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Prediction of slope stability in open-pit mines using intelligent algorithms: SVM and RF optimized by genetic algorithm

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ABSTRACT

Monitoring and predicting slope stability in open-pit mines plays a critical role in enhancing safety, minimizing losses, and improving operational efficiency. Slope instability can lead to severe and often irreversible economic, human, and environmental consequences. Traditional stability analysis methods, such as limit equilibrium and numerical modeling, face limitations due to geometric simplifications, linear assumptions, and their inability to capture complex patterns—factors that reduce their effectiveness in real-world conditions. In recent years, machine learning approaches have emerged as powerful tools in geotechnical analysis. This study aims to predict the stability status of open-pit mine slopes using machine learning models, specifically Support Vector Machine (SVM) and Random Forest (RF). To improve the accuracy of these models, their parameters were optimized using a Genetic Algorithm (GA). The dataset used includes geotechnical and geometric features influencing slope stability, obtained from field investigations and documented sources. The results indicate that the RF–GA hybrid model outperforms the SVM–GA model, achieving 93% accuracy with an AUC of 0.93, compared to 86% accuracy and an AUC of 0.86 for the SVM–GA model. Moreover, the RF model demonstrated higher sensitivity in identifying stable slopes and reduced the number of false negatives. These findings highlight the strong potential of the RF–GA model in delivering reliable predictions and supporting decision-making in slope stability management. The integration of intelligent algorithms with local data offers a robust alternative to traditional methods in geotechnical engineering.

KEYWORDS

Slope stability, open-pit mining, machine learning, optimization, genetic algorithm

I. INTRODUCTION

The slopes of open-pit mines are among the most critical and strategic components of mineral extraction operations, playing a vital role in the safety, efficiency, and economic performance of mining activities. These slopes, often designed and constructed with considerable height and steepness, are influenced by a range of complex factors, including geotechnical properties of the materials (such as unit weight, cohesion, and internal friction angle), hydrological conditions (such as pore water pressure), and slope geometry (angle and height). Any instability in these slopes can result in shear failure, leading to consequences that go far beyond financial losses—posing serious risks to human lives, operational continuity, and the reputation of mining companies (Abramson et al., 2001; Ullah et al., 2020). Shear failures in open-pit mine slopes not only cause temporary or prolonged shutdowns of mining operations but may also result in fatalities, destruction of expensive equipment, and environmental degradation. For instance, slope collapses can bury workers, block access roads, and contaminate water resources due to runoff. Economically, the costs associated with slope reconstruction, damage compensation, and lost production opportunities can be substantial. Therefore, accurate evaluation and prediction of slope stability are not only safety imperatives but also economic and environmental necessities in the mining industry (Abramson et al., 2001; Pourkhosravani et al., 2011). Moreover, with the rising global demand for mineral resources and the expansion of open-pit mining toward greater depths and larger dimensions, the challenges associated with slope stability have become increasingly complex. In deeper and larger mines, the influencing factors on slope stability become more varied and nonlinear, further emphasizing the need for more precise and efficient assessment methods. Consequently, the development of advanced methods for predicting and managing the risk of shear failure has become both a research priority and an operational necessity (Sjöberg, 1996; Stacey et al., 2003).

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In response to these challenges, the present study aims to propose an innovative framework for predicting the stability status of open-pit mine slopes using intelligent methods and machine learning approaches. This strategy not only enhances prediction accuracy but also serves as a powerful tool for mining engineers in strategic decision-making and risk management. Traditionally, limit equilibrium methods have been the main tools for slope stability analysis. These methods operate based on balancing shear and resisting forces along potential slip surfaces. Prominent examples include:

- Bishop's Method, which assumes a linear stress distribution along the slip surface to assess slope stability.
- Janbu's Method, which divides the slope into individual blocks to perform stability analysis.

Despite their widespread use, these classical methods are limited by simplifying assumptions such as fixed slip surface geometry and linear or segmented stress distributions. As such, they may not deliver sufficient accuracy in complex and nonlinear conditions. Additionally, they are generally unable to model the influence of variable parameters such as pore pressure or heterogeneous material properties with high fidelity (Duncan et al., 2014).

In recent decades, advances in computational technologies and the availability of large-scale datasets have positioned machine learning (ML) as a powerful alternative to classical approaches. These methods offer the ability to model complex, nonlinear relationships between geotechnical parameters and slope stability conditions, resulting in significantly improved predictive capabilities (Nanehkaran et al., 2023). Among the most widely adopted ML models in geotechnical engineering are Support Vector Machine (SVM) and Random Forest (RF). SVM excels at identifying optimal separating boundaries in feature space, enabling precise classification of complex data. RF, on the other hand, builds robust predictions by aggregating multiple decision trees. However, the performance of these models depends heavily on the proper tuning of their parameters (Breiman, 2001; Suthaharan, 2016). To enhance the performance of SVM and RF in this study, the Genetic Algorithm (GA)—a powerful optimization technique—was employed. GA effectively searches the parameter space to identify the optimal configurations for each model, leading to significant improvements in prediction accuracy (Gen et al., 1999). The dataset used in this study comprises key geotechnical and geometric parameters of slopes, including unit weight, cohesion, internal friction angle, slope angle, slope height, and pore pressure ratio. These data were collected from field and laboratory studies in open-pit mines and include a diverse set of stable and unstable slope conditions. The main innovation of this research lies in the integration of GA-optimized SVM and RF models for predicting shear failure in open-pit mine slopes. This hybrid approach not only enhances predictive accuracy but also provides a unified framework that leverages the strengths of both models.

Furthermore, by comparing the performance of the optimized models with traditional methods, this study takes a significant step toward replacing conventional techniques with advanced machine learning tools in geotechnical engineering. The results of this study can serve as an effective tool for risk assessment and decision-making in the management of open-pit mining operations.

