PERSPECTIVE

Machine Learning Applications in Mining Industry

GEM

Paving the Way for the Future of Mining

ÍNDICE

ABOUT US

With more than 13 years of experience and more than 400 successful projects implemented worldwide, GEM is the mining industry's leading consultant.

OUR MISSION

We are a supplier of industrial engineering products and services of excellence for the mining industry. We seek to maximize the value of our customers' business by improving their ability to make strategic decisions, through innovative services effectively delivered by a highly qualified professional team.

We have six areas of expertise:

Analytics	Training	Economics
Strategy	Evaluation	Optimization

MACHINE LEARNING APPLICATIONS IN MINING INDUSTRY

Introduction

From the field of computer science, our present-day has been called by two names. Both with profound implications:

The first is "the rebirth of artificial intelligence". This expresses that we are facing a process of proliferation and maturation of artificial intelligence, particularly in the area known as Machine Learning (ML).

We know that the Renaissance (rebirth in French) is also the name given to the cultural movement developed in Europe during the 15th and 16th centuries. Many of the ideas that dominated this period were not new, but rather an assertion of the heritage and work of Greek and Roman cultures.

Similarly, it was in the 1940s that the pioneers of artificial intelligence conceived an impossible but well-defined mission: to recreate human intelligence in a machine.

Although important advances were made in this field during the twentieth century, it was only in the mid-2000s that the great technological breakthrough that validated the discipline materialized. However, this time the mission would be approached with another focus: using large amounts of data from a specific subject, to execute a decision that optimizes a desired result, and. in this way, indirectly reconstruct processes of knowledge generation with the least human interference.

What changed in the course of those years? Basically two things: 1) the computing power of computers and 2) the amount of data available to process.

Naturally these two elements are not and were not new. The difference is that in order for algorithms to actually identify patterns and learn, they needed monumental amounts of data and huge amounts of resources for computing.

It is only at this time that both restrictions have been met.

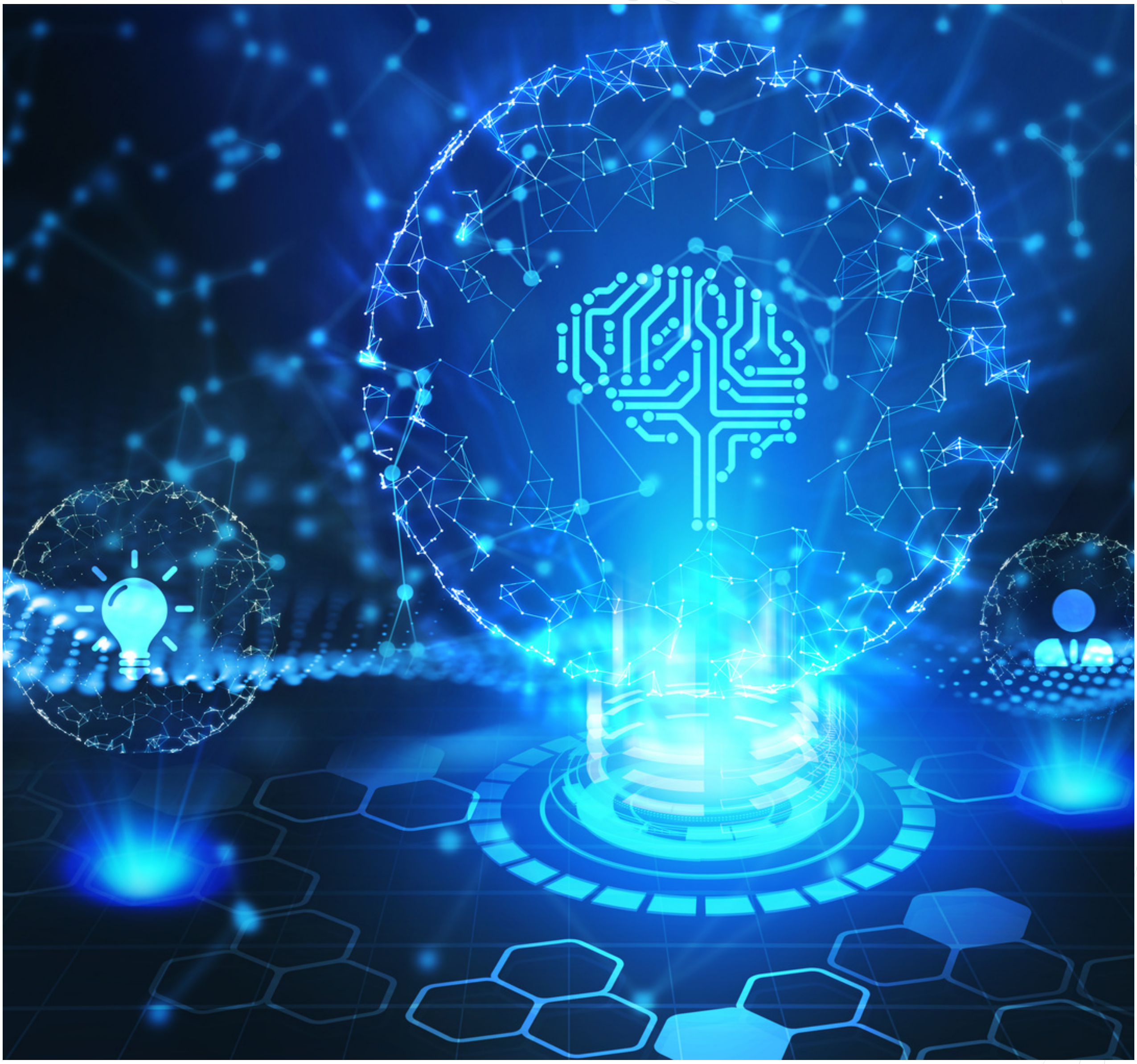
The second name attributed to this period is "the Fourth Industrial Revolution".

