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Machine Learning Algorithms with WSN for Real-time Identification of Structural Deformities and Slope Instabilities in Opencast Mines

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Abstract

Machine learning-based image analysis combined with a Wireless Sensor Network (WSN) in an Internet of Things (IoT) framework can be a powerful approach for identifying structural deformities and slope instabilities in opencast mines. Slope failures cause massive casualties and devastating societal and economic implications, thereby jeopardizing access to sustainable development. Slope stability assessment, which has potential long-term benefits for sustainable development, remains a difficulty for practitioners and researchers. In this study, an automated machine learning approach was proposed for the first time for model generation and slope stability assessments of circular mode failure. Slope failures have disastrous implications in many nations, hence slope stability assessment is of great importance in geotechnical and geological engineering research. In this paper, ML approach is developed for improving slope stability prediction. The suggested technique has the potential for both short-term geo hazard severity mitigation and long-term sustainable development goals.

Keywords: Slope failure; Machine Learning; Geo hazard

1. Introduction

The geotechnical engineers are confronted with a significant challenge every day in the form of slope failure in open-pit mines. At the moment, the open cast mining accounts for the majority of the total production. Mining using open pits, also known as open cast mining, is the simplest and most cost-effective technique of mining. This method also allows for high levels of mechanization and higher productivity. The slope angle of the production benches that are not abandoned during the lifetime of the mine is directly proportional to the amount of profit that may be made from open-pit mining. The demand for a wide variety of minerals is steadily increasing, which has resulted in an increase in the level of mechanization and intensity of open-pit mining operations. As a direct consequence of this, the open-pit mining operations are getting deeper each day. As a result, a substantial quantity of overburden must be excavated and deposited in a space that is as small as possible in order to produce steep high wall slopes. These high wall slopes have failed horribly, which has a negative impact on the working personnel and machinery that have been placed there. There are a lot of different factors that can influence the slope's level of stability[1,2,3]. Geology, groundwater, and geometry are the three components that make up these factors. The geometry depicts the pit slope angle and depth, but the geology indicates the cohesiveness, internal angle of friction, and structural discontinuities among the various strata. Groundwater factors on the slope of the pit, including rainfall and the water table, are thought to have caused the disaster. The Indian mining industry is plagued by a high rate of slope failures, which can be attributed to the industry's lackluster approach to slope design[4,5]. It is possible to avoid this scenario by having competent individuals do routine monitoring and by employing computational heuristics and numerical modelling in order to make a prediction of the state of the slope just before it fails. When designing the slopes of the pit, keep in mind that stability and steepness of slopes are like two sides of the same coin.

The collapse of the slope was brought on by an increase in the shear force that was present in the plane where the failure occurred. The failure of a slope is the result of the interaction of two forces: the driving force, which contributes to the collapse of the slope, and the resisting force, which offers resistance to the failure. The stability of the slope can be stated in the form of a factor of safety. It is certain that a failure will take place if the driving force of the slope plain is larger than the resisting force of that plain. This will result in the plain being unsuccessful. In order to satisfy the growing demand for minerals, the excavation process in open pit mines is being stepped up to match the demand. As a direct consequence of this, open pit mines are getting deeper on a daily basis. This type of operation generates a substantial quantity of garbage that needs to be disposed of in a relatively small space. As the mining activity progresses, the production of waste material and dumping will begin, which will cause the high wall slopes and failure of the dump.

