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Machine learning framework application for modelling geomechanical instabilities: a caving case study

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Abstract

The field of machine learning (ML) has had a significant impact on, and adoption in, many fields of science and engineering, yet in mining is still not very well developed, with many publications exploring scopes of application and potential areas of integration.

As mining reaches deeper environments where most traditional methods of stability analysis have yet to be calibrated, there are good opportunities to apply ML methods to diverse types of, for example, failure phenomena. Still there is a necessity to properly account for adequate data inclusion and problem definition to apply these kinds of analysis, which is why data representation and availability with regards to a particular problem are crucial

In this paper a case study of the application of data extraction and the ML modelling process applied to rock mass failure phenomena taking place in an underground cave mine is presented as an illustrative example of the practical application of ML methods of analysis in mining.

The results show that ML methods have high potential in mining applications when coupled with careful consideration of input variables and the correct choice of ML approaches. The fundamentals and practical aspects are outlined such that the methodology of the case study is generalisable to different kinds of geomechanical problems.

Keywords: *machine learning, mine design, caving mechanics, caving projects*

1 Introduction

While machine learning (ML) has had a significant adoption in many fields of science and engineering, its introduction in applications for the mining industry is still in the early stages. In particular there are recent developments which have been able to produce practical applications in many aspects of the mining cycle, in areas such as mine planning optimisation (Chimunhu et al. 2022), drilling performance evaluation (Heydari et al. 2024) and modelling of rockburst events (Wojtecki et al. 2022).

The potential for ML applications in mining is vast, but the field of geomechanics is of special interest since the industry currently moves towards a general landscape of underground operations taking place at greater depths. With caving operations being one of the main strategies for these purposes, significant engineering challenges in terms of mine design and stability emerge since there are several known critical aspects that these methods are required to control.

In this context, some of the major cave mining operational hazards include rockbursts, inrush, airblast events and collapses (Flores & Catalan 2019). Among these hazards the most common are rockbursts and geomechanical collapse. These phenomena severely affect mine stability and have a complex nature, and their underlying mechanisms have not been thoroughly identified.

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It is at this point where the high amount of data that is now possible to collect can be integrated in a framework that facilitates the application of modern ML methods to exploit their predictive capabilities regarding observable emergent phenomena or as a component in monitoring tools. For the case of the challenges that cave mining involves, the availability of these methods is an opportunity to tackle those severe potential hazards and make them the object of modelling in order to understand and control their development.

As successful applications continue to emerge it becomes more apparent that there are opportunities for incorporating ML models, in conjunction with conventional rock mechanics methodologies, to increase reliability of the prediction of potential hazards while advancing understanding of the underlying physical phenomena (Morgenroth et al. 2019), which can ultimately lead to better design, operational control and risk management.

Critical aspects of the application of ML methods are the availability and integration of different types of data to adequately represent a particular problem. This phase, in the early stages of the definition of the analysis, will condition how the information is considered and categorised for its adequate representation.

This paper presents a case study of an ML modelling approach for the pillar collapse phenomenon in a caving environment, where an automated pre-processing step for capturing geospatial information was developed to adequately represent the information that ML algorithms need in order to perform their modelling steps. The results of the models are displayed, showing that the representation of the variables was sufficient for the ML methods to detect regularity and properly represent the expression of the phenomena though the information they were able to capture.

This procedure can be used as a framework to understand the general implementation of this type of methodology for its application to many different geomechanical-related phenomena.

2 Pillar stability aspects

Generally, pillar stability is assessed via empirical approaches derived from collections of field observations or numerical modelling methods (Zhou et al. 2015), with the latter being the main strategy for modelling the behaviour of underground structures providing convenient alternatives for purposes of design and analysis (Sinha & Walton 2019). Although numerical modelling is a highly advanced tool with capacity to simulate complex phenomena, it has underlying assumptions such as the rock mass being a material that experiences continuity in its deformations which is hardly the case for heterogenous bodies such as rock masses (Sherizadeh & Kulatilake 2016).

Given the nature of caving dynamics and the changes it induces over time on the rock mass, the aforementioned methods may not necessarily be sufficient to capture the complexity of this mode of failure since it does not appear to respond coherently to concepts such as stress to strength ratios and homogeneous behaviour. Along these lines, worldwide expert criteria (Beard & Brannon 2018; Ferguson et al. 2018) states that the management of major instabilities is of utmost importance and has devised a series of operational strategies, considerations and design principles that aim to mitigate geotechnical hazards, including collapses, and ensure the safety and stability of cave mining operations.

