

SUDHIR KUMAR SINGH ^{*}, DEBASHISH CHAKRAVARTY¹**ASSESSMENT OF SLOPE STABILITY USING CLASSIFICATION AND REGRESSION ALGORITHMS SUBJECTED TO INTERNAL AND EXTERNAL FACTORS**

This study aims at developing a machine learning based classification and regression-based models for slope stability analysis. 1140 different cases have been analysed using the Morgenstern price method in GeoSlope for non-homogeneous cohesive slopes as input for classification and regression-based models. Slope failures presents a serious challenge across many countries of the world. Understanding the various factors responsible for slope failure is very crucial in mitigating this problem. Therefore, different parameters which may be responsible for failure of slope are considered in this study. 9 different parameters (cohesion, specific gravity, slope angle, thickness of layers, internal angle of friction, saturation condition, wind and rain, blasting conditions and cloud burst conditions) have been identified for the purpose of this study including internal, external and factors representing the geometry of the slope has been included. Four different classification algorithms namely Random Forest, logistic regression, Support Vector Machine (SVM), and K Nearest Neighbor (KNN) has been modelled and their performances have been evaluated on several performance metrics. A similar comparison based on performance indices has been made among three different regression models Decision tree, random forest, and XGBoost regression.

Keywords: slope stability; non-homogeneous; classification; regression

1. Introduction

The stability of slope tends to have a significant impact on mining and other engineering infrastructures (e.g., opencast pits, earth dams, embankments and transmission roads) as well as on the areas which are prone to landslides. Accurate and good analysis for slope stability can help us to avoid many unforeseen accidents which eventually lead to loss of property and tragic loss of lives. So, keeping in mind the dangers and loss this accident possesses, analysis of slope

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stability is being given due importance in order to minimize the risk. The application of slope stability analysis is numerous, and it directly or indirectly plays a major role in many mining or other engineering projects. Therefore, the scientific study for slope stability analysis should be given as much importance as any other aspects of the project and the study should not be limited to papers but proper implementation should also be given due care. Slope stability analysis is important from a safety and economic point of view. Static and dynamic analysis needs to be carried out from an overall safety point of view as there are regions in seismically active zones and its effect needs to be considered thoroughly.

As we are progressing forward the need of the hour is to make use of recent technological developments such as artificial intelligence techniques and various machine learning algorithms. Their ability to predict accurate and reliable results without being time-consuming and being computationally less extensive is the key highlight of these methods. These techniques make use of already existing databases of scientific studies related to slope failure and predict new results. They take the factors affecting slope stability of slope as input parameters and provide us with a critical Factor of Safety (FOS) and probability of failure along with predicting stability in real-time. The analytical methods such as Limit Equilibrium Method (LEM), Finite Element Method (FEM), Random Finite Element Method (RFEM), etc. have served us in the past but as the complexities and uncertainties in soil and rock mass properties are increasing, we have to turn our attention toward new possibilities which are neither time-consuming nor computationally intensive. Probabilistic slope stability analysis is performed to consider various uncertainties present in the soil and rock mass properties.

The way to predict the stability of slope is by looking at the value of Critical Factor of Safety which gives us an indication of failure if its value is less than 1 and considered stable if it has a value of more than 1. There are numerous factors that can play a role in the instability of slopes and in the determination of FOS but the combination of certain factors needs to be carefully considered to prevent any mishap as compared to other factors which may seem to have little effect when considered individually. But a sense of safety or failure in terms of probability is considered more useful by many and hence probability of failure is also a good indicator from the stability point of view. Various machine learning and artificial techniques have been developed over the years taking into account different factors which can affect the stability of slope to gain some perspective in advance about any failure which might take place to avoid any fatalities. These algorithms help in predicting the value of critical FOS and probability of failure without needing to go in complex slope design and computationally expensive calculations manually. In places where artificial or natural slopes are experiencing seismic vibrations, the critical factor of safety mainly depends on unit weight, internal angle of friction, cohesion and seismic coefficient to take into account horizontal forces due to earthquakes.

Five parameters namely slope angle (β), depth factor (D), stability number (N_s), Coefficient of Variation (COV) of undrained shear strength, and normalized scale of fluctuation (θ/H) for heterogeneous cohesive slope tend to have a greater impact on probability of failure. The normalized scale of fluctuation (θ/H) is taken into account to model spatial variability of soil properties [1].