The first industrial revolution began with the use of steam engines. The second industrial revolution refers to the use of electricity. The third industrial revolution involves the use and diversification of computers and the Internet. The fourth industrial revolution is precisely the implementation of Machine Learning and the manipulation of large volumes of data, among others.

Each of these revolutions has generated enormous advances, knowledge and technologies on specific domains, which are expected to continue contributing to knowledge and innovation.

Also, due to the use of these new technologies, there has been pressure and a trend towards the digitization of processes in industries and companies. This has generated huge volumes of data, which add relevant value when patterns are identified.

Therefore, the aim of this Perspective is to understand the value that exists in the extraction of patterns from data, using Machine Learning techniques, specifically in the field applied to mining. To this end, we will explain the principles of machine learning techniques, the state-of-the-art machine learning applications in the mining industry, and finally a case study of GEM in the application of machine learning to mine prospecting.



I. MACHINE LEARNING

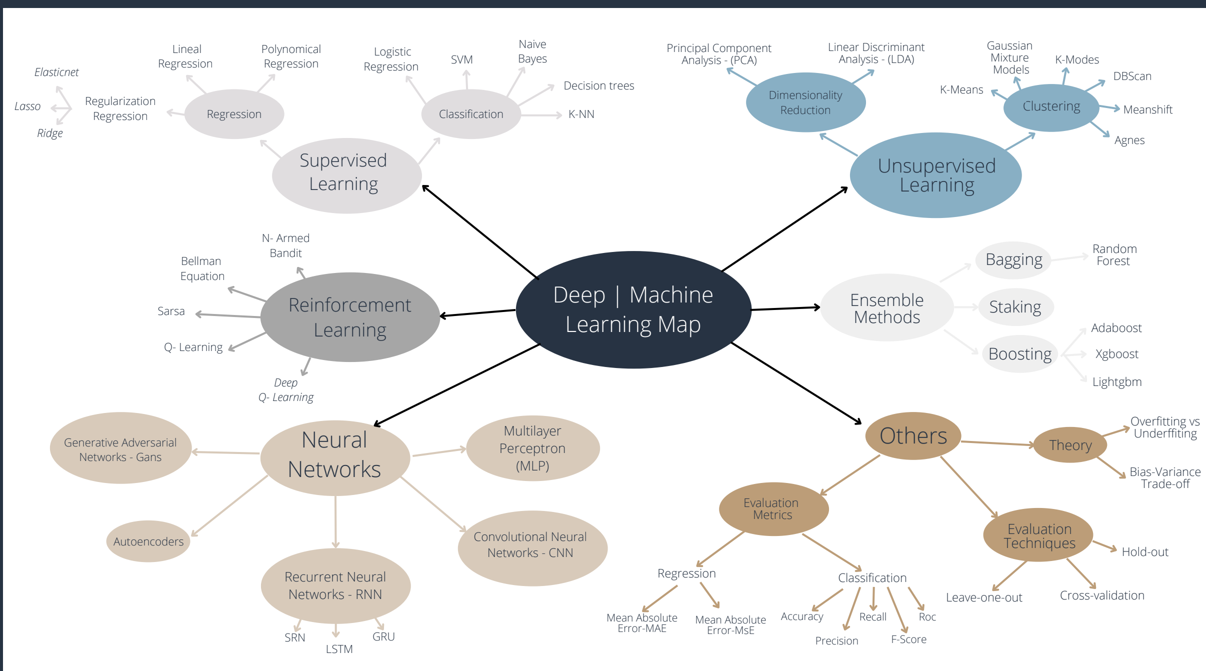
This is not an unknown term. Machine Learning is frequently mentioned in the media. Despite this, it is worth explaining briefly its scope, principles and practical operation.

Today, machine learning and deep learning techniques are used in a wide spectrum of real-world situations. Among these we can find applications as diverse as the detection of human speech, translation of documents, image recognition, prediction of consumer behavior, fraud identification, the decision to grant credit, deliver personal recommendations for content and even drive a car.

Although these applications seem distant and disconnected from each other, they are all based on the algorithms' identification of patterns among large volumes of pre-categorized data.

To do this, depending on the root of the problem, we use techniques to focus on the specific prediction of characteristics (regression problems), or classification, applying supervised learning algorithms, unsupervised, reinforcement, neural networks or other.

Figure 1. Map of Machine Learning & Deep Learning Algorithms



Moya, R. (2020)

Regardless of the algorithm, the process is based on the definition of the explanatory variables and/or the target variables.

