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Assessment of Seismic Hazards in Underground Mine Operations using Machine Learning

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Abstract
The most common causes of coal mining accidents are seismic hazard, fires, explosions, and landslips. These accidents are usually caused by various factors such as mechanical and technical failures, as well as social and economic factors. An analysis of these accidents can help identify the exact causes of these accidents and prevent them from happening in the future. There are also various seismic events that can occur in underground mines. These include rock bumps and tremors. These have been reported in different countries such as Australia, China, France, Germany, India, Russia, and Poland. Through the use of advanced seismological and seismic monitoring systems, we can now better understand the rock mass processes that can cause a seismic hazard. Unfortunately, despite the advancements, the accuracy of these methods is still not perfect. One of the main factors that prevent the development of effective seismic hazard prediction techniques is the complexity of the seismic processes. In order to carry out effective seismic risk assessment in mines, it is important that the discrimination of seismicity in different regions is carried out. The widespread use of machine learning in analyzing seismic data, it provides reliability and feasibility for preventing major mishaps. This paper provides uses various machine learning classifiers to predict seismic hazards.

Keywords: Seismic activity, Seismic bumps, Tremor, Machine learning, underground mines.

I. INTRODUCTION

Besides being hazardous, mining has always been one of the most dangerous occupations. With the increasing demand for minerals and coal, safety in mines has become even more important. Some of these include accidents, roof fall, seismic hazards, dust, toxic gases, and high temperature[1]. The process of coal mining can cause severe risks to the mine's personnel and production. This is why it is important that the various hazards that are involved in the mining industry are studied and analyzed. Aside from these, other risks such as black lung and rock-bursts are also known to occur in coal mines[2]. These are very real issues that mining companies have to consider when it comes to providing safe working conditions for their employees. One of these is a seismic hazard that occurs in underground mines[3]. This type of natural hazard is incredibly difficult to detect and predictable, making it one of the most common threats in the mining industry. Most challenging factors that mining companies have to consider when it comes to identifying and preventing these hazards is the presence of a seismic hazard[4]. Seismic monitoring and prediction [5]are the process that can be used to identify hidden risks and improve the safety of mines. This method is commonly used to prevent fatalities. Due to the complexity of the task, predicting the various hazards associated with coal mining has become a well-documented issue in the field of machine learning[6]. A repository created by UCI's machine learning department provides a collection of seismic bumps, which can be used to analyze and visualize

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data. The process of coal mining can cause severe risks to the mine's personnel and production. Through seismic monitoring[7], we can analyze the effects of the mining on the rock mass and identify the potential hazards. The main goal of the seismic hazard prediction technique is to predict the likelihood of a rock burst and seismic bumps[8] occurring due to increased seismic activity. The analysis is carried out by analyzing the data set generated by the seismic monitoring system.

Seismic hazards in underground mine operations pose a significant risk to the safety of workers and the stability of mining operations. These hazards include rockbursts, seismic events caused by the stress and strain on rock masses, and induced seismicity, earthquakes caused by mining activities. Assessing these hazards is crucial for the development of effective mitigation strategies and the protection of workers and mining infrastructure. Machine learning (ML) is a powerful tool that can be used to assess the severity of seismic bumps in underground mines. The use of ML in this context can help to improve the accuracy and reliability of the predictions made about the bumps, which can in turn help to mitigate the risk of harm and make more informed decisions about how to proceed. One of the main advantages of using ML in this context is that it can learn from the data and improve its predictions over time. This is especially useful in the case of seismic bumps, as the data can be highly variable and difficult to predict. ML models can also handle large amounts of data and can detect patterns and relationships that might be difficult for humans to discern. There are a variety of ML models that can be used to assess seismic bumps, such as Support Vector Machines (SVM), Naive Bayes, Neural Networks, and Random Forest. These models can be trained on historical data of seismic bumps and the resulting ground vibrations, to predict the severity of future bumps. Another important aspect is that ML models can also be used to detect bumps in real-time. These models can be integrated into the monitoring systems of mines and can give early warnings of potential bumps, which can help to minimize the damage caused by these events. In addition to prediction, ML models can also be used for anomaly detection in time series data of vibration and ground movement. This can help to identify bumps that might have been missed by traditional monitoring systems.

