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Decision support system for underground coal pillar stability using unsupervised and supervised machine learning approaches

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Abstract. Coal pillar assessment is of broad importance to underground engineering structure, as the pillar failure can lead to enormous disasters. Because of the highly non-linear correlation between the pillar failure and its influential attributes, conventional forecasting techniques cannot generate accurate outcomes. To approximate the complex behavior of coal pillar, this paper elucidates a new idea to forecast the underground coal pillar stability using combined unsupervised-supervised learning. In order to build a database of the study, a total of 90 patterns of pillar cases were collected from authentic engineering structures. A state-of-the art feature depletion method, t-distribution symmetric neighbor embedding (t-SNE) has been employed to reduce significance of actual data features. Consequently, an unsupervised machine learning technique K-mean clustering was followed to reassign the t-SNE dimensionality reduced data in order to compute the relative class of coal pillar cases. Following that, the reassign dataset was divided into two parts: 70 percent for training dataset and 30 percent for testing dataset, respectively. The accuracy of the predicted data was then examined using support vector classifier (SVC) model performance measures such as precision, recall, and f_1-score. As a result, the proposed model can be employed for properly predicting the pillar failure class in a variety of underground rock engineering projects.

Keywords: coal pillar; K-mean clustering; SVC; t-SNE; underground structures

1. Introduction

1.1 Background

A pillar is usually a key structural column in in-situ rock mass between two or more subsurface foundations (Idris *et al.* 2015). Pillars in subsurface coal excavations plays a significant role for the insurance of mine shafts and surface subsidence control (SHEOREY 1993). Pillars are usually practiced in an underground mine in order to support the weight of overburden material. Consequently, the pillar strength is reduced to such a point where pillars could no longer bear the stress of overburden material. In most cases, predicting the stability of an underground mine is a very complicated task (Federico and Screpanti 2002). The collapse of a single pillar in a mine result in transfer of stress to the neighboring pillars, causing them to break and giving rise to domino type failure (Martin and Maybee 2000). The pillar failure process in a mine is usually a continuous meaning first crack is initiated and propagated causing disruption in surrounding in-situ stresses resuting in the local failures and the development of fracture planes, such like micro processes activities lead to violent pillar failure (Fang and Harrison 2002).

In order to sustain pillar design and stability analysis for coal mines, several techniques have been carried out. For example, based on preliminary empirical formula, two coal pillar strength methods were recommended (Sheorey *et al.* 1986). The impact of non-persistent joints and holes on the failure behavior of rock pillars under uniaxial compressive test were investigated using both experimental and discrete element approaches (Sarfarazi *et al.* 2021). Along the coal mine goaf, a mechanical model of lateral fracturing for the overlaying hard rock strata has been developed (Zhao *et al.* 2021). Traditional pillar design methods taking the calculated of pillar stresses were suggested e.g., tributary area method (Coates 1981), empirical approaches to calculate coal pillar strength (Salamon and Munro 1967), strength formula based on sandstone core (Obert and Duvall 1967), variation of tributary area theory (Hedley and DGF 1972), adding the concept of the point of critical energy release to constitute the long term strength (Santos and Bieniawski 1989), expected factor of safety for pillars (Lunder and Pakalnis 1997), probabilistic approach of underground pillar stability (Griffiths *et al.* 2002), long term coal pillar stability evaluation (Qin *et al.* 2006), limit state design for underground structures (Park *et al.* 2012), micro seismic monitoring and study of induced seismicity source processes (Leake *et al.* 2017) and a recently development considering the effect of interface friction (Prassetyo *et al.*

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2019). Liu et al outlines a way for converting an isolation wall into a double lane without the need of a coal pillar (Liu *et al.* 2021). In order to overpower the stability of underground designing, some improvements were made to the conventional excavation stability methods, including underground mining excavations e.g. probabilistic analysis (Chen *et al.* 1997), excavation reliability (Lilly and Li 2000), probabilistic analysis through stope stability (Idris *et al.* 2011), limit state design (Recio-Gordo and Jimenez 2012), logistic regressions (Wattimena *et al.* 2013) and the influence of Geological Strength Index (GSI) on inceptive pillar in comparison with failed and stable hard rock pillars (Li *et al.* 2021). Besides, it has been shown that the stochastic deterioration modelling approach can assess the structural dependability based on rock burst criteria of deep residual coal pillars in an underground coal mine (Qiu *et al.* 2019).

Some numerical methods for underground mining were also suggested (Brady and Brown 2004) and comparative analysis of pillar model were proposed (Zhou *et al.* 2015) to evaluate pillar stability in underground excavation. The failure pattern of numerous pillar-roof support systems was initially investigated using physical model testing. In a room and pillar mine, deep-hole-blasting was used to increase the stability of the pillar and roof support system, and several practical strategies to reduce the danger of catastrophic collapse were suggested (Chen *et al.* 2019).

Machine learning techniques and artificial intelligence have been widely employed to solve geotechnical engineering problems (Parsajoo *et al.* 2021, Asteris *et al.* 2021). Liang *et al.* used various machine learning algorithms to estimate the pillar stability in hard rock; thus, the findings revealed better performance with high accuracy in prediction using proposed algorithms (Liang *et al.* 2020). Ding *et al.* employed the stochastic gradient boosting (SGB) method to forecast the stability of mine pillars in subsurface mines, with 80% accuracy of the 205 data samples used for training and 20% for testing. In addition, several machine learning models were also analyzed for comparison; consequently, the SGB model exhibited high accuracy in predicting mine pillar stability (Ding *et al.* 2018). A novel formula for soft pillar strength estimation was derived by Rastiello *et al.* and the results of their study were compared in the literature (Rastiello *et al.* 2015). Jian *et al.* applied Fisher discriminant analysis (FDA) and support vector machine (SVM) to forecast the stability of mine pillars in different subsurface coal and stone mines. As a result, the SVM model showed the best performance and significant accuracy in the results (Jian *et al.* 2011). Li *et al.* used various methods, i.e., finite difference method (FDM), neural network (NN), and Monte Carlo simulation (MCS) to evaluate the stability of the pillars in hard rock underground coal excavations (Li *et al.* 2020). Ghasemi *et al.* used a fuzzy model with 399 data samples to design the room and pillar method to forecast the size of the pillar; therefore, their proposed model showed appropriate results for practical use at the mine site (Ghasemi *et al.* 2014). Monjezi *et al.* (2011) suggested a neural network algorithm that includes five indicators and an output to estimate pillar stress (Monjezi *et al.* 2011). Besides, researchers reported that using a random tree to assess pillar stability in subsurface excavation is an effective and feasible method (Ahmad *et al.* 2020). Recently, the combination of unsupervised and supervised machine learning has been successfully applied in a variety of domains and applications such as assessing rock burst potential (Kamran *et al.* 2022), rock lithologies characterization and categorization (Albuslimi *et al.* 2021), but their applications related to coal pillar stability prediction are limited.

In fact, the determining characteristics of coal pillar stability vary across a wide range of subsurface engineering structures. Despite the fact that the large anatomy of pillar failure investigation yields various conspicuous distinct outcomes, coal failure prediction entails probability, stochasticity and ambiguity. There is no precise method for predicting the pillar failure at the moment.

