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Internet of Things-based Intelligent Prediction Framework for Pillar Stability Analysis of Underground Mines

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Abstract

It is crucial to forecast pillar stability in underground mines because weak pillars might provide serious collapse risks. We offer two ground-breaking models—the random forest (RF), C4.5 decision tree (DT), and support vector machine (SVM) algorithms—to address this important issue in the context of IoT for underground mining. These models seek to precisely forecast pillar stability in both stone and coal mines. The W/H ratio, the uniaxial compressive strength of the rock (ucs), the pillar stress (p), the width (W) and height (H) of the pillar, as well as other crucial characteristics, are all used to estimate the stability of pillars. These factors are used as inputs, and the result is the stability of the pillars in the deep mines. Several performance measures, including accuracy, precision, recall, and F1-score, are used to assess the performance of the models. We show that both the RF and C4.5 DT models showed impressive accuracy in forecasting pillar stability through a thorough performance evaluation over the SVM algorithm. Additionally, we contrast the outcomes of our proposed RF algorithm with those of other models already in use, particularly the support vector machine (SVM) and DT, to see whether our model is superior. According to the comparison analysis, the suggested RF model stands out as a valid and workable method for assessing the stability of pillars in deep mines inside the IoT framework.

Keywords: Underground Mines, Internet of Things, Machine Learning, Random Forest, Decision Trree, Support Vector Machine.

1. Introduction

Most underground mines rely heavily on pillars, which serve as critical structural units for maximizing safety and efficiency in ore extraction. A pillar is "the in-situ rock between two or more underground openings," as described by Coates [1]. During excavation and mining, its principal function is to keep workers safe by separating nearby underground apertures and supporting the weight of overburdened material temporarily or permanently [2-7]. Workers are at greater risk of injury from unstable pillars, and the risk of a rapid roof collapse is also increased [8]. In addition, as mining proceeds deeper, ground tensions increase, making pillar failure more common and catastrophic. Therefore, it is crucial to ascertain pillar stability to achieve productive and secure mining.

For the last few decades, numerous academics have developed multiple ways of studying and predicting pillar failures. The factor of safety (FoS) is the ratio of the pillar strength to the load acting on the pillar structure and is commonly used to assess pillar stability. Theoretically, the pillar is secure when the FoS ratio exceeds 1. Nonetheless, research indicates that pillars with FoS beyond this threshold may fail because of irregular geometries, unclear material characteristics, and variations in mining processes [7, 9].

Predictions of pillar durability that consider the characteristics of materials and complex boundary conditions are often made using numerical simulation methods. Shnorhokian et al. [10] used FLAC3D with mining sequence possibilities to foretell pillar equilibrium. Random field theory and an elastoplastic finite element method (FEM) were combined by Griffths et al. [11] to predict pillar durability. Jaiswal et al. [12] researched the stress-strain behavior of coal pillars using a finite element method (FEM) analysis in three dimensions. The Finite-Discrete Element Method (FDEM) was created by Li et al. [13] to investigate pillar failure modes and mechanical behavior. The pillar collapse mechanism and the non-linear rock behavior were studied by Mortazavi et al. [14] using the rapid Lagrangian analysis of continuum (FLAC). Numerical simulation methods have a high degree of imprecision because of the anisotropy of rock mass and the complexity of its non-linear properties [11].

Practical applications of machine learning (ML) algorithms for pillar safety assessment have been made as more and more pillar stability examples become available. Artificial neural networks (ANN) were used by Tawadrous and Katsabanis [15] to investigate the durability features of the surface crown pillars. Ding et al. [16] analyze the feasibility of using the stochastic gradient boosting (SGB) model for pillar stability prediction. Research showed that compared to the random forest (RF), multilayer neural perceptron (MPNN), and support vector machine (SVM), the proposed model performed better. Wattimena [9] presented the multinomial logistic regression (MLR) for forecasting the pillar's stability. The pillar stability charts were created by Ghasemi et al. [17] using the SVM and J48 algorithms. Both models improved to a point where their predictions were reliable. Zhou et al. [18] evaluated the pillar stability of underground mines using support vector machines and fisheries discriminant analysis (FDA). Six different supervised machine learning techniques for pillar stability analysis were compared by Zhou et al. [19]. The study found that SVM and RF were significantly more effective. Most ML algorithms used to anticipate the pillar's stability have been put into practice effectively, but they all have drawbacks. Consider the a priori needs when using an ANN technique, such as the optimal model structure (including the number of hidden layers and model inputs, training procedures, and transfer functions). This is usually accomplished by a method of trial and error. The ANN model's primary flaw is its opaque forecasting mechanism. A matrix of weights and biases, which is not user-accessible, describes the connection between input and output variables [20]. Decision trees, such as random forest (RF), C4.5 decision trees (DT), and Support Vector Machine (SVM), have recently seen widespread success in a variety of domains and applications, including the prediction of surface settlement due to tunnelling and the assessment of soil liquefaction potential [21,22]. However, their use in rock mechanics and mining remains primarily confined to the former two areas.