ML is an important tool for assessing seismic bumps in underground mines. Its ability to learn from data and detect patterns can help to improve the accuracy and reliability of predictions, which can in turn help to mitigate the risk of harm and make more informed decisions about how to proceed. The integration of ML models in real-time monitoring systems can also provide early warning of potential bumps, which can help to minimize the damage caused by these events.. One of the key advantages of using ML in the assessment of seismic hazards is the ability to process large amounts of data. This can include data from monitoring systems, such as seismographs and accelerometers, as well as data from other sources, such as geological surveys and drilling logs. By analyzing this data, ML algorithms can identify patterns and trends that may not be immediately apparent to human analysts. Another advantage of using ML in the assessment of seismic hazards is the ability to make predictions about future seismic activity. This can include predicting the likelihood of future rock bursts or induced seismicity events, as well as predicting the magnitude and location of these events. This information can be used to develop effective mitigation strategies and protect workers and mining infrastructure. The use of machine learning in the assessment of seismic hazards in underground mine operations can provide valuable insights that can help to improve the safety and stability of mining operations. By analyzing large amounts of data and making predictions about future seismic activity, machine learning can help to identify potential risks and develop effective mitigation strategies.

II. SEISMIC HAZARD

A seismic hazard is the likelihood that an earthquake will occur within a certain geographic area within a given time frame fig-1 represent global seismic hazard map. It can be considered as a risk factor that affects various aspects of a project, such as land use planning and building codes. Having an estimate of the hazard can help in identifying areas of potential risk and developing effective strategies to minimize the impact of an earthquake. The increasing risk of mining induced seismicity is a major concern for deep underground mines[9]. The mining process is known to cause seismicity in underground mines. In normal conditions, the rock is stable underground, and there are no seismic events. However, in areas where there is mining, the rock can be unstable[10]. The characteristics of the mine's rock are known to affect its stability. These factors can be determined by the site's geological features, such as the depth of mining, the rate of advance, and the sequence of excavations[11]. Although rock failures can occur in areas with high ground stresses, they can also be controlled by implementing the proper ground support system[12].

As the mine's development progresses, the number of active faces and excavations increases, which can cause stress changes in the rock. High stresses can cause structural damage to the existing openings[11]. Also, due to the varying rock strengths in contact zones, brittle rocks can cause more seismicity. Although large earthquakes are known to cause

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damage, they are relatively rare. Most of the time, mine workers experience small groundfall and strain-bursts triggered by the changes in the rock[13]. To minimize the effects of seismicity, employees should regularly monitor and communicate the changes in the rock. They can also learn how to recognize the signs of change in the ground. Machine learning plays an important role to assess the seismic hazard to save lives[14]. Seismic hazards refer to the potential damage or destruction that can occur as a result of earthquakes or other ground vibrations. These hazards can have a significant impact on both human populations and the built environment. Some common effects of seismic hazards include building collapses, landslides, ground failure, and tsunamis. One example of a mine incident caused by seismic hazards is the 2010 Copiapó mining accident in Chile. A magnitude 8.8 earthquake triggered a cave-in at the mine, trapping 33 workers underground for 69 days. The seismic event caused significant damage to the mine infrastructure, making it difficult to rescue the trapped workers.

