

Review

A Systematic Review on the Application of Machine Learning in Exploiting Mineralogical Data in Mining and Mineral Industry

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Abstract: Machine learning is a subcategory of artificial intelligence, which aims to make computers capable of solving complex problems without being explicitly programmed. Availability of large datasets, development of effective algorithms, and access to the powerful computers have resulted in the unprecedented success of machine learning in recent years. This powerful tool has been employed in a plethora of science and engineering domains including mining and minerals industry. Considering the ever-increasing global demand for raw materials, complexities of the geological structure of ore deposits, and decreasing ore grade, high-quality and extensive mineralogical information is required. Comprehensive analyses of such invaluable information call for advanced and powerful techniques including machine learning. This paper presents a systematic review of the efforts that have been dedicated to the development of machine learning-based solutions for better utilizing mineralogical data in mining and mineral studies. To that end, we investigate the main reasons behind the superiority of machine learning in the relevant literature, machine learning algorithms that have been deployed, input data, concerned outputs, as well as the general trends in the subject area.

Keywords: machine learning; artificial intelligence; mineralogy; mining; mineralogical analysis



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1. Introduction

Artificial intelligence (AI) and machine learning (ML) have been used in a wide range of applications in the development of technology. AI is a branch of science and engineering focusing on the development of techniques to make computers capable of solving certain problems through simulating or extending human intelligence [1,2]. As a subset of AI, ML includes computational approaches aiming at extracting expertise out of experience [3,4]. In other words, the goal of ML is to use past data or known information to extract (learn) meaningful patterns and associations which can be generalized to make relatively accurate predictions [3,4].

In the realm of ML, the process of learning the past information is called *training*. Learning through training experiences to acquire new or improve previous capabilities distinguishes ML methods from traditional explicit programming of computers for performing a specific task [4–6]. Conventional programming relies on explicit modeling of a problem using the physical rules governing a specific system under study. In ML, however, the aim is to analyze the data to predict the behavior of complex systems that cannot be explicitly modeled using conventional approaches. The learning process can be either supervised or unsupervised. While in the former, the training data is labeled and the correct output is known for every instance of the past information, the latter entails the recognition of hidden patterns in the data without knowing specific outcomes a priori [5,7].

With the capability of learning from the past data or experience and generalizing that to the unseen data, ML techniques are able to solve complex problems, which cannot be effectively and efficiently addressed by the traditional methods. Such problems typically involve intricate associations among several variables influencing the system under study, fluctuating environments, and large amount of data which needs to be processed [8].

AI and ML researchers have devised a plethora of effective tools to solve the most difficult problems in computer science and engineering including speech recognition, machine vision, control of autonomous vehicles, robot control, natural language processing, medical diagnosis, climate and power demand forecasting, playing games, filtering spam emails, designing performance-based regulations based on unsupervised ML methods, and optimizing engineering problems using soft computing intelligence, to name but a handful [5,6,9–16]. Such tools have been leveraged in various industries so as to enhance the performance and efficiency. These next generation information tools, that have become more refined over the recent years, have been also applied to the mining industry—a capital-intensive business, thus, conservative and reluctant to radical changes—to improve safety, increase productivity, and reduce costs [17,18].

With the continuously increasing demand for raw materials, deeper mining, facing the complexity of the geological structure of ore deposits, and decreasing ore grade, high-quality and extensive mineralogical information is required [19–22]. The mineralogical analysis is providing critical information for calculating the duration of extraction period of a mine. Intimate knowledge of the mineralogical assembly of ores is key to understanding and solving problems encountered during exploration and mining, and during the processing of ores, concentrates, and related materials [23].

Additionally, mineral process engineering is now evolving. In the past, the practical challenges of managing and optimizing a process plant were very complex and were not effective enough to justify further development of data-based optimization. Most designs were based around empirical characterization tests, and plant operation relied heavily on operator intuition. Given the standard process operating systems, it was a challenge for the plant operators to manage the large amount of process information in a fashion where all of it was used effectively. There also is now technology available that has the capacity to revolutionize how mineral processing plants are designed and how they are operated. Instrumentation used to collect data and information has become much more sophisticated, and capable. This data can be also collected from many more positions throughout the process plant, and it can be collected at a much higher degree of resolution.