ML techniques and certain ML model architectures have the advantage of being able to work with various types of data and identify complex non-linear interactions between input variables that belong to different conceptual domains. This makes it possible to include a set of baseline static parameters such as geological conditions, and couple them with historical operational factors to model the observed responses for the defined target (i.e. collapse occurrence).

3 Collapse phenomenon in caving

Collapses represent one of the most severe types of geomechanical instabilities in caving environments. They create challenging pillar stability problems where progressive deformations take place in the production level drifts and can completely hinder entrance to the works; compromising access to drawpoints in the affected areas and generating severe losses and delays in production schedule rates, according to their magnitude and extent. They have been defined as a gradual failure of the rock mass where deformation progressively develops across drifts, leading to the full closure of the cross-sections in worst-case scenarios (Pardo et al. 2012). They consist of rock mass damage events associated with visible deformations in a plastic strain mode of failure. Such deformations can develop over time and produce significant changes in the shape of galleries and tunnels.

The mechanisms leading to collapses have been studied in the literature although they are still not sufficiently understood (Pardo et al. 2012). Nevertheless, according to previous studies (Gomes et al. 2016; Cornejo & Pardo 2014; Landeros et al. 2012) some of the main contributors that have been identified are:

- the geometry of the cavefront
- the caving front position with regard to the pillars of the production level
- the presence of remnant pillars in the undercut level associated with deficient blasting during undercutting
- damage in the undercut level caused by increased abutment stress
- reduction of the pillar dimensions in the undercut level
- unfavourable global caving front geometry and the extraction angle applied that controls overall caveback geometry
- geological conditions (e.g. presence of major faults perpendicular to the direction of advancement of the caving).

However, the relative contribution of these factors as well as their combined interactions have not been previously studied in quantitative terms.

In addition it should be considered that caving dynamics cause production level pillars to experience high-stress conditions that change over time. Thus overall stability issues and the risk of major geotechnical hazards increase when considering this non-static scenario.

Based on such characteristics, a series of operational considerations have been developed and denoted as 'caving rules'. Derived from technical, operational and empirical expertise and knowledge about caving methods, they aim to summarise critical design aspects and operational principles to ensure the safety and stability of cave mines by regulating their development process at the different stages of establishment, initiation, propagation and breakthrough (Cuello & Newcombe 2018).

The implementation of and compliance with these rules have a wide array of impacts on caving performance, ore production rates, construction costs and schedules, and mine safety and stability.

Aspects of mine development such as sequencing, the undercutting rate, allowable lead-lags, drawbell opening rates and extraction rates are addressed through these rules (Beard & Brannon 2018), ultimately controlling the caveback geometry and growth, which are parameters that have been strongly linked to collapse propensity in previous studies (Landeros et al. 2012; Cornejo & Pardo 2014).

Also, one must consider that in caving methods the stress abutment state presents the most vulnerable condition for production level pillars due to the extensive local loading changes. Its generation as a consequence of the advancement of the caving front, its possible impact over the production level and its management are considered in the caving rules. However, regarding the collapse phenomena, it is important to note that collapses can develop behind the cavefront and not necessarily only in abutment zones. This suggests the existence of additional factors that might not be adequately accounted for in design or operation rules, which is why it is crucial to study other possible relationships.

Therefore it becomes necessary to not only investigate the relationships between collapses and factors covered in caving rules but also other possible driver mechanisms that might contribute to this type of instability.

4 Pillar stability analysis methods

In mining engineering, static deterministic approaches based on empirical methods to assess the stability of supporting structures have been widely used. Usually pillar stability is evaluated based on safety factor (SF) values and requires an accurate estimation of stress (load) and strength (resistance) (Song & Yang 2018). Empirical methods consider the ultimate stress using survey data of the actual mining conditions to analyse pillar stability through the calculation of the SF. However, these methods fail to consider specific failure mechanisms and the material properties such as size, shape, stress conditions and the presence of fractures (Elmo et al. 2021). Moreover, there have been reported cases of pillars suffering failure even when having a SF > 1 (Zhou et al. 2015).

A more sophisticated method of stability analysis that overcomes the limitations of empirical methods is numerical modelling. It constitutes powerful and robust tools that can assess rock mass behaviour and the performance of its structures, which supports rock engineering design while also allowing us to understand the processes behind observed phenomena (Jing & Hudson 2002). These methods are widely used in modern geotechnical analysis and in the last decade have experienced significant computational advancements as well as improvements in their ability to simulate the behaviour of complex dynamics, providing important insights for structure evaluation and design (Sinha & Walton 2019; Morgenroth et al. 2019).

