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Dump slope stability analysis using artificial intelligence

The fourth industrial revolution has introduced several rapidly progressive technologies like big data analytics, the internet of things, simulation, autonomous robots, cloud computing and artificial intelligence. It has reduced the effort and processing time in the manufacturing/production industry through new emerging technologies. In this study, artificial intelligence has been adopted to forecast the stability of multi bench dump slope structure with ease and minimum interval. The supervised machine learning method-based Decision Tree, Gradient Boosting, Multi-variate Nonlinear, Random Forest and Support Vector Machine soft computing models are deployed to assess the dump slope stability. Numerical modelling has been used to generate error-free datasets for the training and testing of models. Hyperparameter tuning has been done to optimize the performance of the machine learning models. The performance of the models has been analyzed based on the Coefficient of Determination and the Root Mean Square error. The study outcomes reveal that the Multivariate Nonlinear regression model predicts the stability of dump slope structure with better accuracy for the considered datasets. It yields a coefficient of determination of 95.4%, while the root mean square error is only 4.6%.

Keywords: Dump slope stability, industry 4.0, numerical modelling, artificial intelligence

1.0 Introduction

The contribution of opencast mines has increased significantly from 89.70 to 94.44% of the total coal production in our country during the period of 2010 to 2020 (Provisional Coal Statistics Report 2020). The volume of overburden (OB) has also generated in huge volume, and it has been increased from 1038.02 to 1754.06 million cubic meters during the same period. Timely acquisition of land and urbanisation have raised the problem of OB dumping space. Hence, safe dumping of such huge OB and maintenance of giant dump slope structure in a limited space is a significant challenge for the mine operators.

Waste dump of Dagushan Iron Mine, China and Goonyella mine, Australia, failed due to clay and moisture-sensitive material at the basement of dump structure, respectively (Wang and Chen, 2016; Richards et al., 1981). Ouyang et al. (2017) observed that excess pore water pressure could cause a dynamic process of the landslide during the construction of a waste landfill at Guangming, Shenzhen, China. Seasonal fluctuations of the porewater pressure caused instability in the waste dump of European lignite mines (Rahardjo et al., 2007; Rahimi et al., 2010). Several internal (like the geometry of dump structure and geotechnical properties of dump material) and external (like seismicity, rainfall, surcharge loading) factors affect the stability of dump slope structure. Some of the major accidents due to dump slope failure which caused environmental damage and significant loss of life, production and machinery like Aberfan, Wales, UK (1966), Buffalo Creek, USA (1972), Quintette Mrmot, BC, Canada (1985), Guangming, Shenzhen, China (2015), Rajmahal, ECL, India (2016) (Bishop, 1973; Fahey et al., 2002; Blight and Fourie, 2005; Ouyang et al., 2017; Zhan et al., 2018; Satyanarayana et al., 2017). Therefore, dump slope stability analysis has become a central attention point for the mine management to avoid losses due to dump slope instability.

Initially, the limit equilibrium method was proposed to analyze the stability of slope structure. Several versions of limit equilibrium based methods are present, like Fellenius, 1936; Janbu, 1954; Bishop, 1955; Morgenstern and Price, 1965; Spencer, 1967; Generalized Limit Equilibrium (Lam and Fredlund, 1993) and two wedge model (Ulusayet al., 1996). These methods are widely used due to their accuracy, simplicity and speed (Duncan et al., 2014). However, it possesses several shortcomings. For example, it has limited applicability with regard to complex slope structures. It also disregards the level of compaction and the stress strain distribution, thus estimating unrealistic FoS in spite of lateral movements (Pasternack and Gao, 1988; Low, 1997; Pascoe et al., 1998; Abramson et al., 2002).

Currently, numerical modelling is used as a primary tool to overcome the shortcomings of the limit equilibrium method. Although it involves complex and repetitive computation processes with prolonged solution time, it provides accurate

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results with insight into the associated phenomena. It is expensive as well and requires sound knowledge to perform the analysis (Abdalla et al., 2015; Koopialipoor et al., 2019). In recent years, several slope stability problems have been assessed through artificial intelligence with high accuracy (Lin et al., 2018; Ferentinou and Fakir, 2018; Feng et al., 2018; Kothari and Momayez, 2018; Nguyen et al., 2020).