ML, a revolutionary new method of handling vast amounts of data, has been developed in the past few years to the point where it can be applied to mineral processing applications. The combination of more sophisticated instrumentation in conjunction with ML has the potential to revolutionize mineral processing standard operating practice. In the past, many mineral processing plants struggled with high variability in throughput, power draw and recovery, where most operations are designed to operate at a steady state of throughput, recovery, and metal production. Poor recovery was often observed as it happened, with limited understanding in why it was happening.

ML, if coupled with quality and timely measurement of the appropriate parameters, has the potential to diagnose the true metrics of good recovery. Time stamped measurements at multiple strategically decisive points in the plant could quantify, for example, how recovery relates to ball mill performance (under grinding or over grinding) or how cyclone performance could interact with final metal reconciliation. The true link between mineral content, mineral texture, and process performance could be quantified.

Using ML, the cause of plant variability could be isolated in real time. Depending on circumstance, this could happen soon enough to make an engineering decision, followed by operational optimization. An example of this could be using a Raman spectrometer instrument to estimate mineral content of the semi-autogenous grinding (SAG) mill feed, the results of which could be used to optimize reagent application at the flotation cells. ML could be used to focus on the best outcome. For instance, in a comminution circuit,

which is the most energy and cost consuming step in mineral processing, it is proposed to use SAG Mill real-time operational variables such as feed tonnage, bearing pressure, and spindle speed in order to predict the upcoming energy consumption via ML and deep learning techniques [24]. It should be highlighted that the authors of [25] achieved impressive accuracy of 97% with the emulation of the industrial grinding circuit by the designed recurrent neural networks for the SAG mill in lead-zinc ore beneficiation process.

The potential here is that the true relationship between process units during operation could be quantified with the application of ML. The whole process flow sheet could be optimized in operation. Additionally, any given example of poor performance could be diagnosed, and the original cause could be isolated to individual process units. If this potential is realized, the next generation of mineral process practice could be developed.

ML algorithms such as artificial neural network (ANN), support vector machine (SVM), regression tree (RT), and random forest (RF) are powerful data driven methods that are becoming extremely popular in such applications as the mapping of mineral prospectivity [26–28], mapping geochemical anomalies [29–31], geological mapping [32–35], drill-core mapping [36–38], and mineral phase segmentation for X-ray microcomputed tomography data [39–41].

Inspired by these remarks, this paper aims to systematically survey the relevant literature for the sake of investigating what has been carried out in the realm of enhanced exploitation of mineralogical analysis data in mining and minerals industry. In a systematic review, the body of knowledge on a specific subject is investigated to answer a set of predetermined questions in such a way that the data and methods used are definite. Given the sufficient details provided in a systematic literature review, the users can more conveniently determine its trustworthiness and the usefulness of the statistics, discussions, and findings it provides [42].

To be more specific, areas examined in this paper include mainly the problems in the field of utilizing mineralogical analysis data for mining and minerals industry that have been solved using ML techniques. The reason behind using ML in such studies, ML tools that have been developed and applied, data inputs, required outputs, as well as the main trends in this subject area are also assessed in this paper.

The remainder of this paper is organized as follows. In Section 2, the main research questions that we aim to answer in this review as well as the search method, information source, and the selection criteria are explained. Section 3 provides answers to the research questions, and lastly, Section 4 concludes the paper.

2. Main Research Questions and Review Methods

As pointed out before, in a systematic review, the main objective is to investigate the body of knowledge to address a set of research questions [42,43]. This must be done using concrete methods and procedures for the sake of transparency and ease of evaluating the objectivity and trustworthiness of the figures and outcomes reported for the potential readers [42].

Considering the groundbreaking advances and flourishing developments in the area of ML, it has been leveraged in various fields to unprecedentedly solve complex problems that could not be tackled via conventional methods effectively. Given the crucial role of mineralogical monitoring at every stage of minerals industry value-chain, from geoscience research and exploration phases to the final processing, and the complexities associated with exploiting valuable information out of mineralogical data, we aim to investigate the steps taken towards adopting ML in this area. In other words, this review focuses on the applications of ML for enhancing and facilitating the mineralogical monitoring and the utilization of mineralogical data in mining and minerals industry. To that end, the main questions that this review aims to answer comprise:

- (1) What problems in the area of mineralogical studies for mining industry have been addressed using ML techniques in the existing literature?
- (2) Why the use of ML in such applications is required?

- (3) What are the outputs predicted or modeled using ML in those problems? What input parameters have been used?
- (4) What ML methods have been employed?
- (5) What are the general trends in the area under study?