The main limitation of numerical analysis is its reliance on continuum mechanics concepts, which contrasts with the fact that most rock masses are heterogeneous in nature and exhibit many types of discontinuities; thus the modelling results might not necessarily capture the actual behaviour (Nikolić et al. 2016; Sinha & Walton 2019; Sherizadeh & Kulatilake 2016). While it is possible to account for this limitation by defining series of boundaries that create delimited volumes with specific properties, they still work under the premise of having the model mechanisms responding to deterministic constitutive laws of material resistance. Specifically, assumptions provide a framework where the aspect of stability is known as *a priori*, leaving aside other possible factors that could be related to rock mass failure such as static fatigue, strength degradation and time dependency (Paraskevopoulou et al. 2018).

As it relates to the case study discussed in Section 5, certain aspects (such as the progressive degradation of production level pillars and collapse events that developed behind the cavefront) strongly suggest that for this phenomenon a strength/stress perspective does not address the full aspect of stability. In contrast with absolute *a priori* assumptions, this problem was approached under a framework that has few initial assumptions of possible mechanistic behaviour and aims to identify the most relevant factors that affect the observed outcome.

To that effect, different types of data were collected in order to analyse their correlation with collapse events ranging from geological and geotechnical factors to operational elements that include time-dependent components and caving rules parameters. For this, a flexible ML architecture with intrinsic capacity to capture non-linearities and interaction effects between different types of data was employed to model the collapse phenomena.

5 Machine learning modelling approach

ML is a subfield of artificial intelligence (AI) composed of a set of methods of data analysis that can automatically detect patterns in data and use them in future tasks like decision-making under uncertainty or to predict future behaviour (Murphy 2012). With these tools it is possible to model functions that map a given set of inputs to an output value by using data which in turn can be used to forecast outcomes and even their respective probabilities.

They can detect complex interactions between the inputs and are able to work with datasets composed of different features that belong to various conceptual domains while still being able to determine relationships between the individual input elements. When modelling an unknown process that encompasses many suspected variables and/or interacting agents, ML can be employed to uncover the main elements that are correlated with the outcome of the modelled phenomena by having the available data drive the initial analysis to incrementally improve knowledge about the process.

These advantages have given AI and ML methods traction in many scientific fields and domains of knowledge, leading to significant breakthroughs due to their ability to handle and model complex problems such as those encountered in rock mechanics (Jordan & Mitchell 2015; Lawal & Kwon 2021).

Regarding pillar stability analysis, ML algorithms offer ways to define complex non-linear relationships between input parameters, numerical model behaviour and observed rock mass phenomena to subsequently conduct more precise sensitivity analyses of the model's inputs to ensure the adequate rock mechanics are being captured (Morgenroth et al. 2019).

In ML modelling, tree-based methods are preferred when there is a need for flexibility and high predictive capacity in the presence of possible interactions and non-linearities in data. They consist of non-parametric methods which gives them the advantage of not relying on prior statistical assumptions, they normally do not require previous variable selection or processing, and they are not hypersensitive to outliers and unbalanced data. These factors make them popular in many different research fields since they provide the flexibility to handle multifaceted data (Carvalho et al. 2018).

Tree-based methods usually refer to ensembles of basic classification and regression decision tree algorithms (CART). These base algorithms create segmentations of the data into subsets by minimising an impurity function; generating splits on the data that aim to create the most homogeneous and different sets (Breiman 2017; Hastie et al. 2009). Following this, ensemble models are built as a conglomerate of simple decision trees which purposely behave as weak function approximators that poorly capture the behaviour of the data by themselves but collectively work together to form a strong and robust function approximator.

Tree-based ensemble learning methods consists of sampling several instances from a dataset through a statistical technique known as bootstrap aggregation (bagging). In this case, a full tree is built on each separate set of bootstrapped randomised instances, being completely independent from each other and forming a whole set of trees called a forest. The sampling of features from the original dataset can also be incorporated for the bootstrapping process, thus increasing randomness in the forest by having each tree randomly biased. Since the forest output is built by averaging the overall set of outputs from every single tree in the forest, such random biases are averaged out and potential overfitting issues are reduced (Breiman 2001).

Such properties make ensemble tree-based models good initial baselines with which to explore non-linear data interactions, and this modelling approach was selected to carry out the analysis of the case study.