Predicting pillar durability in underground coal and stone mines is the primary focus of this research. To accomplish this goal, two models for predicting pillar stability are developed using RF, C4.5 DT and SVM algorithms. While these methods have been successfully applied in other contexts, a literature survey reveals that they have only been lightly investigated for use in evaluating rock mechanic mining. In contrast to different soft computing approaches, the RT and C4.5 DT algorithms may produce a detailed and understandable tree diagram.

Here is how the rest of the paper is structured: The datasets used to ensure the stability of pillars in underground mines are briefly described in Section 2. An overview of the random forest, C4.5 decision tree, and SVM methodologies are presented in Section 3, along with the methodology used to forecast the stability of pillars in an underground mine. The creation of

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the forecasting models is detailed in Section 4. Section 5 presents the proposed models' detailed results organised by performance criteria, while Section 6 draws conclusions and makes recommendations based on those results.

2. Description of Database

To evaluate the efficacy of the proposed RF, C4.5-based DT, and SVM models, this research drew on the pillar stability database amassed by Jaiswal and Shrivastva [26], Mohan et al. [27], and Esterhuizen et al. [28]. Table 1 displays data from underground stone mines in the United States and Indian coal mines that were recently cited by Zhou et al. [18]. Information such as pillar height (H), stress (p), and uniaxial compressive strength of the rock (ucs) are stored in the database. Also included is the pillar width (W).

Table 2 displays the values that can be expected from each of the input variables. Researchers like Goodman [29] agree that Zhou et al.'s [18] choice of input parameters is a full and appropriate set to predict the pillar stability. Many other studies (such as Liang et al. [30]) have also relied heavily on these same characteristics. Table 2 gives a brief summary of the values for each input variable.

According to the pillar failure process and the instability mechanism, the database of pillar case histories is split evenly between successful (14 cases) and unsuccessful (32 cases). Three typical processes of pillar failure due to natural fracture are depicted in Figure 1 [31]. Failure can occur as a result of (a) the lateral kinematic release of pre-formed blocks due to increasing vertical load and lack of confinement, (b) the accumulation of inclined shear fractures that transect the pillar, which is most common in pillars with a relatively low W/H ratio, and (c) failure along with transgressive fractures where the fracture inclination angle with the principal loading axis of the pillar exceeds the angle of friction. The mechanical response of a pillar is particularly pronounced for the thin pillars in all of these mechanisms because of the ground's underlying geological characteristics. The combination of brittle and shearing processes increases the likelihood that broader pillars may collapse. When evaluating the strength, permeability, and deformability of rocks, geological discontinuities in rock strata are crucial. The initial step in learning more about the overall behaviour of rock masses is to characterise the discontinuity in geometry (such as spatial connectedness, persistence length, aperture, and so on) [32]. It is commonly accepted that rock strength qualities are significantly impacted by discontinuities in rock profile. Several cases can be cited from the rock failure literature where the effect of discontinuities on rock strength was underestimated and led to failure. According to Jessu and Spearing [33], even at higher W/H ratios, discontinuities have a significant impact as pillar inclination rises. Using data from laboratory experiments, Shang et al. [34] attempted to quantify the tensile strength of developing rock discontinuities. Data collection is the biggest problem faced for the indicators' applicability, despite the fact that they are considered the fundamental factors for quantitatively detecting the activities in the framework of the pillar. This study therefore takes into account these five factors.

In this work, we considered a total of 40 datasets for the training dataset when applying the RF, C4.5 DT, and SVM for the testing dataset. Both the test and training sets were taken directly from Zhou et al.'s [18] work.