In contrast to the above, data driven analysis methods are less time consuming, robust, flexible and inexpensive (Das et al., 2011; Erzin and Cetin, 2013; Tinoco et al., 2018). Koopialipoor et al. (2019) analyzed the stability of homogeneous slope structures in static and dynamic conditions with hybrid soft computing methods. Artificial neural network (ANN) method was combined with imperialist competitive algorithm (ICA), genetic algorithm (GA), particle swarm optimization (PSO) and artificial bee colony (ABC). The PSO-ANN model possessed the highest accuracy compared to other models. Qi and Tang (2018) evaluated the stability of slope structure using logistic regression (LR), decision tree (DT), random forest (RF), gradient boosting (GrdB), support vector machines (SVM) and multilayer perceptron (MLP) neural network. The study showed that cohesion was an influential primary variable, and the SVM model predicted the stability of slope structure with the highest precision. Kwag et al. (2020) adopted SVM, ANN and Gaussian Process Regression (GPR) to assess the seismic performance of slope structure. It was observed that the difference between the SVM and the nonlinear regression analysis methods was negligible. Moreover, there was a significant improvement in the performance of ANN and GPR, but GPR was relatively more accurate than ANN. Moayedi et al. (2019) examined slope stability through multiple linear regression (MLR), multilayer perceptron (MLP) neural network, radial basis function (RBF) regression, improved SVM using a sequential minimal optimisation algorithm, lazy K-nearest neighbour (KNN), random forest (RF) and random tree models. The coefficient of determination, mean absolute error, root mean square error, relative absolute and root relative squared errors were used to evaluate the efficiency of models. The result showed that RF had the highest predictability than other intelligent models. Numerous soft computing methods have also been successfully applied to assess the stability of slope structures like extreme learning machine, least squares support vector classification, functional networks, naive bayes, chaotic neural network, feed forward neural network, back propagation neural network, adaptive neuro-fuzzy inference system (Samui, 2013; Tinoco et al., 2018; Feng et al., 2018).

In this study, the stability of the multibench dump slope structure is assessed through supervised machine learning methods. Decision tree (DT), gradient boosting (GrdB), multivariate nonlinear (MNL), RF and SVM soft computing models are used for regression analysis. The performance of each model is evaluated based on the coefficient of determination, and root mean square error. The stability state of the dump slope structure (i.e., FoS) is considered as a dependent feature, and geotechnical parameters (density, cohesion, friction angle) and geometrical parameters (total dump height, bench height, bench width, bench slope angle) are assigned as independent features. Response of the models is enhanced by generating accurate datasets using numerical modelling and model optimisation through hyper parameter tunnelling.

2.0 Artificial intelligence

Artificial intelligence (AI) enables the machine, especially computer systems, to perform intellectual tasks like humans by simulating human intelligence in the machine. It helps the machine to learn from the experience. AI can perform several tasks, like learning, planning, reasoning, perception, speech recognition, forecasting, and so on. In this study, AI has been used to predict the stability of dump slope structure using DT, GrdB, MNL, RF and SVM soft computing methods.

Each soft computing model possesses a unique way to establish the relationship between dependent and independent features. The decision tree forecasts the value of the dependent feature by identifying and establishing rules inferred from the whole datasets. Based on ‘if’ and ‘else’ conditions, the working area datasets are divided into treelike structures. DT predicts the dependent features with accuracy at the optimum number of branches of trees (Yeon et al., 2010; Gupta et al., 2019). The gradient boosting model combines many weak models and strengthen them to provide a strong model. Bias or variance of the weak model is reduced by boosting the process (Kotu and Deshpande, 2015). The multivariate nonlinear model uses the least square technique with the minimisation of the sum of errors. This model establishes the relationship between dependent and independent parameters (Moayedi et al., 2019). Random forest consists of several DT model and its prediction is based on the most forecasted output level of the base trees (Gashler et al., 2009; Wu et al., 2014). The support vector model identifies the hyperplane by transforming the original input space into a higher dimensional feature space to forecast the results (Bui et al., 2016; Bui et al., 2019).

