Improving Slope Stability in Open Cast Mines via Machine Learning based IoT Framework

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Abstract*—Slope stability has been a matter of concern for most geologists, mainly due to the fact that unstable slopes cause a greater number of accidents, which in turn reduces efficiency of mining operations. In order to reduce the probability of these slope instabilities, methods like tension crack mapping, inclinometer measurements, time domain reflectometry, borehole extensometers, piezometer, radar systems and image processing systems are deployed. These systems work efficiently for single site slope failures, but as the number of mining sites increase, dependency of one site slope failure on nearby sites also increases. Current systems are not able to capture this data, due to which the probability of accidents at open cast mines increases. In order to reduce this probability, a high efficiency internet of things (IoT) based continuous slope monitoring and control system is designed. This system assists in improving the efficiency of real-time slope monitoring via usage of a sensor array consisting of radar, reflectometer, inclinometer, piezometer and borehole extensometer. All these measurements are given to a high efficiency machine learning classifier which uses data mining, and based on its output suitable actions are taken to reduce accidents during mining. This information is dissipated to nearby mining sites in order to inform them about any inconsistencies which might occur due to the slope changes on the current site. Results were simulated using HIgh REsolution Slope Stability Simulator (HIRESSS), and an efficiency improvement of 6% is achieved for slope analysis in open cast mines, while probability of accident reduction is increased by 35% when compared to traditional non-IoT based approach.

***Keywords*—Opencast; mining; slope; IoT; stability; machine learning; data mining**

I. Introduction

In order to design a highly efficient slope analysis model parameters like apparent dip of cutting slopes, joint dip, angle between slope aspect & joint aspect, friction angle of joint plane, cohesion of joint, joint persistence, height of slope, weight of sliding blocks, uplift force due to water pressure of joints, force due to water pressure in tension crack, etc. must be recorded and analyzed [1]. These parameters require a large variety of sensors, which must be connected in tandem in order to evaluate these values with highest possible efficiency. Depending upon these parameters, different slope stability factors are evaluated, and based on the value of these factors, approximations are done on the stability of slope on the given opencast mining site [2]. For instance, in order to evaluate factor of safety (FoS), measurements of resting moments and disturbing moments are done, and the following equation is evaluated,

$$FoS = \frac{M_R}{M_D} \tag{1}$$

$$MR = c * \emptyset * R2 \tag{2}$$

$$MD = Aregion * \partial * x \tag{3}$$

Where, ‘c’ is a constant, $\emptyset$ is the angle of measurement, ‘R’ is radius of measurement,

A region is area of region, ∂ is weight of soil, and ‘x’ is distance between start point and center of slope, M_R is resting moment, M_D is disturbing moment. A high value of ‘FoS’ indicates that the surface has high resting moment, and low disturbing moment, which indicates that the surface is slope stable and can be used for mining operations with high efficiency. Similar measurements including sheer resistance of force acting on slice, sheer resistance offered by soil, etc. are also used to evaluate FoS values for opencast soil surfaces. Depending upon these values, short-term stability and long-term stability values are evaluated. Short term stability conditions include, stability of slope immediately after construction, which consists of undrained conditions and is evaluated using undrained parameters. Here, change in pore water pressure is totally dependent upon stress change. While long term stability analysis uses effective weight of soil and here changes in pore water pressure is independent of stress changes [3].

More precisely, despite the fact that this study has significantly advanced our understanding of slope stability, it is still limited by the following drawbacks of the aforementioned techniques, which prevent it from being fully resolved:

- The simulations are inaccurate. The slope stability, for instance, can be reflected by the limit equilibrium approach, but the non-uniformity of the stress distribution and the impact of deformation are not taken into consideration. Therefore, this technique cannot accurately reflect the slope's actual level of safety and dependability.

- The safety factor's limitations are ambiguous and undefined. A slope with FS>1.20 is generally considered safe. However, in actual engineering there have been slopes that failed with FS > 1.2.
- These techniques are influenced by human subjectivity.

Throughout the course of an opencast mining operation, slope stability analysis is a crucial part of the process. A terrible social, economic, as well as a major safety catastrophe might result from a failure of slope in the vicinity of a mine being operated. The fundamental failure scenarios are extremely complex & diversified. These failure processes heavily rely on the regional geology, which is rather particular to a particular area of the rock mass. The process of developing slopes is wholly based on the field experience in recent years as well. A better strategy may be created by planning slopes safely.

The major aim of this work is to do numerical modelling for increasing the efficiency of slopes through the simulator with diverse rock qualities and slope diameters. Utilizing HIRESSS, numerical modelling is done to determine the safety factor. Every slope has different characteristics, and each step's safety factor is determined. To determine how the factor of safety alters when the bench parameters vary, these numbers are connected with them. Here our objective is to understand the different types of slope failures and the concepts of Safety.