6 Case study

The Chuquicamata mine has implemented a macro-block caving method as a continuation of the open pit mine to extend its life for another 40 years. This project aims recover 1,700 Mt of copper ore of 0.7% grade at a rate of 140,000 t per day at full production. The implemented macro-block variant considers the development of three levels built under the open pit shell, as depicted in Figure 1.

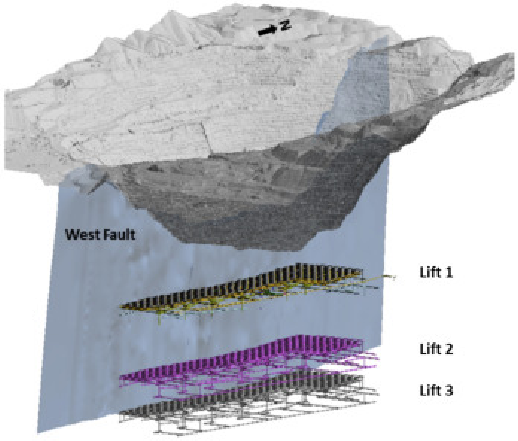
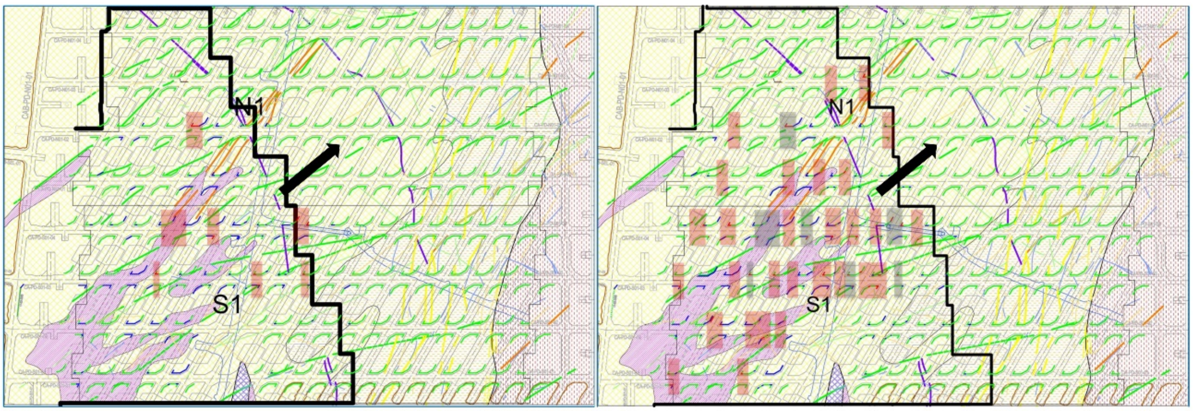


Figure 1 Designed extraction lifts for the Chuquicamata underground mine project (modified after Flores & Catalan 2019)

In the early stages of extraction in the first macro-block, a series of significant events causing rock mass damage to the supporting pillars on the production level was registered. As the caving front advanced, the damage events initially developed ahead of the caving front. Once it continued advancing, they ultimately concentrated behind it (Vásquez et al. 2023).

Although it is possible to consider the initial events of damage as a consequence of the abutment stress derived from caving dynamics, in some locations the damage appeared and/or progressed even after the cavefront continued to advance over the footprint. The situation continued and different degrees of damage and deformation in various pillars and supporting structures were registered.

The events were investigated by mine personnel and categorised as ranging from 'low' to 'high', based on the observed degree of damage. Eventually a significant part of the pillars that experienced deformations ultimately collapsed, compromising the infrastructure and access to the drawpoints in the production level. Figure 2 illustrates the evolution of the observed damage.



(a) (b)

Figure 2 Evolution of observed damage in production level pillars with respect to the cavefront position. Red: newly damaged area at the new cavefront position. Grey: previously developed. (a) Initial detected damage; (b) Progression of damage events concentration behind the cavefront. Arrow indicates direction of cavefront advancement (black outline)

The damage that was initially detected just ahead of the cavefront in the production level was expressed mainly as cracking and fracturing events that propagated through the outer shotcrete layer support installed on the lower portion of the sidewalls and on the upper unsupported portions of the sidewalls.

While it was possible to find events of damage to the roof in the affected galleries, it was only significant once the deformations progressed up to the point where the collapse phenomenon was already taking place; resulting in the roof descending due to the lack of support from the surrounding pillar structure. In contrast to other collapses registered in more resistant rock masses that are sealed and brittle, such as El Teniente mine, these cases displayed no evidence of floor heave.