The purpose of the first two questions is to investigate the sort of problems in the area under study for which the use of ML techniques is advantageous and their specific complexities that favor ML over traditional approaches. Considering that ML techniques are typically used to find useful associations in the data to predict specific outputs in the case of supervised learning or to determine significant patterns among input features in an unsupervised setting, the third question intends to explore the input and output variables employed in the existing literature. This can be particularly useful for understanding potential data that needs to be collected for estimating a specific set of desired output variables. Complementary to the previous question, the fourth question focuses on the methods used to model the relationships between input and output variables. Lastly, the final question will address the general trends in the application of ML in mineralogical monitoring in mining and minerals industry.

2.1. Information Source and Search Strategy

We utilized Scopus [44] as the search engine for finding the relevant publications. Based on our review objectives, we considered three main tiers of keywords, namely target modeling approach, analysis, and industry, each including few relevant keywords as depicted in Figure 1. As illustrated, using the logical operators available in Scopus search tool, we set a query so as to search through the records and reach the publications that include at least one of the keywords in each tier in their title, abstract, or list of keywords. In order to have an estimate of the early works published in the subject area, we did not filter any record based on the publication date in our search query. Nonetheless, as we will discuss in the next section, the works published before 2000 were disregarded during the selection procedure. It is worth mentioning that we set no limitations on the search source, thereby the search query was applied to all the records covered by Scopus—the largest database of peer-reviewed literature [44].

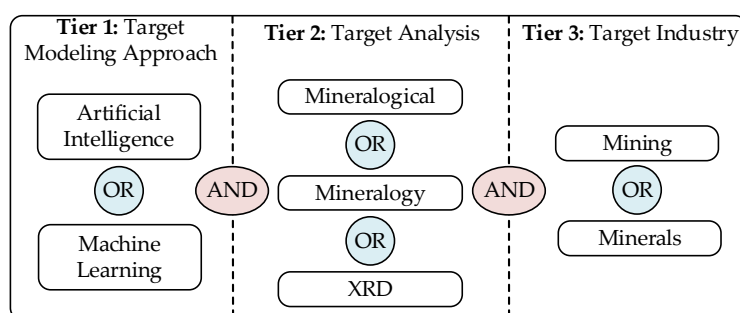


Figure 1. Search keywords and search query logic.

2.2. Eligibility Criteria

Based upon the search method explained in the previous section, we reached 145 candidate scientific publications. As depicted in Figure 2, in the first step, we discarded 9 manuscripts including non-English papers and those published before the year 2000. In the next stage, the review articles and conference reviews were disregarded, a total of 8 records. The remaining 128 records were all sequentially evaluated by each of the authors to select the publications relevant to this review. The evaluation entailed reading the title, abstract, and list of keywords of the records and skimming through the papers if required. Lastly, 55 papers were selected to be included in the review and answer the questions. It is worth mentioning that the publications excluded in the last stage comprise different topics not directly relevant to the mining and minerals industry.

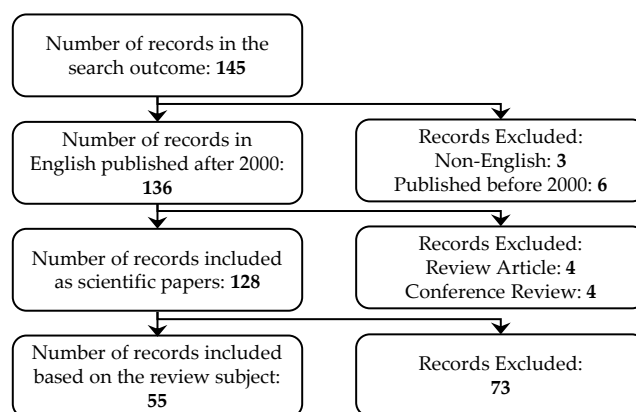


Figure 2. Process of screening the search results.

Figure 3 shows the share of the topics excluded at the last stage of the selection procedure. As per this figure, the majority of the papers excluded are related to petroleum and gas industry, soil, and space exploration. About a quarter of the records excluded is on environmental studies, works in which ML techniques are not employed, and miscellaneous topics such as metallurgy, recycling in cement industry, archaeometry, geophysics, medicine, and sedimentology.