Explanatory variables are all those that will be used to find patterns and explain the objective variable, considering the existence of causality. For example, historical data on humidity, temperature, pressure and rainfall could be used to find relationships that allow for a possible rain forecast classification. This is a simple example, but it allows us to understand two important points:

First, machine learning models need to be trained with explanatory variables and target variables. In the above example, we need to point out to the machine what the conditions were when there was rain and what the conditions were when there was no rain, so that the machine can understand and look for patterns. Therefore, if data from one variable or the other is missing, we will not be able to use this tool.

Second, a priori it is not possible to know if the data will explain the target variable in a good or a bad way. Hence the importance of having a wide variety of data and variables -and at the same time- understanding the causal relationship that is expressed between them. Perhaps the temperature, returning to the example of rain, might not be a good indicator, but if you have data on wind speeds for example, you may improve the classification.

Another important element of the process are the stages of training and validation of results. In order not to generate sub-adjustment or overadjustment bias in the estimate, the total data set is split in two: with the first set we train the algorithms and with the second, we validate the results.

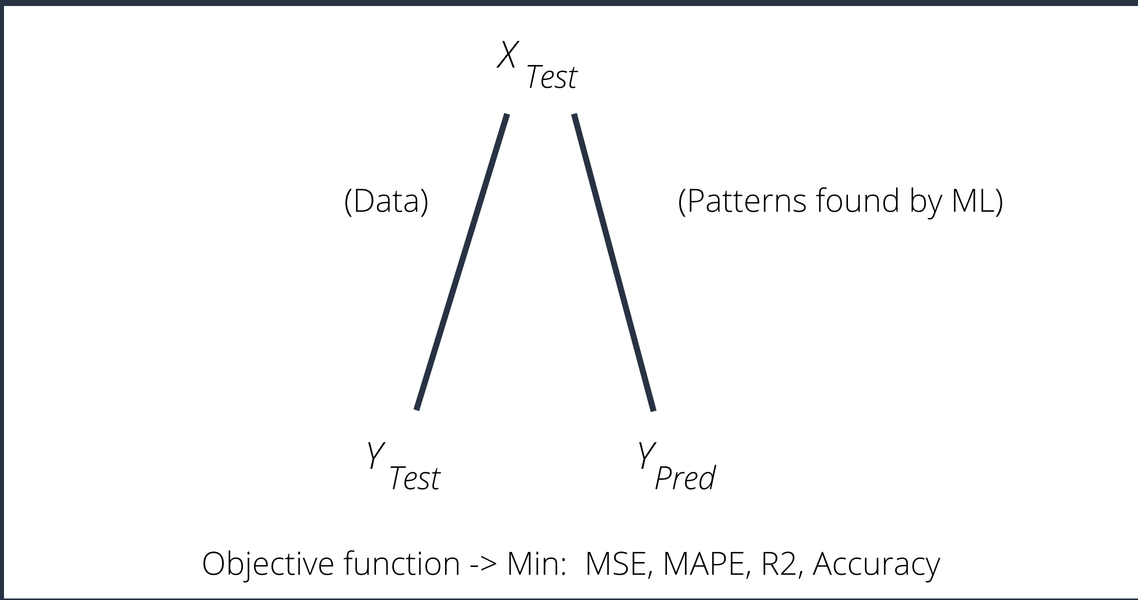
During training, the algorithm adjusts several internal parameters (hyperparameters) in order to predict the target variable from the explanatory variables present in the data.

As the training progresses, the algorithm discovers patterns between the target variable and the explanatory variables, reducing the difference or error between the actual target variable and the predicted target variable, which is defined as a function of the explanatory variables.

When the error defined from statistical indicators such as MSE (Mean Squared Error) or the accuracy percentage is minimal, then the model training is finished.

The second set of validation data is then used to evaluate the accuracy of the prediction made in the training data set for the target variable, from the other explanatory variables.

Figure 2. Prediction scheme for training and validation set



In this way, we can extract significant patterns or associations from the data, which we can generalize to produce relatively accurate predictions, depending on the results.

The advantage of these models is that they present a lot of flexibility with the data. For example, we can use images, sounds, texts and numbers as explanatory variables. On these, artificial intelligence algorithms will look for and find causal patterns existing in the data.

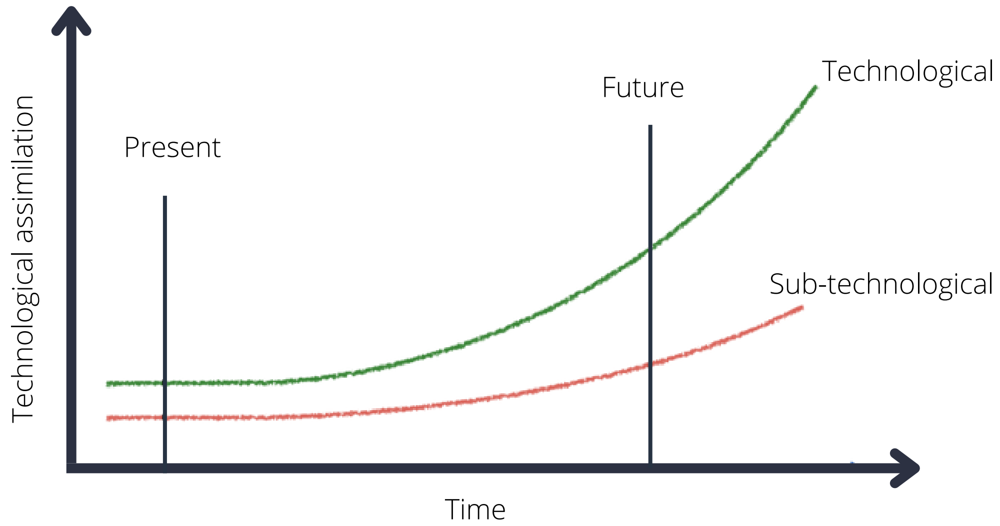
Machine Learning implementation can be very attractive for companies and industries, as a response to the high expectations in the increase of productivity and efficiency for the processes they perform.