1.2 Significance of the study

This study examines multiple techniques for predicting the stochastic nature of coal pillar stability, including t-Distributed Stochastic Neighbor Embedding (t-SNE), K-means clustering, and the Support Vector Classifier (SVC) algorithm. To the best of the author's knowledge, this is the first study to use a combination of unsupervised-supervised learning to forecast coal pillar stability using numerous specific input attributes.

The main objective of this study is to forecast coal pillar stability based on the t-SNE, unsupervised and supervised machine learning techniques. Initially, several types of coal pillar cases were initially gathered from diverse field investigations. Secondly, t-SNE method has been used to deplete the dimension of coal pillar dataset. Thirdly, K-means clustering has been used to categorize the dimensionality reduced coal pillar data. Lastly, SVC model has been developed in this study to forecast the new coal pillar class.

The rest of this paper is organized as follows:

Section 2 describes material and method, section 3 elucidates result and discussion, section 4 explains limitations and future studies, and sections 5 discusses conclusion

2. Material and method

2.1 Data acquisition

To measure the performance of unsupervised-supervised learning, 90 patterns of pillar cases were collected from authentic engineering structures (Mohan *et al.* 2001, González-Nicieza *et al.* 2006). The database consists of various influential indicators including pillar width (w), pillar height (h), depth in meter (D), w/h, uniaxial compressive strength (UCS) in MPa and the corresponding pillar class. The pillar strength in MPa is computed by using Eq. (1) proposed by (Potvin 1989)

$$S_p = \; UCS \; \frac{w}{H} \tag{1}$$

Whereas UCS is uniaxial compressive strength, w is

Table 1 Original data employed in this study

Pillar Cases	**Pillar width**	**Pillar height**	**Depth**	**Uniaxial Compressive Strength**	**w/h**	**Pillar strength**	**Pillar class**
	(w)	**(h)**	(D)	**(UCS)**		**(S_p)**	
	(m)	**(m)**	**(m)**	**(MPa)**		**(MPa)**	
1	5.4	3	36	48	1.8	36.28	Stable
2	9.9	6	48	50	1.65	34.65	Stable
3	8.1	3	270	46	2.7	52.16	Stable
4	9.9	2.7	75	28	3.66	43.12	Stable
…..	…..	…..	…..	…..	…..	…..	…..
87	21	7	210	104	3	131.04	Failure
88	18	14.25	214	104	1.26	55.17	Inceptive Failure
89	17	13	219	104	1.3	57.12	Failure
90	11	7.75	217	104	1.41	61.99	Inceptive Failure

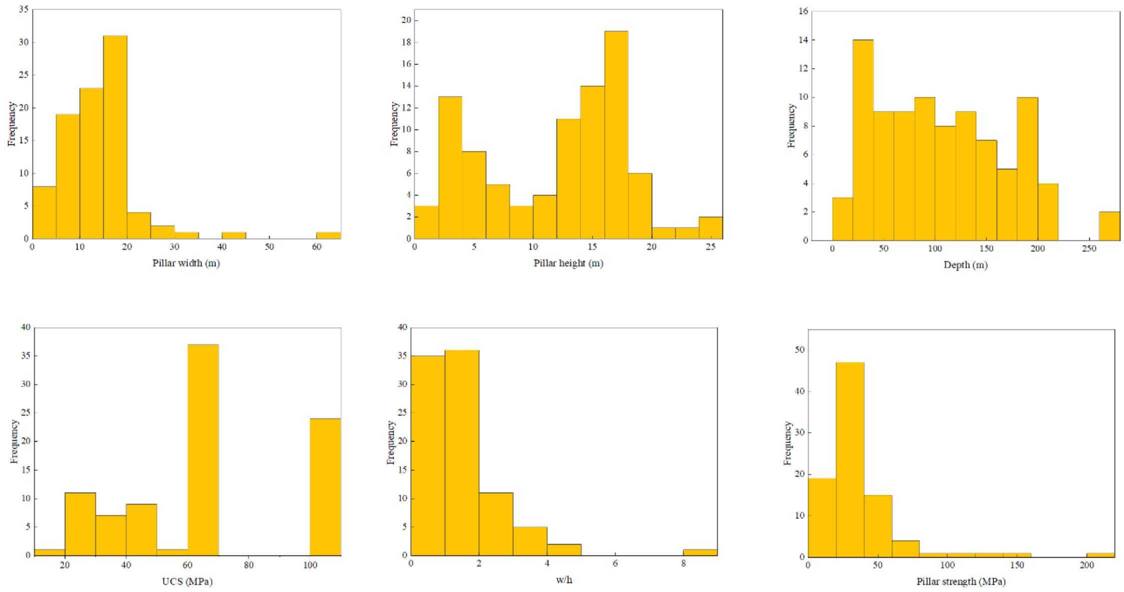

Fig. 1 Histogram of the initial coal pillar dataset

the width, H is the height of the pillar and S_p is the pillar strength. This research would relabel the pillar classes in order to achieve its compatibility. Table 1 presents the original data to be used in this research work. The histogram of each input indicator has been depicted in Fig. 1.

2.2 Visual representation of the data

Python with Scikit-learn module is employed in this study for visual representation of the coal pillar data. A box plot depicts the distribution of numerical data in such manner that it is clear to differentiate parameters or levels of a categorical indicator. Disregarding the data points that are intended to be "outliers" using an arrangement that is inter-quartile range function, the box shows the quartiles of the dataset, whereas the whiskers delineate the leftover dissemination. Fig. 2 shows the boxplot of the data to be analyzed in this study. Several significant visual illustrations can be found in Fig. 2. Firstly, a bunch of indicators including, pillar width, pillar height, UCS, w/h and pillar strength have several outliers. Secondly, the w/h indicator is indirectly proportional to the pillar class. Secondly, no clear relationships exist between pillar width, pillar height, depth, or pillar strength, implying that the relationship between the influencing indicators and pillar class is not obvious. Thirdly, the gaps between the upper and lower quartiles differ at distinct levels for the same metrics. Fourthly, there are some areas of the range of indicator values in distinct levels that overlap. Lastly, the distribution of indicator values is asymmetric since the median is not in the box's center. All these indicators contribute to the difficulty of predicting pillar stability. As a result, all the attributes are included in the final model for pillar class prediction to improve its accuracy. The dataset of 90 patterns for each indicator is distributed with statistical description as depicted in Table 2.