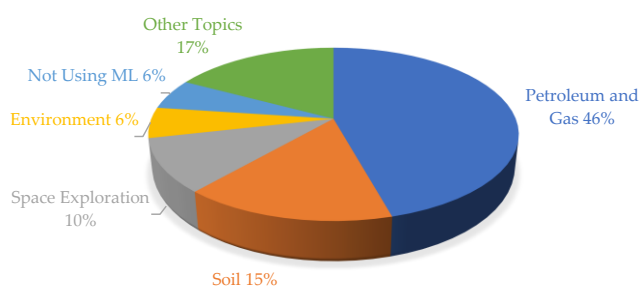


Figure 3. Share of the topics excluded from the review in the last stage of the selection process.

Title of the journals with more than one record in the list of selected records are provided in Table 1.

Table 1. Title of journals with more than one entry in the final list.

Journal Title	Number of Selected Records
Minerals Engineering	6
Journal of Geochemical Exploration	6
Computers and Geosciences	4
Applied Geochemistry	4
Ore Geology Reviews	3
Lecture Notes in Computer Science	3
Remote Sensing	2

3. Results

In this part, the main research questions stated in Section 2 are addressed based upon the assessment of the selected works.

3.1. Problems in the Selected Studies Addressed Using ML Techniques

During the last decade, the number of available multi-parameter datasets in the mining industry increased rapidly as a result of applying advanced technologies to assist in the exploration process. To integrate and handle such large datasets, special tools are

required. One such tool is the ML, which is well suited and proved to be promising for tackling the problem of mapping geochemical anomalies [45–47] and mineral prospectivity, due to its ability to effectively integrate and analyze large geoscience datasets [48–53]. ML and AI are actively used for mining complex, high-level, and nonlinear geospatial data and for extracting previously unknown patterns related to geological processes [45]. These techniques were applied in the identification of mineralization related geochemical anomalies in China [45,47,54–56], as well as generating a prospectivity map for targeting gold mineralization in Canada [49,50] and China [51], for the detection of iron caps in Morocco [57], for creating a continuous mineral systems model for chromite deposits in Iran [58], and geological mapping studies using the characteristics of rocks [59,60]. The authors in [61,62] integrated multi-sensor remote sensing techniques such as drone-borne photography and hyperspectral imaging for processing with ML algorithms in order to generate the geological mapping.

Another important field, where the analysis of the hyperspectral imaging has been applied is drill-core mapping. It is well known that drilling is a decisive step for validating and modeling ore deposits. The hyperspectral imaging technique provides a rapid and non-invasive analytical method for the core samples in terms of mineralogical characterization [63]. Recently, ML techniques have been suggested for automating the process of mineral mapping based on drill-core hyperspectral data [63–68]. However, several obstacles might occur due to the small amount of representative data for training purposes. To tackle this problem, resampling and co-registration procedures for the high-resolution mineralogical data obtained by the scanning electron microscope (SEM)-based mineral liberation analysis (MLA) of the hyperspectral data was implemented in [63,64,67]. The new co-registered data was used for training purposes through a classification algorithm. Mainly, the RF classifier is used due to its high performance when small training samples are available [64,67]. Nevertheless, in [63], three methods, namely RF, SVM, and ANN were employed for the classification and regression tasks. The authors reported that the RF is more robust to unbalanced and sparse training sets.

Mineral processing should always be considered in the context of geological, mineral assemblage, and texture of ores in order to predict grinding and concentration requirements, feasible concentrate grades, and potential difficulties of separation [69]. A promising technique was proposed by the authors of [70] in the context of control of mineral processing plants for the identification of minerals in slurry samples through multispectral image processing. The study was focused on the base metal sulfides minerals and the main goal was to develop set-up aims to enable the measurement of specular-like reflections on the surface of the particles. A supervised classification approach has been used to process the acquired data. In [71], the mineralogical composition of the final products (copper concentrates) was analyzed by a near-infrared hyperspectral camera. ML has been used to provide the mineralogical spatial distribution of the different components in the samples through the analysis of the reflective images.

The application of X-ray microcomputed tomography (μ CT) in the mineral industry has been growing due to its noninvasive nature of sample analysis. X-ray microtomography allows achieving high-resolution images with pixel sizes in the micrometer range. However, the grayscale values of mineral phases in a sample should be different enough to be segmented. Despite the fact that the manual segmentation of those images made by a highly experienced specialist is one of the best methods for segmentation, the process is highly time-consuming. Moreover, the procedure of preparing polished thin-section for microscope is long and the number of core samples is limited. As a consequence, the main challenge in using ML is the limited number of ground-truth (or segmented) images that are available for the training step. For instance, in [72], only 20 images were manually segmented to be analyzed by a convolutional neural network (CNN), thereby resorting the authors to employ data augmentation techniques. The authors in [73] have applied supervised and unsupervised methods to the training data obtained by the matching method for back-scattered electron (BSE) mineral map to its corresponding μ CT slice for

one drill core sample. Classifying voxels in X-ray microtomographic scans of mineralogical samples is another problem that has been solved by applying the ML techniques [74].