The stability number is calculated based on the mean value of cohesion (C_u), unit weight (γ) and height off slope (H). The most influential factors having a significant effect on FOS are slope height, gradient, cohesion, internal angle of friction and seismic coefficient were considered as input parameters for the scientific study [2-3]. Two different Artificial Neural Network (ANN) models were developed to predict FOS using data based on a previous study [4] by considering slope height, unit weight, cohesion, internal angle of friction, gradient and pore pressure as input

parameter [5]. In a different ANN model Total and effective stresses, gradient, cohesion, internal angle of friction, and seismic coefficient were used as input parameters to predict FOS [6]. The least-square support vector machine (LSSVM) model was implemented to conduct the scientific study for slope stability using unit weight (γ), cohesion (c), internal angle of friction (φ), slope angle (β), height (H) and pore water pressure coefficient (r_u) as the main input parameters. Moreover, [7] two different models using ANN and multiple regression were compared for their prediction for critical FOS using set of five (unit weight, cohesion, internal friction angle, slope angle, and height) and four (cohesion, internal friction angle, slope angle, and height) input parameters respectively [8-10]. Different parameters such as the shear strength of the material, the geometry of the slope, the level of underground water, and seismic coefficient influence slope stability [11]. Material properties, cohesion and friction angle, height and angle of slopes and pore pressure were identified as decisive parameters [12]. Other similar factors affecting the risk of slope failure includes undrained shear strength (C_u), slope angle (β), setback distance ratio (b/B), and applied surcharge on the shallow foundation installed over the slope (w). The stability of an earth's structure depends on external factors such as rainfall and seismic loading to a great extent and certain equations have been developed for saturated and unsaturated soil under rainfall and seismic loading. These equations can represent two types of failure translational as well as rotational [13].

A risk-based slope stability assessment using logistic and linear regression has been carried out to determine which slope conditions have the highest impact on slope failure, classify them as intact or failed, and calculate the likelihood of failure as a percentage for an excavated slope structure [14].

An ANN model for studying the shallow foundation was conducted to see the impact of proportion of data on the result obtained. It was found that there is no significant relation between the no. of data that is divided between training, testing & validation of data and the model accuracy [15].

An artificial slope was subjected to seismic coefficient along with other influential parameters such as cohesion, internal angle of friction, and bulk unit weight to develop an ANN model which was later compared with the Multiple Regression (MR) model. The result shows that ANN performed better on several indices such as R^2 , Variance Accounted for (VAF), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) [16]. Two ANN models were developed to predict the critical FOS based on the study conducted earlier and using cohesion, internal angle of friction, unit weight, slope height and pore water pressure coefficient [3-4]. The results obtained were close to the real results. In a different study ANN model was compared with Bishop's LEM to calculate the value of critical FOS by considering cohesion, internal angle of friction, seismic coefficient, total & effective stress and slope angle as influential parameters. The ANN result obtained was in good agreement with LEM result [5].

Two different sets of models were developed for homogeneous finite slope each containing ANN & MR model but with different sets of input parameters. The first set contained cohesion, internal angle of friction, unit weight, slope angle and slope height as input parameters whereas the second set contained cohesion, slope angle, internal angle of friction and slope height as input parameters. The first set performed better which shows the importance of the factors involved in the computation of critical FOS [7].

A probabilistic study was conducted using ANN to predict the probability of failure of slope using Monte Carlo simulation and first and second order reliability methods. The study was applied on a two-layer artificial slope as well as Cannon Dam in Missouri to verify the accuracy and potential of the ANN to be applied in future and many more real-life problems [17]. Various

machine learning algorithms which included Gaussian Process Regression (GPR), Multiple Linear Regression (MLR), Simple Linear Regression (SLR), Multi-Layer Perceptron (MLP), and Support Vector Regression (SVR) were tested against each other to see which performed better as compared to other for predicting the critical FOS by considering the same set of input parameters namely C_u , β , b/B , and w [18]. MLP clearly shows the edge over the other. ANN and MLR models developed for investigating the stability of slope were compared with FEM and the results were promising enough to be used in real life cases. And in the same study it was found that ANN has an edge over MLR due to high accuracy.

This paper investigates the feasibility of developing a machine learning model using classification and regression approaches to predict the critical FOS for non-homogeneous slopes. Previous studies have considered stability analysis for homogeneous materials while considering the limited effect of external factors. In this study a holistic approach has been considered by taking into account 9 different parameters (cohesion, specific gravity, slope angle, thickness of layers, internal angle of friction, saturation condition, wind and rain, blasting conditions, and cloud burst conditions) have been identified for the purpose of this study including internal, external and factors representing the geometry of the slope has been included. Ideally, the developed Random Forest, logistic regression, Support Vector Machine (SVM), and K Nearest Neighbor (KNN) classification model is capable of classifying the slope into three classes namely fail, short-term stable, and long-term stable as well as Morgenstern price LEM method. Decision tree, random forest, and XGBoost regression models perform really well in predicting critical FOS close to the calculated value. The advantage of the developed model is that it takes into account the material inhomogeneity and has significantly less computational time than the LEM approach, although a large number of LEM analyses are initially performed to compile a database that is used to develop and validate the machine learning models.

