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# EFFICIENT AND RELIABLE PREDICTION OF DUMP SLOPE STABILITY IN MINES USING MACHINE LEARNING: AN IN-DEPTH FEATURE IMPORTANCE ANALYSIS

This study rigorously examines the pressing issue of dump slope stability in Indian opencast coal mines, a problem that has led to significant safety incidents and operational hindrances. Employing machine learning algorithms such as Random Forest (RF), k-Nearest Neighbors (KNN), Support Vector Machine (SVM), Logistic Regression (LR), Decision Tree (DT), and Gaussian Naive Bayes (GNB), the study aims to achieve a scientific goal of predictive accuracy for slope stability under various environmental and operational conditions. Promising accuracies were attained, notably with RF (0.98), SVM (0.98), and DT (0.97). To address the class imbalance issue, the Synthetic Minority Oversampling Technique (SMOTE) was implemented, resulting in improved model performance. Furthermore, this study introduced a novel feature importance technique to identify critical factors affecting dump slope stability, offering new insights into the mechanisms leading to slope failures. These findings have significant implications for enhancing safety measures and operational efficiency in opencast mines, not only in India but potentially globally.

**Keywords:** Dump slope stability; Machine Learning; Limit Equilibrium method; SMOTE; Feature Importance

## 1. Introduction

India is the second-largest coal producer in the world, and its reliance on opencast mining methods has been growing to meet rising domestic energy demands. In the financial year 2019-20, India produced a total of 730.84 million tonnes of coal, with 690.393 million tonnes coming from opencast mines and 40.481 million tonnes from underground mines [1]. This increasing dependence on opencast mining has led to the critical issue of managing the stability of overburden dump slopes. India has witnessed several catastrophic slope failure incidents, such

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as the Rajmahal accident in 2016, resulting in 23 fatalities and significant property and resource losses [2]. Traditional methods for slope stability analysis, such as limit equilibrium models and numerical modeling, have been effective but are often time-consuming and resource-intensive [3,4]. These methods have been applied in different parts of the world to analyze the impact of factors like rainfall on slope stability [5-12]. However, these methods struggle when dealing with complex and uncertain situations involving a multitude of interrelated factors. To address these challenges, machine learning and deep learning techniques have gained prominence in geotechnical engineering and geoengineering [13,14]. These techniques have been comprehensively reviewed and their future challenges have been discussed in several studies [13-15]. Machine learning has been successfully applied in various geotechnical applications [16-21]. In the early 1990s, Artificial Neural Networks (ANNs) were introduced as a multi-criteria assessment tool [22]. Since then, ANNs and other machine learning algorithms have been applied to study the stability of pit slopes and dump slopes in opencast mines [23-36]. While these studies have contributed to our understanding of dump slope stability, they often focus on a limited set of parameters, neglecting crucial variables like weather conditions, blasting vibrations, and others [37-40]. In contrast to existing studies that often employ numerical modeling to understand the influence of rainfall on slope stability [6-12], this paper introduces machine learning to assess the stability of dump slopes in the presence of diverse external factors. A comprehensive analysis of 1620 cross-sections of existing dump profiles in Indian mines was conducted. This paper also aims to address the limitations observed in previous studies, such as limited datasets and class imbalances. Furthermore, a novel approach is presented to understand the contribution of each parameter affecting dump slope stability, based on p-values.

It is important to note that this paper does not introduce new machine learning algorithms; rather, it leverages existing algorithms in an innovative manner to solve critical challenges related to dump slope stability. The following sections will elaborate on the methodology used in this study, discuss our findings, and conclude with recommendations for future work.

## 2. Methodology

The methodology used in this paper is based on supervised machine learning algorithms. Machine learning is a field of study that focuses on the development of computer algorithms that can learn patterns from data and make predictions based on that learning. There are various types of machine learning, including supervised, unsupervised, and reinforcement learning. In this paper, we use a supervised learning approach, which involves training a model on labelled data to make predictions on new, unseen data. Within the supervised learning framework, two main types of models can be developed: classification and regression. Classification models aim to predict the class of a given observation based on a set of input features. In contrast, regression models aim to predict a continuous numerical output based on the input features.

The data used in this study consists of input parameters that have been collected from the field. To provide labelled output to the classification model, we have adopted the limit equilibrium method. This method is widely used in geotechnical engineering to analyse the stability of slopes and foundations. It is based on the assumption that the slope section can be divided into a series of slices, and the equilibrium of each slice can be analysed separately. The method is used to generate the output using the collected input parameters from the field. The limit equilibrium method has various sub-methods which are shown in TABLE 1, and in this paper, we use the

Morgenstern-Price method. The reason for selecting Morgenstern Price is that it is the most comprehensive method among others and takes into account least number of assumptions. This method considers all moment and force equilibrium, shear and normal interslice forces, and inclination of shear to normal interslice force as variable while other methods lack one or the other components mentioned. This method involves analysing the stability of the slope by considering the forces acting on each slice and calculating the factor of safety (FOS) for each slice. The FOS is a measure of the stability of the slope, and a FOS greater than one indicates a stable slope.

The dataset consists of 1620 dump slope profiles from opencast mines in Jharkhand, India. Figs. 1 and 2 show the cross-section and model geometry of one of the dump slopes, and the stability of these slopes was analysed using the Morgenstern & Price method in GeoSlope (a student-licensed version (serial number –6801-190910-194630) of the software that includes the SLOPE/W, SEEP/W, and QUAKE/W applications). Among the existing method for performing Limit Equilibrium method. Each of these profiles has been tested under various static and dynamic loading conditions to account for the various factors that could contribute to slope failure, including dry conditions with just geomechanical properties and slope geometry, saturated conditions, the effects of wind and rain, blasting vibrations, and the impact of cloudbursts. The resulting failure surface and the corresponding FOS value for one of the profiles are shown in Figs. 3 to 7, respectively. The exact names of the mines where these profiles were collected have not been disclosed due to confidentiality concerns. Generally, a FOS value above 1 is considered stable, but the required level of safety may vary depending on the accuracy of the input data [41] and other factors such as the size of the slope, the potential consequences of failure, uncertainty in input parameters, the lifespan of the structure, expected changes in design conditions, and the availability of monitoring systems [42]. Time is also a significant factor in the long-term stability of slopes, as the strength of rocks can decrease over time due to continuous deformation. As a result, the FOS value may decrease over time [43]. Therefore, the resulting FOS values have been divided into three classes, as shown in TABLE 2.