The observation of optical properties of a mineral in a polarized microscope rotation stage is a commonly used method for mineral type classification. This task can be automated by the application of digital image processing techniques and AI technologies [75–78].

Interesting solutions by the implementation of an ML methodology to the prediction of material properties from the nepheline syenite deposit was discussed in [79]. The challenges with calculating the amphibole formula from electron microprobe analysis can be solved by applying ML [76]. Another problem in mineralogy study that can be addressed directly via deep learning algorithms is differentiation of quartz from resin in optical microscopy images of iron ores [80].

3.2. The Main Reasons behind Using ML in the Selected Studies

ML techniques are typically employed to solve problems for which the application of traditional approaches is either impossible or very sophisticated [8]. Such problems might entail typical tasks that human beings or animals can perform routinely, yet the process of doing such tasks is relatively unknown, tasks that involve processing an excessive amount of data with complex unidentified relationships and patterns, or tasks that require interaction with constantly changing environments such that high levels of adaptivity are required [4]. Our review of the selected papers revealed that, albeit all these three reasons can account for the necessity of using ML techniques in the area under study, the second category of tasks is more common. In other words, in most of the studies investigated, the researchers attempted to leverage ML techniques to cope with large and complex datasets.

Let us take mineral exploration as an example, new mineral prospect or deposit targets are deeper, thus, more difficult to find [81]. Therefore, it becomes of utmost importance to predict, relatively accurately, regions with higher potentials for new deposits based on the large datasets of various types of measurements. The dataset can contain litho-geochemical [49,82], spatial [49,50], geochemical [45,55,81,83], geophysical [81], geological [81], concentration of indicator elements [47,51,52,54,56,65,68], hyperspectral [57,60,61], spatial proxies [58], total magnetic intensity [52], isostatic residual gravity [52] data. It is worth emphasizing that in most of such studies mineralogical analyses results are either used to generate the input features for the ML models or ground truth for training such models. Obviously, analyzing such massive and complex datasets is challenging, adding to that the nonlinearities and hidden interdependencies and patterns among different features. This calls for deploying multivariate ML models to effectively explore the data and attain valuable insights.

In some applications, especially the tasks entailing image processing, ML is proposed to automate manual operations to enhance productivity via enhancing speed and reducing human errors. As an example, the authors in [78] proposed a technique for the identification and classification of hematite crystals in iron ore using optical microscopic images. Presence of high noise can also result in the ineffectiveness of the conventional techniques, thereby giving rise to the application of ML. For instance, extracting quantitative mineralogical information about composition, porosity, and particle size through processing X-ray microtomography scans of ore samples can be quite challenging due to the presence of noise [74].

Another important driving force for the deployment of ML is the cost reduction. In [47], ML is leveraged to select a small set of indicator elements to detect chemical anomalies with the main goal of avoiding the unnecessary cost of element concentration measurements for mineral exploration. To save time and money through reducing the number of samples on which X-ray diffraction (XRD) measurements must be obtained, the authors in [84] proposed an artificial neural network-based model for estimating the mineralogical compositions based upon the elemental data from X-ray fluorescence (XRF)

instruments. In a conceptually similar manner, ML is used in [85] to reconstruct synthetic 3D models of porous rocks from 2D images of thin sections.

3.3. The Outputs Predicted/Modeled Using ML in the Selected Literature and the Inputs Utilized

Based on the reviewed literature it can be considered that the most widely used input data for analyzing by ML in the mining and mineral industry is a set of *digital images*. As some examples, the hyperspectral data was used for discrimination of lithologic domains in geology mapping [61], and a combination of the multispectral, RGB, and hyperspectral data was analyzed by ML algorithms to create a digital outcrop model for precise geology mapping [62]. Moreover, the hyperspectral imagery has been used for classifying rock type and mineralogy [86], for predicting the presence of specific minerals [64] or mineral abundance [63] in drill-core samples, as well as for drill-core mineral mapping [67,68] and mapping of mine face geology [53]. In [87], a three-stage method is proposed for the segmentation of hyperspectral images with the main goal of preparing the data required for the classification of such images. In order to curb the noise in the spectral domain, Gaussian processes (GP)—a type of supervised ML model—are used in [88] as a preprocessing step before extracting the mineralogical information from the images.