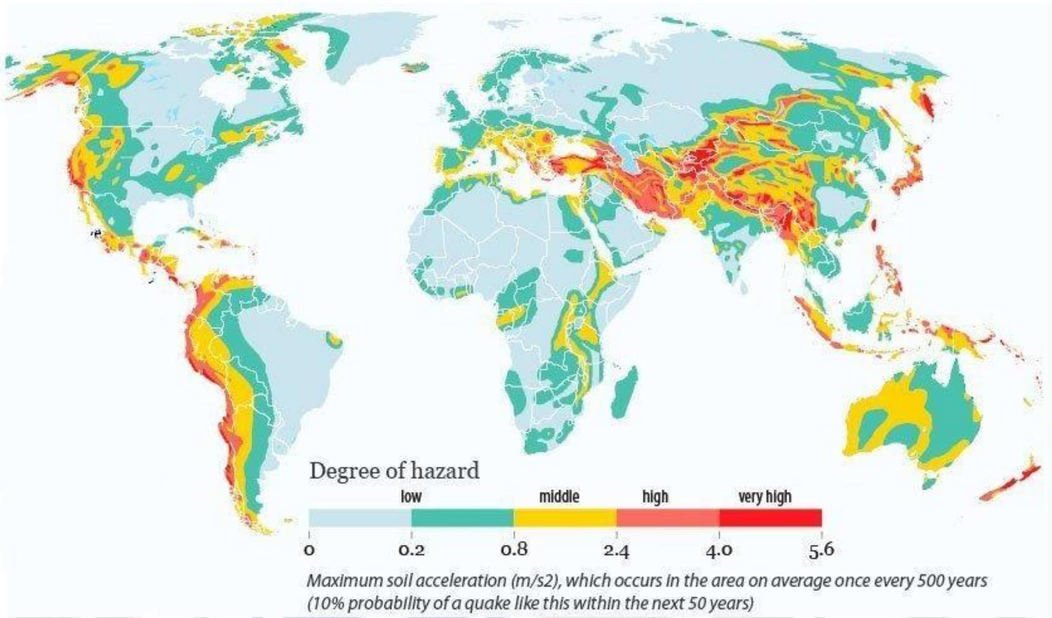

Fig. 1 Global Seismic Hazard Map (Source-Global Seismic Hazard program)

Another example is the 2014 Mount Polley mine disaster in British Columbia, Canada. A dam containing tailings from the copper and gold mine failed, releasing 24 million cubic meters of mining waste into nearby waterways. The failure was later found to have been caused by a combination of poor design and increased water pressure from heavy rainfall, which likely was made worse by the recent seismic activity in the area.

Seismic bumps or precursors are the subtle changes in the earth's surface, in the form of increased micro-seismic activity or ground vibrations, that occur before a larger seismic event. Identifying these bumps in advance can help to mitigate the effects of a seismic event by allowing for the evacuation of at-risk areas and the implementation of emergency response plans. Machine learning (ML) can be used to identify seismic bumps by analyzing patterns in large sets of seismic data. ML algorithms can be trained to recognize patterns in the frequency, amplitude, and duration of micro-seismic activity that are indicative of an impending seismic event. This can help to improve the accuracy and timeliness of seismic hazard warnings, allowing for more effective emergency response planning.

III. MACHINE LEARNING CLASSIFIER

A. Random Forest

The number of decision trees is a critical parameter to consider in order to perform well in classification. It contributes to the computational efficiency and performance of the system. Increasing the number of decision trees can also introduce more random features. The number of decision trees can also provide a representation of the importance of a feature. This parameter is used in the development of feature-based classification techniques. In this study, we introduce a method that aims to optimize the performance of the system by increasing the number of decision trees. Random forest outperforms as compared to another classifier with 93.5% accuracy.

B. Support Vector Machine (SVM)

The SVM framework was originally developed to solve multi-class problems in binary classification. It takes into

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account the various feature points and constructs a hyperplane that can be used to separate classes. In a non-linear problem, it takes advantage of a kernel technique to transform the input space into a higher dimensional space. There are four kinds of commonly used kernel types, namely, the linear kernel, the polynomial kernel, the sigmoid kernel, and the Gaussian radial basis function.

$$K(X_i, X_j) = \exp\left(-\frac{X_i - X_j^2}{2\sigma^2}\right) \quad \text{........ i}$$

$$\gamma = \frac{1}{2\sigma^2} \text{----ii}$$

X_i, X_j denote two feature vectors. The square distance between these two features is known as the square Euclidean distance $X_i - X_j^2$.

C. Neural Network

A neural network is an artificial system that learns to perform a task by exposing itself to various datasets. It then generates its own set of characteristics using the data it has been collected. This method is similar to how biological neural networks learn to perform tasks. A neural network is a type of computational model that can be used to study and develop artificial intelligence. It is based on the combination of mathematics and algorithms. This work has led to improvements in the field of finite automata theory.