Table 2 Statistical characteristics of the original dataset

	Pillar width	**Pillar height**	**Depth**	**Uniaxial Compressive Strength**	**w/h**	**Pillar strength**
	(w)	**(h)**	**(D)**	**(UCS)**		**(S_p)**
	(m)	**(m)**	**(m)**	**(MPa)**		**(MPa)**
Mean	13.98	11.7	106.41	1.5	63.85	37.06
Stan. dev.	8.21	6.03	63.86	1.15	27.35	29.96
Min.	2.9	1.8	2	0.46	19	5.84
Max.	61	24	270	8.33	104	204.96

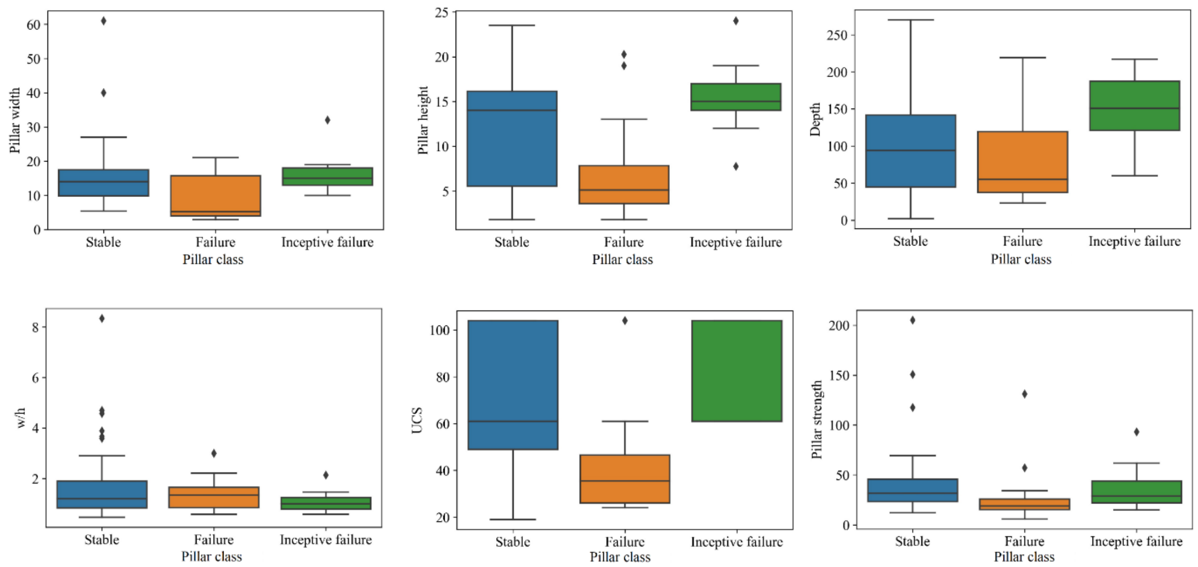

Fig. 2 Visual representation of attributes in the dataset

2.3 t Distributed Stochastic Neighbor Embedding (t-SNE)

Hinton and Roweis (Hinton and Roweis 2002) expanded an enhanced stochastic neighbor embedding (SNE) contingent on t-SNE algorithm. In a high-dimensional database, the SNE replaces the distance between data points with a conditional probability, distributing their correspondence. The SNE then correlates the conditional probability in the high-dimensional database with the conditional probability in the low-dimensional database of other points (map points) (Liu 2021).

In early work, experts have extensively used t-distributed stochastic neighbor embedding (t-SNE) techniques to envisage information in computer vision and other domains (Van der Maaten and Hinton 2008). t-SNE is a dimensionality reducing technique that minimizes high-dimensional information into a small-dimensional implantation space and is mainly used for representation applications. t-SNE calculates the dissemination of pairwise resemblances in the high dimensional information space, and endeavors to improve perception in a low dimensional space by coordinating with the dissemination by Kullback-Leibler (KL) disparity (Joyce 2011). Fig. 3 shows the flowchart of t-SNE mechanism.

2.4 K-mean clustering

2.4.1 K-means

K-means is an unsupervised machine learning and simplest iterative algorithm that splits the provided data into a user-defined number of clusters (Wu *et al.* 2008). K-means is considered a non-hierarchical technique that splits the data into one or more clusters. The data in one set has similar attributes yet has various dissimilar attributes from other data sets. This technique is a distance-based clustering technique that allows the distribution of data into enumerated clusters, though numerical attributes are only of interest to this algorithm. The clustering procedure by of K-means algorithm contingent on the available data and the consequences to be. Following important points can help us to well understand the k-means algorithms:

1. The input should be the cluster numbers.
2. Must be finished with types of numeric attributes.

In the K-means technique, the given data will be divided into several clusters of data that must have similar features and will be collected into one and the same cluster. After

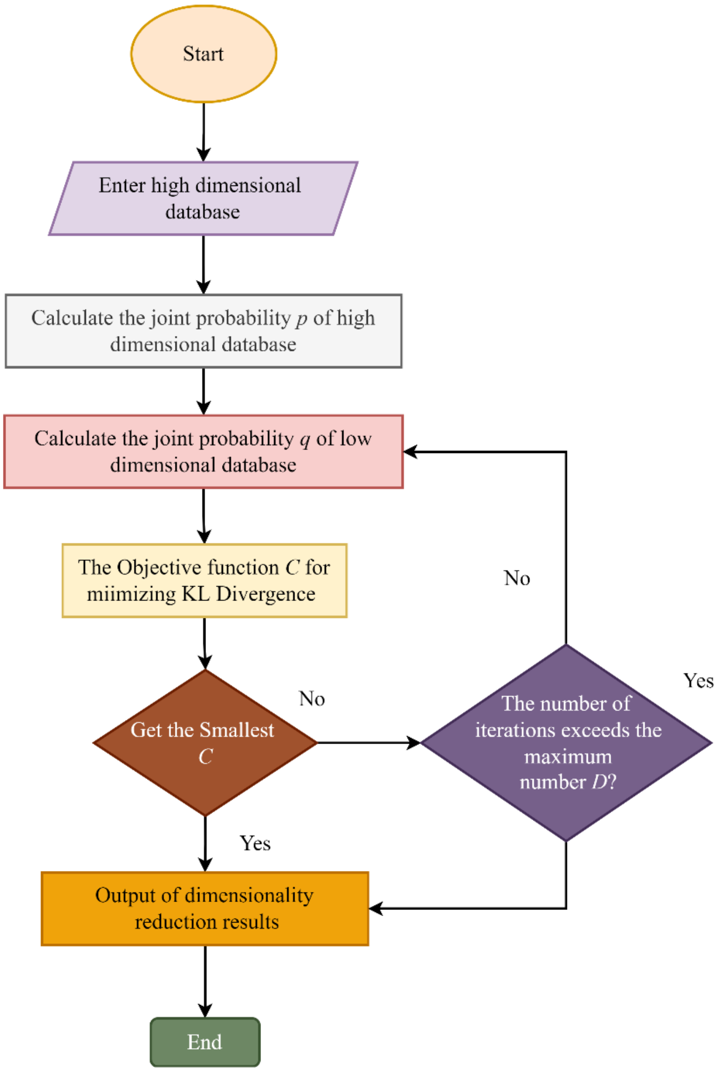

Fig. 3 Flowchart of t-SNE mechanism

that, the data with dissimilar features will be collected into other clusters. Reducing the set of objective functions in the clustering process is the main goal of data clustering, which usually pursues to reduce the fluctuation within clusters and reduce the fluctuation between clusters (Wu 2012). The key mechanism of the K-means algorithm is shown as (Wu 2012):

Step 1: Calculate the cluster numbers.

Step 2: Calculate randomly the centroid point k (i.e., center of cluster).