TABLE 1

Different LEM methods comparison

| Method | Moment equilibrium | Horizontal force equilibrium | Interslice normal (E) | Interslice shear (X) | Inclination of X/E resultant |
|---|---|---|---|---|---|
| Ordinary or Fellenius [44] | Yes | No | No | No | No force |
| Bishop's simplified [45] | Yes | No | Yes | No | Horizontal |
| Janbu's simplified [46] | No | Yes | Yes | No | Horizontal |
| Spencer [47] | Yes | Yes | Yes | Yes | Constant |
| Morgenstern-Price [48] | Yes | Yes | Yes | Yes | Variable |

TABLE 2

Stability conditions of Slope [27]

| Condition | Category | Class Label |
|---|---|---|
| FOS < 1 | Unstable | 0 |
| 1 < FOS <= 1.25<br>(For period up to 6 months) | Short-term stable | 1 |
| FOS > 1.25<br>(For period of more than 6 months) | Long-term stable | 2 |

Fig. 1. Cross-section of Dump slope

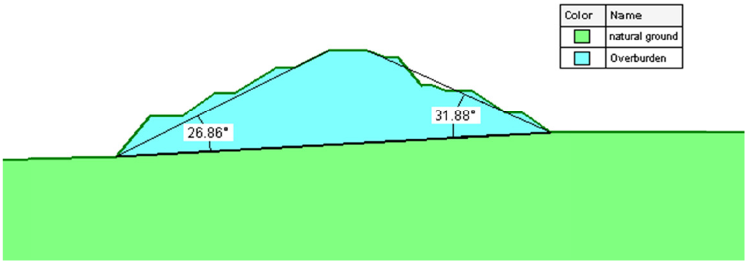


Fig. 2. Model Geometry of Dump slope

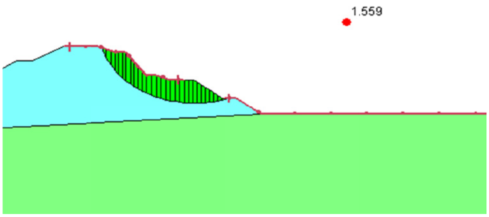


Fig. 3. Critical slip surface (Dry condition)

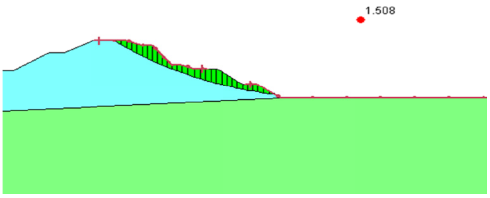


Fig. 4. Critical slip surface (Saturated condition)

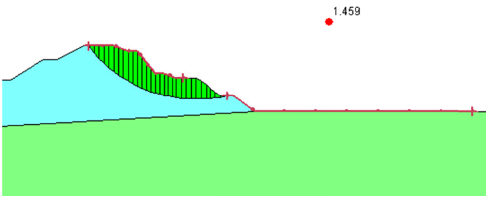


Fig. 5. Critical slip surface (Wind & rain condition)

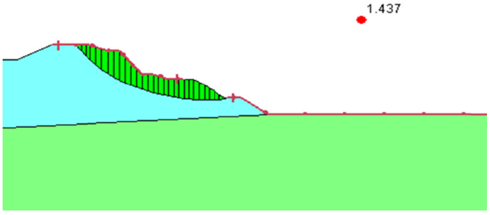


Fig. 6. Critical slip surface (Blasting condition)

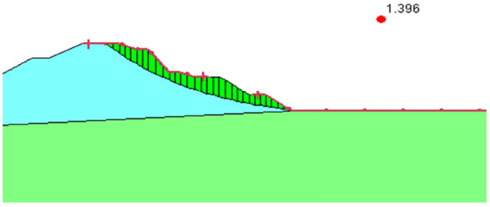


Fig. 7. Critical slip surface (Cloudburst condition)

## 2.1. Understanding Important Input features and Output Variables

The input features considered in this study are important for understanding the stability of dump slopes, and their effects cannot be ignored. The input features include cohesion, which is a measure of the strength of the forces holding the material together; unit weight, which is a geomechanical parameter that reflects the weight of the material; internal angle of friction, which is a factor that affects the shear strength of the material; height, which reflects the geometry of the slope; overall slope angle, which also reflects the slope geometry; saturation, which refers to the water content present between the pores in the material; wind, which is an external factor that can cause instability; rain, which can reduce the shear strength of the material and potentially lead to slope failure; blast vibrations, which can cause instability through the peak particle velocity attained by particles after blasting operations; and cb, which are sudden downpours of large volumes of water that can cause slope failure. Among these input features, only saturation is treated as a categorical variable, with values of 0 or 1, while the others are treated as continuous variables. TABLE 3 presents the descriptive statistics for the input features used in this study. The values of the external factors used in the study to analyse slope stability were collected based on the weather and climate patterns in the different regions of Jharkhand, India where the study was conducted

TABLE 3

Descriptive statistics of input parameters

| | Height (m) | Unit weight (kN/m$^3$) | Cohesion (kPa) | Phi (degree) | Slope angle (degree) | Wind (m/sec) | Rain (m/sec) | Blast (mm/sec) | Cb (m/sec) |
|---|---|---|---|---|---|---|---|---|---|
| **count** | 1620 | 1620 | 1620 | 1620 | 1620 | 1620 | 1620 | 1620 | 1620 |
| **mean** | 42.51 | 24.56 | 62.10 | 25.38 | 23.18 | 15.14 | 0.00291 | 88.09 | 0.03176 |
| **std** | 25.80 | 0.89 | 5.05 | 0.59 | 10.84 | 2.86 | 0.00038 | 7.94 | 0.0034 |
| **min** | 3 | 22 | 50 | 24 | 4.5 | 14 | 0.0025 | 75 | 0.02428 |
| **25%** | 25 | 24 | 59 | 25 | 14.98 | 14.95 | 0.00278 | 83.80 | 0.02929 |
| **50%** | 40 | 24.6 | 62 | 25.3 | 20.51 | 15.54 | 0.00293 | 88.28 | 0.03178 |
| **75%** | 59 | 25.2 | 65 | 25.7 | 30.15 | 16.19 | 0.00309 | 92.72 | 0.03417 |
| **max** | 110 | 26.8 | 74 | 26.9 | 48.37 | 18.3 | 0.00363 | 104.029 | 0.03993 |

Examining the histograms in Fig. 8(a)-(i) of the different input features allows us to analyse the distributions of these features and how the range of values varies significantly from one feature to another. Therefore, it is necessary to standardize the data before creating the machine learning models, as failing to do so may result in the model giving undue importance to factors with high numerical values and producing inaccurate results.

Fig. 9(a)-(i) provides the box plot against all the classes for all the input features used in the classification model

In a supervised machine learning classification model, it is important to have a balance between the output classes to reach an optimal solution, as an imbalanced distribution of the output classes can result in the model being biased towards the class with more instances. However, as shown in Fig. 10, we are dealing with an imbalanced distribution of the different output classes. To address this issue, the SMOTE has been applied, and the results before and after its application have been compared.