The authors in [89] have discriminated a rock texture information through image processing and machine learning algorithms by studying a geologist-labeled digital photograph database from drill-hole samples. The main contribution of this work is “a novel texture characterization technique to compare image textures of drill-hole samples and discriminate between different rock texture classes”.

The study [41] used the association indicator matrix (AIM) and local binary pattern (LBP) texture analysis methods to get quantitative textural descriptors of drill core samples with relatively high accuracy of 84% and 88%, respectively, for AIM and 3D LBP. An automatic method for the classification of hematite textures in Brazilian iron ores according to their textural types through applying an AI technique for analyzing the images from a reflected light microscope and a digital camera is described in [78]. New optical properties have been extracted from the digital images acquired under cross and plane-polarized light from different rock thin sections. ML was deployed for mineral classification by analyzing the optical properties of color and texture of a pair of images of the same mineral taken on different lights [77].

Deep learning and ML have produced accurate results in different applications when various images are available for the training [72]. The researchers in [72,73] proposed implementing ML algorithms to enhance automatic segmentation of mineral phases based on the analysis of the images from the X-ray microcomputed tomography (μ CT). However, it should be noticed that acquiring μ CT images is expensive and time-consuming, which affects the limited available dataset. Therefore, a supervised ML algorithm in which the user pre-defines the underlying pattern of the data, and the computer system builds a prediction model based on the pre-defined pattern (training data) [73] could be successfully applied to tackle this problem even with a small number of images. The supervised classification method was used for generating a 2D mineral map of chromite sample from optical microscopic images [90].

Alongside the image analysis, other input features among the mineralogical study for the mining and minerals industry have been addressed using ML techniques. The dataset containing geochemical data was used for extracting features related to mineralization via a deep learning algorithm and these features were then integrated as an anomaly map [45,47,54,56]. Applying the deep learning algorithms as a subcategory of machine learning algorithms can lead to improving the accuracy of classification or prediction by replacing the manual selection [45]. Such techniques have been employed in recognizing geochemical anomalies related to mineralization via deep autoencoder networks [46], deep variational autoencoder network [45], convolutional autoencoder networks [91], and combining deep learning with other anomaly detection methods [54,56].

The bulk chemistry data from the mining company open-pit database was used as an input for the prediction of laboratory concentrate yield and modal mineralogy for the nepheline syenite deposit in Norway by adopting a neural network approach [79]. The data collected by the electron probe microanalyzer (EPMA) was analyzed with an ML method aimed to be established for calculating the amphibole formula [76].

The lithogeochemical data of sandstones from diamond drill cores [82] and lithogeochemical major oxide data from the Swayze greenstone belt [49] have been used for the identification of sandstones above blind uranium deposits through an ML technique in a first case and for modeling of orogenic gold prospectivity mapping by deploying a support vector machine and an artificial neural network in the second one.

3.4. The ML Methods Leveraged in the Selected Works

ML methods are typically categorized based on different aspects. From the standpoint of the learning type, they are generally regarded as supervised and unsupervised approaches [3,4]. Other classes, namely semi-supervised and reinforcement learning, are also available [3], yet we found no instances for the applications of these methods in the reviewed papers.

In supervised learning, the data is labeled with the correct outputs such that during the training process, the model can understand the underlying associations between input features and output variables. Moreover, for testing the performance of the algorithm, predictions of the trained model for test examples can be benchmarked against the known labels to estimate the accuracy of the resulting model. In stark contrast, unsupervised learning entails unlabeled data from which the learner must find meaningful patterns [3]. In this setting, it can be challenging to estimate the performance of the model [3].

As shown in Figure 4a, the majority of the methods used in the reviewed papers fall in the supervised learning category. More precisely, among the 17% of the reviewed works that used unsupervised learning models, only 6% solely leveraged unsupervised learning [48,55,83], but in the remaining 11%, a combination of the supervised and unsupervised learning techniques is utilized [54,61,73,79,92,93]. In such works, unsupervised learning methods are typically used for the feature extraction and preprocessing of the data to be used in a supervised learning process.