Step 3: To settle the distance between a data, the distance from each point to cluster central point and a cluster will compute which data aligns into that group. The Euclidian distance formula in Eq. (2) can be used to compute the distance between data points and a cluster's center

$$D(i,j) = \sqrt{\left(X_{1i} - Z_{1j}\right)^2 + \left(X_{2i} - Z_{2j}\right)^2 + \cdots + \left(X_{ki} - Z_{kj}\right)^2} \quad (2)$$

where, the data distance from *i* to the cluster's center *j* shown by *D (i, j)*, X_{ki} is the centroid of *k* to *j* and Z_{ki} is the data from *k* to *j*.

2.4.2 Clustering

Clustering is an unsupervised machine learning technique for finding data in one dataset with similar attributes to other datasets. Unlike supervised, unsupervised machine learning methods typically do not require training, testing, or target data (Han *et al.* 2011). Clustering is mainly classified into hierarchical clustering and non-hierarchical clustering. The key discrepancy between hierarchical and non-hierarchical type is that hierarchical clustering clusters 2 or more data by observing at bodies with nearest similarity. Moreover, its process will continue until the required proximity is accomplished, and the resultant group establish a tree starting from the highest resemblance to the smallest resemblance. On the other hand, non-hierarchical clustering is started by calculating the required clusters number. Due to the difference between these two clustering methods, the clusters number is subsequently calculated, and the clustering process is performed at first hand. Therefore, this process is called K-means clustering. Fig. 4 represents the flowchart of k-means clustering employed in this study.

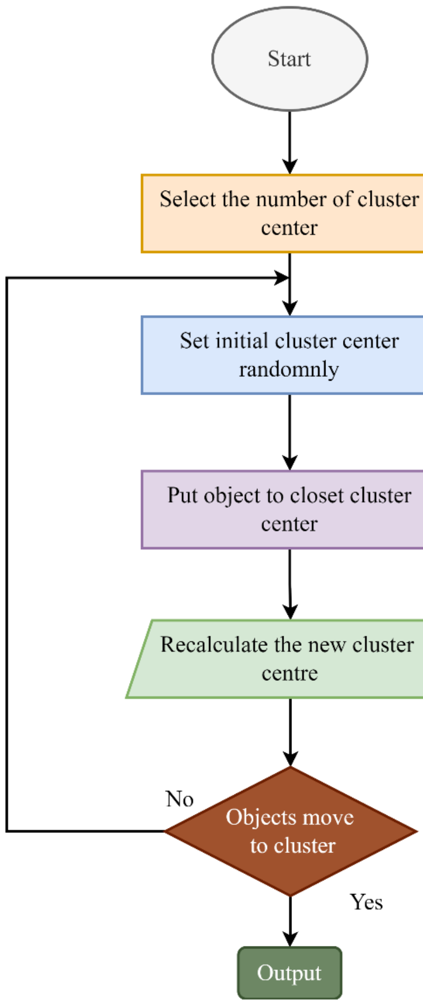

Fig. 4 Flowchart of k-means clustering

2.5 Support Vector Classifier (SVC)

The support vector machine (SVM) is one of the significant supervised learning. This algorithm that can be employed for classification and regression. SVM is widely used for limited data sets because of its long processing time and its ability to solve various types of practical problems, i.e., high dimensional numbers, nonlinearities, and global minima (Ben-Hur and Weston 2010). SVM is an important participant in the overall community of kernel systems. The kernel system is a completely data-dependent algorithm, by means of dot products. The dot product can be replaced with a kernel function and can be computed in a high dimensional characteristic place. The role exhibits two advantages: (1) It can establish non-linear decision-making limits employing classification-enhanced methodologies. (2) The Kernel functions are significantly employed to permit the consumer to apply data to classifiers that can not explicitly specify the location of fixed dimensional vectors (Ventura and Berjaga 2015). The kernel factors have a significant impact on the kernel factors. The polynomial degree of kernel and width variable of the Gaussian kernel overcome the subsequent classifier's accessibility. (Ben-Hur and Weston 2010, Aljanabi *et al.* 2018, Ehteram 2019, Abobakr 2019). Fig. 5 elucidates the mechanism of SVC algorithm employed in this study.

2.6 Step-by-step process of this study

This study discusses the four important aspects of the coal pillar stability phenomenon, summarized as:

(1) Application of t-SNE model in order to truncate the dimensionality of original pillar cases dataset.

(2) Data Cleaning, preprocessing and feature selection in order to determine the most relevant data for machine learning models employed in this study.

(3) Construction of unsupervised machine learning approach i.e., K-means clustering in order to label different classes of coal pillar cases.

(4) Selection of the best model SVC model to predict the pillar cases by validating its performance using the input and output datasets. The flow chart of the study is depicted in Fig 6.