Based on this analysis, a large number systems have been proposed over the past several years [4]. Each of these systems has its own advantages and limitations.

In the outline of this paper, the next section reviews the systems and evaluates best practices that must be used in order to improve the performance of slope stability in opencast mining conditions. This is followed by the section on the design of the proposed model, which is inspired by cutting edge IoT devices, and their interconnections for improved slope stability using a novel data mining approach. Next to this, the result analysis and comparison of the proposed model is done in order to evaluate the performance and performance gaps in existing system. Finally, this text concludes with some interesting observations about the proposed model and suggests methods to improve the same.

II. Literature Review

Slope stability analysis for open cast mines is a multidomain signal processing task, wherein data from different sensors must be captured such that slopes are analyzed with high accuracy. In order to perform this task, various signal processing models are described, for instance, the work in [5] proposes a model that uses Spatio-Temporal Kriging Interpolation for improving slope stability. The model is able to perform highly accurate analysis on both open cast and open pit mines, due to efficient utilization of data interpolation. Similar models can be observed from [6, 7, 8], where Neural Networks, Gaussian processes, and 3D non- linear finite difference analysis are used. These models can be used for high performance applications like highway corridor slope analysis [9] for improving road stability.

Simpler methods like strength reduction [10], and variational calculus [11], can be used for analysing stability of slope analysis for open cast mines, National Highway (NH) development [12], and perched water conditions [13] with high efficiency. Slope stability can also be analyzed for specialized geographies like 3D geometries [14, 15], and methods like Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [16] can be used. These techniques can be extended by referring to different algorithmic models as suggested in [17], wherein Limit equilibrium method, artificial neural network, Vector sum method, Numerical simulation method and Limit analysis method are described. These methods utilize slope height & angle factors [18] while designing slope analysis models, and can be used for specialized applications like Stone Column- Supported Embankments [19]. The performance of these models can be improved via use of deep learning models as described in [20], wherein hybrid stacking ensemble method is used, which is based on finite element analysis and field data. The model is able to achieve high accuracy of slope analysis, and thereby adapt to varying structural scenarios. Various specialized methods for slope analysis can be observed from [21, 22, 23, 24, 25, 26], wherein volumetric behavior of rock salt, electromagnetic radiation mechanism of rock fracturing, uniaxial compressive strength of sandstone, influence of bedding structure, spectral induced polarization, bender element models, and pre-flawed sandstones are studied. These models assist in evaluation of slopes in open cast mines that are located near stone beds, thereby improving their scalability.

Artificial neural networks (ANN) have been applied successfully in slope stability problems (Feng, et. al 2018) [27], however they do have certain drawbacks. The restrictions are detailed below:

- Contrary to other statistical models, ANN models do not reveal the relative relevance of the individual parameters, which is a significant drawback (Samui, P. 2019) [28].
- Since the knowledge learned during training is implicitly stored in ANNs, it can be exceedingly challenging to interpret the network's general structure in a way that makes sense (Baghbani, et.al (2022)[29] has been proposed in their review. This gave rise to the phrase "black box," which many researchers use to describe the behaviour of ANNs.
- Additionally, ANN has certain intrinsic flaws such as sluggish convergence, poor generalisation, finding local minimums, and over-fitting issues.

The author's primary contribution is to provide an output utilizing several classifiers employing IoT devices and a simulator. Its result is used to determine the best course of action to decrease mining accidents. This information is shared with surrounding mining operations in order to alert them to any discrepancies that might arise as a result of the site's current slope variations. The HIgh REsolution Slope Stability Simulator (HIRESSS) was used to model the outcomes, and then it was compared to a conventional, non-IoT based technique.

Models for analysis of submerged pools [30], use of random field Gaussian methods [31], blocky structure systems [32], near-surface rock strength slope analysis [33], and reinforcement learning models [34-37] are also used for high efficiency slope analysis. It can be observed that most of these models do not define sensor placement analysis, due to which their efficiency is limited. In order to improve this efficiency, the proposed model combines various sensing elements, and defines positions for these elements in order to improve stability of slope analysis in open cast mines. The proposed model along with its analysis and comparative evaluation can be observed in the next sections.

III. PROPOSED MACHINE LEARNING MODEL FOR IMPROVING SLOPE STABILITY ANALYSIS USING IOT

In order to improve the efficiency of slope stability analysis in open cast mines, it is mandatory that various conditions like above water table, drained, partly drained, water table 10m above toe, and water table 16m above toe must be analyzed. The significance and primary goal of this work is to put the aforementioned categorization model into practice for predicting the stability state of a soil slope.

- A weak zone in the soil profile is used to perform slope stability, which is a prevalent sort of coal mine failure in many nations.
- Practically significant numerical challenges are addressed for the simulation and investigation of the issue.
- The stability of the mine's slopes is determined by the inclination, shear strength, and water conditions in the weak zone.