II. RESEARCH BACKGROUND

In recent years, due to the complex mechanical behavior of slopes and geological structures, traditional and numerical methods for slope failure prediction have faced several challenges. These challenges include high costs, time-consuming procedures, and the need for extensive and precise datasets. In response to these limitations, machine learning (ML) algorithms have emerged as powerful and modern tools in geotechnical analysis. In particular, algorithms such as Support Vector Machine (SVM) and Random Forest (RF) have gained prominence in slope stability prediction due to their ability to model complex and nonlinear relationships between input and output variables.

One of the earliest notable studies in this area was conducted by Zhao (2008), who applied the SVM algorithm to model the performance function in slope reliability analysis and demonstrated that, even with limited data, this method could achieve high prediction accuracy (Zhao, 2008). Later, Li and Rowe (2012) combined SVM with Monte Carlo simulation and used Particle Swarm Optimization (PSO) to effectively tune model parameters, resulting in a more accurate predictive model (Li et al., 2013). On the other hand, the Random Forest algorithm has also received considerable attention. Thanks to its strong classification capability and resistance to overfitting, RF has proven effective in geoscientific datasets, which are often noisy and scattered. Qi et al. (2018) used RF to predict the stability of hanging roofs in underground tunnels, achieving satisfactory accuracy (Qi, Fourie, et al., 2018). Furthermore, Zhou et al. (2021) developed an effective landslide susceptibility mapping model by integrating RF with feature selection methods such as Recursive Feature Elimination (RFE) and GeoDetector, significantly enhancing spatial prediction accuracy (Zhou et al., 2021). To further improve the performance of ML models, researchers have increasingly combined them with metaheuristic optimization algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Grey Wolf Optimizer (GWO). Demir and Şahin (2022) applied GA to optimize the parameters of both

SVM and RF for soil liquefaction prediction, reporting a substantial increase in model accuracy (Demir et al., 2022). Zhou et al. (2022) also developed a robust model for evaluating liquefaction potential by integrating RF with GA and GWO (Zhou et al., 2022). In another practical study, Shu et al. (2023) developed a hybrid model using RF, PSO, and Least Squares SVM (LSSVM) to predict slope stability in the Sichuan–Tibet highway region, which performed exceptionally well in classifying unstable areas (Shu et al., 2023). Additionally, the application of ML in slope reliability analysis has expanded. Aminpour et al. (2023) utilized SVM and RF combined with Monte Carlo simulation to predict the failure probability of heterogeneous and anisotropic slopes using only 1% of the sampled data (Aminpour et al., 2023). Similarly, Ji et al. (2020) proposed a framework combining GA with Finite Element Method (FEM), resulting in more accurate optimization of slope stability analysis models (Cen et al., 2020).

Overall, the body of research evidence indicates that combining ML algorithms like SVM and RF with optimization techniques has significantly improved the prediction accuracy of slope stability and shear failure probability (Arif et al., 2025; Kurnaz et al., 2024; Lann et al., 2024; Lin et al., 2018; Pham et al., 2021; Rajan et al., 2025; Xue et al., 2014). These hybrid approaches are not only computationally more efficient than traditional methods but also offer greater generalizability across diverse geological settings. Therefore, leveraging such data-driven and intelligent methodologies can play a critical role in enhancing the safety of mining operations and reducing geotechnical risks.

III. DATASET

In this study, data for slope stability analysis and prediction were collected from six credible and relevant sources (Hoang et al., 2016; Lin et al., 2022; Pham et al., 2021; Qi & Tang, 2018; Sakellariou et al., 2005; Zhang et al., 2022). The dataset includes the key parameters influencing slope stability based on failure modeling. These parameters are: unit weight of materials, cohesion, internal friction angle of the slope material, slope angle, slope height, pore pressure ratio, and slope stability status, which is classified into two categories: stable and failed. These parameters are considered fundamental in determining limit equilibrium conditions and the mechanical behavior of slopes. The final dataset comprises 627 samples, including 311 stable slopes and 316 failed slopes. This near-balance between stable and failed samples significantly contributes to maintaining data equilibrium during machine learning model training. The dataset covers a wide range of values with asymmetric distributions, reflecting the diversity of geomechanical and hydraulic conditions represented in the collected data.

To explore the relationships between input variables and identify potential interdependencies, a correlation matrix is presented in Fig. 1.

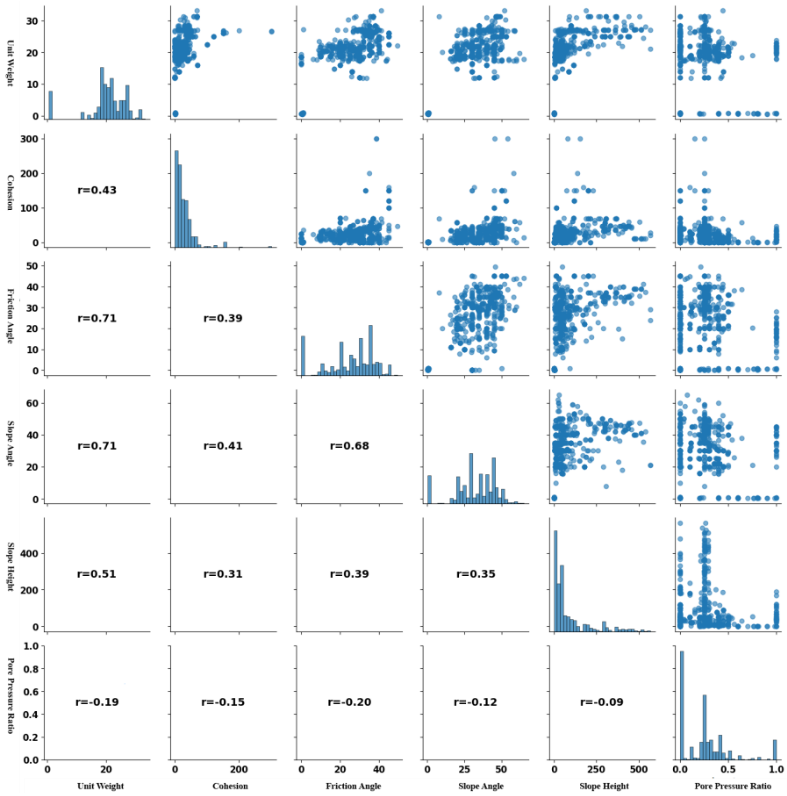

Fig. 1. Correlation matrix plot of the study parameters with corresponding coefficient values