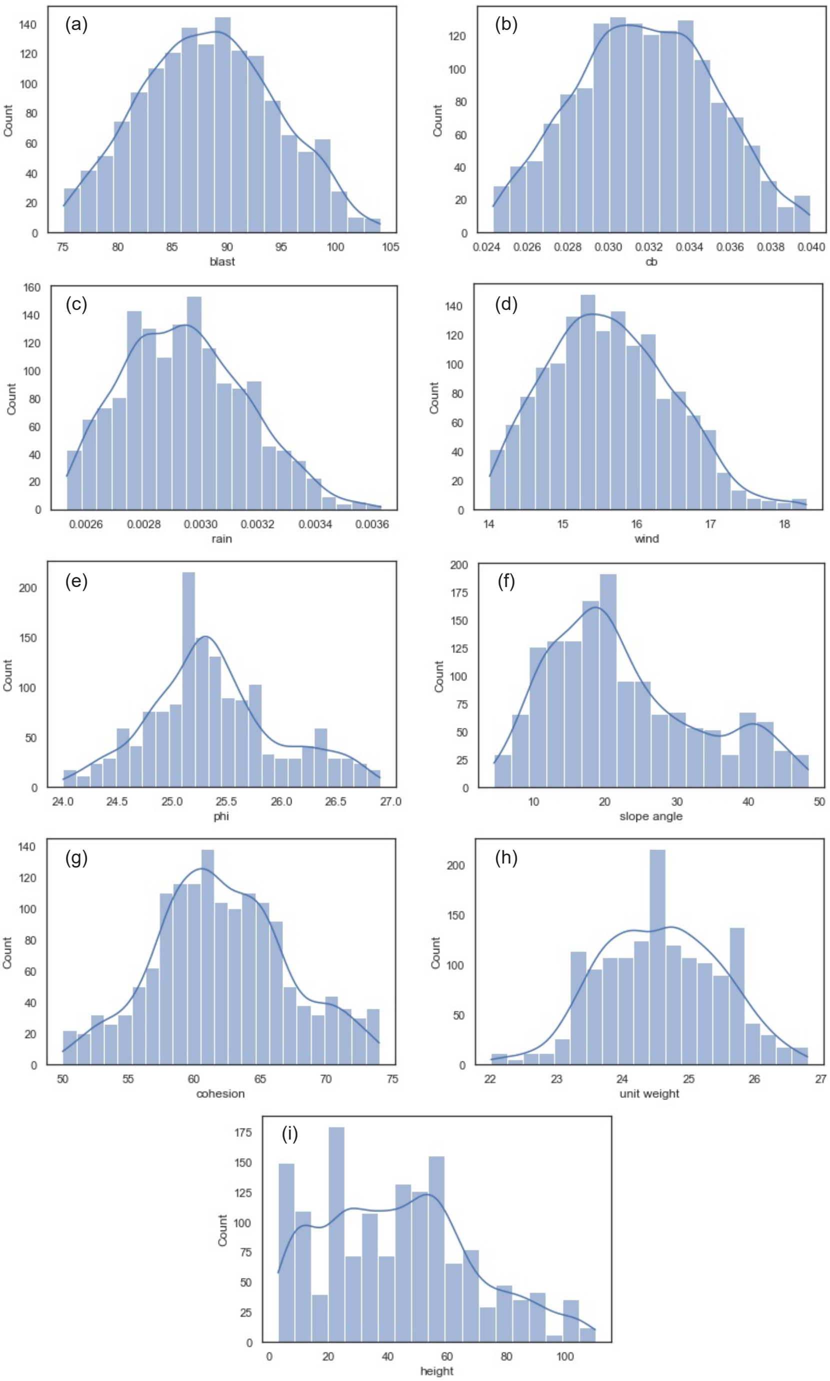


Fig. 8. Histogram of different input features (a) blast, (b) cb, (c) rain, (d) wind, (e) phi, (f) slope angle, (g) cohesion, (h) unit weight, (i) height

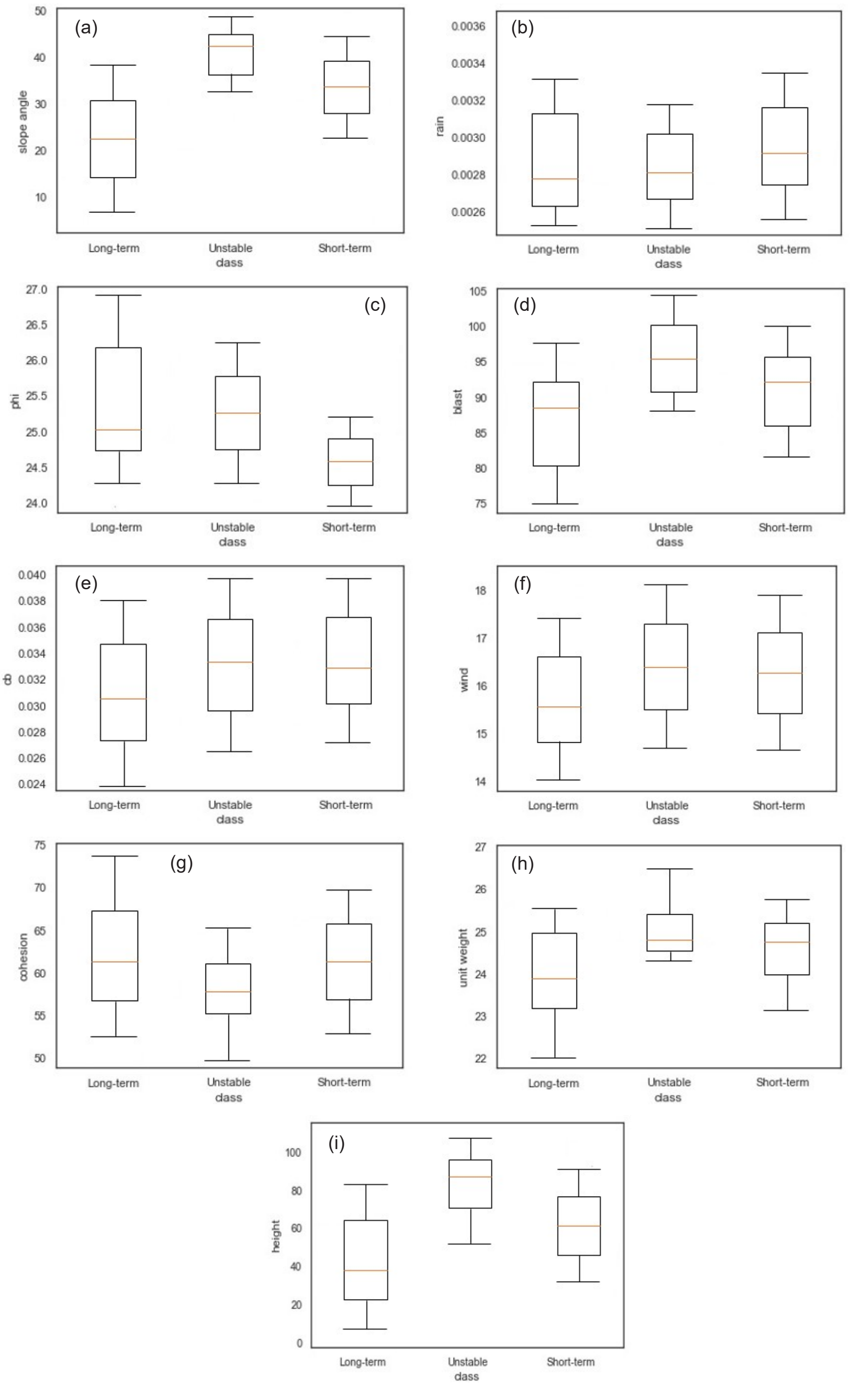


Fig. 9. Box plot of different input features (a) slope angle, (b) rain, (c) phi, (d) blast, (e) cb, (f) wind, (g) cohesion, (h) unit weight, (i) height