The results of these conditions are given to the proposed model in order to reduce their probability of occurrence. Various IoT sensors are placed onsite in order to sense presence of these conditions, and efficient steps are taken to reduce their effect. To improve the efficiency of slope stability analysis, the following process is used, and based on the results of this process action plans are executed for improving the condition of open cast mines.

- Inputs to the model
    - Number of iterations (N_i).
    - Number of solutions (N_s).
    - Maximum number of sensors in the system (S_{max}) (radar, reflectometer, inclinometer, piezometer, borehole extensometer, etc.).
    - Learning rate (L_r).
    - Minimum advisable slope stability (SL_{min}).
    - Maximum advisable slope stability (SL_{max}).
- Outputs of the model
    - Estimated slope (SL_{es}).
- Process of execution
    - For each iteration in 1 to N_i
        - For each solution in to N_s
        - If the solution is marked as 'not to be changed', then skip it and go to the next solution.
        - Else, generate a new solution using the following process,
        - Select a random number of sensors from the list of available sensors = $Sensesel$

$$Sense_{sel} = (1, S_{max}) \quad (4)$$

- For the selected sensors, perform random placement on the mining site, so that different sensor readings can be obtained.
- Using these sensors, measure the slope stability from each sensor using equations 5, 6, 7, 8 and 9.

$$SS_{rader} = \frac{\left(\frac{\text{ABS}(H_{measured} - H_{actual})}{\text{Max}\,(H_{measured}, H_{actual})} + \frac{\text{ABS}(D_{measured} - D_{actual})}{\text{Max}\,(D_{measured}, D_{actual})}\right)}{2} \quad (5)$$

$$SS_{ref} = \frac{\text{ABS}(R_{measured} - R_{actual})}{\text{MAX}\,(R_{measured}, R_{actual})} \quad (6)$$

$$SS_{inc} = \frac{\text{ABS}(I_{measured} - I_{actual})}{\text{MAX}\,(I_{measured}, I_{actual})} \quad (7)$$

$$SS_{piez} = \frac{\text{ABS}(P_{measured} - P_{actual})}{\text{MAX}\,(P_{measured}, P_{actual})} \quad (8)$$

$$SS_{bh} = \frac{\text{ABS}(D_{measured} - D_{actual})}{\text{MAX}\,(D_{measured}, D_{actual})} \quad (9)$$

Where, SS_{ra}, SS_{ref}, SS_{inc}, SS_{piez}, and SS_{bh} are slope stability values for radar, reflectometer, inclinometer, piezoelectric sensor and borehole extensometer, while H, D, R, I, and P are measured height, distance, reflectance, inclination, and soil pressure respectively.

- Based on the number of selected sensors, the value of fitness is estimated using equation 10.

$$F_i = \frac{\sum_{i=1}^{Sense_{sel}} SS_i}{Sense_{sel}} \quad (10)$$

- If the value of F_i satisfies the constraints of equation 11, then use it for processing, else generate a new solution.

$$F_i > SL_{min} \text{ and } F_i < SL_{max} \quad (11)$$

- After generation of all solutions, evaluate the fitness threshold using equation 12, wherein learning rate and other parameters are also utilized.

$$F_{th} = \sum_{i=1}^{N_s} F_i * \frac{L_r}{N_s} \quad (12)$$

- Mark all solutions as 'to be changed', where fitness is less than the threshold, while mark all other solutions as 'not to be changed'.
- At the end of last iteration, the following Table I is formed, which indicates information about each

solution, its stability, number of sensors used, and their placements.

- Select the solution with maximum fitness value, use the sensors and place them in given locations as decided by the algorithm.

Once the sensor placement is complete, then evaluate slope for the given open cast mine, and communicate this value to other locations. Generate 'R' random locations for deployment, and gather slope data from all these locations using the given machine learning model. Once the data is collected, then use a mode operation for find slope analysis.

$$S_{final} = MODE\ (|S_i|R_{i=1}) \quad (13)$$

Based on this evaluation, accuracy of slope stability, precision, recall, and fMeasure values are estimated. This estimation is done on various sites across different open cast mines, and the results are tabulated in the next section. These results are also compared with some of the reviewed models that perform highly efficient slope stability analysis in the same open cast mines.

IV. Result and Analysis

Performance evaluation of the proposed model required in depth analysis and simulations for different open cast sites. In order to perform this task, 20 different open cast mines were simulated on the HIgh REsolution Slope Stability Simulator (HIRESSS) software, and 100 different locations were evaluated for estimation of slope stability analysis. Based on these simulation settings, accuracy of slope stability analysis (ASL) was evaluated using the following equation,

$$A_{SL} = \frac{S_C}{S_T} \quad (14)$$

Where, S_C and S_T are number of sites where slopes were correctly identified, and total number of evaluated sites respectively. We have implemented the methodologies used in [5] and [20] in our simulator and compared them with our proposed work. These results are tabulated in Table I to V, wherein accuracy of the proposed model is compared with other reference models as in Table I.