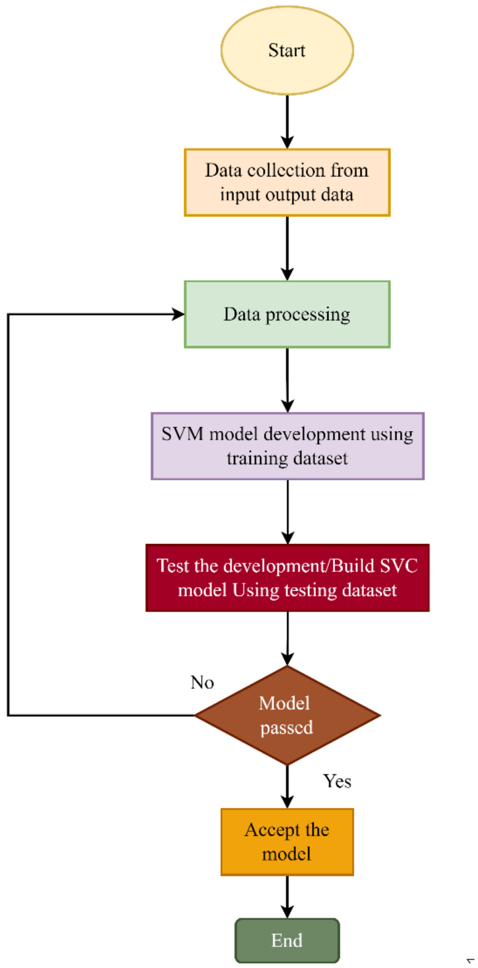

Fig. 5 Flowchart of SVC algorithm

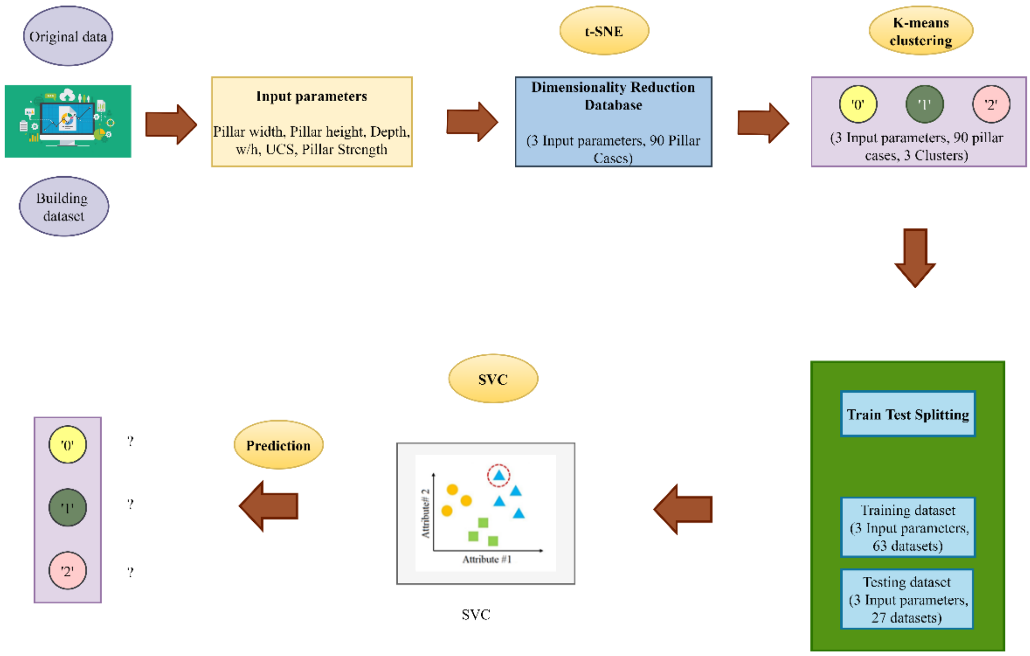

Fig. 6 Flowchart of the study

3. Result and discussion

3.1 Data cleaning and preprocessing

Prior to establish a predictive model for coal pillar failure, the initial and most important stage is data preparation (Akinnikawe *et al.* 2018). Data preparation comprises of data cleaning and preprocessing. The Pandas library has diverse advantages for data cleaning, knowledge extraction (data extraction), data / pattern analysis, manipulation, and visualization (Matplotlib). Two main operations are included in data preparation. Firstly, data cleaning and the lastly feature selection. This operation is consisting of the following steps.

1) Dropping the attributes in a dataset which are not relevant for the machine learning approaches.
2) Dropping the row with missing or null data.
3) Detection and removal of outline. The aim is to detach the incorrect and anomalous data which might be due to human error, measure inaccuracy etc.

3.2 Feature scaling

Since the pillar database exists in different magnitude and proportion with reference to its failure class, it is necessary to bring all attributes to same range and scale. Feature scaling is used to improve and accelerate the performance of machine learning algorithms. The standardization strategy for feature size has been used in this approach, as shown in Eq. (3). The method of rescaling one or more influential variable to a mean of 0 and a standard deviation of 1 is known as data standardization. Standard scaler module in the scikit-learn has been employed to execute the feature scaling.

$$x_{std} = \frac{z - \mu}{\sigma} \tag{3}$$

Whereas x_{std} is the standard score, z is the actual value, σ is the standard deviation and μ is the mean of the dataset.

3.3 Dimension reduction with t-SNE

The t-SNE mimics pairwise resemblances between the upper and lower dimensional space as the uncertain likelihoods $p_{j|i}$ and $q_{j|i}$ as shown in Eqs. (4) and (5) respectively. For example, the uncertain likelihood $p_{j|i}$, can be elucidated as the likelihood that a *j* point is a neighbor of *i* point in a higher dimensional space. The t-SNE executes the probabilities as a Gaussian distribution around each data point in higher dimensional space.

$$P_{j|i} = \frac{\exp(-||z_i - z_j||^2/2{\sigma_i}^2)}{\sum_{k\neq i}\exp(-||z_i - z_k||^2/(2\sigma_i)^2} \tag{4}$$

Whereas z_i, z_j and z_k are the points in the higher dimensional space.

The goal propagation of pairwise resemblance in low-dimensional embedding space as shown in Eq. (5) by applying the coal pillar cases t-distribution around each data point to overwhelm the congestion issue in Gaussian propagation.

$$q_{ij} = \frac{(1+ ||x_i - x_j||^2)^{-1}}{\sum_{k\neq i}(1+ ||x_k - x_l||^2)^{-1}} \tag{5}$$

Whereas x_i, x_j, x_k and x_l are the points in the higher dimensional space.

To reduce the KL disparity, t-SNE uses gradient descent with the gradient calculated as indicated in Eq. (6)

$$\frac{\partial C}{\partial x_i} = 4 \sum_j (p_{ij} - q_{ij}) q_{ij}(x_i - x_j) \tag{6}$$

Eventually after computing k-Nearest Neighbors, a sparse matrix P_{ij} is calculated which retain the nonzero values of P_{ij}. Furthermore, the attractive force computation is decomposed into a series of sparse matrix determination as given in Eq. (7).

$$T = \sum_{k\neq 1}(1 + ||x_k - x_l||^2)^{-1} \tag{7}$$

Whereas T represents the spares matrix.

The t-SNE gradient calculation can be redeveloped as an N-body imitation as shown in Eq. (10) issue by reorganizing the terms into attractive and repulsive forces as shown in Eqs. (8) and (9) respectively.

$$F_{attr} = \sum_{j\in[1,....N]} p_{ij} q_{ij} T(x_i - x_j) \tag{8}$$

$$F_{rep} = -\sum_{j\in[1,....N], j\neq 1} {q_{ij}}^2 T(x_i - x_j) \tag{9}$$

$$\frac{\partial C}{\partial x_i} = 4 \ (F_{attr} + F_{rep}) \tag{10}$$

Python with Scikit-learn module is utilized to execute the t-SNE (Pedregosa 2011). The actual six attributes of 90 patterns of coal pillar dataset in this study were plotted on the three dimensions mainly contingent on subsequent criteria. These six attributes can be considered in three different groups as shown in Fig. 7: the first group comprises of pillar dimensions including width, pillar height, depth, w/h whereas the second group includes the standard laboratory test i.e., UCS which is derived from the original data. The third group consists of pillar strength

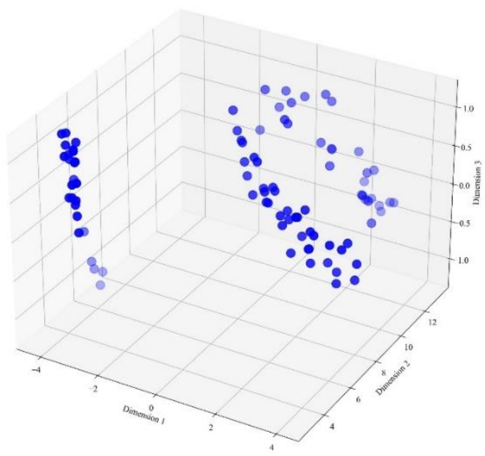

Fig. 7 Data visualization following depletion of features using the t-SNE approach

Table 3 Pillar cases data ensuing features depletion with t-SNE technique

Pillar Cases	1st Dimension	2nd Dimension	3rd Dimension
1	0.65	10.25	0.90
2	0.67	9.97	0.99
3	-0.37	10.83	1.15
4	0.43	12.04	0.97
…..	…..	…..	…..
87	-4.24	6.29	-0.93
88	-4.02	4.31	1.15
89	-3.74	4.41	1.05
90	-4.07	4.57	0.78

which is derived from the empirical formula based on pillar datasets (Ding *et al.* 2018). Moreover, following the data reduction, three features established space can recognize a naive visualization in conjunction with retaining the original data aspects to as much as possible. Table 3 exhibits the data after data reduction. The actual database (90 × 6 matrix) is transformed to a (90 × 3) matrix.