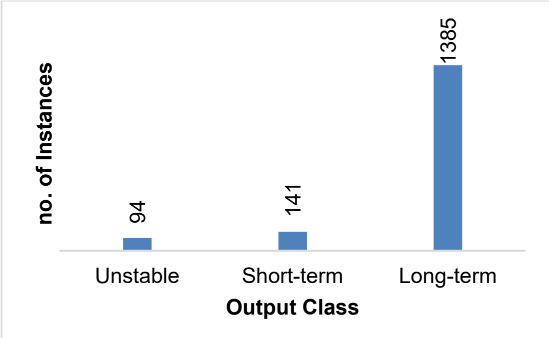


Fig. 10. Distribution of different output classes

## 2.2. Correlation between the features

The correlation between the input features reflects the interaction among these features, that is, how well one feature can be explained using another feature. Generally, if the correlation value is above 0.5 between two variables, one variable can explain the other to some extent, depending on how close the value is to 1. As shown in Fig. 11, there is little or no correlation among the variables, with the exception of cohesion and unit weight, and wind and rain. However, we cannot simply remove one of the variables from each group based solely on the correlation values without considering the importance of each variable in the model.

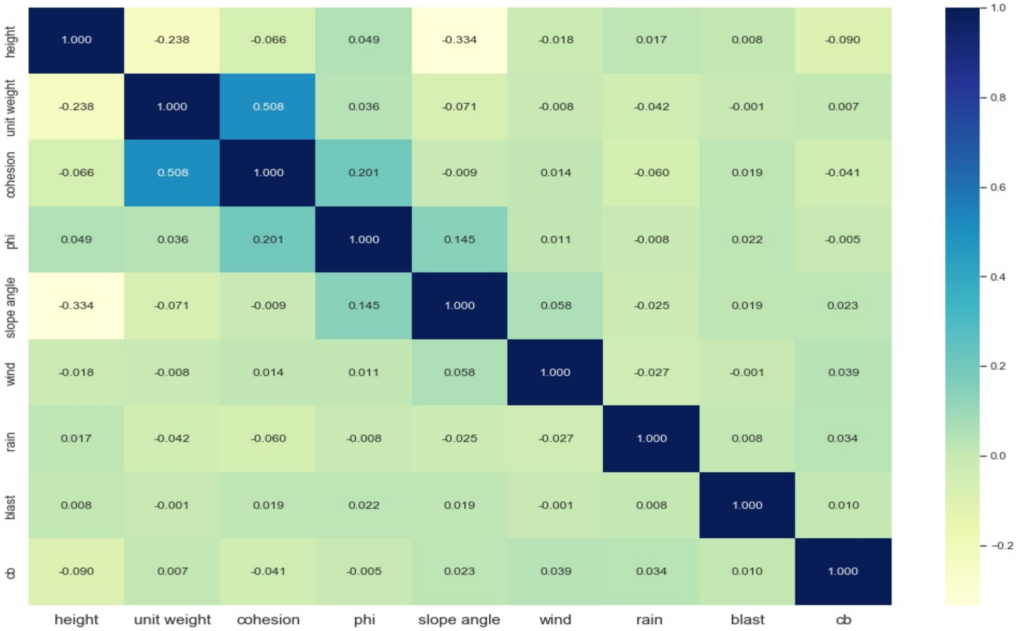


Fig. 11. Correlation matrix of input features

## 2.3. Supervised Classification Algorithms

Machine learning algorithms are powerful tools for modelling the nonlinear and complex relationships among the input features in order to predict the target variable. These algorithms can quickly and efficiently perform calculations that would be time-consuming and computationally expensive using traditional methods, by learning the complex behaviour from the available dataset. These techniques have been widely implemented in various engineering fields, including geotechnical engineering. For this study, six different advanced classification algorithms were used: RF, KNN, SVM, LR, DT, and GNB. Detailed descriptions of these individual classification algorithms can be found in the literature [49-51]. Two different models were created for each classification algorithm, and the results were compared. These models include Model 1, which takes into account all the input features but does not balance the output class. Model 2, which takes into account all the input features and applies SMOTE to address imbalanced data.

Grid Search CV and Stratified 10-fold Cross-Validation were performed for all the models to tune the hyperparameters and prevent overfitting.

## 2.4. Synthetic Minority Oversampling Technique

SMOTE is a powerful technique for dealing with imbalanced data in classification problems. The method, proposed in a 2002 paper by [52] creates synthetic data points based on the original data points, rather than generating duplicates. This ensures that the synthetic data points are slightly different from the original data points, making the algorithm more effective. When dealing with imbalanced data, accuracy is not good machine learning metric as it may lead to a model that appears very accurate but is actually useless. Instead, precision and recall are used to evaluate the performance of the model. When evaluating the performance of a classification model, it is important to consider both precision and recall, which measure how well the model identifies positive cases and all positive cases, respectively. False positives and false negatives are both incorrect predictions, but false negatives may go undetected in business processes while false positives are easier to filter out. Using SMOTE can help reduce false negatives and increase recall, but at the cost of lower precision. In cases of imbalanced data, stratified sampling is recommended to ensure the same class balance in the train and test datasets. Overall, SMOTE is an effective method for dealing with imbalanced data and can help improve the performance of classification models.

The SMOTE algorithm works by selecting instances that are close in the feature space, drawing a line between the instances in the feature space and generating new instances at points along that line. Specifically, it takes a minority class instance and computes the k-nearest neighbors for this instance. The synthetic instances are then created by choosing between the k-nearest neighbors and combining the features of the chosen neighbor with the features of the current instance. Mathematically, the synthetic instance is generated as follows:

$$New\ instance = x_i + \lambda * (x_{zi} - x_i)$$

Where $x_i$ and $x_{zi}$ are feature vectors for the instance under consideration and its chosen neighbor, respectively. $\lambda$ is a random number between 0 and 1.

In research scenarios such as predicting mining hazards or assessing slope stability, where the number of positive instances (e.g., occurrences of hazards) could be significantly lower than negative instances (e.g., non-occurrences), SMOTE can be particularly useful. By creating synthetic instances of the minority class, you can train a model that has a much better understanding of the minority class's characteristics.

### 2.4.1. Without SMOTE

**High False Negatives:** Without SMOTE, the model may predict fewer instances of the minority class (e.g., fewer instances of mining hazards), leading to higher false negatives.
**Low Recall:** The model may not capture all the positive cases, leading to low recall.

### 2.4.2. With SMOTE

**Reduced False Negatives:** By using SMOTE, the model is exposed to more instances of the minority class during training, reducing false negatives.
**Higher Recall:** The model is likely to have improved recall since it is now better trained to recognize the minority class.
**Potential for Lower Precision:** The downside is that the model may start to misclassify some of the majority class instances as belonging to the minority class, reducing precision.

## 2.5. Feature Importance Analysis

After developing a machine learning model, it is essential to understand the importance of each and every feature involved in model development. Because presence of unnecessary features results in higher computational time and complexity. If some features are not significant to the model it should be eliminated to reduce the complexity of model and the feature should be eliminated only if the performance of the model remains unchanged. Therefore, this study utilizes a new technique for determining the importance and significance of each input feature used in developing the model.