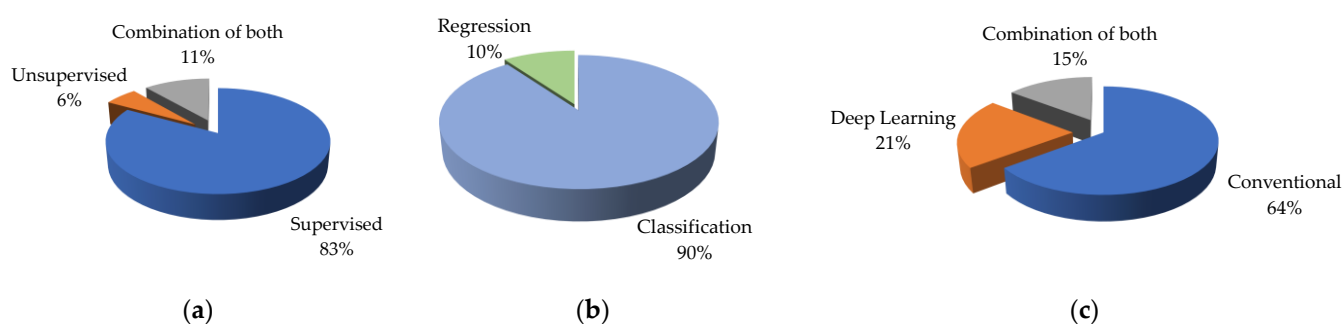


Figure 4. Type of ML techniques employed in the reviewed papers: (a) type of learning; (b) type of problem; (c) type of ML model.

The task of supervised learning can be either classification or regression [8]. In a classification task, the labels are categorical, i.e., have a set of limited values, however, in the case of regression, labels take continuous numerical values. As per Figure 4b, in 90% of the reviewed records, the objective of using ML is classification. Classification tasks can be, for instance, determining the type of minerals [73,77,94,95], texture [66,89], or rock [86,93], class of mineral face [86], class of hematite crystals [78], distinguishing between quartz and resin in optical microscopy images [80], presence or absence of specific minerals in a sample [96], zeolite type [97], material fingerprints [98], class of regolith landform [99], and class of carbonates [100] based on a set of measurements or known features about a

material. On the other hand, in regression problems, the goal is to estimate a continuous numerical value, for instance, prediction of concentrate yield and modal mineralogy [79] and estimation of drill-core mineral abundance [63], mineral density of elements [101], and calculation of amphibole formula [76].

From another perspective, ML methods can be categorized as conventional models and deep learning techniques. The latter is based upon the multilayer artificial neural networks. As presented in Figure 4c, deep learning models have been used in 36% of the reviewed papers from which 21% solely utilized deep learning, whereas the remainder employed both deep learning and conventional machine learning methods to choose the best [49,54,58,63,66,70,96]. It is worth noting that the superiority of an approach depends on the application.

A list of different ML methods used in the reviewed papers together with their frequency of usage is provided in Table 2. As per this table, SVM, RF, and different types of feed-forward ANN are the most frequently used approaches in the supervised learning category. SVM classifiers are very powerful and flexible for linear and nonlinear classification of complex but relatively small-sized datasets [8]. The main idea behind a linear SVM classification is to find an optimal hyper plane that can separate different classes while maximizing the margin of the plane [102]. In the case of nonlinearly separable datasets, the data is mapped to a higher dimension space, where the classes become linearly separable [102]. The mapping is carried out using a kernel function, typically a polynomial or Gaussian radial basis function (RBF) [8]. In most of the reviewed works, SVM is used with a Gaussian RBF kernel.

RF belongs to a category of ML named *ensemble methods*. Ensemble methods are based on the *wisdom of crowd* concept, implying that aggregating the outputs of numerous simple models through a voting system usually performs better than leveraging a single but more complex model [8]. An RF comprises several classification and regression trees, each of which are trained on a bootstrap sample of the original dataset [103]. Notwithstanding their simplicity, RFs are among the most powerful ML techniques [8,104].

ANNs have a relatively long history and were originally developed to simulate the nervous system. An ANN is comprised of numerous basic units called artificial neurons. From a mathematical perspective, an ANN is a complex nonlinear function, which can be tuned for a specific task to perform the desired mapping from an input vector to the output value(s) [104]. ANNs proved to be very powerful tools and outperformed the other ML algorithms in many applications [104].