D. Naïve Bayes

Based on the Bayes theorem, he Nave Bayes algorithm is a form of supervised learning that can be used to solve classification issues. It is very simple to implement and can help in developing fast machine learning models. The Bayes algorithm is also known as a probabilistic classification. This type of classification helps in building models that can predict an object's probability.

IV. DATASET

There are 2584 instances of this dataset[15], out of which 8 features are categorical features, and 6 are numeric. The last column is labeled, where 0 as non-hazardous seismic bumps and 1 as hazardous seismic bump.

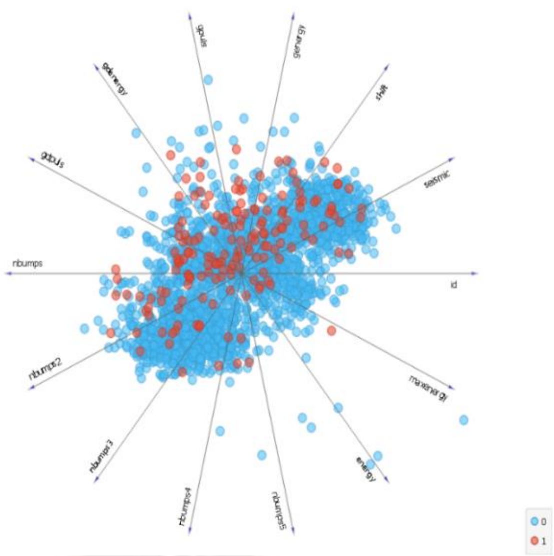

Fig. 2 Visualization of data

A. *Scatter plot*

A scatter plot is a type of mathematical diagram or plot that uses the coordinates of a set of points to display the values of two variables for different positions. It can also be used to display one additional variable if the points are marked with a color or shape. The data collected by the plot is then divided into points, each of which has its own value. Here in fig. scatter plot is plotted with energy and maxenergy as axis. The sample correlation coefficient (r) are 0.99 and 0.97.

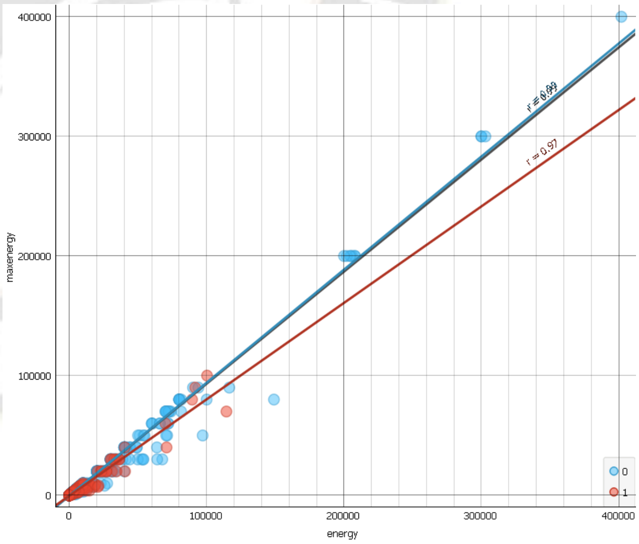

Fig. 3 Scatter plot between energy and maxenergy

B. *Feature statistics*

The Feature Statistics allows to quickly inspect and find interesting features in a data set.

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Table 1 Feature statistic

Name	Mean	Median	Min.	Max.
genergy	90242.52	25485	100	2595650
gpuls	538.58	379	2	4518
gdenergy	12.38	-6	-96	1245
gdpuls	4.51	-6	-96	838
nbumps	0.86	0	0	9
nbumps2	0.39	0	0	8
nbumps3	0.39	0	0	7
nbumps4	0.07	0	0	3
energy	4975.27	0	0	402000
maxenergy	4278.85	0	0	400000

V. RESULT

1.1. Receiver operating characteristic (ROC) curve

The ROC curve is a representation of the model's performance when it comes to distinguishing between negative and positive cases. It shows the difference between the true positive rate and the false positive rate at various settings. The term recall or sensitivity refers to the proportion of positive predictions in the actual cases. The term fall-out refers to the proportion of positive predictions that are not true.