Based on this analysis it can be observed that the proposed model is 5% more effective than [5], and 6% more effective than [20] under different open mining sites. Using similar simulation settings, recall of slope stability analysis (P_{SL}) was evaluated using the following equation,

$$P_{SL} = \frac{S_{CI}}{S_T} \quad (15)$$

Where, S_{CI} and S_T are number of sites where slopes were correctly identified but had lower slope values when compared with actual and total number of evaluated sites respectively. These results are tabulated in Table II, wherein Precision of the proposed model is compared with other reference models.

Based on this analysis it can be observed that the proposed model is 6% more effective than [5], and 5% more effective than [20] under different open mining sites. Using similar simulation settings, recall of slope stability analysis (RSL) was evaluated using the following equation,

$$R_{SL} = \frac{S_{CC}}{S_T} \quad (16)$$

TABLE I. Accuracy of Slope Stability Analysis for different Sites

Number of site locations	A_{SL} [5]	A_{SL} [20]	A_{SL} Proposed
2000	0.72	0.76	0.81
3000	0.74	0.77	0.83
4000	0.77	0.79	0.84
5000	0.78	0.80	0.85
6000	0.79	0.81	0.86
7000	0.80	0.81	0.87
8000	0.81	0.82	0.88
9000	0.81	0.83	0.89
10000	0.82	0.84	0.90
11000	0.83	0.86	0.91
12000	0.84	0.87	0.92
13000	0.85	0.88	0.94
14000	0.87	0.89	0.95
15000	0.88	0.90	0.96
16000	0.89	0.91	0.97
17000	0.90	0.92	0.97
18000	0.91	0.93	0.98
19000	0.93	0.93	0.98
20000	0.94	0.94	0.99

TABLE II. The Precision of Slope Stability Analysis for different Sites

Number of site locations	P_{SL} [5]	P_{SL} [20]	P_{SL} Proposed
2000	0.68	0.72	0.77
3000	0.70	0.73	0.78
4000	0.73	0.75	0.80
5000	0.74	0.76	0.81
6000	0.75	0.76	0.81
7000	0.76	0.77	0.82
8000	0.76	0.78	0.83
9000	0.77	0.79	0.85
10000	0.78	0.80	0.86
11000	0.79	0.81	0.87
12000	0.80	0.82	0.88
13000	0.81	0.83	0.89
14000	0.82	0.84	0.90
15000	0.83	0.86	0.91
16000	0.84	0.87	0.92
17000	0.86	0.87	0.92
18000	0.87	0.88	0.93
19000	0.88	0.89	0.93
20000	0.89	0.89	0.94

TABLE III. RECALL OF SLOPE STABILITY ANALYSIS FOR DIFFERENT SITES

Number of site locations	R_{SL} [5]	R_{SL} [20]	R_{SL} Proposed
2000	0.72	0.76	0.81
3000	0.74	0.77	0.83
4000	0.77	0.79	0.84
5000	0.78	0.80	0.85
6000	0.79	0.81	0.86
7000	0.80	0.81	0.87
8000	0.81	0.82	0.88
9000	0.81	0.83	0.89
10000	0.82	0.84	0.90
11000	0.83	0.86	0.91
12000	0.84	0.87	0.92
13000	0.85	0.88	0.94
14000	0.87	0.89	0.95
15000	0.88	0.90	0.96
16000	0.89	0.91	0.97
17000	0.90	0.92	0.97
18000	0.91	0.93	0.98
19000	0.93	0.93	0.98
20000	0.94	0.94	0.99

Where, S_{CC} *and* S_T are number of sites where slopes were correctly identified but had higher slope values when compared with actual, and total number of evaluated sites respectively. These results are tabulated in Table III, wherein Recall of the proposed model is compared with other reference models.

Based on this analysis it can be observed that the proposed model is 5% more effective than [5], and 4% more effective than [20] under different open mining sites. Using similar simulation settings, fMeasure of slope stability analysis (F_{SL}) was evaluated using the following equation,

$$F_{SL} = 2 * P_{SL} * \frac{R_{SL}}{R_{SL} + R_{SL}} \quad (17)$$

These results are tabulated in Table IV, wherein FMeasure of the proposed model is compared with other reference models.

Based on this analysis it can be observed that the proposed model is 5% more effective than [5], and [20] under different open mining sites. Similarly, analysis of probability of accidents (P) on each site was estimated using equation 18, and results were tabulated using Table V, where a major difference in accident reduction probability can be observed.

$$P_{ACC} = \frac{Accidents\ Occoured}{Totel\ Accident\ Scenarios} \quad (18)$$

From this analysis, it can be observed that the proposed model is able to reduce number of accidents by over 35% when compared with reviewed models. This can also be observed from Fig. 5.