2. Methodology

2.1. Slope Stability Analysis

Slope stability analysis has been carried out with the help of Limit Equilibrium Analysis for the purpose of this study. Limit Equilibrium Analysis is the most popularly used method in the field of geotechnical engineering and the freely available student licensed (serial number – 6801-190910-194630) 2018 version of GeoSlope where SLOPE/W, SEEP/W, and QUAKE/W applications are used to carry out the task of stability analysis. Among the different LEM methods available Morgenstern Price Method has been chosen due to the following reasons [19]:

- It considers both inter slice forces,
- Assumes interslice force function,
- Allows selection for interslice force functions,
- Computes FOS for both force and moment equilibrium,
- It can work for non-circular critical slip surface.

A total of 1140 different cases have been studied in GeoSlope to create an extensive database for classification and regression-based models.

- Different factors taken into consideration for the purpose of this scientific study are as follows:

- Thickness of different layers/materials which takes into account material inhomogeneity. Four different types of material have been used in this study namely soil, sandstone, shale and coal.
- Corresponding to each material different geo mechanical properties used are: cohesion, specific gravity and internal angle of friction.
- Overall slope angle to take into consideration geometry of the slope.
- Different external factors used for analysis are: Saturation condition (Dry/Fully Saturated), Wind & Rainfall, Blasting (in the form of Peak Particle Velocity), Cloudburst.

The sections of actual pit slopes existing in the field has been studied and the corresponding FOS has been recoded. Generally, a critical FOS value greater than 1 is considered stable but in practice the level of safety must be adapted to the accuracy of input data [20]. The FOS for slopes shall be selected based on slope size, consequence of failure, uncertainty in input parameters, life of structure, expected change in design conditions, prepared in monitoring, etc. [21].

Therefore, a critical FOS value considered for this study is summarized as below:

- $FOS < 1.2$, Slope Failure,
- $1.2 \leq FOS < 1.5$, Short-term stable (for period up to 6 months),
- $FOS \geq 1.5$, Long-term stable (for period of more than 6 months).

Time plays a significant role in long-term stability. In long term, both macroscopically and microscopically strength reduction of rocks takes place. Due to continuous deformation over a certain period of time, the factor of safety of slope continuously goes on decreasing [22].

2.2. Classification Models

Classification will be carried out with the help of following algorithms: Random Forest, (KNN), SVM, and Logistic Regression. The output of the classification algorithms will be segregated into three different classes used for the purpose of this study namely Fail, Short-term stable, Long-term stable.

Hyper tuning of the parameters available for different algorithms will be carried out to select the best set of parameters in order to derive the best performance out of these algorithms. The result of the different algorithms will be compared based on accuracy (f1 score) of their performances on test set data. A confusion matrix will also be presented for better understanding of the result.

2.3. Regression models

Regression based analysis will also be carried out to determine the critical value of FOS using three different algorithms Decision Tree, Random Forest & XGBoost and the results will be compared based on performance indices like MAE, Mean Squared Error (MSE), and RMSE on test set data.

2.4. Data Preparation

This section describes different input parameters for the classification and regression-based models. The frequency distribution for each input variable is presented below. The data in Table 1 presents the geotechnical properties of soil, sandstone, shale, and coal as collected from different

mines in the Dhanbad region of Jharkhand. Due to the local geological distributions of different opencast mines considered for the purpose of this study across different parts of Jharkhand namely, Jharia, Katras, Nirsa, and Chapapur only soil, sandstone, shale, and coal are considered as geotechnical materials for LEM analysis and for machine learning models.

TABLE 1

Different input features and their range of values

Material	Feature	Range of Values	Remarks
Soil	height_1	2-16 m	The cases where the frequency distribution is showing some frequency for the value '0' for different input parameters shows the absence of that material for that section of pit slope.
	sp. gravity_1	16-20 kN	
	cohesion_1	38-46 kPa	
	phi_1	9-11 degree	
Sandstone	height_2	16-160 m	
	sp. gravity_2	24-26 kN	
	cohesion_2	160-200 kPa	
	phi_2	25-27 degree	
Shale	height_3	2-25 m	
	sp. gravity_3	26-28 kN	
	cohesion_3	260-300 kPa	
	phi_3	29-31 degree	
Coal	height_4	6-26 m	
	sp. gravity_4	12-16 kN	
	cohesion_4	16-20 kPa	
	phi_4	22-24 degree	