The damage tracking over time showed that most of the collapse events were mainly correlated to the progression of the cavefront positioning, but not all initial events of damage ultimately progressed and evolved into collapses.

The final collapse distribution is presented in Figure 3.

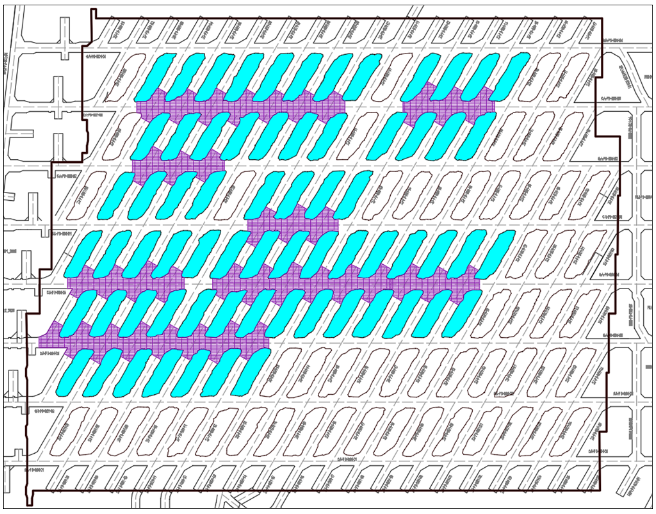


Figure 3 Final pillar collapse distribution across the footprint. Purple colour represents closure of the drifts due to high-scale deformation of the neighbouring affected pillars, which are marked in blue. Pillars suffering high-scale deformation leading to drift closure are considered collapsed (blue)

6.1 Data collection and pre-processing

For all the collapse events that occurred in the production level, information related to the nature and condition history of the pillars was collected. This comprised factors such as rock-resistance properties, local structural geology, and operational conditions that characterised the pillars intrinsically and over time.

These factors were associated with the pillar centroids as analysis units in space, representing both the position of the pillars in the footprint and their states (stable or collapsed).

Exploratory data analysis was carried out on the collected dataset to eliminate information redundancy that could hinder the performance and interpretation of the obtained results, considering the tree-based nature of the ML model architecture.

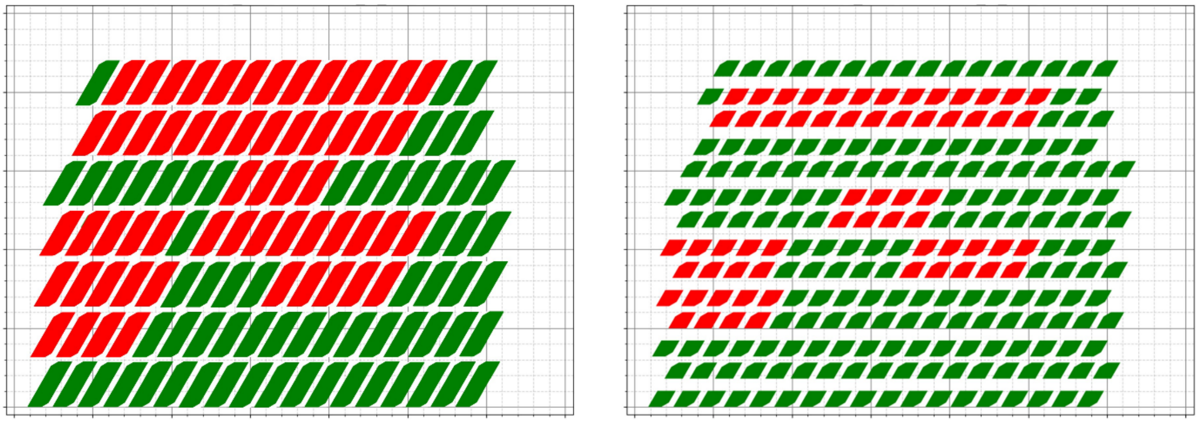
The final set of descriptive features is presented in Table 1.