TABLE IV. FMEASURE OF SLOPE STABILITY ANALYSIS FOR DIFFERENT SITES

Number of site locations	F_{SL} [5]	F_{SL} [20]	F_{SL} Proposed
2000	0.70	0.74	0.79
3000	0.72	0.75	0.80
4000	0.75	0.77	0.82
5000	0.76	0.78	0.83
6000	0.77	0.78	0.84
7000	0.77	0.79	0.85
8000	0.78	0.80	0.86
9000	0.79	0.81	0.87
10000	0.80	0.82	0.88
11000	0.81	0.83	0.89
12000	0.82	0.84	0.90
13000	0.83	0.86	0.91
14000	0.84	0.87	0.92
15000	0.85	0.88	0.93
16000	0.87	0.89	0.94
17000	0.88	0.90	0.95
18000	0.89	0.90	0.95
19000	0.90	0.91	0.96
20000	0.91	0.91	0.96

TABLE V. ACCIDENT PROBABILITY FOR DIFFERENT SITES

Number of sit e locations	P_{ACC} [5]	P_{ACC} [20]	P_{ACC} Proposed
2000	0.56	0.59	0.37
3000	0.58	0.60	0.38
4000	0.60	0.61	0.39
5000	0.61	0.62	0.40
6000	0.61	0.63	0.40
7000	0.62	0.64	0.41
8000	0.63	0.64	0.41
9000	0.64	0.65	0.42
10000	0.64	0.66	0.42
11000	0.65	0.67	0.43
12000	0.66	0.68	0.43
13000	0.67	0.68	0.44
14000	0.68	0.69	0.44
15000	0.68	0.70	0.45
16000	0.69	0.71	0.46
17000	0.70	0.72	0.46
18000	0.71	0.72	0.47
19000	0.72	0.73	0.47
20000	0.73	0.73	0.48

A. Simulation Results

As per our proposed work different statistical measure has been performed. A comparison study has been performed as shown in table from Table I to Table V by taking different site locations. The simulation results of the above mentioned analysis have been shown in Fig. 1 to Fig. 5. It has been found that our proposed work is comparatively showing good result in different analytical aspects.

This reduction assists in making it useful for safe and highly accurate slope estimations. The estimated slopes can be used for taking suitable actions for estimation of open cast mine accidents, and avoiding them with high efficiency.

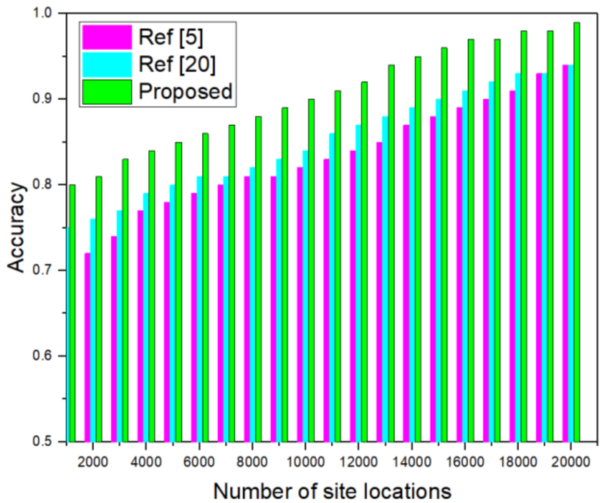

Fig. 1. Accuracy of Slope Stability Analysis for Different Sites.

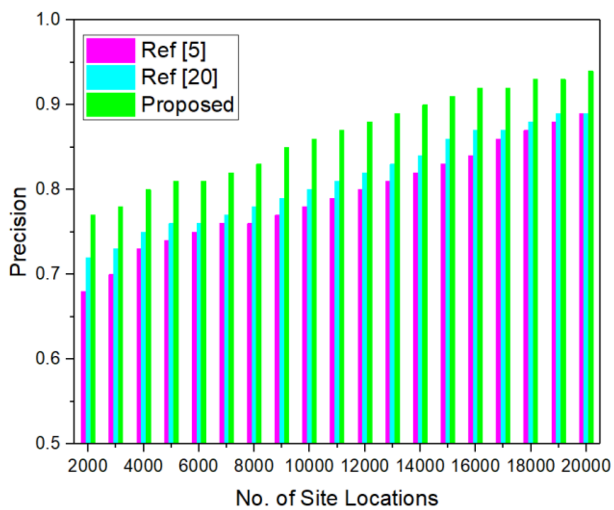

Fig. 2. Precision of Slope Stability Analysis for Different Sites.