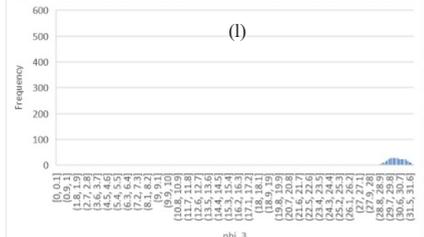
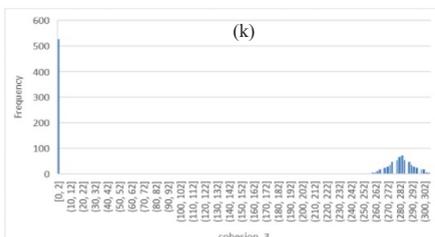
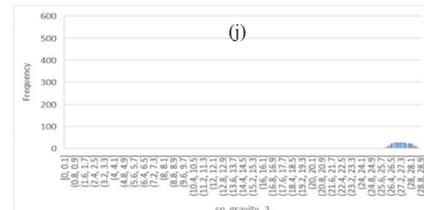
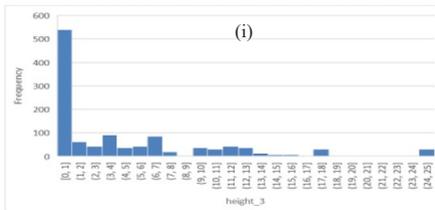
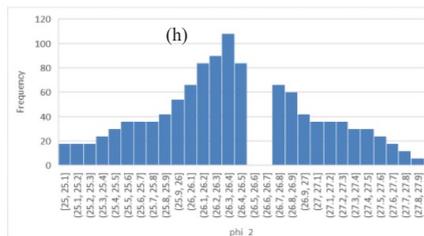
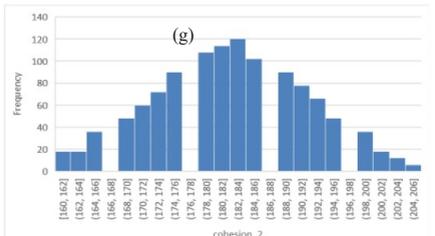
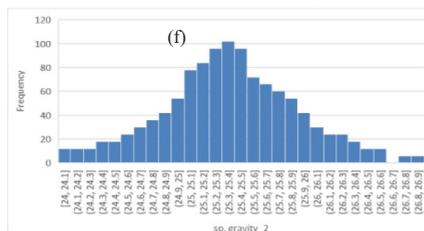
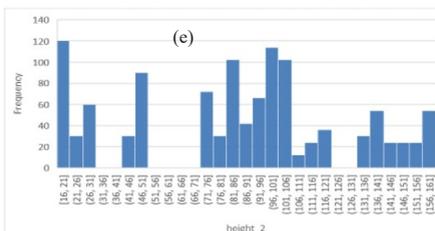
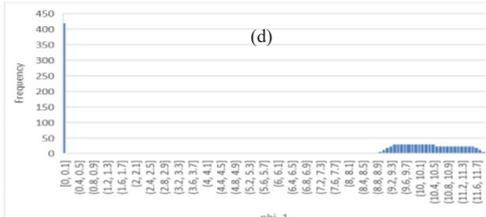
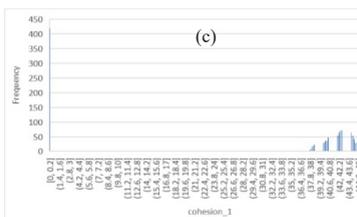
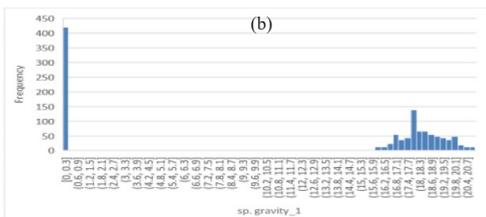
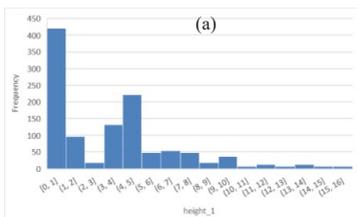
The data in Table 2 presents the range of values for the external factors used in the study for slope stability analysis collected in accordance with the weather and climate pattern existing in different regions of Dhanbad where the study has been conducted.

TABLE 2

Factors applicable to all materials

Material	Feature	Range of Values
Soil/Sandstone/Shale/Coal	Slope Angle	4.5-49.5 degree
	Saturation	0 – Dry Condition; 1 – Fully Saturated
	Wind	15-18 m/sec
	Rain	6-18 mm/hr
	Blast	80-100 mm/sec
	Cloudburst	80-120 mm/hr

Fig. 1(a-v) presented below describes the data distribution of various different input parameters for different material types such as soil, sandstone, shale and coal and for different external factors as mentioned in Table 1 & Table 2 above. we can see in the figures below that the value of zero has significant distribution for soil Fig. 1(a-d), shale Fig. 1(i-l), and coal Fig. 1(m-p) due to the absence of these materials at certain locations due to different geological distributions.