3.4 K-Mean clustering

In K-Mean clustering, the most significant problem is determining the best estimate of the number of clusters., which is usually taken prior to data execution. The criterion function in K-means clustering is given by Eq. (11).

$$SSED = \sum_{n=1}^{k} \sum_{z \in C_i} (z - \overline{z_i})^2 \tag{11}$$

Whereas SSED is the summation of centroid and its corresponding squared Euclidean distance between different data, z is the observed value, and $\overline{z_i}$ is the arithmetic mean of actual values. By employing the criteria function, the developed group can be compact to the maximum extent, whereas different clusters can be self-sustained.

The WCSS technique is used in this work to compute the cluster numbers. Moreover, the k data points can be considered as the vector centroid. The formula of WCCS is given below from Eq. (12) to Eq. (14).

$$\vec{z_i} = \frac{1}{C_i} \sum_{z \in C_i} (\vec{z}) \tag{12}$$

$$WCCS_k = \sum_{z \in C_i} |(z - \overline{z_i})^2| \tag{13}$$

$$WCCS = \sum_{k=1}^{k} WCCS_k \tag{14}$$

Whereas $WCCS_k$ depicts the interval of each point in class k with respect to its center and $WCCS$ represents the summation of $WCCS_k$ in all the classes of *k*.

Python with Scikit-learn module is utilized to execute the K-Mean clustering (Han *et al*. 2011). The elbow approach has been used to find the clusters number on pillar cases dataset. The elbow approach is based on the sum of squared distances between each data point and the cluster's centroid to estimate a small cost function. Our aim is to find a modest k value that still possess a low cost. The elbow approach works by running k-means clustering for a range of k values on the dataset, then calculating the cost function value for entire value of k. If the chart resembles an arm, the value of k is the 'elbow' on the arm. Fig. 8 represents the line graph for cost function rate. The elbow point k-3 (described by number 0, 1 and 2) is applied in this study to relabel the original data. For each iteration value we have different results.

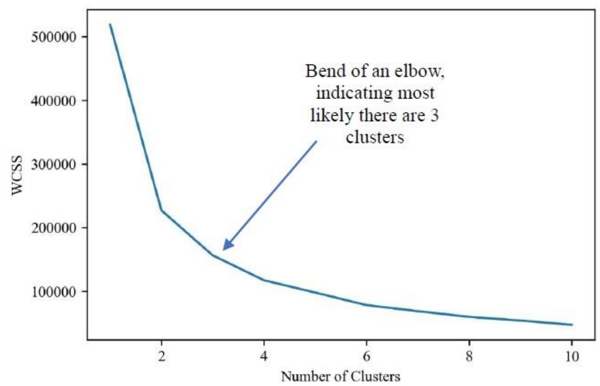

Fig. 8 The relationship between number of cluster and WCSS

Table 4 Data obtained after feature deletion with t-SNE technique

Pillar Cases	Original pillar class	Clustering class
1	I	2
2	I	2
3	I	2
4	I	0
…..	….	…..
87	F	1
88	I	1
89	F	1
90	I	1

Fig. 9 indicates various iterations stages employed in the study. The results of clustering were stable after 20 rounds of iteration, the center of all the three clusters were (0.93, 0.40, -0.71), (-1.47, -1.23, 0.21), (0.13, 0.55, 0.65) respectively. After clustering mechanism, all the pillar cases were grouped by character '0', '1' and '2'. Table 4 elucidates the original pillar cases and the new classes following the clustering mechanism. For the actual pillar cases class 'F' represents Failure pillar class, 'I' represents inceptive failure class and class 'S, represents the stable pillar cases. Furthermore, a line plot has been drawn in order to present the cost function value for each k. The original pillar class is from different pillar categories assessment characteristics, which mark them inconsistent.