2. Overview of an ML approach in slope stability prediction

To improve slope stability prediction in the presence of structural deformity, machine learning (ML) techniques can be employed [6, 7, 8, 9, 10]. Here is an overview of an ML approach that can be developed for this purpose:

- Data Collection: Gather a dataset that includes information on slope characteristics (e.g., slope angle, geological properties, soil parameters), structural deformity features (e.g., crack patterns, bulges), and stability indicators (e.g., slope failures, displacement measurements). Ensure that the dataset contains examples of slopes with varying degrees of deformity and stability outcomes.
- Feature Engineering: Preprocess and engineer relevant features from the collected data. This may involve transforming or normalizing numerical data, encoding categorical variables, and creating new features based on domain knowledge. For example, you could derive features related to the size, orientation, or density of structural deformities.
- Labeling and Training Data Preparation: Define the stability condition labels for the dataset, such as stable or unstable, based on observed slope failures or displacement thresholds. Split the dataset into training and testing sets to evaluate the performance of the developed model.
- ML Model Selection: Choose an appropriate ML model for slope stability prediction. Some suitable models for this task may include decision trees, random forests, support vector machines (SVM), or neural networks. Consider the characteristics of the dataset,

such as the number of features, sample size, and desired interpretability of the model, when selecting the algorithm.

- Model Training and Validation: Train the selected ML model using the labeled training dataset. Apply appropriate model validation techniques, such as k-fold cross-validation or hold-out validation, to assess the model's performance. Optimize hyperparameters of the model to enhance its predictive capability.
- Model Evaluation: Evaluate the trained ML model using the testing dataset to measure its predictive accuracy, precision, recall, or other suitable metrics. Assess the model's ability to correctly predict slope stability in the presence of structural deformity.
- Interpretability and Insights: Analyze the ML model's feature importance or coefficients to gain insights into the influence of different features on slope stability. This can provide valuable information about the significance of structural deformity characteristics in predicting stability.
- Model Deployment and Integration: Once satisfied with the model's performance, deploy it for practical use. This could involve integrating it into an existing monitoring system or decision-making framework for early warning or risk assessment of slope stability in the presence of structural deformity.

It is important to note that the success of the ML approach depends on the availability of high-quality data, appropriate feature selection, careful model development and validation, and domain expertise in interpreting the results[11,12,13,14,15]. Collaborating with geotechnical engineers and ML experts can ensure the effectiveness and reliability of the developed ML approach for improving slope stability prediction in the presence of structural deformity.

3. Result Analysis

Simulated slope design refers to the process of creating and evaluating slope designs using computer simulations and modeling techniques. It involves the use of software tools and numerical methods to analyze the stability and performance of slopes under various conditions.

Here is an overview of the steps involved in simulated slope design:

- Data Collection and Site Characterization: Gather information about the site where the slope is to be designed, including geological data, soil properties, groundwater conditions, and any other relevant information. This data helps in accurately representing the site conditions in the simulation models.
- Selection of Simulation Software: Choose appropriate software tools or numerical models that are capable of simulating slope behavior. There are various options available, such as finite element analysis (FEA) software, distinct element method (DEM) simulations, or slope stability analysis software.
- Model Development: Set up the simulation model based on the selected software. This involves creating a digital representation of the slope geometry, incorporating material properties, defining boundary conditions, and applying appropriate loadings. The model should reflect the real-world conditions as closely as possible.
- Stability Analysis: Perform stability analysis on the simulated slope to assess its stability under different loading and boundary conditions. The analysis typically involves calculating factors of safety or other stability indicators to determine if the slope is likely to fail or deform under specific circumstances.
- Sensitivity Analysis and Optimization: Conduct sensitivity analyses to identify critical parameters that significantly affect slope stability. This helps in understanding the relative importance of various factors and optimizing the slope design accordingly.

Parameter optimization techniques, such as genetic algorithms or gradient-based methods, can be employed to find the best combination of design variables that maximize stability.

- Performance Evaluation: Evaluate the performance of the simulated slope design over time. This can involve analyzing the long-term behavior of the slope under different scenarios, such as changes in groundwater conditions, seasonal variations, or the influence of external factors. The analysis may include assessments of deformation, displacement, stress distribution, and other performance criteria.
- Iterative Design: Based on the results of the simulations and performance evaluations, refine the slope design iteratively. Adjust the slope geometry, reinforcement strategies, or other design aspects to improve stability, minimize deformations, and enhance long-term performance.
- Documentation and Reporting: Document the simulated slope design process, including the input data, simulation models, analysis results, and design recommendations. This information is valuable for communicating the design rationale, justifying design decisions, and facilitating future monitoring and maintenance activities.