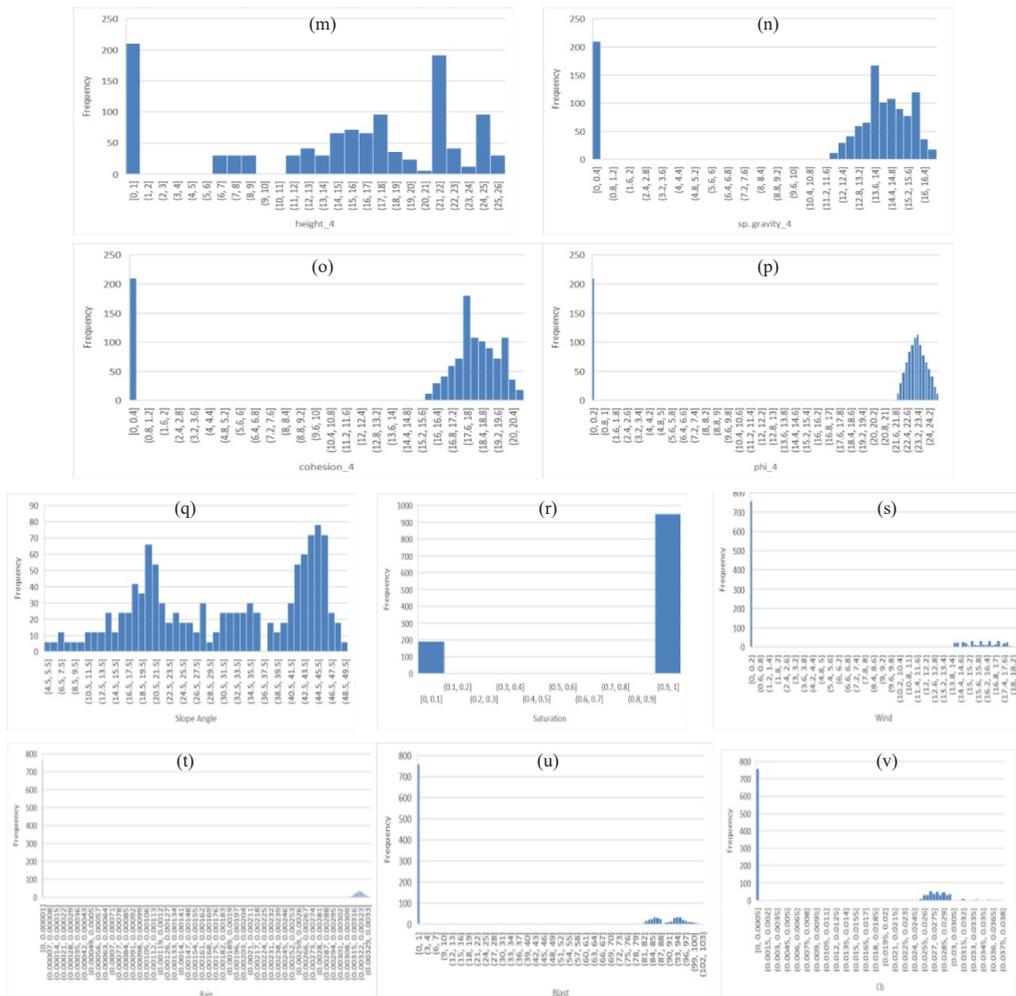


Fig. 1. Frequency Distribution of (a) height_1 (b) sp. gravity_1 (c) cohesion_1 (d) phi_1 (e) height_2 (f) sp. gravity_2 (g) cohesion_2 (h) phi_2 (i) height_3 (j) sp. gravity_3 (k) cohesion_3 (l) phi_3 (m) height_4 (n) sp. gravity_4 (o) cohesion_4 (p) phi_4 (q) Slope Angle (r) Saturation condition (s) Wind (t) Rain (u) Blast (v) Cloudburst

2.5. Feature Importance

We performed the analysis to determine the importance of different input parameters in the classification and regression algorithms which are presented in Fig. 2 below.

2.6. Correlation Matrix

Correlation matrix has been analysed to visualize the dependence of input parameters on each other in Fig. 3. The blue bar indicates a positive correlation and the red bar indicates a negative

correlation while the length of the bar defines the strength of correlation. We can see from the matrix below that the internal angle of friction for coal and specific gravity for coal has a high correlation value, and the height of the coal seam and specific gravity & internal angle of friction for coal seam also shows a slightly high correlation value.

