was evaluated and presented using a comprehensive set of three evaluation metrics comprising the mean absolute error (MAE), the mean squared error (MSE), and the coefficient of determination ($R^2$). They provided a detailed understanding of the strengths and weaknesses of the algorithms. Table 3 shows the performance evaluation scores of the models. Figs. 8 to 10 show a graphical representation of the relationship between predicted and actual FS values through a correlation plot.

**Table 3** Performance evaluation scores

| Models | Metrics | | |
|---|---|---|---|
| | **MAE** | **MSE** | **$R^2$** |
| RF-ACO | 0.0425 | 0.009 | 0.9428 |
| RF-GWO | 0.0483 | 0.0107 | 0.9324 |
| RF-WOA | 0.0416 | 0.0086 | 0.9656 |

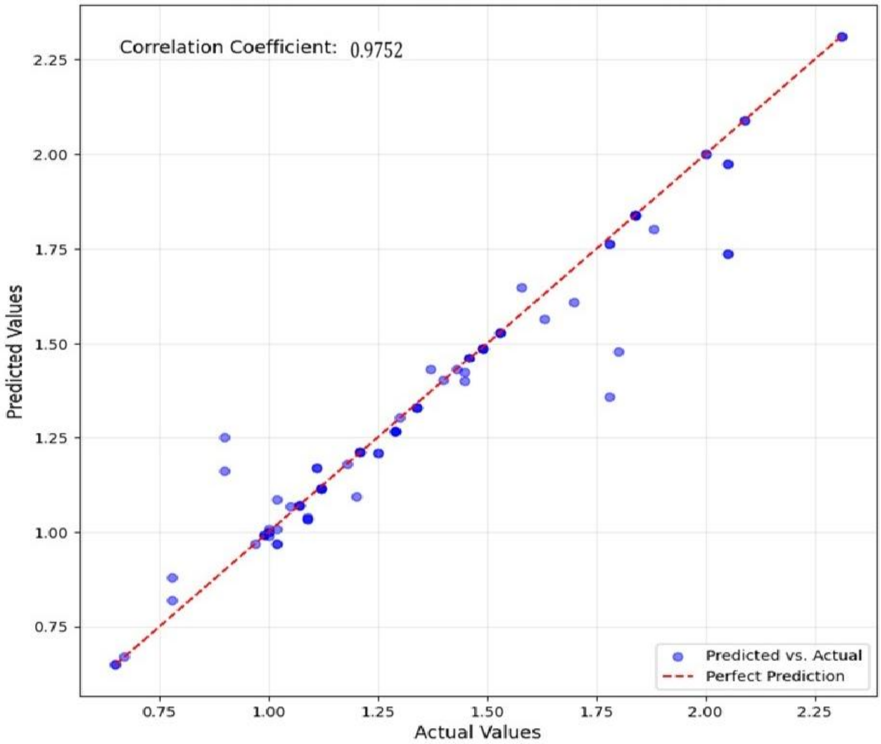


**Fig. 8** Predicted vs Actual Values of FS for RF-WOA

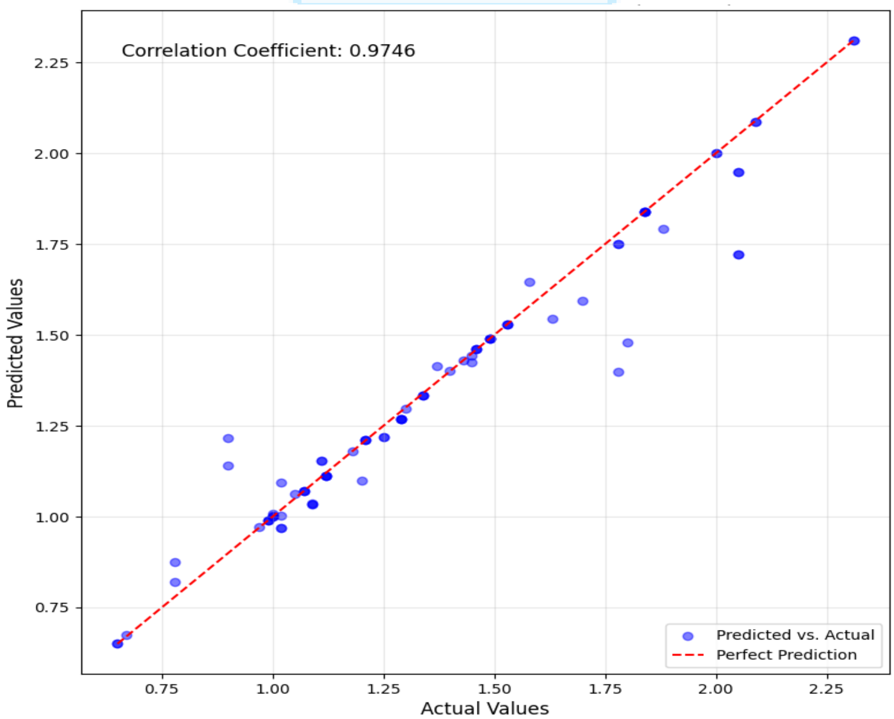


Fig. 9 Predicted vs Actual Values of FS for RF-ACO

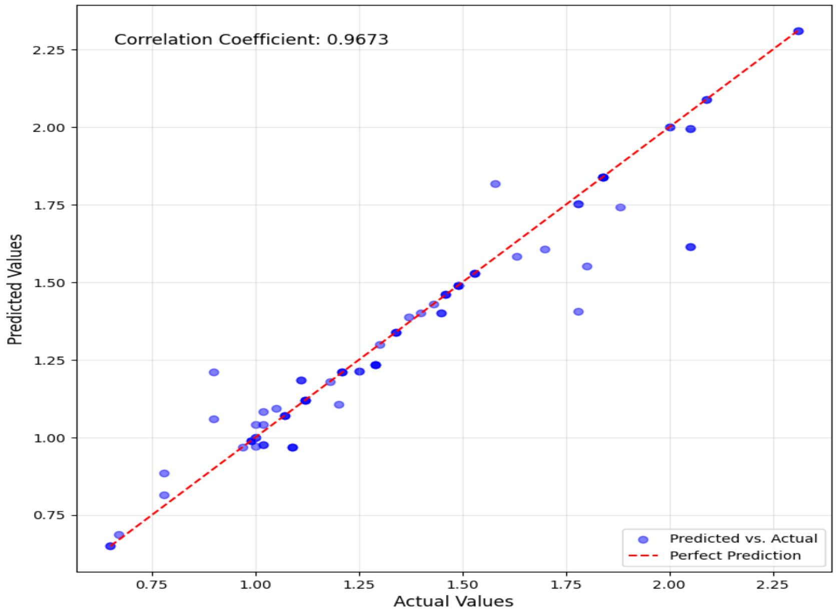


Fig. 10 Predicted vs Actual Values of FS for RF-GWO

### 3.2 Feature Importance Score

The input parameters exhibited varying degrees of influence on the predicted FS, depending on the specific metaheuristic algorithm used. This technique assigned a score to each characteristic indicating its relative importance in predicting FS. A visual representation of the results for the best model is provided in Fig. 11.