The correlation analysis reveals several meaningful relationships among geotechnical variables. Unit weight shows the strongest correlation with both friction angle and slope angle (r = 0.71), indicating that as unit weight increases, these two parameters also rise significantly. A relatively strong correlation (r = 0.68) is also observed between the friction angle and the slope angle, suggesting that materials with higher internal resistance can sustain steeper slopes. Slope height demonstrates a moderate correlation with unit weight (r = 0.51), implying that heavier materials may offer more stability at greater heights. Cohesion also exhibits moderate correlations with unit weight, slope angle, and friction angle, reflecting the interdependent nature of strength parameters. In contrast, the pore pressure ratio has weak or even negative correlations with the other variables (ranging from -0.20 to 0.19), which may indicate an indirect or nonlinear influence of pore pressure within this system. Overall, the correlation pattern suggests that strength-related parameters such as friction angle, cohesion, and unit weight have a defined structural relationship with slope geometry. Meanwhile, the influence of pore pressure appears to be more complex and may require advanced analysis and modeling techniques to be fully understood.

Additionally, Table 1 presents the descriptive statistics for the input features in the dataset, including the minimum, maximum, mean, and standard deviation values for each parameter.

Table 1. Descriptive statistics of the study variables

Input Data	Range	Median	Mean	Std. Dev.
Unit Weight (γ) (kN/m^3)	0.492 – 30.160	20.959	20.185	7.044
Cohesion (c) (kPa)	0 – 300	19.690	25.600	31.036
Friction Angle (°)	0 – 49.500	28.800	25.308	12.331
Slope Angle (°)	0.302 – 65	34.980	32.605	13.711
Slope Height (m)	0.018 – 565	45.800	90.289	120.140
Pore Pressure Ratio	0 – 1	0.250	0.254	0.260

IV. MACHINE LEARNING ALGORITHM

Machine learning, as a core branch of artificial intelligence, enables systems to automatically learn from data and identify complex patterns without explicit programming. This technology employs various algorithms to create models that can be used for predicting future outcomes, classifying information, and supporting intelligent decision-making. The fundamental operation of such systems relies on detecting and extracting hidden relationships within existing datasets (Alpaydin, 2021; Mitchell et al., 1997). Among the different machine learning approaches, supervised learning is considered one of the most widely used. In this approach, the model is trained using labeled training data. Common examples include linear regression for predicting continuous values, support vector machines for data classification, and decision trees for modeling nonlinear relationships. In contrast, unsupervised learning focuses on discovering hidden structures and patterns in unlabeled datasets, with typical applications such as data clustering using the K-Means algorithm or dimensionality reduction through PCA. A third type, known as reinforcement learning, takes a different approach in which the learning agent interacts with the environment and gradually learns optimal behavior by receiving feedback in the form of rewards or penalties. This method has found widespread application in fields such as robotics, computer games, and intelligent control systems. The selection of a particular method and its associated algorithm depends directly on the nature of the problem, the type of available data, and the desired level of accuracy (Mitchell et al., 1997). The development and enhancement of machine learning models are often accompanied by several challenges, including the selection of appropriate features, the prevention of model overfitting, and optimal tuning of algorithm parameters. To overcome these challenges, various techniques have been developed, among which intelligent optimization methods such as genetic algorithms have proven effective. These algorithms, by simulating the process of natural evolution, can efficiently explore the parameter space and identify the optimal values for model parameters (Sra et al., 2011).

A. Support Vector Machine Algorithm

Support Vector Machine (SVM) is a supervised learning method used for both classification and regression tasks. The core mechanism of SVM is based on finding an optimal hyperplane that can separate data from two classes with the maximum possible margin (Fig. 2). In its linear form, the decision function is defined as:

$$f(x) = b + xw^T \quad (1)$$

Where w is the weight vector (The superscript T denotes the transpose of the vector w) and b is the bias. For nonlinearly separable data, kernel functions such as RBF or polynomial kernels are used to map the data into a higher-dimensional space. The optimization problem in SVM is formulated as follows:

$$\min_{w,b} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i \quad (2)$$

Where C is the penalty parameter for classification errors and ξ_i are slack variables. Selecting the appropriate values for C and kernel parameters has a direct effect on model performance (Stitson et al., 1996; Suthaharan, 2016).

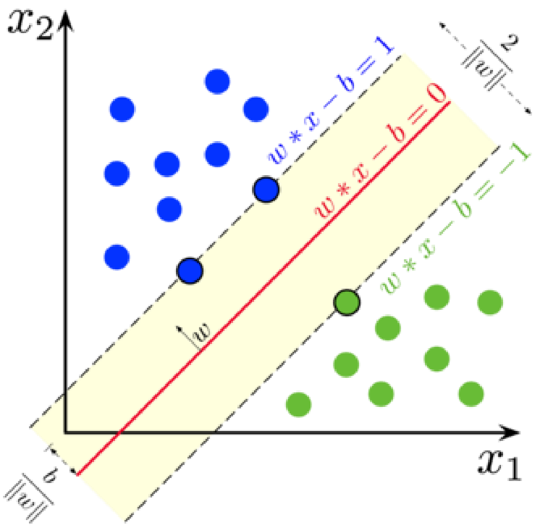

Fig. 2. Maximum-margin hyperplane and margins of a trained SVM (two-class problem). Samples lying on the margins are denoted as support vectors.