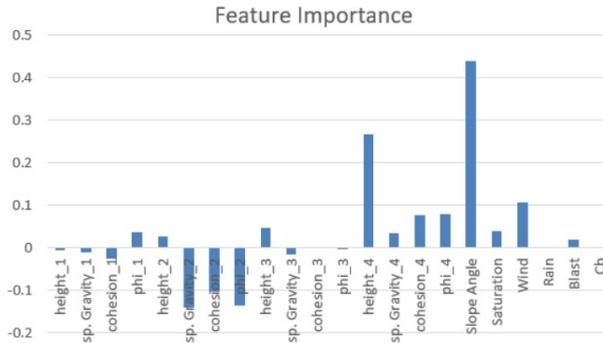


Fig. 2. Feature importance of different input parameters

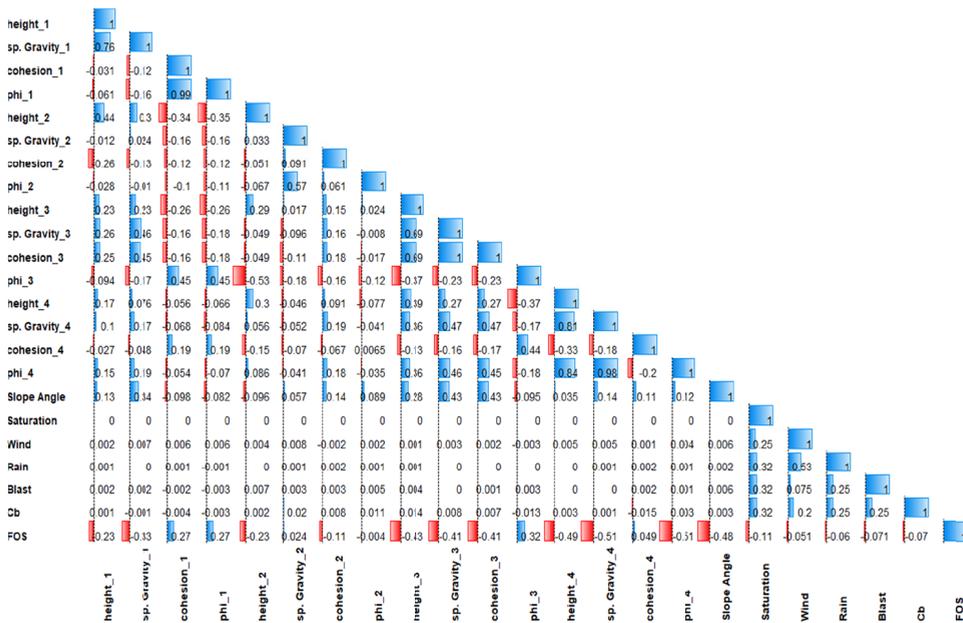


Fig. 3. Correlation Matrix for different input parameters

2.7. Output Distribution

Distribution of output belonging to different classes has been represented pictorially below in Fig. 4.

Class '0' representing failed cases – 370 instances,
 Class '1' representing Short-term stable cases – 405 instances,
 Class '2' representing Long-term stable cases – 365 instances.

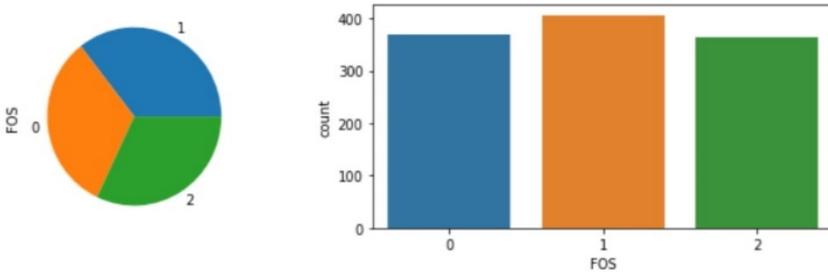


Fig. 4. Output Distribution for different classes

2.8. Hyperparameter Tuning for classification algorithms

Machine learning algorithms have several hyperparameters that allows us to tailor the behaviour of the algorithm to our specific dataset to get the best performing model.

Hyperparameters are different from parameters, which are weights or biases for a model found by the learning algorithm. Unlike parameters, hyperparameters are specified by the user while configuring the model.

Grid Search strategies have been used in this study for finding the best hyperparameters for each of the classification algorithms.

Different values of hyperparameters obtained after tuning has been presented below for each algorithm:

- Random Forest - {'max_features': 'sqrt', 'n_estimators': 1000}
- KNN - {'metric': 'manhattan', 'n_neighbors': 7, 'weights': 'uniform'}
- SVM - {'C': 50, 'gamma': 'scale', 'kernel': '(Radial basis function) rbf'}
- Logistic Regression - {'C': 100, 'penalty': 'l2', 'solver': 'newton-cg'}

A split of 70% and 30% is made for training and testing data respectively for classification and regression-based models.