Following steps are performed to determine the significance and importance of each feature in the model:

- The best performing model is identified based on the performance metrics score.
- After the model selection is done the same model is trained and tested by first eliminating one feature at a time, then all possible combination of two features at a time, till (N/2) combination of features are eliminated. In our case N = 10 therefore, combination of 5 features is eliminated.
- The model is run after eliminating the features and test accuracy is recorded.
- Then, a database is made by combining all the above feature elimination steps (dropping one feature, then two feature, then three so on till set of 5 features) and corresponding accuracy obtained.
- Then a multiple linear regression model is fit to above data and significance of each variable is tested using p-value and value of coefficients is obtained.

Based on the value of coefficients for each variable and whether each variable is significant the real importance of each feature is computed.

### 2.6. Performance metrics used in the study

The dataset was divided into training (75%) and testing (25%) datasets for the purpose of model training and testing. The confusion matrix for the different classification algorithms on the test dataset is presented in a subsequent section. Equations 1 to 4 present the metrics used to measure the performance of the classification algorithms.

**Equation 1:** Accuracy Calculation

$$Accuracy = \frac{TN + TP}{TN + FP + TP + FN}$$

**Equation 2:** Precision Calculation

$$Precision = \frac{TP}{TP + FP}$$

**Equation 3:** Recall Calculation

$$Recall = \frac{TP}{TP + FN}$$

**Equation 4:** F1-score Calculation

$$F1score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

## 3. Results and discussions

This section presents the findings of the machine learning based solution implemented for predicting the stability of dump slopes. Six different classification models namely RF, KNN, SVM, DT, LR, and GNB has been deployed in order to achieve the desired objective. All classification models are evaluated based on the performance metrics mentioned in the previous sections.

TABLES 4-27 presents the confusion matrix and values for the performance metrics for the test set before and after applying SMOTE for each of the six models considered in the following study. As discussed in above section that for this study it is desirable for the model to have a high recall which may come at a price of slight decrease in precision. So, we can clearly see from the tables below that after applying SMOTE the recall for all the models has improved significantly but as discussed above precision has reduced slightly which is acceptable in our case. Overall accuracy for all the models except LR and GNB has also increased. Therefore, the overall best performing model in our study is found to be Random Forest with overall accuracy of 98% very closely followed by SVM also having overall accuracy of 98%.

TABLE 4

Confusion Matrix for RF before SMOTE

| Actual/Predicted | Class 0 | Class 1 | Class 2 |
|---|---|---|---|
| Class 0 | 24 | 1 | 5 |
| Class 1 | 0 | 18 | 9 |
| Class 2 | 0 | 4 | 363 |

TABLE 5

Confusion Matrix for RF after SMOTE

| Actual/Predicted | Class 0 | Class 1 | Class 2 |
|---|---|---|---|
| Class 0 | 323 | 5 | 2 |
| Class 1 | 2 | 347 | 2 |
| Class 2 | 6 | 6 | 372 |

TABLE 6

Confusion Matrix for KNN before SMOTE

| Actual/Predicted | Class 0 | Class 1 | Class 2 |
|---|---|---|---|
| Class 0 | 16 | 1 | 13 |
| Class 1 | 11 | 3 | 13 |
| Class 2 | 2 | 2 | 363 |

TABLE 7

Confusion Matrix for KNN after SMOTE

| Actual/Predicted | Class 0 | Class 1 | Class 2 |
|---|---|---|---|
| Class 0 | 296 | 33 | 1 |
| Class 1 | 3 | 347 | 1 |
| Class 2 | 38 | 38 | 308 |

TABLE 8

Confusion Matrix for SVM before SMOTE

| Actual/Predicted | Class 0 | Class 1 | Class 2 |
|---|---|---|---|
| Class 0 | 28 | 1 | 1 |
| Class 1 | 4 | 19 | 4 |
| Class 2 | 2 | 2 | 363 |

TABLE 9

Confusion Matrix for SVM after SMOTE

| Actual/Predicted | Class 0 | Class 1 | Class 2 |
|---|---|---|---|
| Class 0 | 321 | 9 | 0 |
| Class 1 | 0 | 351 | 0 |
| Class 2 | 11 | 11 | 362 |

TABLE 10

Confusion Matrix for LR before SMOTE

| Actual/Predicted | Class 0 | Class 1 | Class 2 |
|---|---|---|---|
| Class 0 | 11 | 0 | 19 |
| Class 1 | 0 | 5 | 22 |
| Class 2 | 0 | 7 | 360 |

TABLE 11

Confusion Matrix for LR after SMOTE

| Actual/Predicted | Class 0 | Class 1 | Class 2 |
|---|---|---|---|
| Class 0 | 211 | 71 | 48 |
| Class 1 | 59 | 244 | 48 |
| Class 2 | 69 | 69 | 246 |

TABLE 12

Confusion Matrix for DT before SMOTE

| Actual/Predicted | Class 0 | Class 1 | Class 2 |
|---|---|---|---|
| Class 0 | 23 | 4 | 3 |
| Class 1 | 2 | 22 | 3 |
| Class 2 | 3 | 3 | 361 |

TABLE 13

Confusion Matrix for DT after SMOTE

| Actual/Predicted | Class 0 | Class 1 | Class 2 |
|---|---|---|---|
| Class 0 | 317 | 5 | 8 |
| Class 1 | 5 | 338 | 8 |
| Class 2 | 6 | 6 | 372 |

TABLE 14

Confusion Matrix for GNB before SMOTE

| Actual/Predicted | Class 0 | Class 1 | Class 2 |
|---|---|---|---|
| Class 0 | 10 | 0 | 20 |
| Class 1 | 0 | 15 | 12 |
| Class 2 | 0 | 77 | 290 |

TABLE 15

Confusion Matrix for GNB after SMOTE

| Actual/Predicted | Class 0 | Class 1 | Class 2 |
|---|---|---|---|
| Class 0 | 130 | 188 | 12 |
| Class 1 | 9 | 330 | 12 |
| Class 2 | 96 | 96 | 192 |

### 3.1. Random Forest

TABLE 16

RF performance before SMOTE

| Class | Precision | Recall | f1 score | Support |
|---|---|---|---|---|
| 0 | 1 | 0.87 | 0.93 | 30 |
| 1 | 0.86 | 0.67 | 0.75 | 27 |
| 2 | 0.97 | 0.99 | 0.98 | 367 |
| accuracy | | | 0.96 | 424 |
| macro avg. | 0.94 | 0.84 | 0.89 | 424 |
| Weighted avg. | 0.96 | 0.96 | 0.96 | 424 |

TABLE 17

RF performance after SMOTE

| Class | Precision | Recall | f1 score | Support |
|---|---|---|---|---|
| 0 | 0.99 | 0.99 | 0.99 | 330 |
| 1 | 0.97 | 0.99 | 0.98 | 351 |
| 2 | 0.99 | 0.97 | 0.98 | 384 |
| accuracy | | | 0.98 | 1065 |
| macro avg. | 0.98 | 0.98 | 0.98 | 1065 |
| Weighted avg. | 0.98 | 0.98 | 0.98 | 1065 |