3.0 Methodology

Strength reduction method based FLAC 2D software was utilised to generate the errorfree datasets for the training and testing of soft computing models. Total 158 multi bench dump slope structures were simulated. Datasets were divided in the proportion of 7:3 where 70% of datasets were used for training the model and 30% of the datasets were used to test the model performance. Coefficient of determination and root mean square error were the base parameters to examine the performance of models. The coefficient of determination (R^2) measures the variation in the dependent parameter that can be accounted by the model. It can range from 0 to 1. Generally,

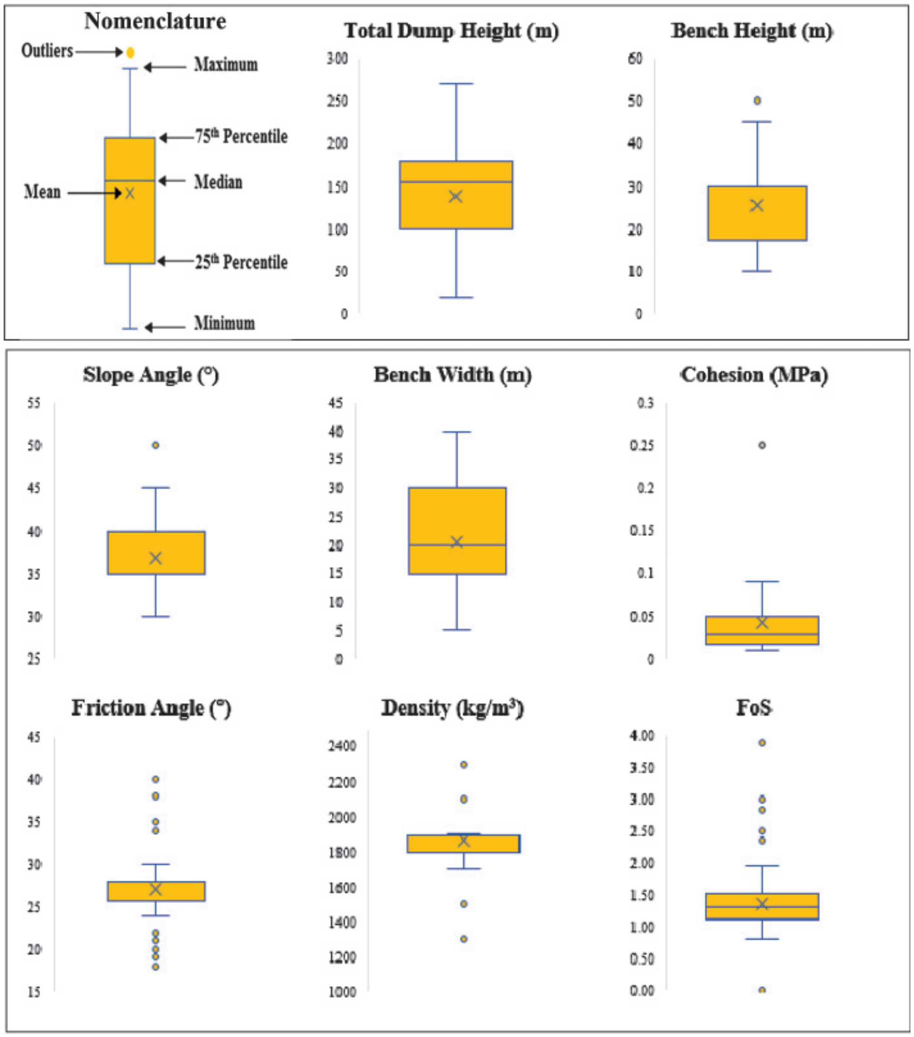

Fig.1: Distribution summary of input and output features

models were trained through 70% of datasets, and the performance of each model was evaluated using the remaining 30% of datasets by comparing the difference between actual and predicted value. Fig.2 shows that MNL has the highest R^2 value (i.e. 95.4%) followed by SVM, GrdB, RF and DT, respectively. The difference between the actual and predicted value is high in DT model and low in MNL model, as shown in Fig.3. GrdB, RF and SVM have a high percentage of error compared to MNL.