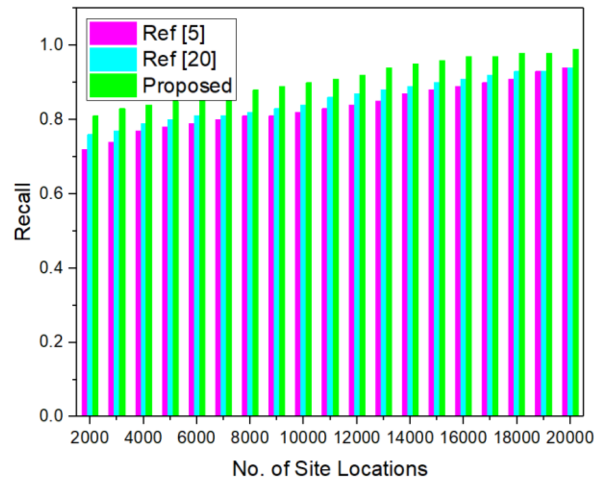

Fig. 3. Recall of Slope Stability Analysis for Different Sites.

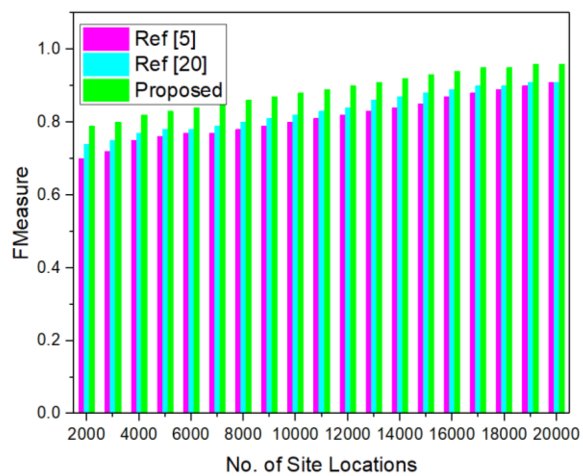

Fig. 4. FMeasure of Slope Stability Analysis for Different Sites.

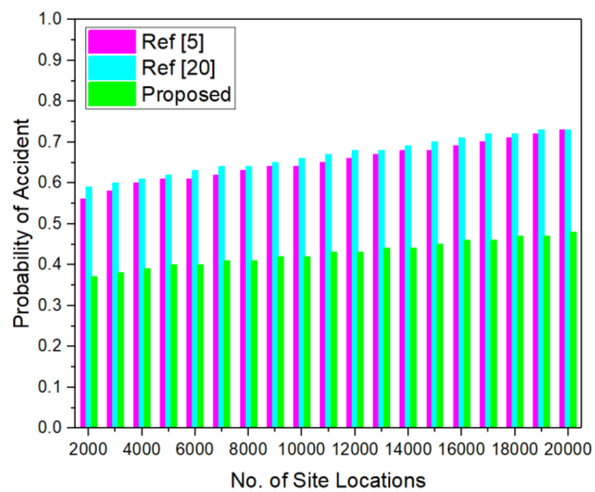

Fig. 5. Accident Probability for Different Sites.

V. Conclusion and Future Scope

Based on the extensive result analysis, it can be observed that the proposed model is capable of improving the accuracy of slope stability analysis by 6% when compared with state-of-the-art models, while similar results are obtained for precision, recall, and F-measure values. Due to this, the number of accidents at these mines is drastically reduced, which enforces better safety measures, and thereby assists in reducing cost of mining operations. All these parameters are improved due to proper sensor placement, and improvement of stability analysis models by the machine learning model. Stochastic placement of sensors, and randomized inference of models positions from these placements further assists in identification of new placement spots on the site, thereby improving site coverage and utility. In future, researchers can improve this performance via use of deep learning models, wherein more number of sensors can be integrated in order to improve stability of slope analysis.

References

[1] S. Li, L. Wu, X. Bian, C. Song, P. Li and Z. Han, "Statistically Analysis for the Stability of Various Protection Modes of Expansive Soil Cutting Slope," 2019 International Conference on Virtual Reality and Intelligent Systems (ICVRIS), 2019, pp. 320-323, doi: 10.1109/ICVRIS.2019.00084.

[2] Y. Yang, H. Xu, Y. He and Z. Yin, "Stability Analysis of Earth-rock Dam Slopes based on Big Data Fuzzy Ant Colony Clustering," 2019 IEEE 3rd Information Technology, Networking, Electronic and Automation Control Conference (ITNEC), 2019, pp. 2153-2156, doi:10.1109/ITNEC.2019.8729524.

[3] H. Zhi-Fang, "Analysis on the Impact of Expansive Soil Slope Stability by Rainfall Infiltration," 2018 International Conference on Engineering Simulation and Intelligent Control (ESAIC), 2018, pp. 26-30, doi: 10.1109/ESAIC.2018.00014.

[4] Y. Lin, K. Zhou and J. Li, "Prediction of Slope Stability Using Four Supervised Learning Methods," in IEEE Access, vol. 6, pp. 31169-31179, 2018, doi: 10.1109/ACCESS.2018.2843787.