The mathematical formula for TPR is:

TPR = True Positives / (True Positives + False Negatives)

The mathematical formula for FPR is:

FPR = False Positives / (False Positives + True Negatives)

A ROC curve is a representation of the difference between a model's sensitivity and specificity when it comes to dealing with different threshold values. A perfect model will have both a TPR of 1 and an FPR of 0, which results in a ROC curve that's centered around the top left corner of the chart. The AUC, or Area Under the Curve, is a representation of the model's overall performance.

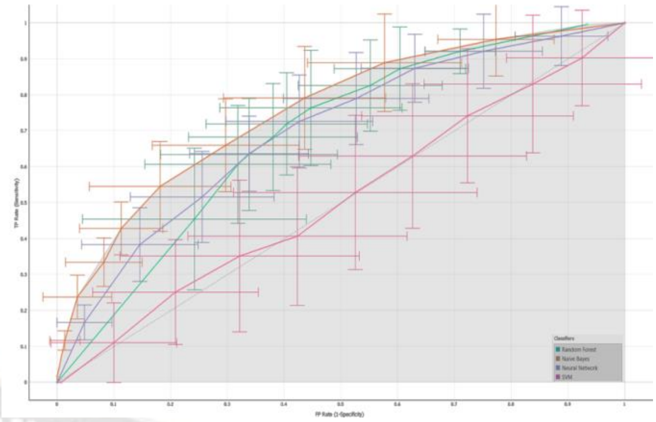

Fig. 4 ROC Curve

1.2. Confusion Matrix

The confusion matrix is a statistical measure that shows the performance of a given classification model when the true values of the data are known. It can only be used to determine the model's true performance if the values are known. Although it can be easily understood, the related terms may be confusing. An error matrix is also a type of matrix that shows the errors in the model's performance. The matrix is composed of two dimensions, which are the predicted values and the actual values. The former is the representation of the model's predictions, while the latter is the true values of the data.

Confusion matrix for Random Forest

		Predicted		
		0	1	∑
Actual	0	94.00%	48.40%	2414
	1	6.00%	51.60%	170
	∑	2553	31	2584

Confusion matrix for Neural Network

		Predicted		
		0	1	∑
Actual	0	93.70%	71.40%	2414
	1	6.30%	28.60%	170
	∑	2549	35	2584

Confusion matrix for Naive Bayes

		Predicted		
		0	1	∑
Actual	0	96.70%	80.80%	2414
	1	3.30%	19.20%	170
	∑	2052	532	2584

Confusion matrix for SVM

		Predicted		
		0	1	∑
Actual	0	93.30%	93.70%	2414
	1	6.70%	6.30%	170
	∑	2089	495	2584

Fig. 5 Confusion matrix

1.3. Evaluation Parameters

i. **Area Under Curve (AUC) -** AUC stands for "Area Under the Receiver Operating Characteristic Curve" and it is a measure of a model's ability to distinguish between positive and negative cases. It is a scalar value between 0 and 1, where a value of 1 indicates perfect discrimination and a value of 0.5 indicates that the model is no better than random guessing.

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The AUC is calculated by taking the area under the ROC curve, which is a plot of the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. The TPR, also known as sensitivity or recall, is defined as the proportion of true positive predictions among the actual positive cases. The FPR, also known as fall-out, is defined as the proportion of false positive predictions among the actual negative cases. The mathematical formula for AUC is:

$$AUC = \int (TPR(FPR))\, dFPR = \left(\frac{1}{2}\right) \int [TPR(FPR) + TPR(1-FPR)]\, dFPR$$

ii. **Classification Accuracy (CA)-** Classification accuracy is the measure of how accurate it is when we use the term accuracy. It is calculated by taking into account all the correct predictions that were made by the various samples.

$$Accuracy = \frac{No\ of\ correct\ predictions}{Total\ no.of\ predictions\ made}$$

iii. **F1- Score-** The F-score or accuracy measure is a combination of the precision and recall of a test. It is calculated by taking into account the number of positive results that were identified correctly and the number of samples that were not. This measure is also referred to as positive predictive value. In diagnostic binary classification, the recall is also referred to as sensitivity.

$$F1\ score = 2.\frac{precision\ .\ recall}{precision + recall}$$

iv. **Precision -** The precision ratio is the number of positive samples that a scientist has correctly classified. It is calculated by taking the number of positive samples that are actually positive and adding those that are not.