Simulated slope design provides valuable insights into slope behavior, allowing engineers to optimize designs, predict potential failures, and develop mitigation strategies. It helps in assessing the stability of slopes under different conditions, reducing risks, and ensuring the safety and longevity of engineering structures[16,17,18].

SLIDE 6.0 of Rocsience was used to carry out the slope failure analysis. The probabilistic and deterministic analysis is carried out in the SLIDE software using the limit equilibrium method. In probabilistic analysis probability of failure is found to be 8.6 % and the mean FOS is 2.076 whereas the deterministic value of FOS is 1.978. Figure 1 indicates the simulated slope design.

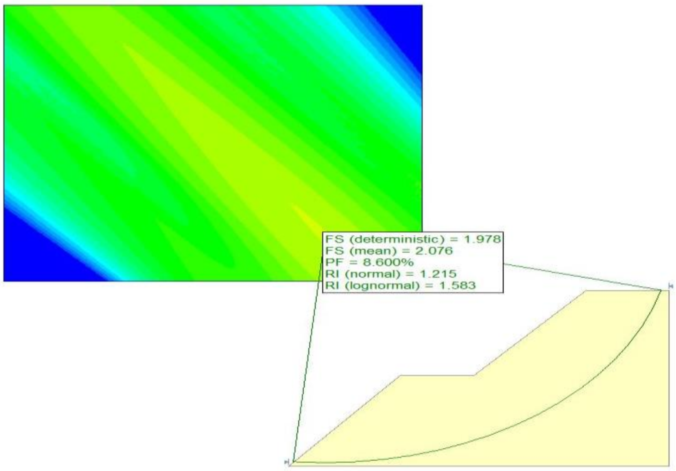

Fig 1. Simulated slope design

3.1. Factor of Safety (FoS):

The factor of safety is a measure of the stability of a slope or a soil mass. It is defined as the ratio of the resisting forces to the driving forces acting on the slope [19,20]. Mathematically, it is expressed as FoS = Resisting Forces / Driving Forces.

- Resisting Forces: These forces include the shear strength of the soil or rock mass, which is influenced by parameters such as cohesion and frictional resistance. The higher the shear strength, the greater the resisting forces against slope failure.

- Driving Forces: These forces are the external forces acting on the slope, such as the weight of the soil or rock mass, groundwater pressure, and any additional applied loads. The higher the driving forces, the greater the potential for slope failure.

The factor of safety provides an indication of how close a slope is to failure. A factor of safety less than 1 indicates that the driving forces exceed the resisting forces, indicating an unstable slope. A factor of safety greater than 1 indicates a stable slope, with a higher value indicating a higher level of stability.

3.2. Internal Angle of Friction (ϕ):

The internal angle of friction is a geotechnical parameter that represents the shear resistance of a soil or rock material. It is defined as the angle between the shear plane and the normal to the shear plane.

The internal angle of friction influences the shear strength of the soil or rock mass and plays a crucial role in slope stability analysis. A higher internal angle of friction corresponds to a higher shear strength and can contribute to a higher factor of safety. The relationship between the factor of safety and the internal angle of friction can be understood as follows:

- Increasing the internal angle of friction typically leads to an increase in the shear strength of the soil or rock mass. This, in turn, can increase the resisting forces acting on the slope and contribute to a higher factor of safety.

- Conversely, reducing the internal angle of friction decreases the shear strength of the soil or rock mass, reducing the resisting forces and potentially leading to a lower factor of safety.