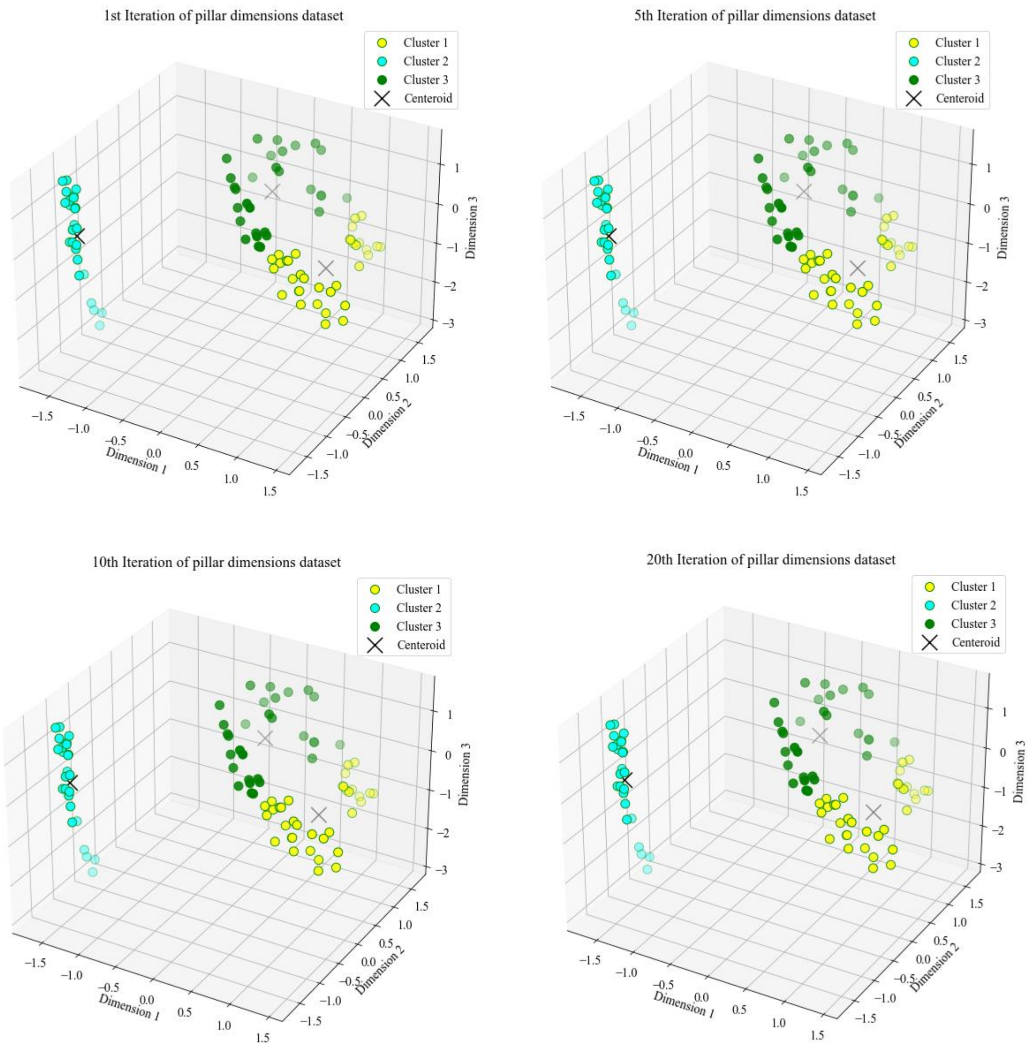

Fig. 9 Clustering strategy visualization on coal pillar data

To determine the outcome obtained from the clustering algorithm a ground truth label data should be defined (Kamran and Shahani 2022). Hence prior to the estimation of coal pillar classes for three cluster, a ground truth has been truth described for any pillar class assessment criteria, keeping with the failure procedure and instability mechanism of coal pillars, the intensity of the stability of pillars is classified into three classes i.e., failure, inceptive failure and stable. 'Failure pillar class' always that the pillar is squash and has marked conspicuous, which indicates a high level of surface subsidence risk. The stable pillar shows that the pillar depicts no intimation of stress caused rupture, or only has an insignificant spalling which do not result in the stability of pillar. The inceptive failure shows that the pillar is moderately and has a significant failure but still maintain stability. On the other hand, the comparative strength of pillar classes for 'Low pillar class' and 'Moderate pillar class' possibly uncertain among various benchmarks. As shown in the Fig. 10, for 90 pillar cases, cluster two represents 35 coal pillar cases for failure coal pillar (39 percent of the total data), 25 coal pillar cases for inceptive failure coal pillar (28 percent of the total data) and 30 coal pillar cases for stable coal pillar class (33 percent of the total data) respectively. This research would relabel the pillar classes to achieve its compatibility.

Based on the above explanation, we assigned three different values to numerically categorize each pillar stability class. Hence failure, inceptive failure and stable pillars are presented by '0', '1' and '2' class respectively. A total of 90 cases of label coal pillar records from the K-means are selected as training samples and validation samples. The data was randomly selected as testing samples to authenticate the machine learning model. Hence a total of 63 pillar cases (70% of the total data) were chosen as training sample and 27 pillar cases (30% of the total data) were chosen as testing samples.

3.5 Establishment of SVC model

Usually, SVC model can perceive binary classification, as a result of which it can only predict 'happen' or 'not happen' coal pillar. In order to predict the three distinct severities of coal pillar classes, a binary classification SVC is extended for multiclass classification using a voting algorithm. The voting algorithm for multiclass is executed by multiple one-verse-one classifications among the pillar

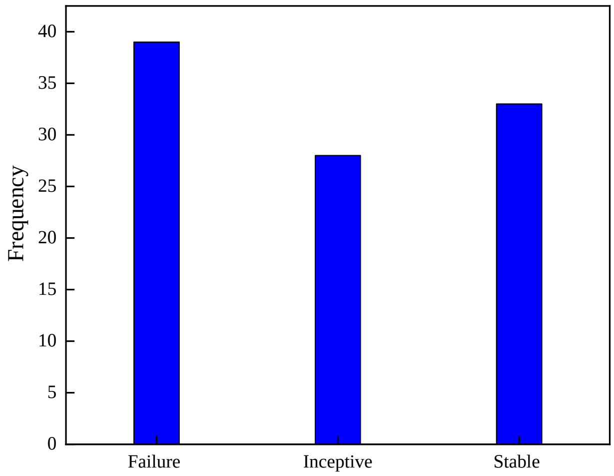

Fig. 10 Coal pillar class for cluster 2

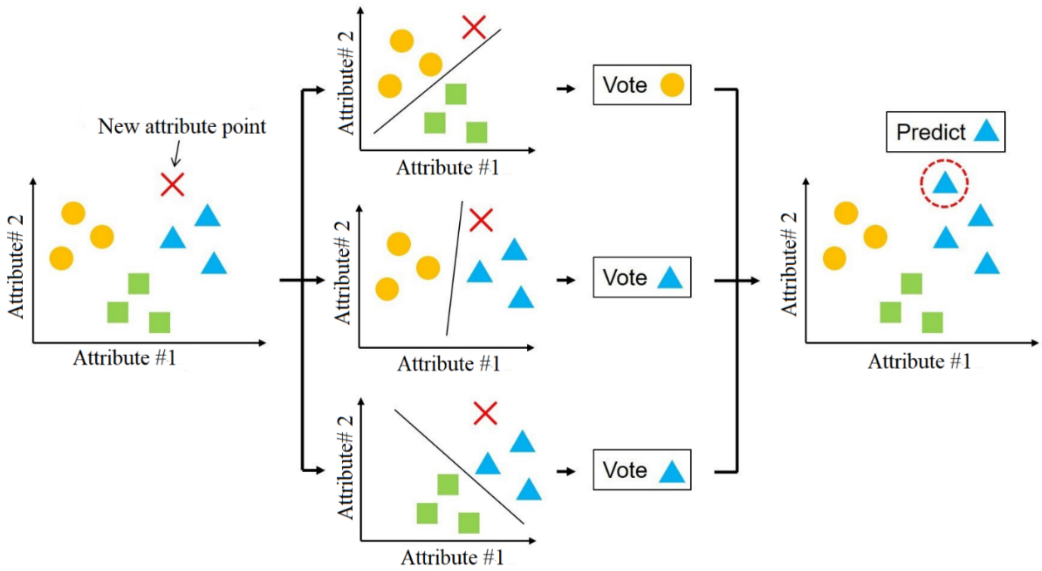

Fig. 11 Voting technique for the SVC algorithm

classes. Fig. 11 depicts the voting technique for the classification encompassed by three classes. The three dimensions depletion k-mean clustering data is plotted as the triangle, square and circle on an indicator plane of feature #1 and #2 in Fig. 10. A red-crossed mark has been added to the plot as a new data point. As indicated in the second row of Fig. 11, a new data point is classified intervening any two of the three classes, and a new vote has been set out to the determined class. As a result, the triangle class gathered the maximum votes, hence triangle class will be the final classification of the additional data point. Python with Scikit-learn module is utilized to execute the multi-classification SVC.

3.6 Model performance indicators

Precision (Pr), recall (Re), and f_1-score measures have been employed to assess the execution of classification-based ML algorithm (Zhou et al. 2022, Ahmad et al. 2020). Precision is the capacity to correctly anticipate datasets; recall is the ability to accurately predict the original features to the greatest extent possible; and the f_1-score is a universal metric that measures both recall and precision performance. As a result, these performance indicators are used in this study to evaluate the model's performance. Assume that Eq. (15) defines the confusion matrix. A confusion matrix is a practice benchmark for illustrating the performance of a classification model on a testing dataset with known

$$W=\begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1u} \\ w_{21} & w_{22} & \cdots & w_{2u} \\ \vdots & \vdots & \ddots & \cdots \\ w_{u1} & w_{u2} & \cdots & w_{uu} \end{bmatrix} \tag{15}$$

Where u represents the number of pillar stability classes, w_{11} is the number of features accurately predicted for class a, and w_{ab} depicts the number of features of class that are categorize to class b.