B. Random Forest Algorithm

Random Forest is an ensemble learning method that combines multiple decision trees to improve accuracy and reduce variance. This method uses two main mechanisms: bootstrap sampling and random feature selection. During training, a random subset of the training data is selected for each tree, and at each node, only a subset of features is used for splitting. Final predictions are made based on the majority vote (in classification) or the average (in regression) across all trees (Fiq. 3). Key parameters in random forest include the number of trees, tree depth, and the minimum number of samples required in leaf nodes. Proper tuning of these parameters can significantly enhance model performance (Breiman, 2001).

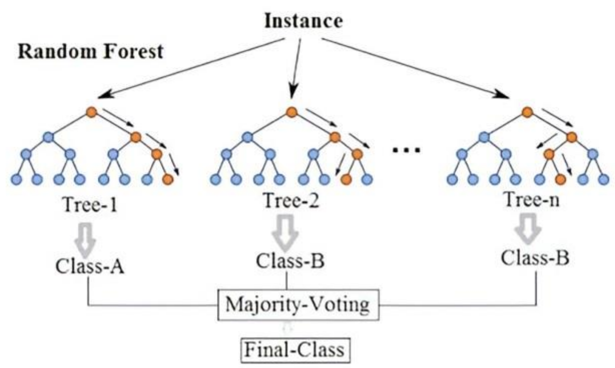

Fig. 3. Schematic illustration of the Random Forest algorithm

C. Genetic Algorithm

Genetic Algorithm (GA) is an evolutionary optimization method inspired by natural selection and population genetics. It begins with an initial population of chromosomes (encoded solutions), each representing a point in the search space. In each generation, the fitness of each chromosome is evaluated using an objective function. Then, using genetic operators such as selection (e.g., roulette wheel or rank selection), crossover (combining segments of parent chromosomes), and mutation (minor random alterations), a new population is generated. This iterative process leads the population to gradually converge toward optimal solutions (Fig. 4). GA is particularly effective for solving multi-objective, nonlinear optimization problems with large search spaces, as it incorporates diversity mechanisms to avoid getting trapped in local optima. In machine learning applications, GA is commonly used for hyperparameter optimization by encoding parameters into the chromosome structure and defining the fitness function based on model evaluation metrics (Gen et al., 1999).

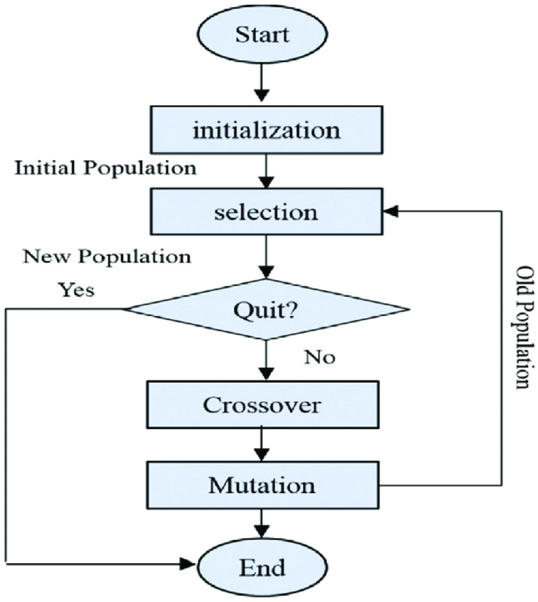

Fig. 4. Genetic Algorithm (GA) optimization flowchart

A genetic algorithm is an innovative method for finding the best configurations in machine learning models, inspired by the natural evolution process. It functions like an intelligent search system that improves solutions over time. For instance, when searching for the optimal parameter combinations for two popular models—SVM and RF—GA initially generates a set of random combinations. For SVM, these may include various values for parameters like C and gamma. Each combination is treated as an organism whose fitness is determined by the accuracy of the model it produces. Better-performing combinations have a higher chance of reproducing. In the next step, the top combinations are crossed to create a new generation of parameter sets. This mimics natural reproduction, where the traits of the parents are passed down to the offspring. In addition, random mutations are applied to maintain diversity and avoid convergence to local optima. This process is repeated multiple times until the optimal combination of parameters is found. For RF, a similar approach is used to tune parameters such as the number of trees, maximum tree depth, and the minimum number of samples per leaf node. GA automatically adjusts these parameters to achieve the best possible performance. A significant advantage of this method is its ability to search a wast parameter space and find combinations that might be overlooked using traditional trial-and-error approaches (Hu et al., 2024; Shu et al., 2023).

This optimization approach is especially valuable when dealing with complex models and multiple parameters. By simulating the process of evolution, genetic algorithms offer an efficient and automated solution for finding optimal configurations that save time and lead to improved results. In essence, this method acts like an intelligent assistant that tests all possible combinations and identifies the best option.

D. Model Evaluation

The confusion matrix is one of the fundamental tools for evaluating the performance of classification models. It provides a tabular representation of the model's ability to predict different classes accurately and is particularly useful in binary classification problems, such as identifying slope stability or failure (Mitchell et al., 1997).

Table 2. Confusion Matrix

	Predicted Stable (0)	Predicted Failure (1)
Actual Stable (0)	True Positive (TP)	False Negative (FN)
Actual Failure (1)	False Positive (FP)	True Negative (TN)

Here, True Positive (TP) represents the number of samples that are actually stable and were correctly predicted as such by the model. False Negative (FN) refers to stable cases that were incorrectly classified as failures. False Positive (FP) refers to failed cases that were mistakenly classified as stable, and True Negative (TN) are failed cases correctly identified by the model.