-It is important to note that the internal angle of friction is just one factor among several that influence the shear strength and stability of a slope. Other factors, such as cohesion, groundwater conditions, and slope geometry, also play significant roles in slope stability analysis. Factory of safety vs internal angle of friction is shown in Fig-2 and Probability distribution curve is shown in Fig-3.

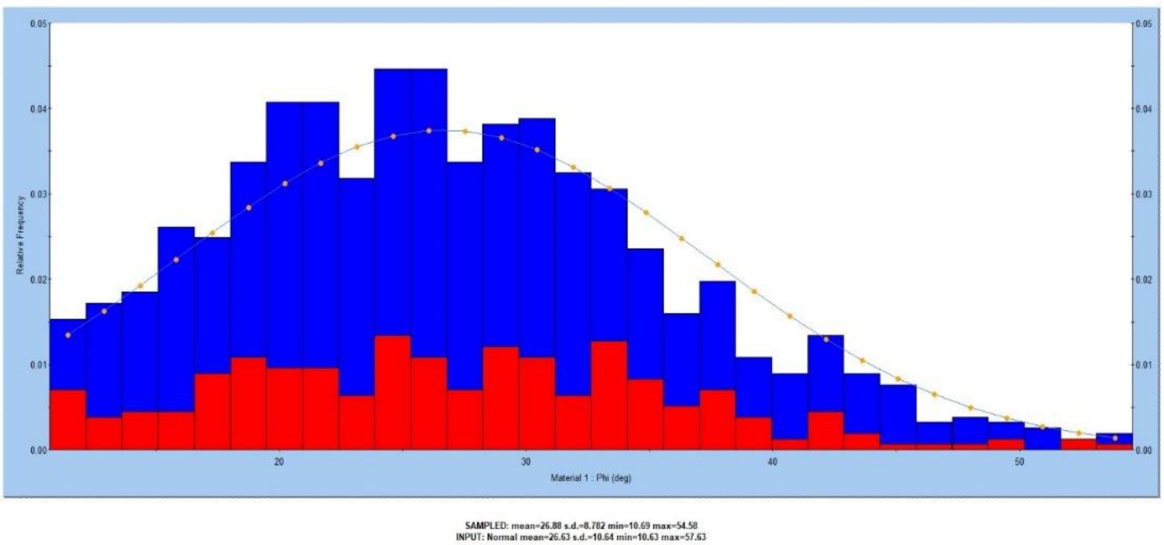

Fig 2. Factory of safety vs internal angle of friction

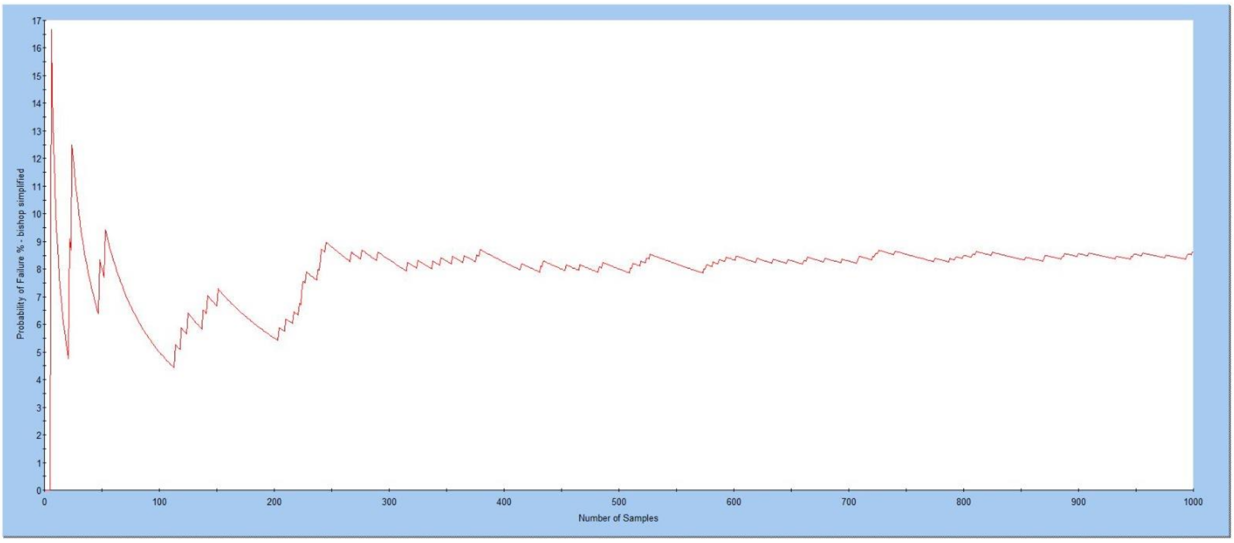

Fig 3. Probability distribution curve

3.3. Machine Learning Model

3.3.1 Logistic Regression

LR (Logistic Regression) is a popular machine learning algorithm used for binary classification problems. Despite its name, logistic regression is a statistical model that is widely applied in machine learning due to its simplicity and interpretability[21,22,23]. Here's an overview of how the LR algorithm works:

1. Model Representation: In logistic regression, the goal is to predict a binary outcome, typically denoted as 0 or 1. The algorithm models the probability of the positive outcome (class 1) using a logistic function (also known as the sigmoid function).

2. Hypothesis Function: The logistic regression hypothesis function calculates the probability of the positive outcome based on the input features. It uses a linear combination of the feature values, weighted by coefficients (also known as weights or parameters), and passes the result through the logistic function. The hypothesis function is given by:

$h\theta(x) = \sigma(\theta\text{^}T * x)$

where:

- $h\theta(x)$ is the predicted probability of the positive outcome for input features x.

- σ is the logistic (sigmoid) function that maps the linear combination to a value between 0 and 1.

- θ is the vector of coefficients (weights) that are learned during the training process.

- x is the vector of input features.

3. Cost Function: Logistic regression uses the maximum likelihood estimation to estimate the optimal values of the coefficients θ. The cost function, also known as the log-loss or cross-entropy loss function, measures the difference between the predicted probabilities and the actual class labels. The goal is to minimize the cost function to find the best-fitting coefficients.