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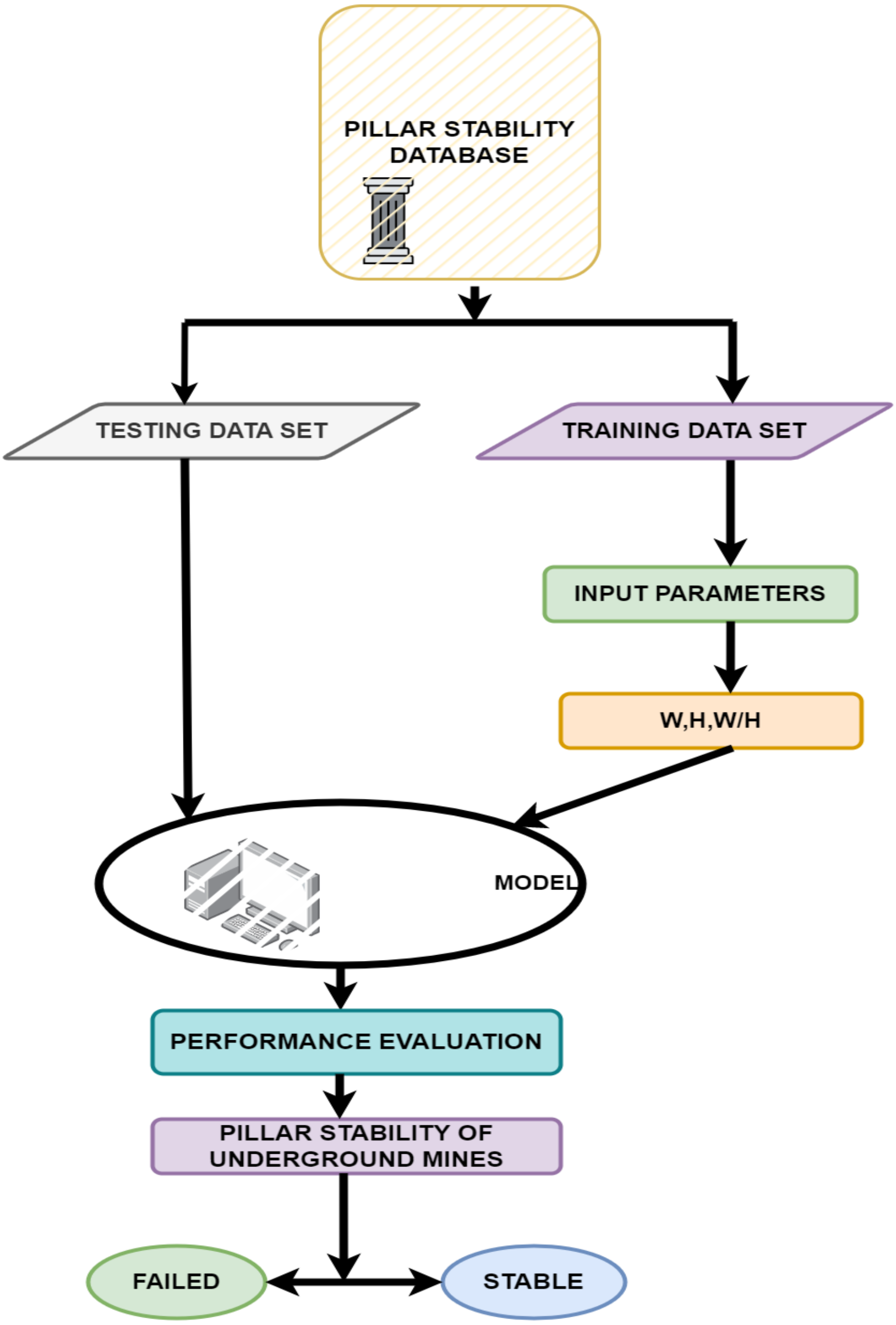

Figure 1: Overview architecture of the proposed framework.

3.System Model

There are many data mining and machine learning (ML) techniques available; for classification, the most popular ones are random forest (RF), C4.5 decision trees (DT), and SVM [24]. These algorithms, which are represented as decision trees, employ a divide-and-conquer strategy through induction learning. The classification of patterns within datasets is made possible by the tree structure, which is a hierarchically connected network of nodes. Each internal node evaluates a decision constant in respect to an input characteristic or feature to determine the following descending node. The task of locating instances that match a given label falls to the leaf nodes [35].

3.1Random Forest

One of the most well-liked and successful machine learning techniques is the Random Forest algorithm, which is particularly good at forecasting conditions in underground mines. Its appeal stems from the fact that it needs little effort to model and prepare data while continuously producing findings that are quite accurate. As was already noted, Random Forest relies on the idea of decision trees but instead of using a single tree to make predictions, it generates a group of trees, which it appropriately calls "Random Forests." Compared to employing individual decision trees, this ensemble approach improves prediction accuracy.

The Random Forest algorithm functions as follows in the context of forecasting conditions in underground mines: A random subset of n variables is chosen from the feature set and placed at each node of the decision tree. The optimal split is then decided by the algorithm using these randomly selected factors. Each tree in the forest goes through this process repeatedly, developing on its own using a different subset of the initial dataset.

The Random Forest's power lies in its capacity to produce numerous decision trees and combine their forecasts through voting or averaging. The risk of overfitting is decreased by this aggregation procedure, which also produces a more stable and reliable prediction model. Additionally, the variety among the different trees is ensured by the randomness added during variable selection and bootstrapping, resulting in a more generalised and precise overall forecast.

The Random Forest method performs exceptionally well when used to forecast conditions in underground mines. It is ideally suited to capturing the complicated correlations between various features and mine conditions due to its capacity to handle large and multidimensional data sets. The Random Forest can accurately forecast likely future conditions by examining previous data on mine conditions and the accompanying features, offering insightful information to mine operators and safety experts. Algorithm 1 shows how this algorithm for predicting underground mines operates and how the collection of decision trees works together to get the final forecast. Ultimately, Random Forest has become a potent instrument for underground mine prediction, providing accurate and dependable solutions to raise mining operations' safety and efficiency.