In this study, model performance was evaluated using metrics such as classification accuracy, sensitivity, and the ROC curve. Classification accuracy, derived from the confusion matrix, indicates the percentage of total records correctly classified and is calculated using the following formula (Mitchell et al., 1997):

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (3)$$

Sensitivity, also known as recall, provides a more detailed assessment of the model's ability to correctly identify a specific class (e.g., failure cases). It represents the proportion of actual positives correctly identified and is calculated as follows (Mitchell et al., 1997):

$$\text{Sensitivity} = TP / (TP + FP) \quad (4)$$

The ROC (Receiver Operating Characteristic) curve is a graphical tool used to evaluate the performance of classification models. This curve plots the false positive rate (FPR) against the actual positive rate (TPR) at various threshold settings. TPR, which is equivalent to sensitivity, indicates how many actual positives have been correctly identified, while FPR indicates the proportion of negatives incorrectly classified as positives. The closer the ROC curve is to the upper left corner, the better the model's performance. The area under the ROC curve, known as AUC, provides a single measure of overall model performance. An AUC close to 1 indicates excellent performance, while an AUC around 0.5 suggests performance no better than random guessing (Fig. 5) (Hoo et al., 2017).

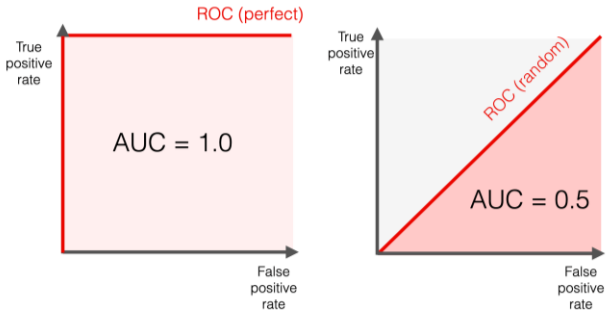

Fig. 5. Principle of Receiver Operating Characteristic (ROC) curves

V. MODELING

In the modeling phase, the preprocessed dataset was first divided into training (70%) and testing (30%) subsets. This split was performed with careful consideration of statistical principles. A stratified sampling method was used to ensure that the proportional distribution of stable and failed slope classes was maintained across both the training and testing sets. As a result, the model was exposed to the full spectrum of conditions, allowing for a more unbiased evaluation of its performance. Implementation was conducted using the train_test_split function from scikit learn with stratify=*y* to preserve class ratios, and random_state=42 to ensure reproducibility. Importantly, all preprocessing steps—including normalization and standardization—were applied based solely on statistics derived from the training set, effectively preventing data leakage into the test set. This data-splitting strategy offers multiple advantages: firstly, the training set retains sufficient volume (70%) to capture the complexity of underlying patterns. Secondly, the test subset (30%) acts as an independent, representative sample of the population, enabling valid and unbiased model evaluation. Thirdly, maintaining class balance across both subsets prevents model bias toward majority classes. To verify the robustness of the results, the splitting and training process was repeated with different random seeds. Evaluation metrics across runs demonstrated standard deviations below 2%, indicating the method's stability and reliability. Such rigor in data partitioning is critical, in sensitive domains like geotechnical prediction, as it ensures reliable model performance under realistic conditions.

A. SVM Modeling

For the SVM model, an RBF kernel was employed, with two key hyperparameters, C and γ, optimized using a genetic algorithm. The GA started with an initial population of 50 chromosomes, each encoding random values for C and γ. The fitness function was defined based on classification accuracy on a validation dataset. Uniform crossover and Gaussian mutation operators were applied to generate new generations. The optimization trend presented in Table 3 (Fig. 6) illustrates an evolving process across 20 consecutive generations. Initially (generation 0), the population started with an average fitness of 0.6999 and a maximum fitness of 0.8337, followed by systematic improvements. By generation 20, the average fitness rose to 0.71208, while the highest fitness peaked at 0.847159 in generation 13. A notable jump occurred at generation 8, where the maximum fitness increased sharply from 0.829321 (gen 7) to 0.845896 (gen 8), likely due to the discovery of a well-suited parameter combination. This variant was retained and further refined in subsequent generations. The number of evaluations per generation ranged from 34 to 43, reflecting the algorithm's efficiency in managing population size—possibly via adaptive population-control mechanisms that deepen searches in promising regions. From generation 15 onward, the maximum fitness stabilized around 0.847, signaling convergence to an optimal solution. Over time, the gap between average and best fitness values diminished—from 0.1338 initially to 0.1345 at generation 20—indicating population homogenization and reduced genetic diversity. Nevertheless, the modest continuing improvement in average fitness in later generations suggests ongoing fine-grained exploration of the search space. Overall, the GA implementation effectively leveraged evolutionary operators to identify high-quality solutions while avoiding local optima gradually.

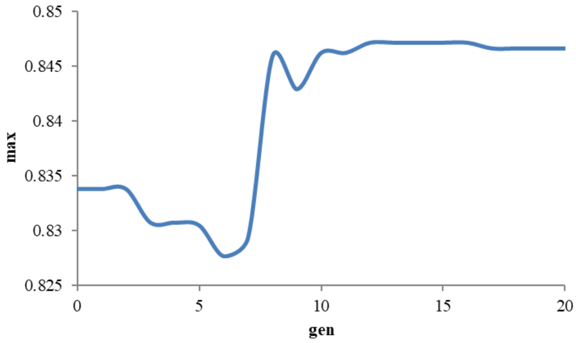

Fig. 6. Evolutionary trend of maximum fitness across generations of the Genetic Algorithm for the SVM model

The final optimized parameters reached were C=12.5 and γ=0.01. The confusion matrix and performance results are shown in Fig. 7 and Table 4.