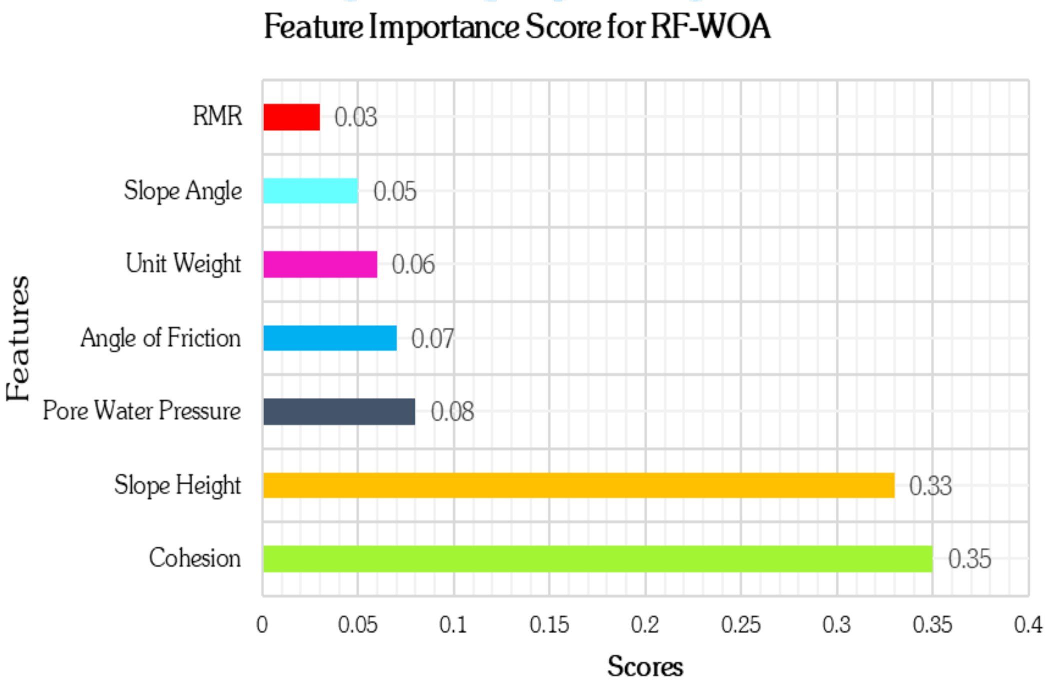


**Fig. 11** Feature importance scores for RF-WOA

### 3.3 Model Evaluation and Comparison

The varying degrees of predictive accuracy exhibited by the models were analysed and interpreted on the basis of the three-evaluation metrics employed.

The RF-WOA model exhibited a mean absolute error (MAE) of 0.0416 indicating a high degree of predictive accuracy, with predictions deviating relatively minimal from the actual FS values. The RF-ACO model (0.0425) followed suit, demonstrating its ability to predict FS with a high level of precision, although slightly lower than the RF-WOA model. The RF-GWO model displayed a higher MAE of 0. 0483, indicating a low level of precision in its predictions from actual FS values and suggesting room for improvement in its predictive capabilities.

By evaluating the models with mean squared error (MSE), the RF-WOA model stood out with a MSE of 0.0085, achieving high precision in its predictions with minimal variability. The RF-ACO model (0.0090), followed closely with its respective MSE. It demonstrated reasonably accurate predictions, although with slightly more variability than that of the RF-WOA model. In contrast, the RF-GWO model showed a notable increase in MSE, that is, 0.0107, indicating a greater dispersion in its predictions. This resulted in significant variability in its predictions, deviating substantially from the actual values.

In the evaluation by coefficient of determination ($R^2$), the RF-WOA model achieved an impressive $R^2$ value of 0.9656, which means that its predictions can explain 96.56% of the variance in the FS. The RF-ACO model with $R^2$ of 0.9428 indicates that 94.28%, respectively, of the variance in the FS is predictable from their predictions. The RF-GWO model showed the lowest $R^2$ value of 0.9324, which explained 93.24% of the variance in the FS, which indicates the least predictive power among the three models.

Based on the correlation plots, Fig. 8 revealed that the RF-WOA model exhibited the strongest correlation (0.9752) between the predicted and actual results. Its predicted values were closely aligned with the actual values. The RF-ACO model in Fig. 9, closely showed a strong correlation of 0.9746 although slightly less pronounced than the RF-WOA model. The RF-GWO model in Fig. 10 demonstrated correlation with a score of 0.9673 which indicated that its predictive performance was relatively weaker compared to the top-performing RF-WOA model. The correlation plots collectively indicate that the RF-WOA model excelled in predicting accurate results.

The results show that the RF-WOA model surpassed the other models in all evaluation metrics, showcasing exceptional accuracy, explanatory power, and predictive precision with predicted values closely mirroring the actual results. This implies that the metaheuristic algorithm Whale Optimisation Algorithm (WOA) has a higher predictive power and performs well with the Random Forest machine learning algorithm. Furthermore, the metaheuristic algorithm Ant Colony Optimisation (ACO) predicted considerably good values with the Random Forest algorithm in the RF-ACO model, however, the predictive power and precision of this model are lower than those of the RF-WOA model. Lastly, the Grey Wolf Optimisation (GWO) algorithm with the Random Forest algorithm developed a model that delivered reasonable results. However, these results struggled with larger prediction errors.

### 3.4 Sensitivity of Input Parameters

The analysis of the importance of the characteristics of RF-WOA revealed that cohesion was the most crucial factor that influenced slope stability, with a score of 0.35, accounting for a greater portion of the total influence. The slope height followed closely with a score of 0.33, indicating its significant impact on the prediction of FS. The ranking of importance was followed by Pore water pressure (0.08), Angle of friction (0.07), Unit weight (0.06) and Slope Angle (0.05). In particular, the Rock Mass Rating had a negligible impact on the prediction with a score of only (0.03), indicating its least significance in predicting the FS.