### 3.2. KNN

TABLE 18

KNN performance before SMOTE

| Class | Precision | Recall | f1 score | Support |
|---|---|---|---|---|
| 0 | 0.88 | 0.77 | 0.82 | 30 |
| 1 | 0.67 | 0.15 | 0.24 | 27 |
| 2 | 0.93 | 0.99 | 0.96 | 367 |
| accuracy | | | 0.92 | 424 |
| macro avg. | 0.83 | 0.64 | 0.67 | 424 |
| Weighted avg. | 0.91 | 0.92 | 0.90 | 424 |

TABLE 19

KNN performance after SMOTE

| Class | Precision | Recall | f1 score | Support |
|---|---|---|---|---|
| 0 | 0.95 | 1.00 | 0.97 | 330 |
| 1 | 0.84 | 0.98 | 0.91 | 351 |
| 2 | 0.99 | 0.80 | 0.88 | 384 |
| accuracy | | | 0.92 | 1065 |
| macro avg. | 0.93 | 0.93 | 0.92 | 1065 |
| Weighted avg. | 0.93 | 0.92 | 0.92 | 1065 |

### 3.3. SVM

TABLE 20

SVM performance before SMOTE

| Class | Precision | Recall | f1 score | Support |
|---|---|---|---|---|
| 0 | 0.96 | 0.90 | 0.93 | 30 |
| 1 | 0.82 | 0.67 | 0.73 | 27 |
| 2 | 0.97 | 0.99 | 0.98 | 367 |
| accuracy | | | 0.96 | 424 |
| macro avg. | 0.92 | 0.85 | 0.88 | 424 |
| Weighted avg. | 0.96 | 0.96 | 0.96 | 424 |

TABLE 21

SVM performance after SMOTE

| Class | Precision | Recall | f1 score | Support |
|---|---|---|---|---|
| 0 | 0.98 | 1.00 | 0.99 | 330 |
| 1 | 0.95 | 1.00 | 0.97 | 351 |
| 2 | 1.00 | 0.94 | 0.97 | 384 |
| accuracy | | | 0.98 | 1065 |
| macro avg. | 0.98 | 0.98 | 0.98 | 1065 |
| Weighted avg. | 0.98 | 0.98 | 0.98 | 1065 |

### 3.4. LR

TABLE 22

LR performance before SMOTE

| Class | Precision | Recall | f1 score | Support |
|---|---|---|---|---|
| 0 | 0.55 | 0.37 | 0.44 | 30 |
| 1 | 0.83 | 0.19 | 0.30 | 27 |
| 2 | 0.90 | 0.98 | 0.94 | 367 |
| accuracy | | | 0.88 | 424 |
| macro avg. | 0.76 | 0.51 | 0.56 | 424 |
| Weighted avg. | 0.87 | 0.88 | 0.86 | 424 |

TABLE 23

LR performance after SMOTE

| Class | Precision | Recall | f1 score | Support |
|---|---|---|---|---|
| 0 | 0.73 | 0.77 | 0.75 | 330 |
| 1 | 0.62 | 0.66 | 0.64 | 351 |
| 2 | 0.72 | 0.64 | 0.68 | 384 |
| accuracy | | | 0.69 | 1065 |
| macro avg. | 0.69 | 0.69 | 0.69 | 1065 |
| Weighted avg. | 0.69 | 0.69 | 0.69 | 1065 |

## 3.5. DT

TABLE 24

DT performance before SMOTE

| Class | Precision | Recall | f1 score | Support |
|---|---|---|---|---|
| 0 | 0.96 | 0.87 | 0.91 | 30 |
| 1 | 0.74 | 0.85 | 0.79 | 27 |
| 2 | 0.98 | 0.98 | 0.98 | 367 |
| accuracy | | | 0.96 | 424 |
| macro avg. | 0.89 | 0.90 | 0.89 | 424 |
| Weighted avg. | 0.96 | 0.96 | 0.96 | 424 |

TABLE 25

DT performance after SMOTE

| Class | Precision | Recall | f1 score | Support |
|---|---|---|---|---|
| 0 | 0.98 | 0.98 | 0.98 | 330 |
| 1 | 0.97 | 0.97 | 0.97 | 351 |
| 2 | 0.96 | 0.97 | 0.96 | 384 |
| accuracy | | | 0.97 | 1065 |
| macro avg. | 0.97 | 0.97 | 0.97 | 1065 |
| Weighted avg. | 0.97 | 0.97 | 0.97 | 1065 |

## 3.6. GNB

TABLE 26

GNB performance before SMOTE

| Class | Precision | Recall | f1 score | Support |
|---|---|---|---|---|
| 0 | 0.50 | 0.33 | 0.40 | 30 |
| 1 | 0.16 | 0.56 | 0.25 | 27 |
| 2 | 0.93 | 0.79 | 0.85 | 367 |
| accuracy | | | 0.74 | 424 |
| macro avg. | 0.53 | 0.56 | 0.50 | 424 |
| Weighted avg. | 0.85 | 0.74 | 0.78 | 424 |

TABLE 27

GNB performance after SMOTE

| Class | Precision | Recall | f1 score | Support |
|---|---|---|---|---|
| 0 | 0.87 | 0.36 | 0.51 | 330 |
| 1 | 0.47 | 0.95 | 0.63 | 351 |
| 2 | 0.89 | 0.50 | 0.64 | 384 |
| accuracy | | | 0.61 | 1065 |
| macro avg. | 0.74 | 0.60 | 0.59 | 1065 |
| Weighted avg. | 0.74 | 0.61 | 0.60 | 1065 |

Now, after model evaluation is done, we need to find out the importance of each feature and how significant it is in developing a model. So, as we saw above that Random Forest is the best performing models among others therefore feature importance has been derived on the basis of Random Forest model and the same has been presented in Fig. 12. Slope angle seems to be most influential among all followed by height and unit weight. The feature importance obtained

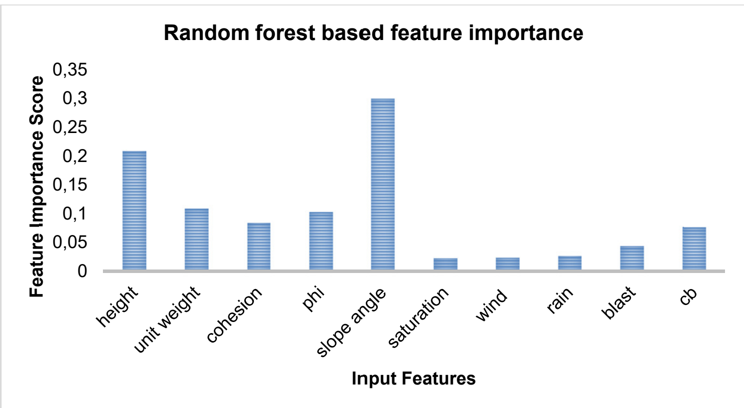


Fig. 12. Feature importance using RF model

from Random Forest just gives the importance score it does not tell us about the significance of the parameter whether the parameter is really important from model point of view or the model performs equally as well by eliminating that feature or group of features. So, as discussed in the previous section the Random Forest model has been run by eliminating each feature at a time and significance testing in the form of p-value has been obtained for each parameter. And it has been found that the p-value for each parameter is less than 0.05 threshold thus, proving the significance of each parameter. And also, a plot has been presented in Fig. 13 showing the value of coefficients for each parameter after showing the real importance of each feature in contributing to the accuracy of the model.