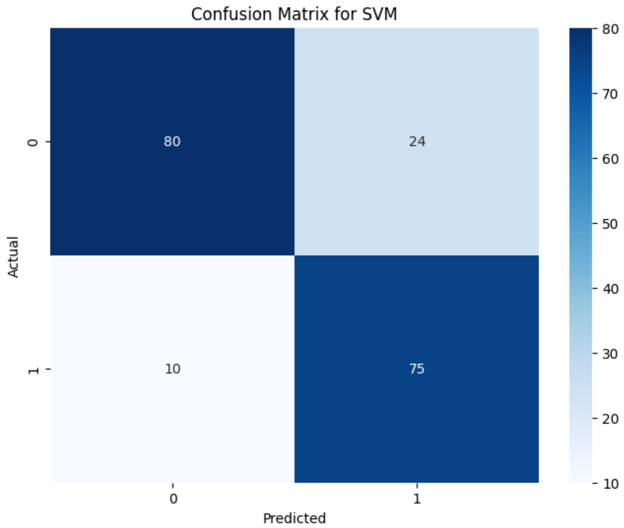

Fig. 7. Confusion Matrix for the SVM Model

Table 4. Performance Evaluation Metrics of the SVM Classifier

Model	Class	Accuracy	Sensitivity
SVM	Stability	0.89	0.77
	Failure	0.76	0.88

Table 3. Progression of mean and optimal fitness values over GA generations (SVM model)

Generation (gen)	Evaluations (nevals)	Average Fitness (avg)	Maximum Fitness (max)	Generation (gen)	Evaluations (nevals)	Average Fitness (avg)	Maximum Fitness (max)
0	50	0.699947	0.833797	11	38	0.708902	0.846228
1	40	0.703025	0.833797	12	40	0.707368	0.847159
2	38	0.70514	0.833797	13	40	0.706324	0.847159
3	39	0.708114	0.830728	14	34	0.706736	0.847159
4	43	0.705524	0.830728	15	37	0.711051	0.847159
5	41	0.705038	0.830471	16	42	0.711108	0.847159
6	43	0.707131	0.82766	17	38	0.709795	0.846636
7	34	0.709932	0.829321	18	34	0.710476	0.846636
8	40	0.706877	0.845896	19	41	0.712082	0.846636
9	39	0.707192	0.84291	20	39	0.711791	0.846636
10	43	0.707144	0.846228				

The ROC curve demonstrates an AUC of 0.92 (Fig. 8), indicating strong discriminatory performance between classes.

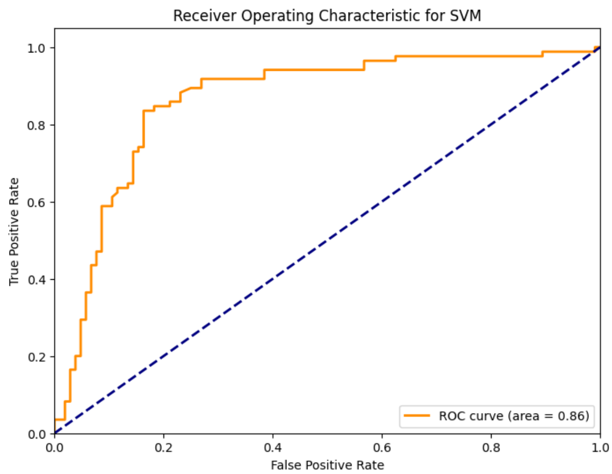

Fig. 8. ROC Curve and AUC Value for the SVM Model

B. Random Forest Modeling

For Random Forest modeling, primary hyperparameters—number of trees, maximum depth, and minimum samples per split—were optimized using GA within defined search ranges: 50–200 trees, depth 3–20, and minimum split samples 2–10. The search ranges for the Random Forest hyperparameters were selected based on prior literature and initial experiments. Specifically, the number of trees (50–200) offers a practical balance between model accuracy and computational cost, as values beyond this range tend to increase runtime with minimal performance gain. The maximum tree depth (3 to 20) covers both shallow and relatively deep trees to prevent overfitting while capturing data complexity. The minimum number of samples per split (2–10) is widely used to regulate tree growth and improve generalization. These ranges ensure effective exploration during optimization while maintaining reasonable computational efficiency. This time, the fitness function was based on the F1-score to balance precision and recall. The optimization trend presented in Table 5 (Fig. 9) spans 21 generations. Initially (generation 0), the average fitness was 0.868824 with a maximum of 0.913117, suggesting a high-quality initial population. From generations 1–5, average fitness improved gradually from 0.869686 to 0.871378, showcasing effective GA operations. Peak fitness reached 0.915419 at generation 4 and remained stable in the 0.910–0.915 range thereafter. The consistency of top performers highlights the GA's ability to preserve high-quality parameter combinations. Middle generations (6–10) saw average fitness oscillate between 0.868986 and 0.871233, reflecting maintained population diversity. Evaluations per generation varied between 25 and 46, indicating the presence of adaptive search strategies. In later generations (11–20), average fitness settled between 0.866457 and 0.867799—a slight decline likely due to mechanisms preserving diversity—while maximum fitness remained above 0.91, illustrating retention of high-performing solutions. The relatively stable gap (~0.0443) between average and best fitness, from generation 0 to 20, suggests gradual convergence—a pattern atypical in many GA optimizations, perhaps due to the peculiarities of this search space. Overall, the GA successfully uncovered and preserved high-quality parameter combinations, with consistent maximum fitness levels across all 21 generations, indicating strong identification of near-optimal solutions.

Consequently, the optimized parameters were determined to be 150 trees, maximum depth 10, and minimum split samples of 4. The resulting confusion matrix and performance metrics, compared to SVM, are shown in Fig. 10 and Table 6, indicating superior performance.