[5] Acharya, B., Sarkar, K., Singh, A.K. et al. Preliminary slope stability analysis and discontinuities driven susceptibility zonation along a crucial highway corridor in higher Himalaya, India. J. Mt. Sci. 17, 801–823 (2020). https://doi.org/10.1007/s11629-019-5524.

[6] N. Gunasekaran, N. M. Thoiyab, P. Muruganantham, G. Rajchakit and B. Unyong, "Novel Results on Global Robust Stability Analysis for Dynamical Delayed Neural Networks Under Parameter Uncertainties," in IEEE Access, vol. 8, pp. 178108-178116, 2020, doi: 10.1109/ACCESS.2020.3016743.

[7] B. Hu, G. Su, J. Jiang, J. Sheng and J. Li, "Uncertain Prediction for Slope Displacement Time-Series Using Gaussian Process Machine Learning," in IEEE Access, vol. 7, pp. 27535-27546, 2019, doi: 10.1109/ACCESS.2019.2894807.

[8] B. Hu, J. Li, J. Sheng and Z. Ye, "Crack Cause in the High Slope of Chinese Ancient Copper Mine Relics: A Three-Dimensional Non-Linear Finite Difference Analysis," in IEEE Access, vol. 8, pp. 13987-13997, 2020, doi: 10.1109/ACCESS.2020.2965593.

[9] 6H. Xiao, Z. Zhang, L. Chen and Q. He, "An Improved Spatio-Temporal Kriging Interpolation Algorithm and Its Application in Slope," in IEEE Access, vol. 8, pp. 90718- 90729, 2020, doi: 10.1109/ACCESS.2020.2994050.

[10] Liu, F. Stability Analysis of Geotechnical Slope Based on Strength Reduction Method. Geotech Geol Eng 38, 3653–3665(2020). https://doi.org/10.1007/s10706-020-01243-3.

[11] Belandria, N., Úcar, R., León, F.M. et al. Stability analysis of slopes with planar failure using variational calculus and numerical methods. Front. Struct. Civ. Eng. 14, 1262–1273 (2020). https://doi.org/10.1007/s11709-020-0657-9.

[12] Kumar, A., Sharma, R.K. & Mehta, B.S. Slope stability analysis and mitigation measures for selected landslide sites along NH-205 in Himachal Pradesh, India. J Earth Syst Sci 129, 135 (2020). https://doi.org/10.1007/s12040-020-01396-y.

[13] Tang, D., Jiang, Z., Yuan, T. et al. Stability Analysis of Soil Slope Subjected to Perched Water Condition. KSCE J Civ Eng 24, 2581–2590 (2020). https://doi.org/10.1007/s12205-020-1728-0.

[14] Yu, G., Xie, M., Liang, J. et al. A GIS- based 3D slope stability analysis method based on the assumed normal stress on the slip surface. Sci Rep 10, 4442 (2020). https://doi.org/10.1038/s41598-020-61301-x.

[15] Bunn, M., Leshchinsky, B., & Olsen, M. J. Geologic Trends in shear strength properties inferred through three- dimensional back analysis of landslide inventories. Journal of Geophysical Research: Earth Surface, 125, 2020. https://doi.org/10.1029/2019JF005461.

[16] Wenqiang Chen, Yufei Zhao, Lipeng Liu, Xiaogang Wang, "A New Evaluation Method for Slope Stability Based on TOPSIS and MCS", Advances in Civil Engineering, vol. 2020, Article ID 1209470, 10 pages, 2020. https://doi.org/ 10.1155/2020/1209470.

[17] Ullah, Sami & Khan, Muhibullah & Rehman, Gohar. A Brief Review Of The Slope Stability Analysis Methods, Geological Behavior. 4. 73-77. 10.26480/gbr.02.2020.73.77.

[18] Shiferaw, H.M. Study on the influence of slope height and angle on the factor of safety and shape of failure of slopes based on strength reduction method of analysis. Beni- Suef Univ J Basic Appl Sci 10, 31 (2021). https://doi.org/10.1186/s43088-021-00115- w.

[19] Dar, L.A., Shah, M.Y. Deep-Seated Slope Stability Analysis and Development of Simplistic FOS Evaluation Models for Stone Column-Supported Embankments. Transp. Infrastruct. Geotech. 8, 203–227 (2021). https://doi.org/10.1007/s40515-020-00134-7.

[20] Kardani, Navid & Zhou, Annan & Nazem, Majidreza & Shen, Shui-Long Improved prediction of slope stability using a hybrid stacking ensemble method based on finite element analysis and field data. Journal of Rock Mechanics and Geotechnical Engineering, 2020 13.10.1016/j.jrmge.2020.05.011.

[21] Azabou, Mejda & Rouabhi, Ahmed & Blanco-Martìn, Laura, Effect of insoluble materials on the volumetric behavior of rock salt. Journal of Rock Mechanics and Geotechnical Engineering. 13, 2020. 10.1016/j.jrmge.2020.06.007.