Table 1 Descriptive features

Feature name	Domain	Description
Pillar area	Operational	Pillar area as a plan view projection, used as a proxy for the total active volume of the actual pillar, assuming a constant height
Abutment time	Operational	Time that a pillar is subjected to an abutment stress condition due to cavefront positioning
Open drawpoints	Operational	Average of open drawpoints surrounding a pillar before the cavefront reaches its position
T_drawbell_idle	Operational	Time between drawbell opening and its incorporation into extraction activities under the caving line
Column height	Operational	Column height from UCL floor, averaged between right and left sides of a pillar
Oversize	Operational	Cumulative ratio of oversize events during production stages. Omitted in the sequential modelling case.
SIG Y	Local stress/strength	Compressive stress Y-axis component extracted from numerical model information
UCS	Local stress/strength	Uniaxial compressive strength of pillar
FF	Local stress/strength	Average mapped fracture frequency observed on rock mass
UCS/FF ratio	Local stress/strength	Ratio between UCS and FF values
Max_step	Cavefront	Maximum lead-lag
CF_curvature	Cavefront	Local curvature of a smoothed projection of the cavefront in plan view as a measure of concavity or convexity

It is important to note that all this information relates to instances distributed across space where one point of analysis is composed of several properties that characterise it.

Furthermore, the definition of the unit of analysis conditions the way the information will be ultimately represented in magnitude and representativity across instances. To illustrate this concept, the alternative for pillar collapse representation across the footprint is presented in Figure 4.



(a) (b)

Figure 4 Alternatives for spatial representation and condition of a pillar: (a) General collapsed pillar unit; (b) Independent collapsed pillar components. Red: collapsed unit. Green: stable unit

The alternative of considering each pillar unit as a whole component that can experience failure represents a lower resolution analysis of the problem. This type of representation suffers from not reproducing the exact manifestation of the failure expression. However, data integration can be simpler, as well as the subsequent model analysis, due to lower variability across feature values.

The second alternative considers that while each one of the individual pillar tips can experience failure independently from the others, a middle portion of the pillar units is excluded from the analysis. This increases the potential local variability in the features magnitudes to be encoded, better represents the failure development and makes the ulterior analysis more detailed.

The second alternative was selected for the case study to conduct the data representation and modelling steps. For this, each one of the collapsed pillar tips was encoded using a binarised response of 0 for stable pillars and 1 for collapsed pillars. This defines a dataset composed of a selected filtered set of inputs serving as descriptive factors of the local pillar conditions plus the observed collapse response. The exercise took place with the binarisation of the pillar condition in space, according to Figure 4b.

In the context of information being represented through heatmaps in spatial data (such as geological data) it becomes necessary to transform such information into tabular data. The available data was comprised of the parameters presented in Table 1 in terms of their distribution across space, which included mine-operational parameters and geological features. To address this, a standardised processing methodology was developed to extract features with high fidelity.

The approach follows these steps:

1. Filtering – visual information from images or plans was filtered, retaining only the colours corresponding to categories or magnitudes.
2. Alignment and positioning – the filtered images were adjusted to a standard resolution and precisely aligned with a superimposed image showing the mine's footprint and pillar locations.
3. Colour standardisation – the positioned images were pre-processed to standardise their colours, removing any remaining artifacts or defects from the initial cleaning process. This resulted in the final image mask.
4. Magnitude mapping – the remaining RGB colours were mapped to specific magnitudes. Pillar tip shapes in space were used to extract pixel RGB values, which were then converted to corresponding magnitudes.
5. Feature value calculation – by combining magnitudes and pixel counts, the mean value of a given property displayed in the image was calculated for each pillar tip.

This process is illustrated in Figure 5.