The Pr, Re, and f_1-score metric for each pillar stability class are computed based on the confusion matrix as shown by Eq. (16) to Eq. (18).

$$Pr = \frac{w_{aa}}{\sum_{a=1}^{u} w_{ab}} \tag{16}$$

$$Re = \frac{w_{aa}}{\sum_{b=1}^{u} w_{ab}} \tag{17}$$

$$f_1 - score = \frac{2 * \quad Pr * Re}{Pr + Re} \tag{18}$$

3.7 Prediction results

From the label data of k-means clustering, there are three dimensions for pillar data, which have different proportions. In order to prevent the overtraining and the negative outcomes of different proportion in the label data, uniformization will be employed to process t-SNE dimensionally reduction data prior to parameters optimization. Eq. (3) has been employed for data normalization. A non-linear SVC with RBF kernel function has been employed in this study to predict the testing samples obtained from k-means clustering. Prior to the determination of the nonlinear SVC model for the prediction of testing sample, two different indicators C and g should be set on subjectively. The indicator C defines a penalty attribute, which execute a retribution for misclassification where g is an attribute in RBF which is used to regulate the distribution of the data in new space after mapping determine the implied a parameter which implicitly determines the data distribution in the new and then prediction results are acquired from the SVC algorithm. After the data optimization, the training dataset from the k-means clustering has been used to train SVC model. With this trained model, we predict using testing dataset and get prediction results. Fig. 12 shows the confusion matrix of SVC algorithm in testing dataset. The main diagonal values stipulate the number of samples correctly predicted. The off-diagonal values stipulate the number of datasets misclassified by SVC. As mentioned earlier, the test data contains 27 pillar cases (30% of the total data), so the confusion matrix also incorporates 27 prediction results. The horizontal and vertical metrices are the prediction and ground truth of SVC, meaning that the prediction result is more accurate if the data appear in the diagonal, from upper- left to lower-right, of the matrix. Fig. 12 shows the confusion matrix of SVC model in three different pillar cases. From the Fig. 12, it is clear that none of the class '0', '1' and '2' are misclassified as compared to the several models proposed by Li et al 2022 using logistic model tree (Li et al. 2022). From Fig. 13, it is clear that most samples were accurately classified by using SVC algorithm. Also, it can be seen the value of Pr, Re, and f_1-score were 0.98, 0.98, and 0.98 in training and 0.97, 0.97, and 0.97 in testing, respectively. Based on the above overall performance indicators investigation, it can be summarized that the SVC framework is reliable and feasible for forecasting the stability of pillars in subsurface coal excavations.

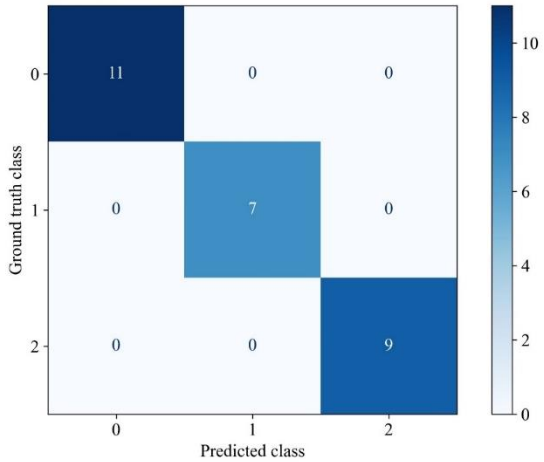

Fig. 11 Confusion matrix of SVC algorithm testing data

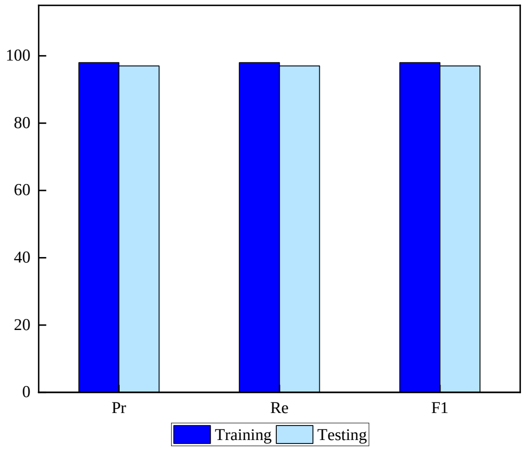

Fig. 12 Overall performance indicators of SVC algorithm

4. Limitations and future studies

Despite the fact that SVC model coupled with t-SNE dimensionality and k-means clustering has accomplished acceptable outcomes in forecasting the stability of coal pillar, some limitations ought to be tended to in upcoming studies. As a data-driven approach, machine learning (ML) techniques intensively depend on supporting databases. In this study, 90 data collected for SVC training were comparatively too small by comparison with other typical ML assignments. A key result of too small training dataset is model overfitting, which brings down model's soundness and consistency. A bigger supporting dataset would enhance the competency of the framework to be used in future studies. While the forecasting results exhibited acceptable speculation capacity for SVC framework, we are still concerned about whether the training and testing data can satisfy the i.i.d (independent identical distribution) process, that is a crucial presumption for ML datasets. In future studies, this problem should be approached numerically and engineeringly. In parallel, in this paper, we are unable to achieve relative significance of six coal pillar prominent indicators by prevailing strategies since the training data given into the SVC framework are amplitude depletion data. To put it another way, we only could obtain the general significance of three dimensionality depletion features which didn't represent a particular actual implication. Methods for calculating the relative relevance of the original training features if they are dimensionally decreased may be the focus of future research. The relevance of explicit features in ML applications in engineering helps to increase the model's interpretability as well as generalizability.

5. Conclusions

Pillar stability prediction is one of the significant tasks in underground rock engineering to ensure safety for mining operation. This study investigated the performance of t-SNE, unsupervised and supervised machine learning algorithms to predict the pillar stability. Six quantifiable distinguishing attributes of 90 coal pillar cases i.e., pillar width, pillar height, depth in meter, w/h, UCS in MPa, pillar strength in MPa and pillar class for each pillar class were selected in this study. The correlation between each input attributes and coal pillar class were determined using a boxplot. A pioneering feature depletion method, t-SNE has been utilized in this study to reduce significance of original data attributes. The six dimensionality data attributes were considered in three dimensionality spaced groups: the first group includes pillar dimensions characteristics including pillar width, pillar height, depth, w/h whereas the second group comprises of the UCS, and the third group entails pillar strength. The employed t-SNE technique has decreased the relevance among the original six features of coal pillar dataset. Moreover, a three-dimensional dataset was visualized in this study.

Although each pillar case has an original corresponding class, however it was not clear that which coal pillar class criteria was followed by each pillar class case. Hence an unsupervised machine learning algorithm k-means method was employed in the study to relabel each pillar class based on its own attributes only. After the execution of k-mean technique, three cluster were opted to reflect the coal pillar class. The original labels distributions were computed to establish the relative class of coal pillar among the three clusters. The relabeled data acquired from k-means clustering was further utilized as training and testing data for SVC model. The prediction outcomes showed a best match with the original labels which revels the feasibility, reliability, and effectiveness of our model. Due to the advancement in the sensor-based knowledge acquisition, new measurement will be available in the future rock mechanics projects. So, the influence of other attributes on the coal failure prediction outcomes are required to be analyzed.

Conflict of interest

The authors declare no competing interests.

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