Figs.4 to 8 show the difference between the actual and predicted value of FoS in testing datasets of different machine learning models.In DT (Fig.4) and RF (Fig.7), the predicted value coincided with the actual value in very few casesonly. The prediction capability improved to some extent in the case of Grd B and SVM (Fig.5 and 8). The MNL model forecasted the FoS value closer to the actual value than the other models (Fig.6). All these plots indicated that the proportion of underestimated values was higher than overestimated values against the actual values of the FoS. In DT and SVM, the proportion of underestimated values were slightly higher, whereas, in GrdB and RF, very few cases were

it is observed that the model predicts the dependent parameter precisely when the R^2 value is closer to 1. Root mean square error (RMSE) shows the average error between the actual and the indicated value.

4.0 Results

Total dump height, bench height, bench slope angle and bench width were considered in geometrical parameters and cohesion, internal angle of friction and density were included in geotechnical parameter. The geotechnical and geometrical parameters were the independent features and FoS was the dependent feature. The range and distribution of each feature are shown in Fig.1 in the form of a box plot. The minimum, maximum, different percentiles, mean, median and outliers of each parameter are shown in the box plot. Total dump height and bench width are free from outliers, while bench height, slope angle, and cohesion have only one outlier. However, friction angle, density and FoS have significant outliers.