4. Gradient Descent: To minimize the cost function and find the optimal values of θ, an optimization algorithm such as gradient descent is used. Gradient descent iteratively updates

the coefficients by taking steps proportional to the negative gradient of the cost function. The learning rate determines the size of the steps taken during each iteration.

5. Training: During the training phase, the LR algorithm iteratively adjusts the coefficients using the gradient descent algorithm. The algorithm updates the coefficients until convergence, where the cost function is minimized or reaches a predefined threshold.

6. Prediction: Once the LR model is trained and the coefficients are determined, it can be used to predict the probability of the positive outcome for new input data. The predicted probability can be converted into a binary classification by applying a threshold. For example, if the threshold is set at 0.5, probabilities above 0.5 are classified as class 1, while those below 0.5 are classified as class 0.

Logistic regression is a linear model, which means it assumes a linear relationship between the input features and the logarithm of the odds of the positive outcome[24,25]. If the relationship between the features and the outcome is more complex, techniques like feature engineering, polynomial features, or using more advanced models may be necessary.

3.3.2 Support Vector Classifier

SVC (Support Vector Classifier), also known as SVM (Support Vector Machine) for classification, is a popular machine learning algorithm used for both binary and multi-class classification problems[26,27]. SVC works by creating a hyperplane in a high-dimensional feature space to separate different classes of data points. SVC is a powerful algorithm that is effective in handling complex decision boundaries and works well with both linearly separable and non-linearly separable data. However, it can be sensitive to the choice of kernel function and the regularization parameter, which may require tuning for optimal performance.