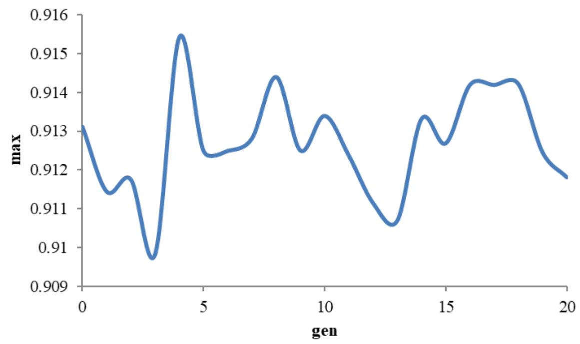

Fig. 6. Evolutionary trend of maximum fitness across generations of the Genetic Algorithm for the RF model

Table 3. Progression of mean and optimal fitness values over GA generations (RF model)

Generation (gen)	Evaluations (nevals)	Average Fitness (avg)	Maximum Fitness (max)	Generation (gen)	Evaluations (nevals)	Average Fitness (avg)	Maximum Fitness (max)
0	50	0.868824	0.913117	11	38	0.867400	0.912377
1	34	0.869686	0.911541	12	40	0.867429	0.911155
2	25	0.870766	0.911760	13	42	0.866612	0.910704
3	40	0.870110	0.909841	14	38	0.867621	0.913319
4	37	0.870954	0.915419	15	34	0.866457	0.912691
5	35	0.871357	0.912498	16	39	0.867539	0.914193
6	40	0.870477	0.912498	17	30	0.867748	0.914193
7	37	0.870867	0.912818	18	38	0.867799	0.914218
8	38	0.870233	0.914396	19	38	0.867181	0.912460
9	42	0.868986	0.912507	20	41	0.867522	0.911819
10	46	0.869928	0.913398				

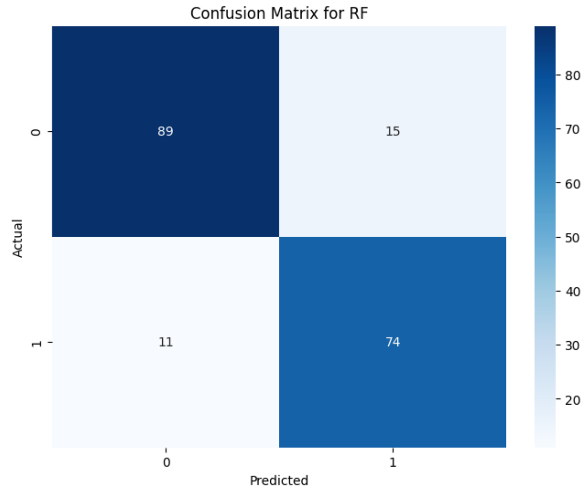

Fig. 7. Confusion Matrix for the RF Model

Table 4. Performance Evaluation Metrics of the RF Classifier

Model	Class	Accuracy	Sensitivity
RF	Stability	0.89	0.86
	Failure	0.83	0.87

The ROC curve calculated an AUC of 0.94 (Fig. 11), representing an approximately 2% improvement over the SVM model, particularly excelling in classifying minority class instances.

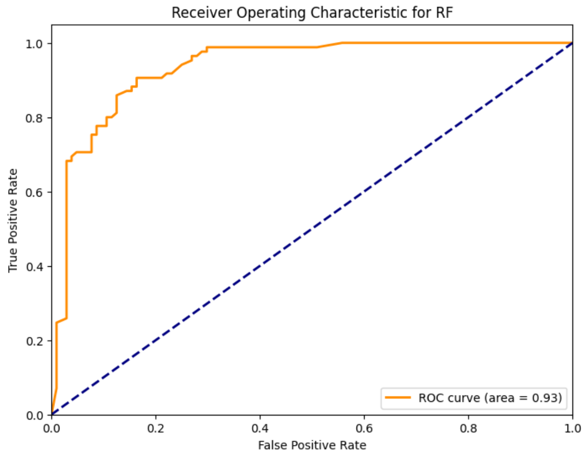

Fig. 11. ROC Curve and AUC Value for the RF Model

A key insight from the RF model in this study is the analysis of feature importance in predicting the stability of open-pit mine slopes (Fig. 12). This analysis identifies the contribution of each geotechnical and geometric parameter to model performance, guiding practitioners on which variables to emphasize during slope design, analysis, and stabilization efforts. According to the RF results, the unit weight of materials had the highest importance (0.25), indicating its dominant role in slope behavior. A higher unit weight increases the gravitational driving force, thereby elevating the potential for sliding if shear resistance is insufficient. Cohesion, with a relative importance of 0.21, ranks second and is a key component of shear strength in the Mohr–Coulomb model. Lower cohesion, especially in fine-grained or weathered materials, significantly reduces the factor of safety and increases failure risk. The internal friction angle, with an importance of 0.175, is ranked third; this parameter measures the material's resistance to frictional sliding and is particularly significant in granular or fractured rock with filled joints. Slope height carried a similar weight (0.17), illustrating its effect on increasing vertical and shear stress at the slope base, thereby promoting deep-seated failure. The slope angle, with a relative importance of 0.14, also plays a crucial but less dominant role compared to height—reflecting the complex interplay between geometry and material strength. Finally, the pore pressure ratio, with the lowest importance value of 0.11, contributed the least among the evaluated factors. However, under conditions such as localized saturation, heavy rainfall, or seepage, pore pressure can increase abruptly and critically affect slope stability. Therefore, its lower importance in this model likely reflects the relatively dry or semi-arid conditions of the data used, rather than indicating negligible practical relevance.

In summary, this analysis demonstrates that among various factors influencing open-pit mine slope stability, the physical and strength-related properties of the materials—namely unit weight, cohesion, and internal friction angle—are the most significant drivers of slope behavior.