Algorithm-1 Random forest algorithm

```
RandomForestAlgorithm(dataset, num_trees, num_features):
forest = []
for t in range(num_trees):
    selected_features = random_subset(num_features, dataset.num_features)
    bootstrap_sample = bootstrap_sampling(dataset)
    decision_tree = build_decision_tree(bootstrap_sample, selected_features)
    forest.append(decision_tree)
return forest
PredictCondition(random_forest, new_data):
predictions = []
  for tree in random_forest:
    prediction = make_prediction(tree, new_data)
    predictions.append(prediction)
    final_prediction = aggregate_predictions(predictions)
return final_prediction
```

The primary function that creates the Random Forest in the pseudo-code above is called RandomForestAlgorithm. The dataset containing historical information on mine conditions and the value num_trees, which specifies the number of decision trees to be created in the forest, are provided as inputs. The number of features that will be taken into account at each split when building the tree is num_features.

Based on the trained Random Forest (random_forest), the PredictCondition function predicts the condition of a new data point (new_data). It creates forecasts for each tree in the forest, then aggregates the outcomes to arrive at the final projection.

3.2Decision Tree

The Decision Tree algorithm with the C4.5 (or ID3) algorithm is a potent method for building a tree-based model that can forecast mine conditions based on input data in the context of underground mines prediction. The ID3 algorithm, created by Ross Quinlan, is expanded upon in the C4.5 algorithm. A thorough explanation of the Decision Tree with C4.5 algorithm is provided below:

1. Data Preparation: The dataset including historical data on mining conditions and the relevant features must first be prepared. Each data point represents a particular mine state, and the features list several characteristics related to that situation.
2. Selection of Attributes: The C4.5 algorithm builds the decision tree using a top-down, recursive method. Based on the attribute's capacity to maximise information gain or gain ratio, it chooses the optimum attribute to split the data at each node of the tree. Information gain quantifies the decrease in entropy (or impurity) of the data following attribute splitting, whereas gain ratio takes into consideration the intrinsic information of the attribute.
3. Data Splitting: After the best attribute has been chosen, the dataset is divided into subsets according to the distinct values of the attribute. The approach builds sub-trees for each branch of the decision tree using each subset as a representation of a branch.
4. Missing Values Management: The C4.5 algorithm can handle missing values in the dataset. In order to accommodate missing values during attribute selection and data splitting, it either assigns the majority class or computes the weighted average of the class distribution.
5. Pruning: The C4.5 algorithm uses pruning strategies after building the tree to prevent overfitting. Pruning entails cutting out branches that don't make a meaningful difference in boosting prediction accuracy. This keeps the tree's generalisation ability while simplifying it.
6. Assignment of Leaf Nodes: The decision tree's leaves correspond to the expected conditions in the mine. The projected condition for each branch of the tree is given as the majority class, or the class that occurs the most frequently in each leaf node.
7. Prediction: The decision tree can be used to anticipate the state of fresh data points after it has been built. The tree moves along the branches based on the values of the input features starting at the root node and continues until it reaches a leaf node, which offers the expected mine state.

The C4.5 method is well-liked because it can handle both categorical and numerical variables and can create decision trees that can be understood by humans. However, it could experience overfitting, like other decision tree algorithms, particularly if the tree is overly complex. As was already mentioned, the use of Random Forest reduces overfitting by combining many decision trees.

Algorithm-2 C-4.5-based Decision Tree Algorithm

```
DecisionTreeC45Algorithm(dataset, features):
 if all_data_points_belong_to_same_class(dataset):
return LeafNode(class_label)
if no_more_features_to_split(features) or maximum_depth_reached()
return LeafNode(majority_class_label)
    best_attribute = select_best_attribute(dataset, features)
    decision_node = DecisionNode(best_attribute)
    subsets = split_dataset(dataset, best_attribute)
    for subset_value, subset_data in subsets:
    sub_tree = DecisionTreeC45Algorithm(subset_data, remaining_features(features, best_attribute))
        decision_node.add_branch(subset_value, sub_tree)
    return decision_node
PredictCondition(decision_tree, new_data):
    current_node = decision_tree
    while current_node is not LeafNode:
        attribute = current_node.attribute
        value = new_data[attribute]
        current_node = current_node.get_branch(value)
    return current_node.class_label
```

DecisionTreeC45 is used in Algorithm 2.The C4.5 algorithm's primary purpose in decision tree construction is algorithm. It accepts a dataset containing historical information about mine conditions as input, along with features that describe the attributes needed to segment the dataset. By choosing the optimal attribute for splitting, making decision nodes, and adding branches to represent the different subsets of data, the function iteratively constructs the decision tree. Based on the trained decision tree (decision_tree), the PredictCondition function is used to forecast the condition of a new data point (new_data). Starting at the root node, it moves up the tree, following branches based on the input feature values, until it reaches a leaf node. The leaf node's class label is then used to determine the projected mine condition.

3.3Support Vector Machine Algorithm

The Support Vector Machine (SVM) algorithm is a potent and commonly utilised machine learning technique in the area of predicting subterranean mines. It is possible to use the supervised learning algorithm SVM for both classification and regression problems. Finding the separating hyperplane that best splits the data points into different classes while maximising the distance between the hyperplane and the nearest data points (support vectors) is its main goal. SVM ensures improved generalisation and robustness of the model by maximising the margin. By utilising the kernel approach, which raises the initial feature space's dimension, SVM can handle both linearly and non-linearly separable data.