3. Results and discussion

3.1. Classification Results

The results for different classification algorithms have been tabulated below in the form of confusion matrix and accuracy score table.

We can observe from Table 3 that the random forest model achieves an overall accuracy of 0.94. But we can also see from the confusion matrix represented by Fig. 5 that the accuracy with which the model predicts the class '0' is highest and that is what we want that the data falling in the 'failed' class to be classified as failed not as short term stable or long-term stable.

Confusion Matrix for Random Forest Model

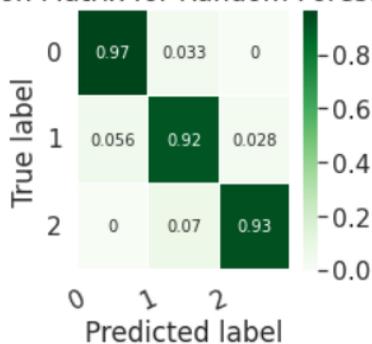


Fig. 5. Confusion Matrix for Random Forest classification

TABLE 3

Accuracy score for Random Forest classification

Class	Precision	Recall	f1-score	Support
0	0.94	0.97	0.95	120
1	0.92	0.92	0.92	143
2	0.96	0.93	0.95	114
accuracy	—	—	0.94	377
macro avg.	0.94	0.94	0.94	377
Weighted avg.	0.94	0.94	0.94	377

We can observe from Table 4 that the k Nearest Neighbor model achieves an overall accuracy of 0.93. But we can also see from the confusion matrix represented by Fig. 6 that the accuracy with which the model predicts the class ‘0’ is highest and that is what we want that the data falling in the ‘failed’ class to be classified as failed not as short term stable or long-term stable.

Confusion Matrix for kNearest Neighbor Model

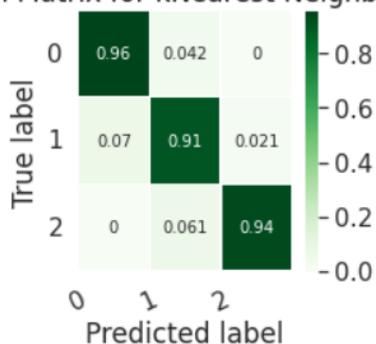


Fig. 6. Confusion Matrix for KNN classification

TABLE 4

Accuracy score for KNN classification

Class	Precision	Recall	f1-score	Support
0	0.95	0.96	0.94	120
1	0.89	0.91	0.89	143
2	0.96	0.94	0.95	114
accuracy	—	—	0.93	377
macro avg.	0.93	0.93	0.93	377
Weighted avg.	0.93	0.93	0.93	377

We can observe from Table 5 that the logistic regression model achieves an overall accuracy of 0.89. But we can also see from the confusion matrix represented by Fig. 7 that the accuracy with which the model predicts the class '0' is highest and that is what we want that the data falling in the 'failed' class to be classified as failed not as short term stable or long-term stable.

Confusion Matrix for Logistic Regression Model

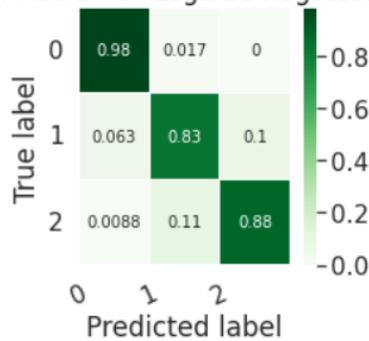


Fig. 7. Confusion Matrix for Logistic Regression classification

TABLE 5

Accuracy score for Logistic Regression classification

Class	Precision	Recall	f1-score	Support
0	0.92	0.98	0.95	120
1	0.89	0.83	0.86	143
2	0.87	0.88	0.87	114
accuracy	—	—	0.89	377
macro avg.	0.89	0.90	0.89	377
Weighted avg.	0.89	0.89	0.89	377

We can observe from Table 6 that the SVM model achieves an overall accuracy of 0.89. But we can also see from the confusion matrix represented by Fig. 8 that the accuracy with which the model predicts the class '0' is highest and that is what we want that the data falling in the 'failed' class to be classified as failed not as short term stable or long-term stable.

After analysing results of all the classification algorithms, it is safe to say that Random Forest outperforms other algorithms.