This is especially important in the mining industry, where the ore grade is lower over time, the exploration cost required to develop new projects is higher, the pressure for lower environmental impact increases, and the demand for commodities is constantly growing. Despite this, the mining industry has historically been quite conservative and reluctant to change due, among other factors, to the high impact and cost faced by projects that do not meet expectations.

However, the late assimilation of new technology has profound implications. Diego Comin, professor of economics at Dartmouth College, has investigated the technological assimilation between countries and how the assimilation or lack thereof produces disparity (Comin, 2018). This also applies to those who delay the implementation of new technology and tools. Over time, these industries and companies lag behind, gaps increase and it is harder to stay competitive compared to those who did early implementation (Figure 3).

iFor all of the above, the mining industry is at the "right time" to adopt the key technological elements of the Fourth Industrial Revolution.

Figure 3. Increase in technological assimilation gaps between companies over time.



Note::
Over time, companies that develop technological efforts (green curve) are increasing their competitiveness, productivity and technological assimilation compared to those that are left behind or delay these efforts (red curve).

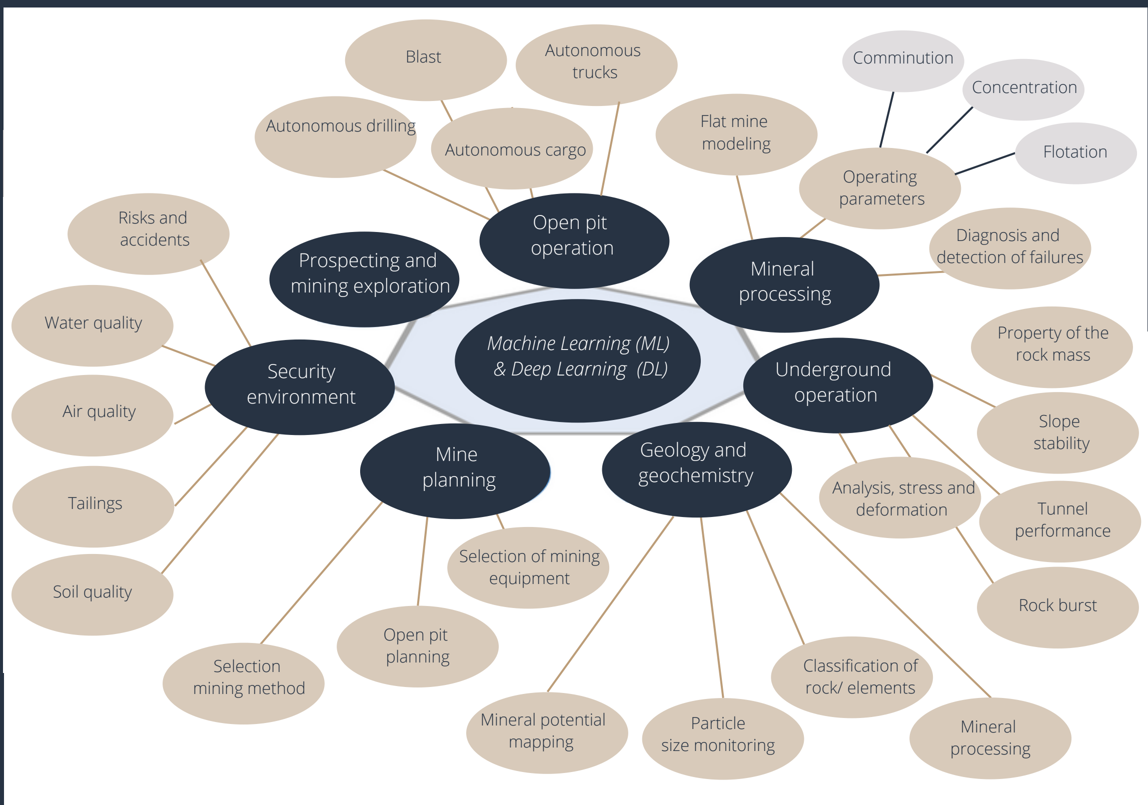
II. STATE-OF-THE-ART MACHINE LEARNING APPLICATIONS IN MINING

Considering the growing challenges facing the mining and mineral processing industry, deep analyses that take advantage of available information -using powerful techniques such as Machine Learning- have increasingly been developed over the last five years (Figure 4).

In the following pages, we offer an excerpt from the systematic review conducted by GEM on the efforts made by the industry and the academy in developing solutions based on autonomous learning algorithms.