This enables SVM to separate data points even when they are not linearly separable in the original space using a hyperplane. SVM is useful in underground mine prediction because it can handle high-dimensional feature spaces and noisy data, where different variables are connected to mine conditions. To obtain best performance, hyperparameter adjustment and the computational cost of SVM should be taken into account. Despite these factors, SVM continues to be a well-liked and dependable option for predicting conditions in underground mines, offering precise insights into mine conditions and improving safety and operational effectiveness.

Algorithm-3 Support Vector Machine Algorithm Pseudocode

```
SVMAlgorithm(dataset, C, kernel, kernel_params):
    X, y = prepare_data(dataset)  # X contains feature vectors, y contains corresponding labels
    X_scaled = feature_scaling(X)  # Normalize or standardize features
    model = train_svm(X_scaled, y, C, kernel, kernel_params)
    return model
PredictCondition(svm_model, new_data):
    new_data_scaled = feature_scaling(new_data)
    prediction = predict_svm(svm_model, new_data_scaled)
    return prediction
```

The primary function that implements the SVM algorithm for underground mines prediction in the aforementioned pseudo-code is SVMAlgorithm in Algorithm-3. The dataset containing historical data on mine conditions is provided as input, along with the C parameter controlling the trade-off between maximising margin and minimising classification error, the kernel specifying the kernel function to use (e.g., linear, polynomial, radial basis function, etc.), and kernel_params denoting any additional parameters needed by the selected kernel function.

The function prepare_data takes the dataset's feature vectors X and related labels Y and extracts them. The function feature_scaling scales the feature vectors to a common scale by normalising or standardising them. Using the scaled feature vectors X_scaled and the labels y, the train_svm function trains the SVM model. It creates the ideal hyperplane that divides the data points using the supplied C and kernel together with its related kernel_params. PredictCondition is a function that uses the trained SVM model svm_model to forecast the condition of a new data point new_data. It utilises feature_scaling to scale the new data before applying the SVM model to forecast the value of the new data point.

4.Dataset Description

The proposed C4.5-based decision tree, Support Vector Machine (SVM), and Random Forest models were evaluated and their performance was compared using a pillar stability database that had previously been compiled by Jaiswal and Shrivastva [26], Mohan et al. [27], and Esterhuizen et al. [28]. The dataset, which was most recently cited by Zhou et al. [18], comprises of 46 pillar examples from both Indian and American underground coal mines. The database contains a number of input variables, including the pillar W/H ratio, pillar stress, and uniaxial compressive strength of the rock (ucs). Based on the failure process and instability mechanisms discovered in the pillars, the database's pillar instances are divided into two categories: stable (14 cases) and failed (32 cases).

Three typical failure modes for naturally fractured pillars are shown in Figure 1. These include failure with lateral kinematic release of pre-formed blocks due to increasing vertical load and lack of confinement, failure from inclined shear fractures traversing the pillar (common in pillars with low W/H ratios), and failure along transgressive fractures where the fracture inclination angle exceeds the angle of friction. Particularly for thin pillars, a pillar's mechanical reaction is intimately correlated with the geological composition of the ground, but larger pillars are more susceptible to collapse as a result of a confluence of brittle and shearing forces. The strength, permeability, and deformability of rock masses are greatly influenced by the existence and features of geological discontinuities. Analysing the behaviour of rocks requires an understanding of the geometry and characteristics of these discontinuities. For the purpose of quantitative analysis and pillar stability prediction, the study focuses on five primary parameters: pillar width, pillar height, pillar W/H ratio, pillar stress, and uniaxial compressive strength of the rock. Although gathering data to evaluate the relevance of these indicators remains difficult, they are thought to be essential for examining pillar activities in the context of the current research.

5.Results and Discussions

The accuracy, precision, recall, and F-score performance metrics for the three algorithms -- RF, DT with C4.5, and SVM -- when trained on the underground mines dataset for the "failed" class are shown in the barplot in Figure 2. The outcomes demonstrate how well each algorithm predicted the failed class. With the highest accuracy, precision, recall, and F-score among the three algorithms, RF outperforms the competition on all criteria. This shows that the majority of failed instances are correctly classified by RF, leading to fewer false positives and false negatives and a more accurate and dependable forecast. While accuracy, precision, recall, and F-score fall between the best and worst performing algorithms, DT with C4.5 exhibits intermediate performance. It does reasonably well in forecasting the failed class, but the RF method outperforms it. Although SVM is regarded as a powerful algorithm in many applications, it performs minimally in this situation. In comparison to the other methods, SVM has considerably poorer accuracy, precision, recall, and F-score. This suggests that SVM has trouble correctly identifying instances of the failed class, which results in more misclassifications and less accurate prediction.