DT, GrdB, MNL, RF and SVM supervised machine learning

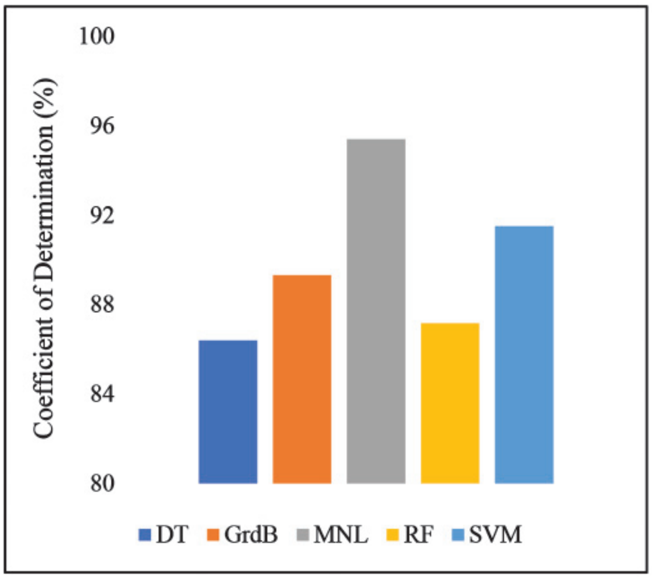

Fig.2: Coefficient of determination of machine learning models

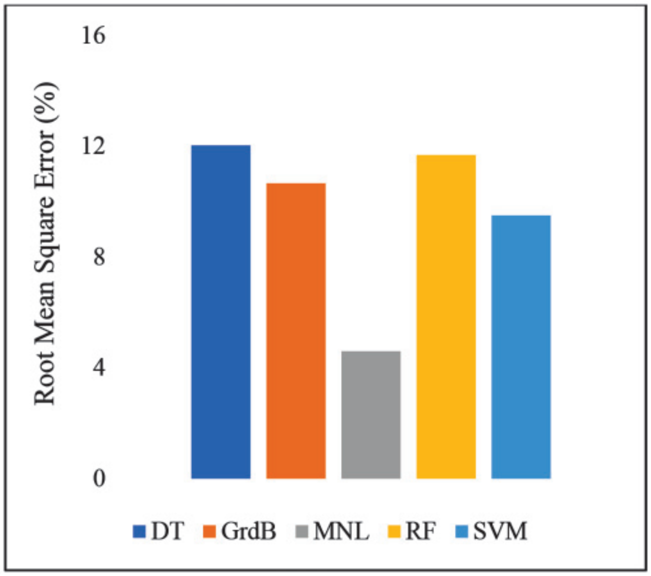

Fig.3: Root mean square error of machine learning models

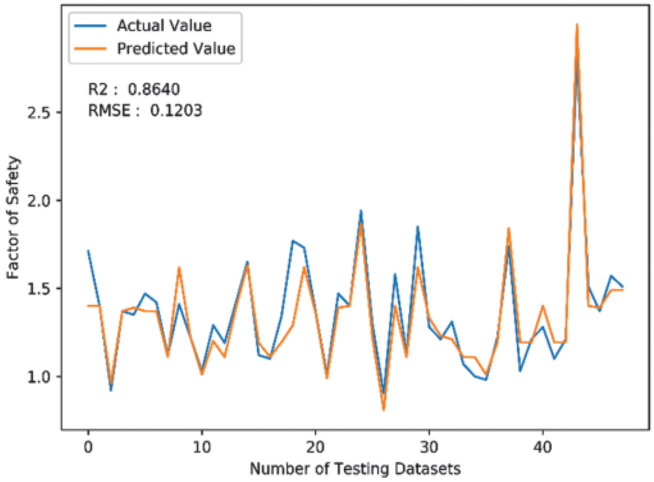

Fig.4: Decision tree based actual vs. prediction value

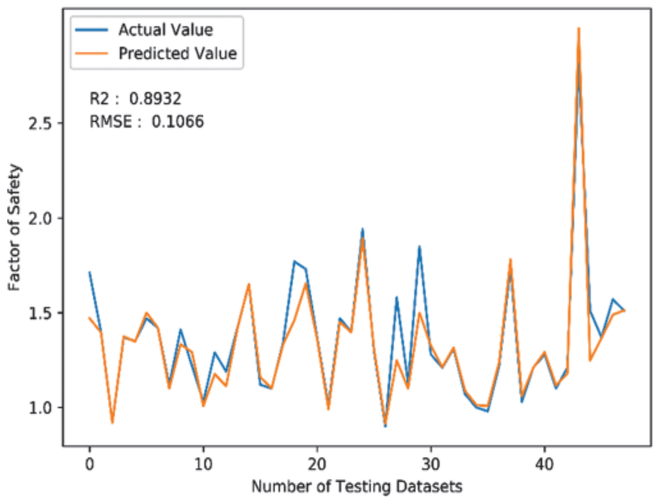

Fig.5: Gradient boosting based actual vs prediction value

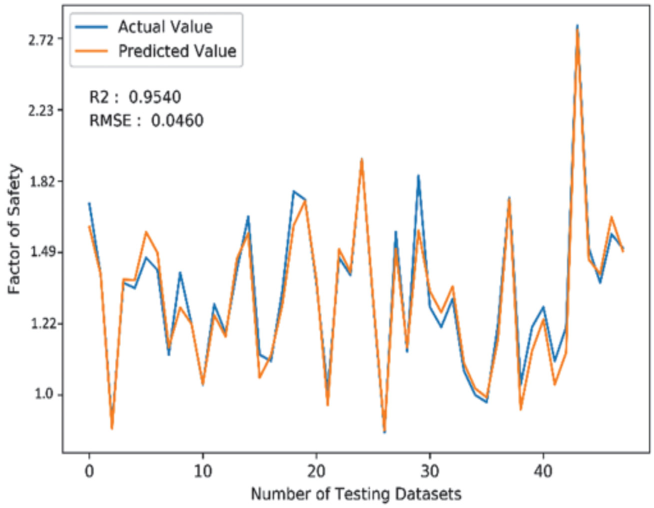

Fig.6: Multivariate nonlinear based actual vs prediction value

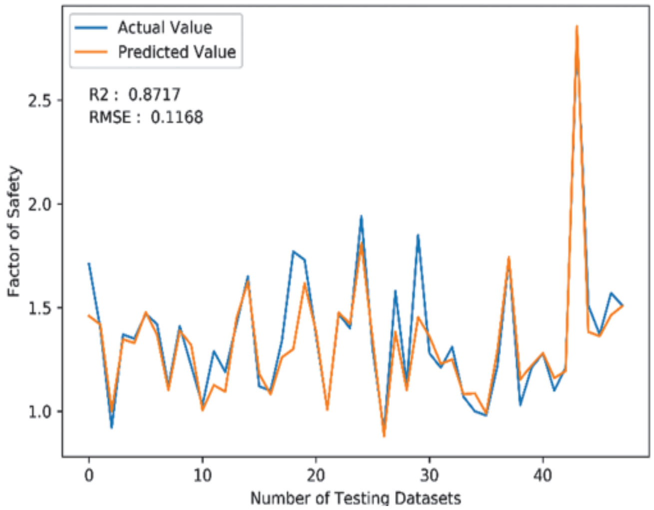

Fig.7: Random forest based actual vs prediction value

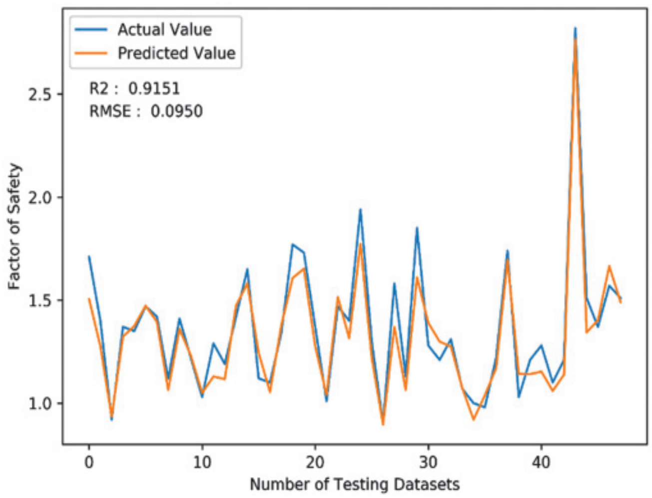

Fig.8: Support vector based actual vs prediction value

TABLE 1: OPTIMAL HYPERPARAMETERS OF CLASSIFIERS

Machine learning models		Hyper parameters	
DT		Max depth = 20	
GrdB	Learning rate = 0.3	n_estimators= 90	Max Depth = 4
RF	Max depth = 12	n_estimators = 10	
SVM	C = 4	Gamma = scale	Kernel = rbf epsilon=0.1

overestimated. In MNL, both overestimated and underestimated values were present, but significant predictions coincided with the actual value.

The performance of each soft computing model was optimised through hyper parameter tuning. Table 1 shows some of the major governing hyper parameters of DT, GrdB, RF and SVM models. The remaining hyper parameters, including the MNL model, were set to their default value. Max depth is the depth of a tree where all leaves are pure. The learning rate shrinks the contribution of each tree. The n_estimators provide the number of boosting stage during the analysis process. The kernel is used to solve the lower dimension data into higher dimension due to a set of mathematical function. "C" is the regularisation factor. Epsilon specifies the epsilontube where no penalty occursduring the training loss function with points forecasted within a distance epsilon from the actualvalue.

5.0. Discussion

