ABSTRACT

Support pillars are an essential structure found throughout the mining industry. The primary purpose of such pillars is to provide stability during the extraction of ores. The traditional method of determining pillar stability is to calculate the safety factor, defined as the ratio of pillar strength to pillar load. The pillars are considered to have failed when the safety factor falls below one. Various methodologies, such as tributary area theory, numerical modelling, and other computational methods, are used to estimate the pillar load. Similarly, empirical equations obtained from the examination of failed and stable situations can be used to determine the strength of the pillars. As the mining advances deeper, pillar failure becomes more common and critical because of the significant increase in ambient loads. Because of their relevance in the safe and cost-effective extraction of underground ores, mine pillars and their design have been examined by several researchers.

Every generation of rock engineers has tried to establish the best ways for effective designs for pillars. However, no ideal solution has yet been found to incorporate all of the essential variables contributing to the pillars' stability mechanics. Even the interaction of these parameters on mine pillar mechanics is subject to ongoing adjustment. Recently, mathematical techniques and software have been successfully used to analyze the relative influence of this multi-parametric phenomenon.

Over the past decades, deterministic (empirical, statistical, or analytical) methods for estimating mine pillar stability have been developed. Researchers have been very much attracted to machine learning algorithms(ANN) and statistical tools such as PCA, SSE techniques.

Given the above, the main objective of this thesis is to :Investigate the suitability of different machine learning (ML) algorithms to predict pillar stability of hard rocksin underground mining. Develop a robust and transparent modelexplaining the impact of features and simultaneously for the assessmentand final predictionof the stability of the support pillars.

The collateral objectives are:To develop a research methodology for the comparison of the performance of different Supervised Learning (SL) algorithms Feature ranking to obtain the discriminating ability of different features in the prediction of pillar stability.To investigate the relative importance of influencing variables affecting pillar stability in underground mining.To select pillar stability parameters affecting factor of safety by Principle Component Analysis (PCA) and Step-wise Selection and Elimination (SSE) techniques in underground mines, and to develop a suitable model using PCA and SSE for statistical analysis and validate the obtained equation or model with the remaining data.

This study attains significance in light of newer challenges posed to underground mining. As underground mining is getting deeper, the risk and cost of production are also at high risk. To handle these risks, we need to study the challenges like rockbursts, gas outbursts and redistributed stresses etc., posed by the pillars in underground mining, reduce risk factors, and increase production. As we move into the new digital era, the rise of novel approaches like artificial intelligence, PCA, and soft computing has entered every research field. The studies of these methods could give valuable ideas in improving the understanding of pillar stability in underground mining, further reducing the risk and increasing ores production.

Machine learning algorithms and Statistical tools such as PCA, SSE ANN, etc., were used to understand the pillar stability conditions and improve the prediction performance of pillar stability of underground mines. For the prediction of pillar stability (PS), two input parameters, namely, w/h ratio (pillar width to pillar height) and the ratio of average induced pillar load (PL) over the uniaxial compressive strength (UCS) of the intact rock (PL/UCS) has been used. The output of pillar stability is characterized into three classes: a). Stable b). Unstable and c). Failed

Three principles for selecting parameters have been relied upon for establishing the classification models. Firstly, the sensitive and stable parameters reflecting properties of pillar stability should be used as the discriminant indicators. Secondly, the parameters should be physically independent of each other. Finally, the parameter data should be obtained easily or readily available.

Due to the importance of features, the feature ranking algorithm, namely: fuzzy rough attribute evaluator, was used to obtain the rank of the features in the classification task. Experiments were conducted using various classification algorithms, namely Naïve Bayes, PART, Jrip, SMO, and Random Forest(RF), by changing the number of features from most significant to least significant.

The relative evaluation of the prediction of the five machine learning algorithms was performed by utilizing threshold-dependent and threshold-independent parameters. These parameters were calculated from the values of the confusion matrix, namely: True Positives (TP) (the number of correctly predicted pillar stability), False Negatives (FN) (the number of incorrectly predicted pillar stability), True Negatives (TN) (the number of correctly predicted pillar un-stability with failure) and False Positives (FP) (the number of incorrectly predicted pillar un-stability with failure). Accuracy, Area under the curve (AUC), and Mathew's correlation coefficient (MCC) were determined for each case.TheReceiver Operating Curve (ROC) was used to represent the classifiers visually.

From the present research, the following conclusions have been drawn:

The best performance was produced by Random Forest with an accuracy of 83.3%, AUC of 0.920, and MCC of 0.740. Ranking of different features based on fuzzy rough feature evaluator in which pillar width to pillar height ratio got the maximum rank value of 0.04185 this shows the importance of this feature.The PCA technique selected two important parameters affecting Pillar Strength, W/H and UCS. On the other hand, the SSE technique selected W/H and B(Gallery Width). The R^2value for the developed model using PCA in predicting pillar strength was 0.86, and the root mean square error was 0.112. Similarly, for SSE, it was 0.84 and 0.123, respectively. The PCA has a better ability to predict the pillar strength. The validation performed on the proposed model by PCA and SSE(using the datasets shown in Table B of the annexure) showed that we can express a higher level of statistical assurance on the proposed models.PCA has better accuracy in the prediction of Factor of safety(FoS). The comparison curve for FoS strengthens the result that the PCA has higher assurance in the prediction of FoS than SSE.