When three algorithms—RF, DT with C4.5, and SVM—were tested on the underground mines dataset for the "failed" class, the accuracy, precision, recall, and F-score metrics for each are shown in the barplot in Figure 3 for the "failed" class. In every statistic, RF exceeds the competition, showing the highest accuracy, precision, recall, and F-score. This shows that the majority of the test set's unsuccessful cases are accurately classified by RF, resulting in fewer false positives and false negatives and a more accurate and balanced forecast. With its accuracy, precision, recall, and F-score falling between RF and SVM, DT with C4.5 exhibits intermediate performance. Although it predicts the failed class in the test set rather well, RF performs better all around. Despite having a reputation for being a strong algorithm in many applications, SVM performs poorly in this situation. When compared to the other algorithms in the test set, it displays much worse accuracy, precision, recall, and F-score. This shows that SVM has difficulty correctly identifying instances of the failed class, which results in more incorrect classifications and fewer precise predictions. In conclusion, the barplot's outcomes show that RF, followed by DT with C4.5, is the most successful method for predicting the "failed" class in the underground mines dataset. SVM performs poorly in this particular prediction job, hence RF is recommended for obtaining reliable and accurate results.

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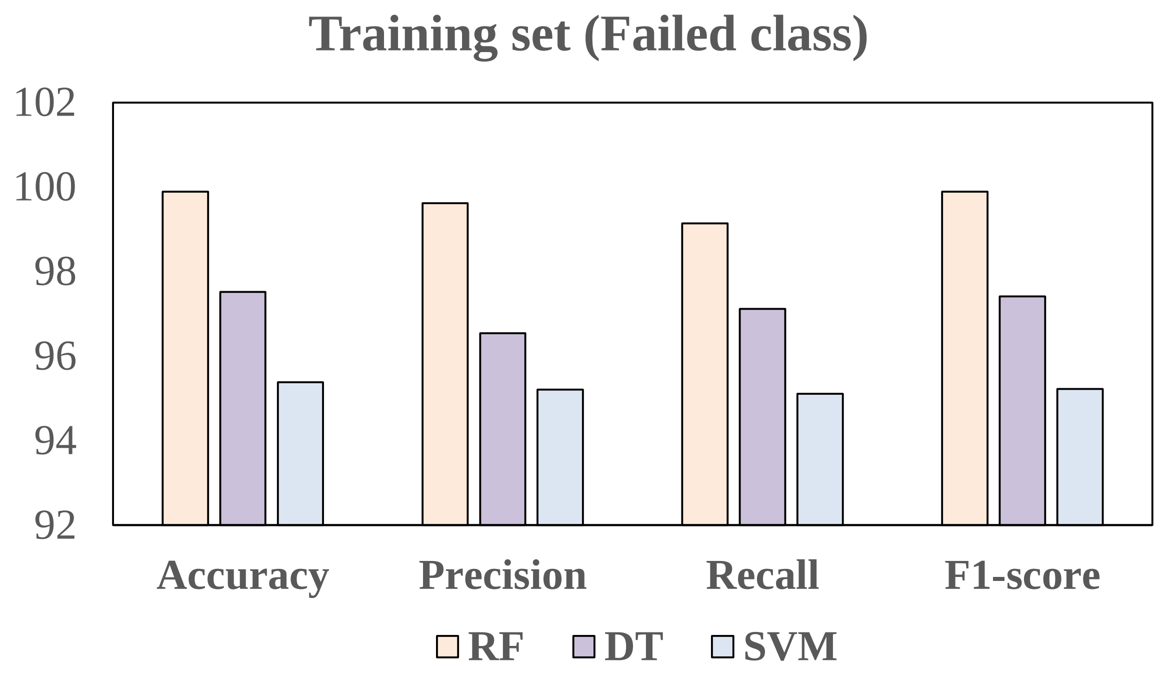

Figure 2: Comparison of performance metrics for different machine learning models over the training set for failed classes.