Confusion Matrix for Support Vector Classifier

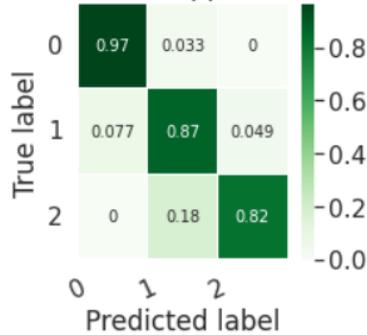


Fig. 8. Confusion Matrix for SVM classification

TABLE 6

Accuracy score for SVM classification

Class	Precision	Recall	f1-score	Support
0	0.91	0.97	0.94	120
1	0.84	0.87	0.86	143
2	0.93	0.82	0.87	114
accuracy	—	—	0.89	377
macro avg.	0.89	0.89	0.89	377
Weighted avg.	0.89	0.89	0.89	377

3.2. Regression Results

The results for different regression algorithms have been tabulated below in Table 7. We can see from the table 7 that Decision tree regression has the lowest value for MAE, MSE and RMSE as compared to other two algorithm. A decision tree has been represented pictorially by Fig. 9.

TABLE 7

Performance of different Regression Algorithms

Regression Algorithms	MAE	MSE	RMSE
Decision Tree Regression	0.0237	0.0015	0.0390
Random Forest Regression	0.0279	0.0018	0.0424
XGBoost Regression	-0.056	-0.010	-0.092

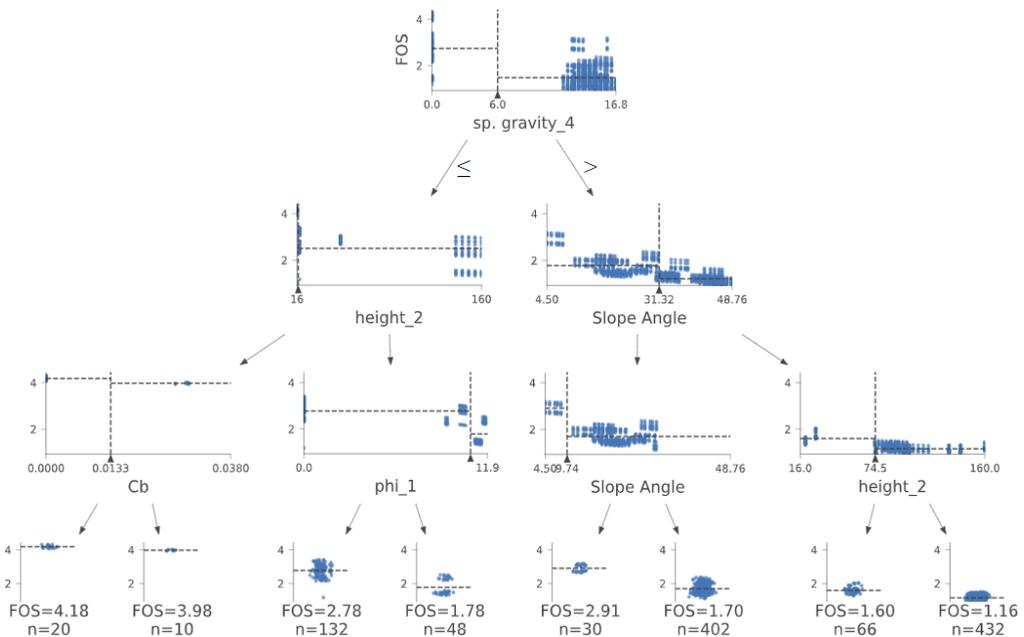


Fig. 9. Decision Tree representation for Decision Tree Regression

4. Conclusion

Considering the importance of scientific study for slope stability analysis in the field of geotechnical engineering and keeping in mind the dangers possessed in case of failure the main objective of this study was to evaluate the stability of open cast mine pit slopes using classification and regression-based models. A different section of slopes taking into consideration material inhomogeneity and the critical factors affecting the stability of slope are namely Height (thickness of different layers has been taken), slope angle, cohesion, specific gravity, internal angle of friction, Saturation condition, Wind & rainfall, Blast and cloudburst considered in this study. A total of 1140 cases has been analysed in GeoSlope utilizing Morgenstern Price method of LEM. The performance of different classification algorithms are as follows: Random Forest (0.94), KNN (0.93), SVM (0.89) and Logistic Regression (0.89). Random Forest performed better among the following and also the misclassification of the failed case was accurate in almost all the classification algorithms (i.e., the data belonging to failed class has been classified most accurately because we don't want failed data to be classified as stable). The performance of different Regression models is mentioned as follows: Decision Tree (MAE: 0.0237, MSE: 0.0015, RMSE: 0.0390), Random Forest (MAE: 0.0279, MSE: 0.0018, RMSE: 0.0424), and XGBoost (MAE: -0.056, MSE: -0.010, RMSE: -0.092). Decision Tree Regression outperformed others. Therefore, it can be seen that the machine learning models are giving good results and are in good agreement with the results produced by LEM methods for slope stability analysis.

Conflict of Interest

The authors declare no conflict of interest.

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