[22] Padhy, S., Dash, S., Routray, S., Ahmad, S., Nazeer, J., & Alam, A. (2022). IoT-Based Hybrid Ensemble Machine Learning Model for Efficient Diabetes Mellitus Prediction. Computational Intelligence and Neuroscience, 2022.

[23] Padhy, S., Dash, S., Malla, P. P., Routray, S., & Qi, Y. (2021, November). An Energy Efficient Node Localization Algorithm for Wireless Sensor Network. In 2021 IEEE 2nd International Conference on Applied Electromagnetics, Signal Processing, & Communication (AESPC) (pp. 1-5). IEEE.

[24] Lin, Peng & Pengcheng, Wei & Wang, Cheng & Kang, Shengzu & Wang, Xin. Effect of rock mechanical properties on electromagnetic radiation mechanism of rock fracturing. Journal of Rock Mechanics and Geotechnical Engineering, 2021, 10.1016/j.jrmge.2021.01.001.

[25] Zhang, Jinyuan & Shen, Yanjun & Yang, Gengshe & Zhang, Huan & Wang, Yongzhi & Xin, Hou & Sun, Qiang & Li, Guoyu. Inconsistency of changes in uniaxial compressive strength and P-wave velocity of sandstone after temperature treatments. Journal of Rock Mechanics and Geotechnical Engineering. 13,2020, 10.1016/j.jrmge.2020.05.008.

[26] Li, Xiaying & Lei, Xinglin & Li, Qi & Chen, Dianguo, Influence of bedding structure on stress-induced elastic wave anisotropy in tight sandstones. Journal of Rock Mechanics and Geotechnical Engineering. 13. 98-113, 2021, 10.1016/j.jrmge.2020.06.003.

[27] Bate, Bate & Cao, Junnan & Zhang, Chi & Hao, Na & Wang, Song, Journal Pre-proof Monitoring lime and cement improvement using spectral induced polarization and bender element techniques Monitoring lime and cement improvement using spectral induced polarization and bender element techniques. Journal of Rock Mechanics and Geotechnical Engineering. 13, 2020, 10.1016/j.jrmge.2020.06.005.

[28] Ke Zhang, Xianghua Liu, Yulong Chen, Heming Cheng, Quantitative description of infrared radiation characteristics of preflawed sandstone during fracturing process, Journal of Rock Mechanics and Geotechnical

Engineering, Volume 13, Issue 1, 2021, Pages 131-142, ISSN 1674-7755, https://doi.org/10.1016/j.jrmge.2020.05.003.

[29] Feng, X., Li, S., Yuan, C., Zeng, P., & Sun, Y. (2018). Prediction of slope stability using naive Bayes classifier. KSCE Journal of Civil Engineering, 22(3), 941-950.

[30] Samui, P. (2019, September). Application of artificial intelligence in geo-engineering. In International Conference on Inforatmion technology in Geo-Engineering (pp. 30-44). Springer, Cham.

[31] Baghbani, A., Choudhury, T., Costa, S., & Reiner, J. (2022). Application of artificial intelligence in geotechnical engineering: A state-of-the-art review. Earth-Science Reviews, 228, 103991.

[32] Wang, W, Griffiths, DV. Analysis of the critical pool level of partially submerged slopes. Int J Numer Anal Methods Geomech. 2020; 44: 405–417. https://doi.or g/10.1002/nag.3022.

[33] Zhu, B, Hiraishi, T, Pei, H, Yang, Q. Efficient reliability analysis of slopes integrating the random field method and a Gaussian process regression-based surrogate model. Int J Numer Anal Methods Geomech. 2021; 45: 478– 501. https://doi.or g/10.1002/nag.3169.

[34] Jia, C, Huang, Q, Wang, G. Stability analysis of blocky structure system using discontinuity layout optimization. Int J Numer Methods Eng. 2020; 121: 5766– 5783. https://doi.org/ 10.1002/nme.6523.

[35] Panda, R., Dash, S., Padhy, S., & Das, R. K. (2023). Diabetes Mellitus Prediction Through Interactive Machine Learning Approaches. In Next Generation of Internet of Things (pp. 143-152). Springer, Singapore.

[36] Townsend, K. F., Gallen, S. F., & Clark, M. K. (2020). Quantifying near-surface rock strength on a regional scale from hillslope stability models. Journal of Geophysical Research: Earth Surface, 125, e2020JF005665. https://doi.org/10.1029/202 0JF005665.

[37] Wei Chen, Dongbai Li, Ting Ma, Helin Fu, Yanpeng Du, "Stability Analysis of a Slope considering Two Reinforcement Processes", Geofluids, vol. 2020, Article ID 8828747, 13 pages, 2020. https://doi.org/ 10.1155/2020/8828747.