The results from the RF-WOA model confidently identified Cohesion as the most critical factor influencing slope stability, with the highest feature importance score. This highlights its decisive impact on predicting FS and emphasises its importance in ensuring slope stability.

In contrast, Rock Mass Rating (RMR) showed the lowest influence in the model receiving the lowest feature importance score. This indicates that RMR had a relatively insignificant impact on the FS predictions, suggesting that the model did not rely significantly on this parameter to make predictions. Therefore, RMR had a relatively minor influence on the prediction outcomes.

### 3.5 Computational Performance

The computational performance was evaluated using a Lenovo 81YT system with Intel(R) Core(TM) i7-10750H CPU @ 2.60GHz (12 CPUs) and 64GB RAM. Using the dataset of 281 data points (195 training, 86 testing) with seven input parameters (Slope Height, Slope angle, Cohesion, Friction Angle, Unit Weight, Rock Mass Rating, and Pore water pressure), model training times varied among the hybrid models: RF-WOA required 1.97 seconds, RF-ACO needed 2.15 seconds, and RF-GWO took 1.68 seconds for training completion. The substantial RAM capacity (64GB) ensured efficient handling of the dataset and model optimisation processes without memory constraints. Interestingly, while RF-GWO showed the fastest training time at 1.68 seconds, it demonstrated lower prediction accuracy compared to RF-WOA. The RF-WOA model, despite requiring slightly more computational time (1.97 seconds), achieved the best prediction accuracy while maintaining reasonable computational efficiency, making it suitable for practical implementation in slope stability monitoring systems. The minimal differences in computational times among the models (range of 0.47 seconds) suggest that processing speed should not be a limiting factor in model selection for real-world applications. These efficient processing times demonstrate that the models can handle real-world mining datasets effectively, making them practical tools for slope stability analysis in operational mining environments.

## 4. Conclusions

The study's findings indicate that the hybridised metaheuristic model (RF-WOA) is highly effective in predicting slope stability by delivering the most accurate results. The RF-WOA model outperformed other hybrid models, achieving the lowest mean absolute error (0.0416), mean squared error (0.0086), and the highest coefficient of determination (0.9656). Comparatively, the metaheuristic algorithms (WOA, ACO, and GWO) which hybridised the machine learning algorithm RF developed robust models that improved the machine learning algorithm's accuracy and predictive performance. They performed very well, with RF-WOA being the best model among the three models that were developed. In particular, cohesion emerged as the key factor that influenced the Factor of Safety predictions, while the rock mass rating had a minimal impact. The success of the RF-WOA model opens avenues for exploring additional metaheuristic algorithms and their combinations with other machine learning techniques to further enhance predictive capabilities in slope stability analysis.

For practical implications, AngloGold Ashanti Iduapriem is advised to adopt the RF-WOA model and explore additional metaheuristic algorithms to leverage these insights. The mine should implement a continuous monitoring and updating protocol, ensuring meticulous data collection, and conducting regular cohesion tests to help maintain the accuracy and relevance of predictions, ultimately improving slope stability analysis and preventing machine learning errors. Additionally, the mine could use this model to optimise its slope designs, potentially allowing steeper pit walls when conditions permit, thus reducing stripping ratios and improving economic outcomes while maintaining safety standards.

**Statements and Declarations**

**Conflicts of interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Ethical statement**

The research adhered to rigorous ethical standards.

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**Data access statement**

The research data can be obtained by contacting the corresponding author upon a reasonable request.

**Author contributions**

Conceptualisation: FK-S, SO, JKAN, JN, Data curation: JKAN, JN; Formal analysis: SO, JKAN, JN; Funding acquisition: FK-S; Investigation: JKAN, JN; Methodology: FK-S, SO, JKAN, JN; Project administration: SO, JKAN; Resources: FS-K, JN; Software: FK-S; Supervision: FK-S; Validation: FK-S, SO; Visualisation: FK-S, JKAN, JN; Writing – original draft: SO, JKAN, JN; Writing – review & editing: FK-S. All authors have read and agreed to the published version of the manuscript.

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