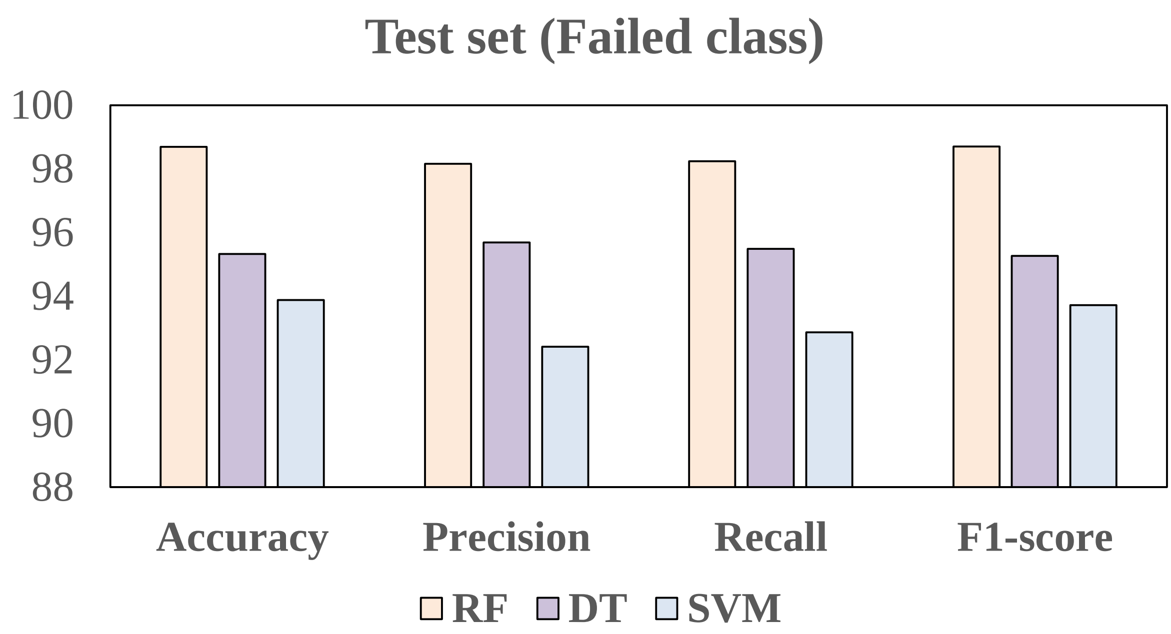

Figure 3: Comparison of different performance parameters for different machine learning models for test set of the failed class.

In Figure 4, the barplot comparison for accuracy, precision, recall, and F1-score performance metrics for the three algorithms like RF, DT with C4.5, and SVM, when trained on the underground mines dataset for the "stable" class are shown in the barplot. The findings are intended to evaluate how well each method predicts occurrences of the stable class. In terms of all measures, RF performs best, outperforming the other two algorithms in terms of accuracy, precision, recall, and F1-score having respective values of 97.67, 97.41, 97.12, and 97.67. This suggests that RF correctly categorises the vast majority of stable cases in the training set, producing fewer false positives and false negatives and producing a more accurate and balanced forecast. While accuracy, precision, recall, and F1-score fall between the best and worst performing algorithms, DT with C4.5 exhibits average performance with values of 95.31, 94.32, 95.11, and 95.20 respectively. It does reasonably well at predicting the stable class in the training set, although the RF algorithm outperforms it. SVM exhibits nominal results in this situation despite. For the stable class in the training set, SVM's accuracy, precision, recall, and F1-score are relatively lower than those of the other algorithms with values 93.16, 93.18, 93.90, and 93.01 respectively. This shows that SVM has trouble correctly identifying instances of the stable class, which results in more misclassifications and less accurate prediction.

In Figure 5, the barplot comparison for test set pertaining to the stable class of underground mines dataset shows the different performance evaluation adopted in this study for the three machine learning models such as RF, DT, and SVM. It was observed that the RF outperforms the other two algorithms by providing accuracy, precision, recall, and F1-score of 95.36, 95.13, 95.21, and 95.40 respectively. Further the DT with C4.5 implementation provides a fairly average performance metrics of 92.01, 92.36, 92.16, and 92.24 respectively for accuracy, precision, recall, and F1-score, which is lower as compared to the RF algorithm. Finally, the SVM algorithm provides the lowest performance of 90.59, 89.31, 89.54, and 90.69 for accuracy, precision, recall, and F1-score values respectively over the test set for stable classes, which is observed to be significantly lower as compared to the RF algorithm.

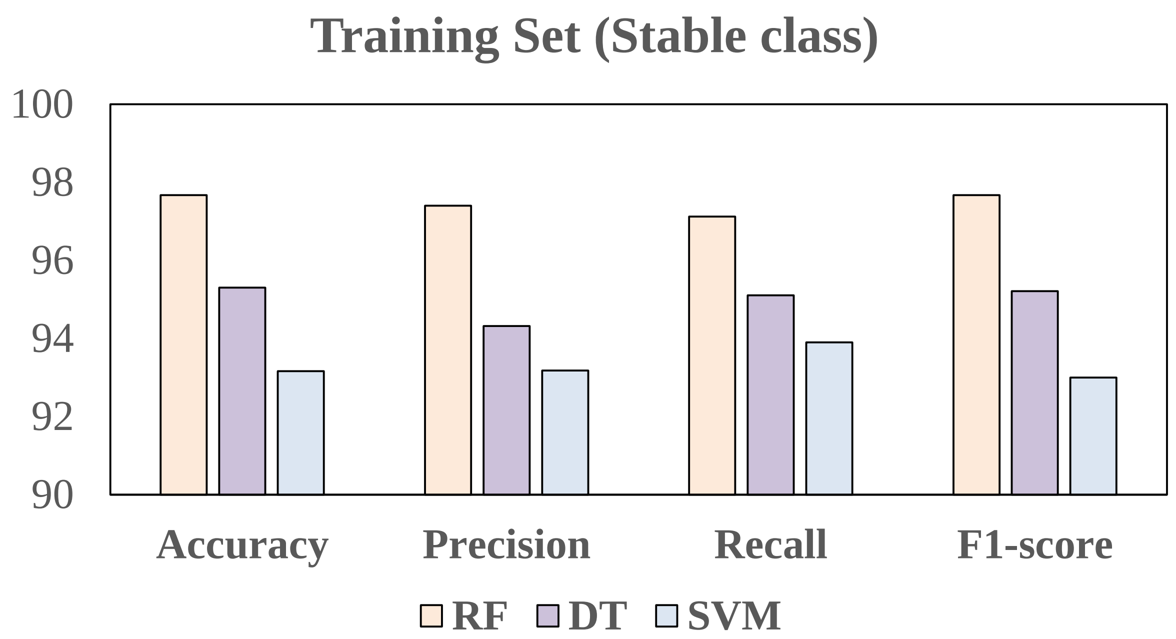

Figure 4: Comparison of different performance parameters for different machine learning models for training set of the stable class.