$$\text{Precision} = \frac{\text{True positive}}{\text{True positive+False positive}},$$

v. **Recall -** The recall is a statistical measure that shows how many positive samples the model can detect. It takes into account the number of samples that are correctly classified as Positive and the number of those that are not.

$$\text{Recall} = \frac{\text{True positive}}{\text{True positive+False Negative}}$$

Table 2 Evaluation parameters

Model	AUC	CA	F1	Precision	Recall
SVM	51.4	76.7	81.5	87.6	76.7
Naive Bayes	77.3	80.7	84.9	91.6	80.7
Neural Network	71.3	92.8	90.6	89.4	92.8
Random Forest	69.3	93.5	91.3	91.2	93.5

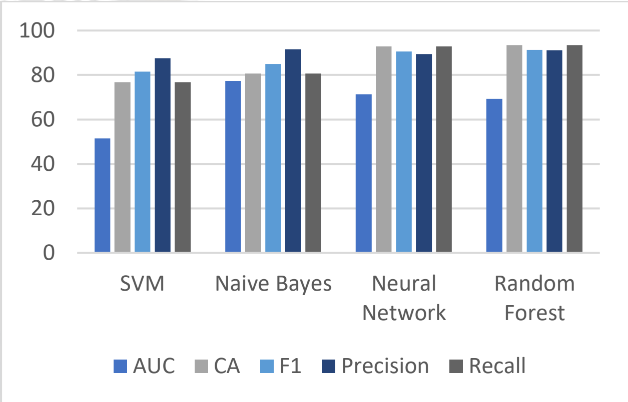

Fig. 6 Comparative graph of various ML models

Seismic bumps in underground mines are a common occurrence and can cause serious damage to both the mine and the equipment. It is important to accurately assess the severity of these bumps in order to mitigate the risk of harm and make informed decisions about how to proceed. A model assessment is a process used to evaluate the capabilities of various seismic models to predict the severity and frequency of seismic bumps. Some of these include the Support Vector Machine, Neural Networks, Random Forest, and Naive Bayes. The AUC is a measure of how well a model can distinguish between negative and positive cases. The higher the AUC, the more accurate the model is in distinguishing between the two types of classes. For instance, the Naive-Bayes model has an AUC of 77.3. The percentage of correct predictions that the model makes is known as the CA. For instance, the Neural Network model is the most accurate at making 92.8 percent of its predictions. Other metrics that are used to evaluate models include recall, precision, and F1. Recall is the proportion of correct predictions that a model makes in relation to the actual cases, while precision refers to the accuracy of the predictions made in relation to the positive ones. The Neural Network model is also the most accurate at achieving the F1 score of 91.6. The other models that were evaluated in this case, namely the SVM, Naive Bayes, and Random Forest, had an AUC of 79.3. Different factors such

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as the mine's requirements and decision-making process can determine which model is most suitable.

VI. Conclusion

In conclusion, the assessment of seismic bumps in underground mines is an important task that requires accurate and reliable models. The models used in this case, such as SVM, Naive Bayes, Neural Networks, and Random Forest, have different strengths and weaknesses, as shown by the AUC, CA, F1, Precision, and Recall metrics. The Naive Bayes model has the highest AUC, the Neural Network model has the highest CA, and the Neural Network model has the highest F1, Precision, and Recall. These models can be used to make informed decisions about how to proceed in the event of a seismic bump. However, there are also some limitations that should be considered when using these models. One limitation is that these models are based on a limited amount of data and may not be able to generalize well to new unseen data. Additionally, these models are based on certain assumptions about the data that may not hold true in all cases. In future, it would be interesting to consider more sophisticated models, such as Deep Learning based models, which have been shown to be very effective in other domains. Additionally, more data and more diverse data could be used to improve the performance of these models. This could include data from different mines, different types of equipment, and different types of seismic events. Overall, the assessment of seismic bumps in underground mines is an important task that requires accurate and reliable models. While the models used in this case have their strengths and weaknesses, they can be used to make informed decisions about how to proceed in the event of a seismic bump. However, there is room for improvement and further research in this area.

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