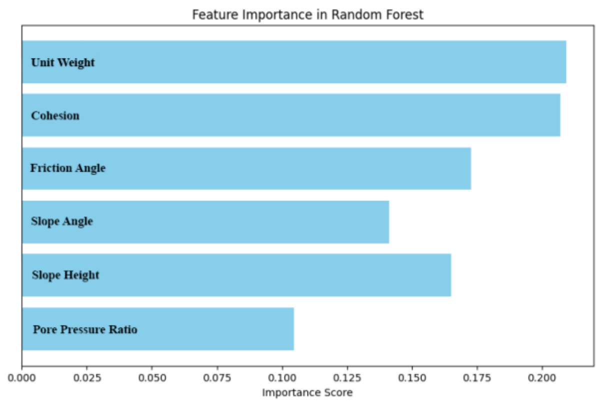

Fig. 12. Feature Importance Derived from the RF Model

VI. DISCUSSION

The evaluation results of the two genetic algorithm–optimized machine learning models—Support Vector Machine (SVM) and Random Forest (RF)—demonstrate significant differences in their performance for classifying slope stability and shear failure events. The Area Under the ROC Curve (AUC), indicative of each model's discriminative ability, is 0.93 for the RF model compared to 0.86 for the SVM. This 0.07 (approximately 8%) difference clearly indicates the RF model's superior capacity to distinguish between the two classes. A class-level analysis further elucidates these performance differences. In the stable slope class, both models achieve an equal precision of 0.89. However, RF's sensitivity is 0.86—substantially higher than SVM's 0.77—indicating that RF is more adept at correctly identifying stable cases and less prone to type II errors. In other words, RF is less likely to misclassify genuinely stable slopes as failures. Conversely, in the failure class, both models show similar sensitivity (RF: 0.87, SVM: 0.88), but RF attains higher precision (0.83 vs. 0.76). This demonstrates RF's superior ability to reduce false positives, thereby minimizing instances where stable slopes are wrongly labeled as failure risks. The overall superiority of RF can be attributed to its inherent ensemble structure, which aggregates multiple decision trees to reduce variance, guard against overfitting, and better capture complex relationships among variables. Such capabilities are particularly crucial in modeling phenomena influenced by heterogeneous factors—like shear failure prediction. It is noteworthy that optimizing parameters using genetic algorithms improved both models. Nevertheless, RF's architecture seems more amenable to effective optimization, resulting in superior final performance in terms of generalizable accuracy and precision. From a practical standpoint, these optimized models hold significant value for engineering decision-making and structural health monitoring systems. Reducing both false positives and false negatives not only increases predictive accuracy but also has direct implications for operational efficiency, cost reduction, and safety enhancement. RF's balanced performance in precision, recall, and specificity makes it particularly valuable in real-world contexts.

In the stable class, RF's higher sensitivity (0.86 vs. SVM's 0.77) means fewer cases of wrongly flagging stable slopes as failures—an important advantage for engineering applications such as infrastructure, mining, deep excavation, and rock slope monitoring. Correct classification avoids unnecessary stabilization measures (e.g., injections, rock bolts, costly retaining structures), thereby saving resources and time. In early-warning systems, minimizing such errors increases user trust and reduces alarm fatigue. In the failure class, RF's higher precision (0.83 vs. SVM's 0.76) reduces false alarms, limiting unwarranted operational interruptions, planning disruptions, resource waste, and cost overruns. When critical decisions—such as site evacuation, work stoppage, or emergency stabilization—depend on model outputs, minimization of such errors directly improves operational efficiency and lowers risk. Moreover, RF's robustness positions it well for integration into advanced decision-support systems. Coupled with real-time sensor inputs (e.g., pore pressure, displacement, vibration data), remote sensing outputs, or imagery, RF can be embedded into intelligent monitoring platforms, early-warning systems, and geotechnical risk analysis tools. In design phases, the model can also be used to simulate behavioral scenarios for rock masses and perform sensitivity analyses of geotechnical parameters, providing deeper insights into potential stability issues.

In summary, the GA-optimized Random Forest model not only demonstrates superior laboratory and analytical performance compared to SVM but, given its practical advantages, offers a reliable and precise decision-support tool for slope stability management, failure risk analysis, and crisis prediction.

VII. CONCLUSIONS

This research establishes that using machine learning, particularly models optimized via genetic algorithms, can profoundly enhance the analysis of open-pit mine wall stability. Comparison of two widely used classifiers, SVM and RF, reveals that the RF model—optimized with GA—delivers higher accuracy, sensitivity, and specificity, with powerful performance in detecting both stable and failing conditions. These advantages are critical in operational mining scenarios, where interventions, shutdowns, or stabilization measures depend on model outputs. Additionally, employing genetic algorithms for hyperparameter tuning not only improves model accuracy but also enhances robustness and real-world generalizability. Practically, this framework can serve as a precise and trustworthy decision-support mechanism in monitoring systems, early-warning platforms, and slope design and optimization tasks across mining project stages. Ultimately, this study emphasizes the necessity of transitioning from traditional, simplified geotechnical methods to intelligent, data-driven models. Considering the increasing complexity of deep mines and the evolving capabilities of data collection technologies, integrating advanced machine learning with detailed field and lab data can unlock new horizons for intelligent risk management in mining. Accordingly, it is recommended that mining design and operations officially adopt these innovative tools to elevate safety, productivity, and operational stability.

Recommendations for Future Research

1. Expanding the dataset across diverse geological and geographic conditions to enhance model generalizability.
2. Exploring deep learning algorithms, particularly when complex data like images or time series are available.
3. Integrating topographic and satellite imagery within AI models.
4. Fusing numerical geotechnical data with radar, LiDAR, or satellite inputs to develop hybrid models that detect progressive slope changes for early-warning systems.
5. Live implementation of decision-support systems, using real-time sensors to monitor slope stability and issue alerts when needed.
6. Comparative studies of optimization methods, exploring alternatives such as Particle Swarm Optimization, Imperialist Competitive Algorithm, and Bat Algorithm for hyperparameter tuning.

7. Extending models to temporal forecasting, aiming to predict not just current status but future stability trends for proactive risk management.

Given the rising importance of mine safety and the promise of machine learning in geotechnical analysis, future studies that expand and implement these innovative methodologies in real-world settings can significantly advance mining operational safety and efficiency.

Conflict of Interest

The authors declare that there is no conflict of interest related to this article.

Ethical Approval

The authors confirm that the content of this article has not been published in any other journal.

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