To this end, we point out the main applications, income data and objectives, as well as the main trends in mine prospecting and exploration, open-pit and underground operations, mineral processing, mine planning, geology and geochemistry, safety and the environment.

Figure 4. State of the art of Machine Learning & Deep Learning applications in mining.



III. MINE PROSPECTING AND EXPLORATION

In the mine prospecting and exploration category, advances have been made to predict in a limited area the most favorable exploration sites (Lin et al., 2020), the generation of prospecting maps in large areas (Zhang (2015), Tabaei (2017)), or the prediction of gold deposits based on auxiliary variables such as alteration maps, lithologies, or other information (Xu et al. (2019), Maepa et al. (2021)).

Shirmard et al. (2022) also reports different sources that consider image processing for geological and mineralogical mapping.

With the help of these models exploration costs can be saved by generating locations with greater mineral presence favorability.

In this field, image processing has generated impact by the possibility of generating maps with high continuity of objective variables due to the relevant information provided by each image-pixel.

IV. OPEN-PIT MINING

Regarding open-pit mining we include efforts to automate and make drilling, blasting, loading and transport operations more efficient through algorithms.

In drilling, models have been designed to predict the drilling rate and at the same time identify process deviations, which together guarantee an autonomous and intelligent drilling process.

In blasting, models can already estimate the fragmentation size distribution based on the amount of explosive used and other factors, as well as estimate the optimal blasting parameters.

This aims to reduce costs to a minimum, so that on the one hand the mineral size distribution is not too large, as to cost too much in milling processes or there is less area for mass transfer in leaching.

On the other hand, the aim is that the mineral size distribution is not too small, so the processing of fine minerals is not feasible (Monjezi et al. (2012) and Morgenroth et al. (2019)).

Furthermore, models have been developed for autonomous cargo with object recognition for trucks, excavators and freighters, so that they can perform the required tasks with lower rates of delay and failure.

In addition, productivity is increased by optimizing the use of machines, saving fuel and decreasing the accident rate.

The use of autonomous trucks is already a tangible reality in the mining industry and we expect that such technology will be increasingly adopted in the coming years.

V. MINERAL PROCESSING

Mineral processing includes the comminution, leaching, flotation and mine-plant modeling categories.

For comminution it is possible to separate low-grade ore before processing (Okada et al.). In addition, it is possible to estimate the ore grade that is being processed, which allows improving processes (Tessier et al., 2020).

For leaching and flotation the final mineral recovery can be estimated with different parameters and image processing (Flores et al. (2021), Jahedsaravani et al. (2014) and Horn et al. (2017).

As for the mine-plant modeling, the idea is to anticipate the plant mineral recovery scenarios depending on the mine scenarios, in addition to estimate the processing rate and the energy required in the comminution process based on mine drilling parameters (Both et al., 2021).

VI. MINE PLANNING

Using Machine Learning algorithms, we can determine the extraction method to exploit the deposit: open pit, room and pillar, sublevel stope, block caving, among others (Bui et al. (2021), Fu et al. (2018) and Liang et al. (2018). This is an additional tool in the analyses that are carried out, in order to confirm or continue to study how to optimize resources. Through Deep Learning, the blocks can also be assigned to a phase sequence that maximizes the value of the deposit exploitation (Loor, 2020).

Likewise, with genetic algorithms, entropy methods and fuzzy theory, we can determine the mining equipment that should be used, such as drills, shovels, trucks, etc. ((Bui et al. (2021), Samatemba et al. (2020)).

VII. UNDERGROUND MINING

In underground mining there are applications on the domains of classification of rock massif properties, slope stability, tunnel performance, rock burst and stress / strain analysis.

It is possible to predict the properties of rock massif based on neural network algorithms if data such as laboratory tests and site conditions are available (Morgenroth et al., 2019).

Algorithms such as neural networks, support-vector machines or random forests can make predictions of the movement of slopes along with predictions of failure volume (Morgenroth, 2019).

With geological data, excavation methods, seismic data and field mapping, it is possible to predict tunnel support and deformation estimates that can be generated.

Regarding rock bursting, it is possible to predict the magnitude and location of events, fault magnitude, performance of supports and probability of occurrence of events, which is extremely relevant to evaluate security and contingency measures.

For this, models need seismic events data, geological mapping, rock classification, among others.

Finally, through tunnel images and their processing, it is possible to predict the stress and deformation, in addition to estimate the change of these deformations in time.

VIII. GEOLOGY AND GEOCHEMISTRY

In geology and geochemistry multiple models have been made that receive geological and geochemical characteristics such as alteration indices, lithologies, chemical compositions, among others, with which it is possible to make regression or classification models in order to determine the grade of the mineral or whether they are high or low grade.

In addition, imaging and deep learning techniques have been employed for the recognition of geochemical anomalies related to mineralization, as well as mineralogical data for predicting sample recovery in laboratory tests (Jooshaki et al., 2021).

IX. SAFETY AND ENVIRONMENT

In safety and the environment, the applications associated with the themes of air quality, water, tailings, soil quality, risks and accidents stand out.
Using satellite imagery and other monitoring data, you can see and detect dust as well as other sources of dangerous gases.

In water management, using hisperespectral satellite images it is possible to identify water bodies.