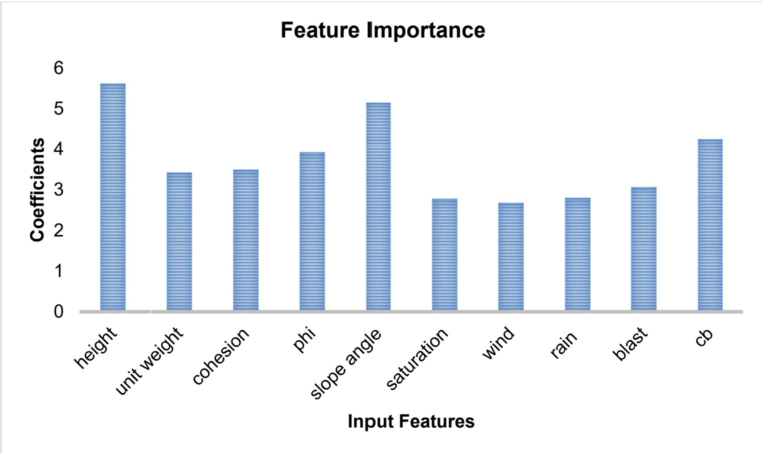


Fig. 13. Feature importance using new technique

# 4. Validation

For the purpose of validation two actual existing mines in Jharkhand, India has been considered. Due to data confidentiality policy the exact location and name of mines has not been disclosed but the plans and sections for different dump profiles has been presented in the Fig. 14 and Fig. 18. For the purpose of validation, the values of geomechanical properties and external factors have been taken as mean value of the respective parameters provided in table.

## 4.1. Mine 1

For Mine 1, Dump section 100, section 300, section 600 has been considered for validation in this study. Fig. presents the model geometry for different dump slopes which has been used as input in GeoStudio for predicting the stability of slopes. TABLE 28 presents the comparison of stability status of the section of slopes under different conditions mentioned in the table between Morgenstern-price method predicted stability and random forest based predicted Stability.


Fig. 14. Section of overburden dumps for Mine 1

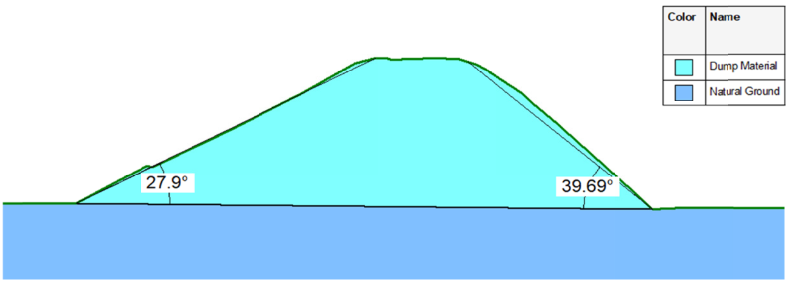


Fig. 15. Model geometry of section-100

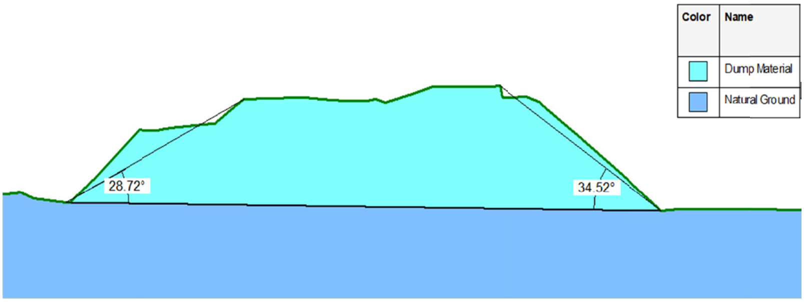


Fig. 16. Model geometry of section-300

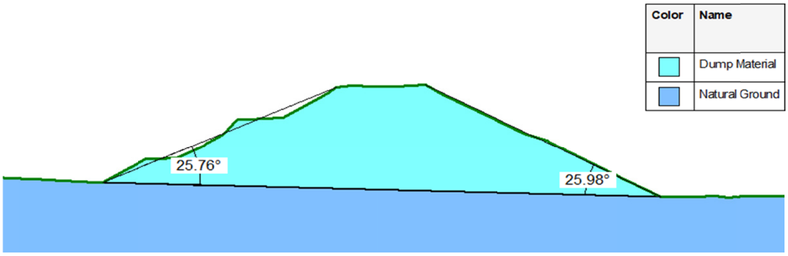


Fig. 17. Model geometry of section-600

TABLE 28

Comparison of stability as predicted by Morgenstern price method and RF model for Mine 1

| Cross-section analysed for stability analysis | Sections subjected to different external factors | Stability by Morgenstern Price method | Stability prediction by Random Forest based classification model |
|---|---|---|---|
| Section 100 | Dry | Long-term stable | Long-term stable |
| Section 100 | Saturated | Long-term stable | Long-term stable |
| Section 100 | Wind & Rain | Long-term stable | Long-term stable |
| Section 100 | Blast | Long-term stable | Long-term stable |
| Section 100 | Cloud Burst | Short-term stable | Long-term stable |
| Section 300 | Dry | Long-term stable | Long-term stable |
| Section 300 | Saturated | Long-term stable | Long-term stable |
| Section 300 | Wind & Rain | Long-term stable | Long-term stable |
| Section 300 | Blast | Long-term stable | Long-term stable |
| Section 300 | Cloud Burst | Long-term stable | Long-term stable |
| Section 600 | Dry | Long-term stable | Long-term stable |
| Section 600 | Saturated | Long-term stable | Long-term stable |
| Section 600 | Wind & Rain | Long-term stable | Long-term stable |
| Section 600 | Blast | Long-term stable | Long-term stable |
| Section 600 | Cloud Burst | Long-term stable | Long-term stable |

## 4.2. Mine 2

For Mine 2, Dump section aa1, section xx1 has been considered for validation in this study. Figs. 19 and 20 presents the model geometry for different dump slopes which has been used as input in GeoStudio for predicting the stability of slopes. TABLE 29 presents the comparison of stability status of the section of slopes under different conditions mentioned in the table between Morgenstern-price method predicted stability and random forest based predicted Stability.