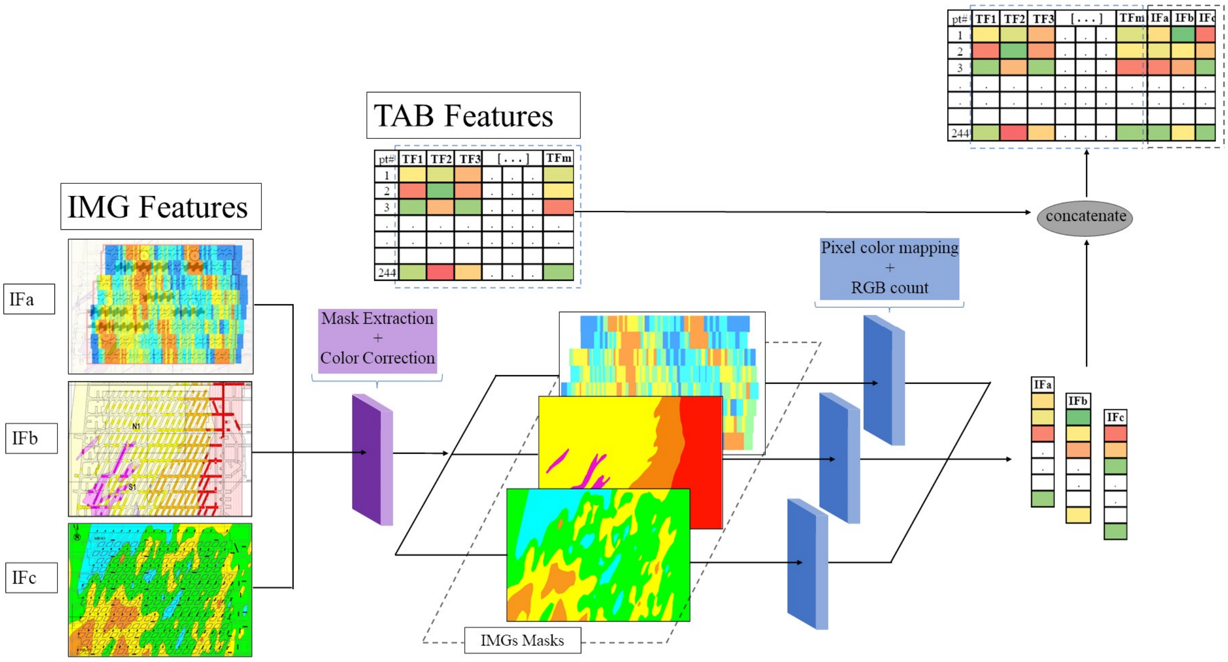


Figure 5 Train and test set instances in footprint. Transparent instances compose the testing set while solid instances are in the training set

6.2 Modelling process

The original dataset was split into two distinct sets for different purposes. The first one, denoted as the training set, was used to make the model learn the intrinsic relationships between the input values of the features and the response value (i.e. the binarised pillar condition). The second set, denoted as the test set, was used to evaluate the final performance of the model once it had been trained by using the training data. This is illustrated in Figure 6.

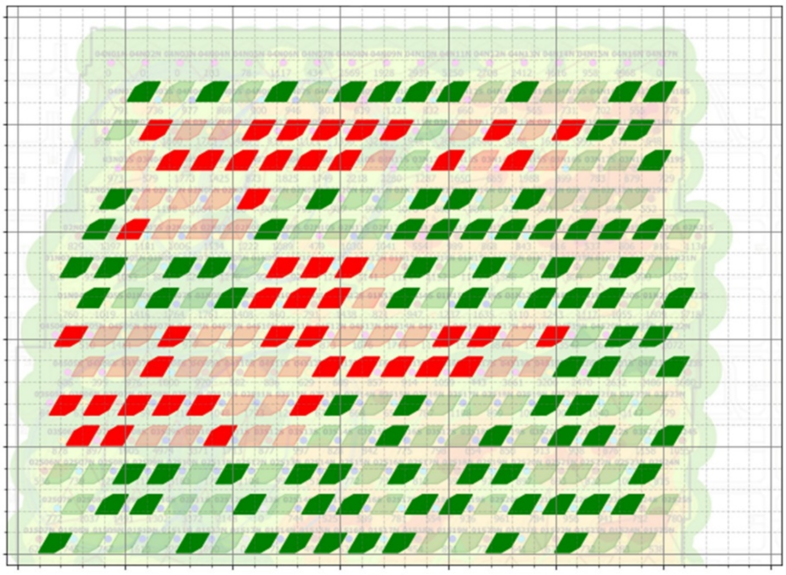


Figure 6 Train and test set instances in the footprint. Transparent instances compose the testing set while solid instances are in the training set. Red: collapsed unit. Green: stable unit

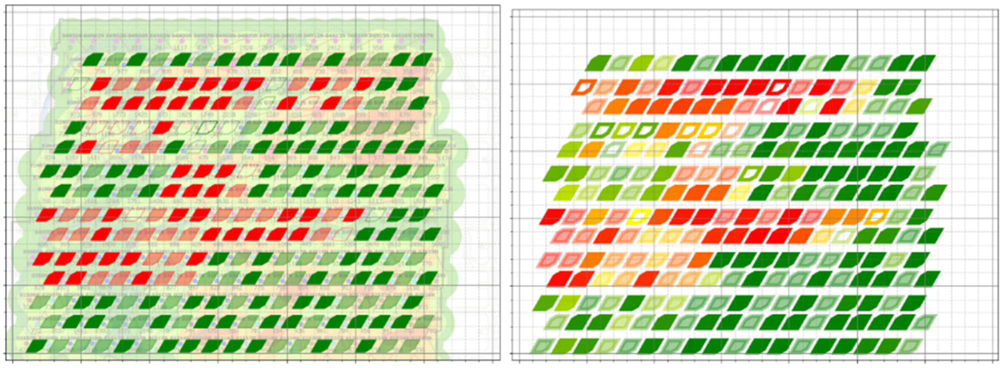
A randomised train/test split with 45% of the samples for testing is used, leaving 134 pillar tip instances as training instances. It is crucial to note that the spatial coordinates of the pillars (X, Y, Z positions) were not included in the final set of features to avoid fitting the model to specific positional information, and to instead make it focus on generalisable parameters of rock mass condition and operational history.