For tailings, it is possible to identify and monitor tailings dams with their geographical distribution and surface erosion monitoring.

Fire gas monitoring and intelligent underground mine ventilation strategies have been implemented in hazards and accidents (Bui et al. (2021).

CASE STUDY

MACHINE LEARNING APPLICATIONS IN MINING PROSPECTING

In the range of options offered by Machine Learning for processing massive amounts of data and identifying patterns for decision-making in the mining industry, It highlights the use of satellite images and geological information to support and predict prospecting and geological exploration.

This type of analysis comes from the discipline of Remote Sensing or remote sensing, which is based on obtaining the characteristics of the elements despite not being in direct contact with them (Gupta, 2019).

Just as a telescope can give us information about planets, stars and galaxies without being in direct contact with them, it is possible to use tools such as sensors and satellite images to better pinpoint information about rocks, minerals and/or geographical characteristics.

Georeferenced satellite images that capture wavelength bands of the electromagnetic spectrum are used to perform the mineral search using Remote Sensing. It is estimated that these capture certain mineral indicium characteristics.

These images are elaborated "to the measure", in order to amplify certain reflective characteristics that have the rocks that contain the mineral that is sought.

In the same way that a green leaf acquires its pigmentation by absorbing most of the colors or wavelengths of light (even if they are outside their tonality), seeks to characterize rocks from reflective signatures or wavelengths that better specify their properties even though they are not in the visible electromagnetic spectrum.

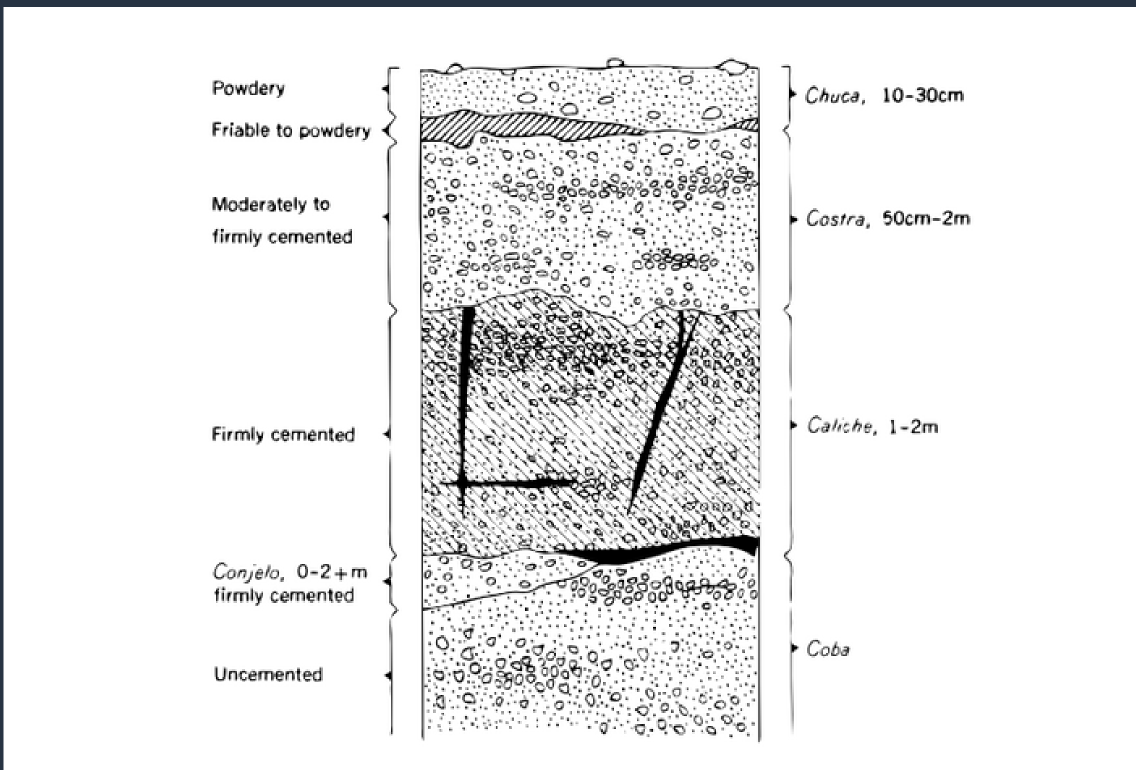
Based on these principles, GEM has developed and successfully applied models of iodine classification in northern Chile, in order to establish strategic mining planning decisions related to determining the favorability of these domains.

From a geological point of view, caliche deposits correspond to stratified deposits of low power that are associated with rock types such as carbonates, clays, limonites and/or gypsum, just to name a few.

At the same time, such deposits are negatively associated with mafic and ultramafic rock types (Pérez, 2013).

Through the use of satellite images, the presence of rock types associated with caliche can be detected on coarse territories through the analysis of electromagnetic bands that characterize these rock types.