Here's a description of how SVC works:

- Data Representation: SVC operates on a labeled dataset, where each data point is represented by a set of features and assigned a class label (e.g., 0 or 1 for binary classification). The algorithm learns patterns in the feature space to classify new, unseen data points.
- Feature Space and Hyperplane: SVC maps the input features into a higher-dimensional feature space using a kernel function. In this space, the algorithm tries to find an optimal hyperplane that best separates the data points of different classes. The hyperplane is a decision boundary that maximizes the margin, which is the distance between the hyperplane and the nearest data points from each class.
- Margin and Support Vectors: Support vectors are the data points that lie closest to the hyperplane and play a crucial role in defining the hyperplane. The margin is the region between the support vectors of different classes. SVC aims to find the hyperplane that maximizes this margin, as it provides better generalization and robustness to new data.
- Kernel Trick: SVC utilizes the kernel trick to implicitly map the input features into a higher-dimensional space without explicitly computing the transformation. The kernel function measures the similarity between pairs of data points in the high-dimensional space. Common kernel functions include linear, polynomial, radial basis function (RBF), and sigmoid. The choice of the kernel function depends on the characteristics of the data and the complexity of the decision boundary.
- Optimization: The goal of SVC is to find the optimal hyperplane that separates the data with the maximum margin. This is formulated as an optimization problem that minimizes the classification error while maximizing the margin. The optimization is typically solved using quadratic programming or convex optimization techniques.

- Soft Margin and Regularization: In cases where the data is not perfectly separable or contains outliers, SVC allows for a soft margin by introducing a regularization parameter (C). This parameter controls the trade-off between maximizing the margin and allowing some misclassifications. A higher value of C allows fewer misclassifications, but the margin may become smaller, while a lower value of C prioritizes a larger margin at the cost of potentially more misclassifications.
- Prediction: Once the SVC model is trained, it can be used to classify new, unseen data points by evaluating which side of the hyperplane they belong to. The decision is made based on the sign of the classification function, which depends on the learned coefficients and the kernel function. ML based comparison accuracy is shown in Figure 4.

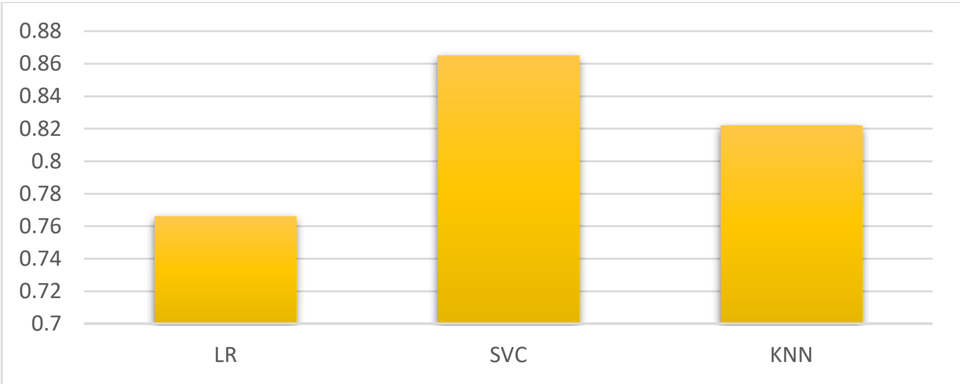

Figure 4: ML comparison accuracy

4. Conclusion

It is revealed that numerical modelling and three-dimensional techniques are utilized for the analysis of slope stability of various geological structures. But in the case of complex geological structures, these methods are impotent whereas soft computing methods like artificial neural networks and machine learning are more proficient. The proposed hybrid stacking ensemble which had already been trained by the synthetic data was applied to simulated cases of the slopes to accelerate the performance of ML algorithms. Simulated slope design allows engineers to evaluate different design options, predict potential failure mechanisms, and optimize slope configurations before implementing them in the field. It helps in minimizing risks, enhancing safety, and reducing the costs associated with slope instability.

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