6.3 Modelling results

The selected tree-based architecture was fed with the tabular representation of the spatial features coupled with the binarised response for the pillar tip status.

The resulting model allows for the absolute and probabilistic estimation of a collapse response in terms of the conditional set of features for each one of the instances. While the positional information was not fed to the model, it is possible to trace back the position of each one of the instances and assign the model response for each one, thereby reconstructing their spatial location.

Through this method it was possible to observe the model response across the footprint, which adequately and sufficiently reproduces the collapse distribution. This is shown in Figure 7.



(a) (b)

Figure 7 Machine learning model results of the spatial generalisation of the collapse response: (a) Model results in binary output; (b) Probabilistic model results. For (a), red = collapsed (1); green = stable (0). For (b), the colour scale follows a transition from 0 to 100% (green to red) collapse probability according to the model. For both figures, non-filled polygons represent model errors at producing the correct output

With the model accuracy being 85% for the testing set instances plus the spatial reconstruction, it is possible to say that the model generalisation was acceptable, and that the information contained in the selected features was enough to allow the development of the collapse phenomena to be sufficiently and adequately captured by the tree-based ML model.

7 Discussion

The usage of ML models can be an effective tool for modelling complex phenomena without necessarily needing a deep understanding of the inner workings of the data or the algorithms. Still, there is a need to incorporate adequate sets of data from which the algorithms can extract useful information. For these reasons it might seem convenient to use as many different types of available information as possible to supply them to the models, however, it is not wise to blindly include features without assessing their significance.

Proper usage of ML needs to proactively address aspects such as input feature selection, interpretation versus complexity trade-offs and result analysis (Rudin 2019; Lawal & Kwon 2021; McGaughey 2020). This helps to draw conclusions by analysing model behaviour and is the reason why the data was thoroughly pre-processed, and the input variables carefully selected, before the modelling step. Considering the sampling method, the model accuracy and the information extracted from the interpretation approach the coherence of the results with expert criteria hypotheses.

The selected features shown in Table 1 contain sufficient information to correctly model the phenomena and confirm the validity of concepts in the caving rules as being significant parameters that can control overall stability in this caving scenario. This strongly validates that such design and operational parameters are incidental factors that affect pillar stability and collapse propensity.

8 Conclusion

The presented ML approach allows us to effectively incorporate selected variables from different domains to study their potential contribution to the collapse-type rock mass failure phenomenon, based on the application of a learning algorithm that weighs several hypothesised mine design elements under the scope of expert criteria. It becomes possible to further analyse previously suspected mine design and time-dependent factors that are not accounted for when employing other stability analysis methods such as numerical modelling or empirical formulas, and it was shown how those parameters serve as contributors to this type of rock mass failure. This suggests that stress analysis alone might not necessarily capture the full complexity of this type of rock mass failure, and judicious use of ML approaches might offer a flexible complementary tool to address stability analyses.

The data-driven methodology is reproducible and fairly generalisable to other geomechanics applications where emergent observed behaviour has an inherently complex nature and cannot be simply explained by reductionist approaches or first principles mechanics. Thus training an ML algorithm with data based on a given set of specific features and sufficient samples that carry enough information essentially allow the trained ML model to be employed as a system that can estimate the potential observed in situ behaviour when trained correctly.

Regarding the results obtained from the case study, the specific points are:

- The operational and design aspects exert significant control over the development of collapses in the production level as the ML model was able to extract useful information to reproduce the spatial manifestation of the phenomena based on such data.
- The elements that were accounted for and incorporated as features correlate highly with aspects about caving methods design and implementation that have been widely agreed on by experts and condensed in the concept of caving rules.
- This methodology, coupled with ML model interpretation, can serve as a step in understanding how caving rules affect the outcome of collapses in relative and quantitative terms, and can help guide and improve future mine design based on the measured effects the elements have on stability terms.

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