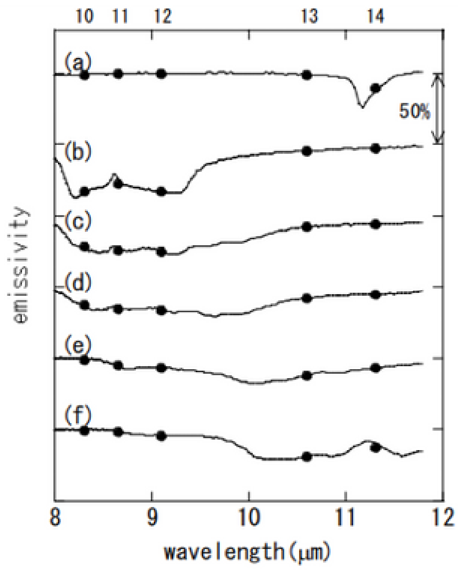
Figure 5: Stratification characteristic of a caliche tank



Ericksen, 1981.

As Figure 5 shows below, we can observe that there are certain wavelengths in which certain types of rocks show a greater or lesser spectral emissivity, which allows us to differentiate the different types of existing rocks.

Figura 6: Emisividad espectral comparado con los datos de ASTER por tipo de rocas: (a) Carbonato; (b) Roca silicia; (c) Roca félsica; (d) Roca intermedia; (e) Máfica y (f) Ultramáfica. Arriba se encuentran las longitudes de onda que mide cada banda del satélite



Ninomiya, 2002.

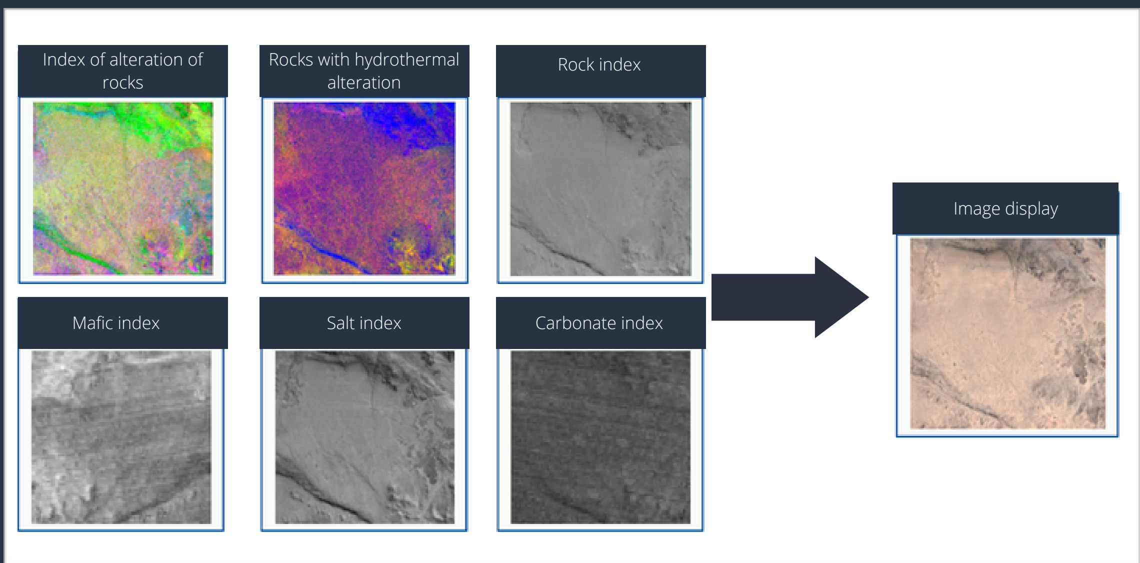
Since many of the wavelengths are outside the visible range, specialized instruments such as the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) or the Landsat-satellite are needed8, to take images about the electromagnetic ranges SWIR (Short Wave Infrared), TIR (Thermal Infrared) and VNIR (Visible and Near Infrared).

At the same time, it is widely used in scientific literature to perform a mathematical operation or combination on electromagnetic bands, in order to amplify certain characteristics present in certain rocks. As a sample of the above, Figure 8 shows the Carbonate Index, widely documented in the literature (Ninomiya, 2002) (Ninomiya, 2005) (Pour & Hashim, 2011) (Gupta, 2019), which is obtained mathematically as the ratio of band 13 and band 14 (B13/B14) and which is used to detect the presence of high carbonate rocks in satellite images.

Based on the presence of rocks and the relationship they have with caliche, the in-depth analysis of the data starts by selecting the indices of satellite images, which as explanatory variables, represent in a better way the spectral characteristics that the geography to analyze and the minerals of interest to study.

As a representation of the above, for a representative land area, the satellite images of the indices that characterize rock types on an extension with known presence of caliche are shown below.