Scientific studies regarding the stability analysis of dump slope structure are continuously evolving to avoid instability and provide accurate results in minimum time with less effort. Currently, numerical simulation provides the result with more accuracy and insight. However, it is a time consuming, expensive analysis method and requires sound knowledge. Therefore, in alignment with the digital transformation of the production industry and value creation process, this study has generated errorfree datasets through numerical modelling analysis method and forecasted the stability of multi bench dump slope structure using artificial intelligence. It was noted that total dump height and bench width furnishes additional insight into the instability analysis of giant dump slope structures (Gupta et al., 2018 and 2019). Consequently, total dump height and bench width parameters were also incorporated along with the already proven stability governing parameters (bench height, bench slope angle, cohesion, density and frictionangle) (Lin et al., 2018; Qi and Tang, 2018; Luo et al., 2019; Chebrolu et al., 2020). The application of artificial intelligence reduced the analysis time significantly compared to numerical modelling. All machine learning models performed well with a minor error. The performance of the model depends on the accuracy of training datasets. In addition to this, hyper parameter tuning plays a crucial role in deciding the optimal performance of the model.

6.0 Conclusions

In this study, the stability of the multi bench dump slope structure has been assessed using the supervised machine learning method. Total dump height, bench width, bench height, bench slope angle, cohesion, friction angle and density parameters have been considered for instability analysis. Among the DT, GrdB, MNL, RF and SVM soft computing models, MNL and SVM had a coefficient of determination of more than 90%, but the error of SVM was twice the error of MNL. DT model had the lowest R^2 and RMSE value. Therefore, MNL soft computing method is suggested as an efficient model to forecast the instability of multi bench dump slope structure for the considered range of input parameters and analysis method. This trained soft computing model function can be used to assess the stability of the dump slope structure with ease.

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