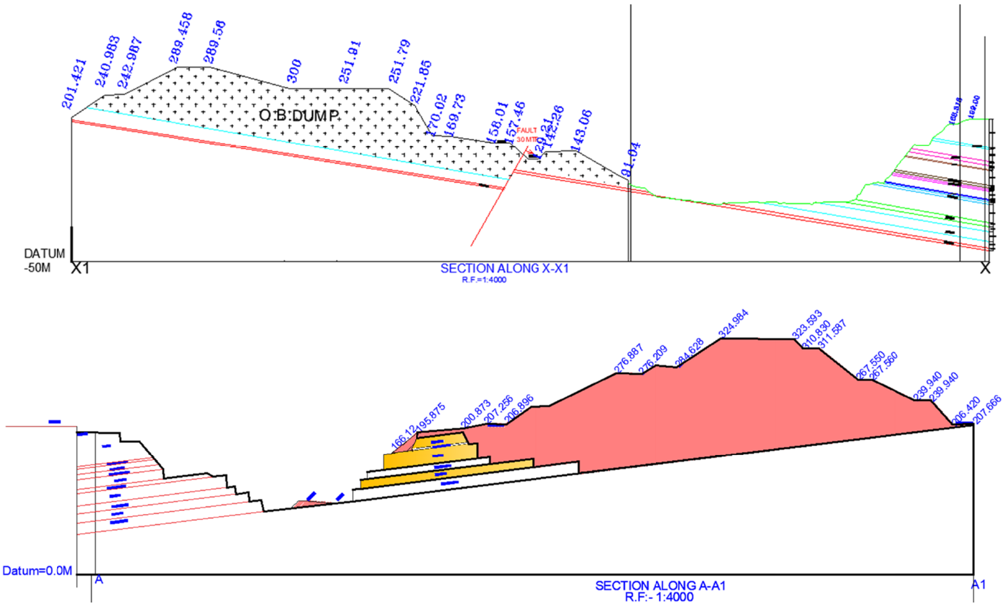


Fig. 18. Section of overburden dumps for Mine 2

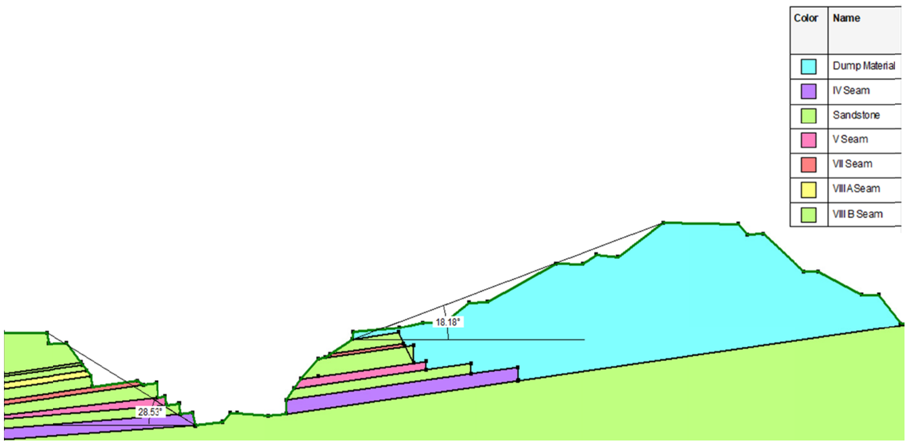


Fig. 19. Model geometry of section-aa1

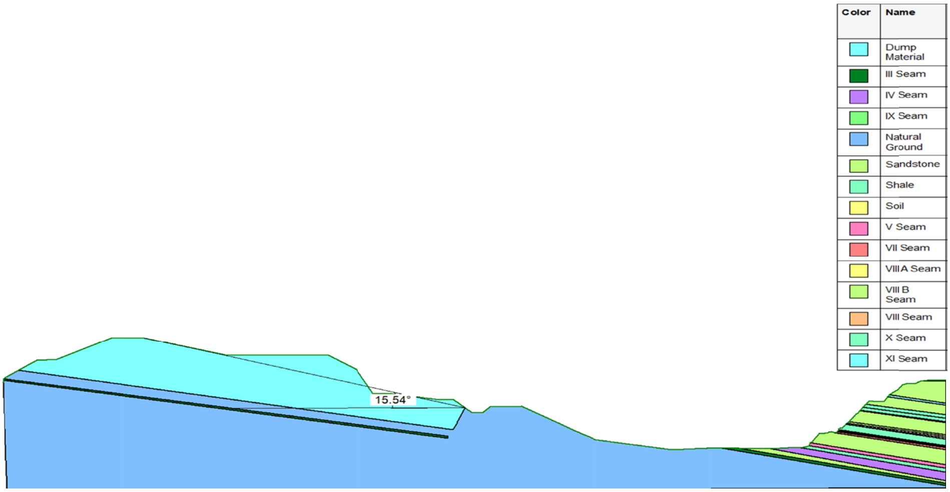


Fig. 20. Model geometry of section-xx1

TABLE 29

Comparison of stability as predicted by Morgenstern price method and RF model for Mine 2

| **Cross-section analysed for stability analysis** | **Sections subjected to different external factors** | **Stability by Morgenstern Price method** | **Stability prediction by Random Forest based classification model** |
|---|---|---|---|
| Section xx1 | Dry | Long-term stable | Long-term stable |
| Section xx1 | Saturated | Long-term stable | Long-term stable |
| Section xx1 | Wind & Rain | Long-term stable | Long-term stable |
| Section xx1 | Blast | Long-term stable | Long-term stable |
| Section xx1 | Cloud Burst | Short-term stable | Short-term stable |
| Section aa1 | Dry | Long-term stable | Long-term stable |
| Section aa1 | Saturated | Long-term stable | Long-term stable |
| Section aa1 | Wind & Rain | Long-term stable | Long-term stable |
| Section aa1 | Blast | Long-term stable | Long-term stable |
| Section aa1 | Cloud Burst | Long-term stable | Long-term stable |

From the TABLE 28 and TABLE 29 it can be observed that out of 25 cases analysed for the purpose of validation the model predicted 24 of them accurately and misclassified in one of the instances.

# 5. Conclusion

In this comprehensive study, we've employed machine learning algorithms to address a critical issue in the mining industry – specifically, the stability of dump slopes in Indian opencast mines. Through meticulous hyperparameter tuning and rigorous testing with both training and validation datasets, we've demonstrated the exceptional performance of Random Forest, Support

Vector Machine (SVM), and Decision Tree algorithms. Our Random Forest model exhibited the highest accuracy, reaching a remarkable 98% on the test data and 96% when validated using real-world dump slope sections from two different opencast mines in India. One of the significant contributions of this research is the solution it offers for previous challenges in the field of geotechnical engineering. These include dealing with class imbalances in the dataset and accounting for a variety of external factors such as weather conditions, blast vibrations, and cloudbursts. These have often been overlooked or inadequately addressed in prior studies. Furthermore, we introduced a novel technique for determining feature importance, which establishes the significance of each input parameter in model development. This analysis revealed that while all the input factors considered are significant, the overall slope angle and height emerged as the most crucial variables. Conversely, wind conditions were found to have the least impact on dump slope stability. The advantages of our approach are manifold. Not only is it more economical, but it also requires less computational power compared to traditional methods like limit equilibrium and numerical modelling. This makes our model both efficient and reliable, opening new avenues for future research and potential real-world applications in maintaining the safety and operational efficacy of opencast mines.

In summary, this study represents a landmark contribution to both the field of machine learning and geotechnical engineering. It offers a robust, efficient, and economical solution to a long-standing and complex problem, thereby laying a solid foundation for future research endeavours.

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