Figure 7: Satellite images showing different characteristics of the same land

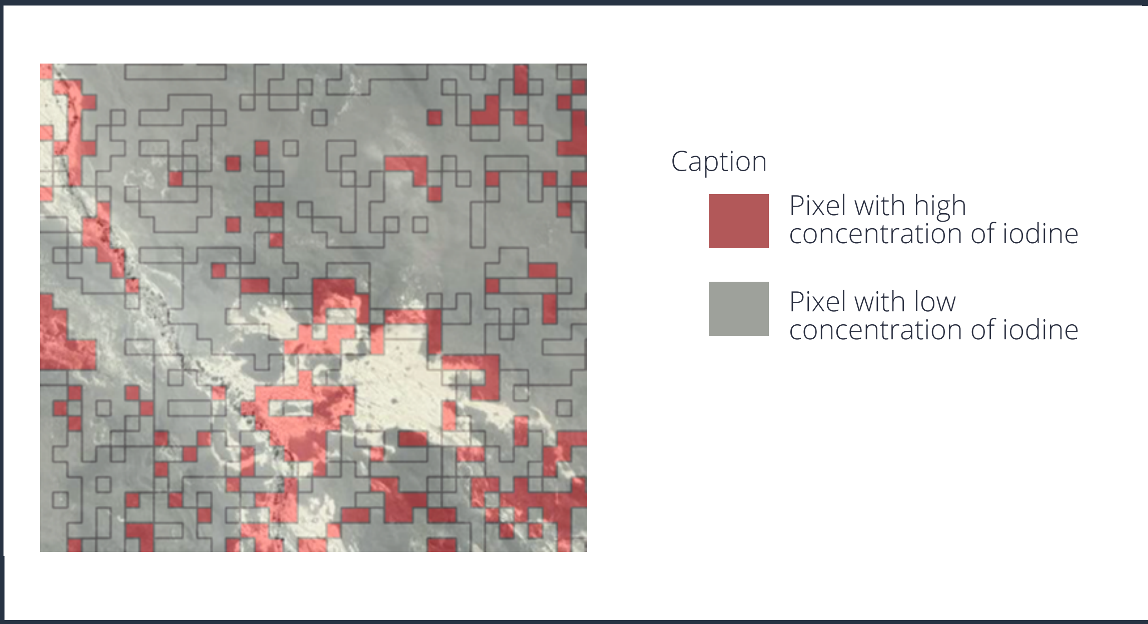


Based on this information, we seek to identify domains with high concentrations of salts.

For this, it is considered a system of classification of two categories: low salt concentration and high salt concentration. This classification can be expanded to more categories.

Given the strategic rather than estimation purposes of the analysis, it is chosen to use categories to improve prediction in terms of only deciding whether the extent of land is associated with a known range of concentrations, rather than predicting the exact value of such concentrations (which in turn are more uncertain and potentially lead to greater error).

Figure 9: Field extension image display, categorized for iodine.



At this point, there is information that gives several of the characteristics, but that mostly would present non-linear relationships or patterns difficult to assimilate with respect to the target variables (concentrations of iodine in the rock).

Due to non-linear patterns between satellite images and iodine concentrations, it is necessary to use AI models, who are able to identify the intricate and complex patterns present between the different images and the expected concentrations.

Supervised models are used as part of the analysis, which consider the use of labeled samples. Using labeled samples means passing to the model real data of the phenomenon to be analyzed. So for example, following the example of rain, it involves specifying the days when there was or was not rain. This would be the sample labeled as target variable. For the case study of nitrates and iodine, it means giving the model the land extensions and their respective concentrations of iodine and nitrates that will serve as training and testing data.

Given the strategic rather than estimation purposes of the analysis, it is chosen to use categories to improve prediction in terms of only deciding whether the extent of land is associated with a known range of concentrations, rather than predicting the exact value of such concentrations (which in turn are more uncertain and potentially lead to greater error).

Among the models supervised there are a large number of models such as SVM (Support Vector Machines), RF (Random Forest), Naive Bayes, Logistic Regression, Gradient Boosting and XGBoost, just to name the best known. Several of the models within this set were tested by empirical tests, and it was obtained that the model that presented the best management of the broad generated database and the best training and testing speed was XGBoost.

Compared to the other algorithms, some of the distinctive advantages of this model are:

(1) High training speed, which was observed up to 5 times faster than other algorithms.

(2) The model can handle large amounts of data.

(3) The results of this model being an assembly type model are generally more robust.

Once the model is chosen and the database is complete and validated, the database is divided into two. Part of the base is intended for model training and part for testing or validation, which is used to test the model and understand how good the predictions are.

The results obtained by GEM showed an accuracy in classifying validation samples greater than 65% in iodine. This means that if the model predicts a specific value for a pixel in the field, it is observed that over 65% of the time the salt concentration will be correct.

CONCLUSIONS

As part of the development of this exercise the following lessons remain:

(1) Machine Learning models are useful and used in various disciplines including mining.

(2) These models support decision-making at several different levels.

(3) As the mining prospection example shows, there are several proven cases - academics and companies- in which Machine Learning guarantees its technical superiority of analysis over other tools.

(4) Artificial intelligence will be increasingly used by organizations due to increased data generation and computational processing capacity.

However, the advantages of using artificial intelligence far exceed the points raised above. Just to mention the advantages of using satellite images and geological indexes in mining prospecting we can find among others:

(1) The review of large areas of land that have even reached in some cases 15 Mha (Granek, 2016).

(2) Supporting geologists in eliminating subjective judgements for reliable mapping and drilling campaigns that avoid wasting resources.

(3) Obtaining geological characteristics for areas particularly difficult to access, affected by difficult climatic and terrain conditions.

(4) The identification of patterns and characteristics which are normally outside the visible spectrum.

Thus, Machine Learning and AI-based solutions are expected to be an integral and growing part of the innovations of the coming years in the field of mining and mineral processing.

Due to the accelerated growth of research, innovations and solutions related to the mass processing of data with greater computing capabilities, the precise space of application of these techniques on the challenges of mining of the future is being created.

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