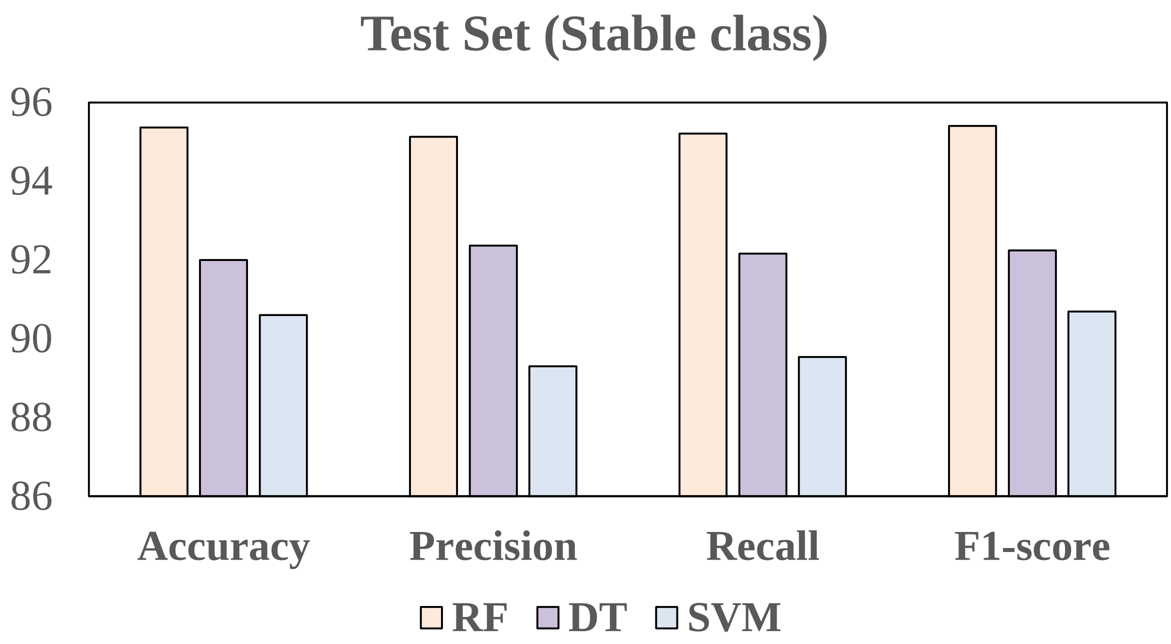

Figure 5: Comparison of different performance parameters for different machine learning models for test set of the stable class.

Conclusions and Future Works

This study uses data gathered from mines in the USA and India to apply RF, C4.5-based DT, and SVM models to estimate the pillar stability in underground mines. The created models use important input factors, such as pillar width (W), pillar height (H), pillar W/H ratio, uniaxial compressive strength, and average pillar stress to forecast the stability of pillars in the context of IoT and underground mining.

The following are the study's main conclusions:

1. Contrary to many sophisticated soft computing techniques, the proposed models are simple to use and don't require much training. Their conclusions are well in line with engineering judgements and intuitions since they explicitly establish links between the input and output variables.
2. The RF model obtains a remarkable classification accuracy of 99.89% and 97.67% respectively, during both the training stage of the failed and stable classes, while the testing accuracy was at 98.69% and 95.36% respectively for the failed and stable classes, depicting the efficacy of the RF algorithm. These impressive accuracy levels show the model’s effectiveness and practical application in real-world situations.
3. The implemented RF model has comparable performance to the DT and SVM model, and its simplicity enables simple interpretation through graphical results. However, the implicit processing that occurs during the training phase of SVM makes it difficult to understand the network's general structure, suggesting that it may lack understanding of the underlying mechanics of the issue.
4. The RF model outperforms the C4.5 decision tree model and SVM in terms of model performances, showing more accurate predictions regarding pillar stability in underground mines.
5. The presented models offer a great deal of room for growth in the future, especially with the acquisition of more comprehensive and well-balanced pillar stability databases. The

ability of the models to predict outcomes can be improved by expanding the amount of data available.

To properly assess the accuracy of these models for predicting pillar stability in diverse underground mining settings, it is advised to work with larger and more balanced pillar stability databases in future study. Additionally, these models can be extended and modified by taking into account other ground type and structural geology-related parameters, enabling a more thorough evaluation of pillar stability in IoT-based underground mining applications. Exploration and integration of this data will help us understand the pillar stability prediction problem better, which will lead to new opportunities for improving underground mining operations' efficiency and safety.

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