On the other hand, in the class of unsupervised learning techniques, K-means and hierarchical clustering are used more frequently compared to the other techniques. K-means algorithm partitions datapoints into a predetermined number of clusters such that the similarity among the points in a cluster is the highest, while it is the lowest for the datapoints falling in different clusters. To achieve this goal, in K-means method, an optimization model is solved to minimize the sum of the distances of the datapoints to the nearest cluster center, where the positions of the cluster centers are the decision variables of the optimization model [105]. In contrast to the K-means algorithm, which is centroid-based, i.e., assigning a datapoint to the cluster with the nearest cluster center, in hierarchical clustering datapoints with distances lower than a specific threshold are assigned to the same cluster [106].

Aside from the ML techniques presented in Table 2, the implementation of real-time expert systems in mineral processing operations is discussed in [107], where generating quantitative data using natural language processing (NLP) of process data including ore mineralogy is proposed.

Table 3 summarizes the applications of ML methods as well as the type of datasets utilized in the reviewed papers. As per this table, principal component analysis (PCA) is the most frequently used technique for feature engineering, more specifically for dimensionality reduction [48,49,56,67,76,82,83,95,96]. Weight of evidence (WOE) [49], minimum noise fraction (MNF) [61], orthogonal total variation component analysis (OTVCA) [61,62,65],

stacked denoising autoencoder (SDAE) [56], hierarchical clustering [56], CNN [72,80], grey-level co-occurrence matrix (GLCM) statistics [66], local binary patterns (LBP) [66], maximum margin metric learning (MMML) [55], and K-means++ [93] are the other techniques leveraged in the selected works for feature engineering.

Table 2. ML models leveraged in the selected papers.

Category	ML Method	Reference
Supervised	Support vector machine (SVM)	[49,52,54,57,59,61–63,65,66,68,86,87,92]
	Random forest (RF)	[47,58,63,64,66–68,73,82,87,90–93,97]
	Feed-forward artificial neural network (FF-ANN)	[58,63,66,70,79,84,87,94–96,99]
	k-nearest neighbors (k-NN)	[66,71,73,77,87,89]
	Convolutional neural network (CNN)	[50,51,72,80,85]
	Gaussian processes (GP) ¹	[53,60,86,88]
	Decision tree (DT)	[75,77,87,96]
	Linear discriminant analysis (LDA)	[70,78,82,92]
	Radial basis function neural networks (RBFNN)	[49,81]
	Adaptive Coherence Estimator (ACE)	[55]
	Bayes nets	[100]
	Isolation forest (IF)	[56]
	Linear regression (LR)	[101]
	Naive Bayes (NB)	[78,87]
	Principal components regression (PCR)	[76]
	Quadratic discriminant analysis (QDA)	[92]
	Support vector regressor	[101]
	Variational autoencoder (VAE) network	[45]
Unsupervised	K-means clustering	[48,73,92,93]
	Hierarchical clustering	[48,79,92]
	Deep belief networks (DBNs)	[54]
	Fuzzy C-means clustering	[73]
	Gaussian mixture model (GMM) clustering	[48]
	Unsupervised random forest	[83]

¹ With either the squared exponential (SE) or the observation angle dependent (OAD) covariance functions.

3.5. General Trends and Research Gaps in the Application of ML in the Selected Literature

Development of effective methods together with the availability of large datasets and more powerful hardware have resulted in flourishing of ML in recent years [6,8]. This has been reflected in the application of ML in various science and engineering domains. Figure 5 shows the yearly distribution of reviewed literature and their type, namely research articles and conference papers. As per this figure, the number of publications has increased rapidly since 2018. It is worth mentioning that 9 out of 55 papers reviewed are open access.

Table 3. ML models leveraged—application and dataset.

Application	Dataset	Feature Engineering Method	ML Technique
Calculating amphibole formula	Routine electron microprobe analysis (EMPA) data	PCA [76]	PCR [76]
Characterizing the composition of igneous rocks	Raman spectra of mineral samples	PCA [96]	DT [97]; ANN [96]
Classification and prediction of alteration facies	Multi-element geochemical data	Hierarchical clustering [92]; K-means [92]	SVM [92]; LDA [92]; QDA [92]; CART [92]; RF [92]
Classification of inorganic solid materials of known structure	Topological attributes of Delaunay simplex properties	_1	RF [97]
Classifying hematite crystals	Optical microscope images	LDA [78]	NB [78]
Detecting potential Cu mineralization in bedrocks based on the composition of basal till	Geochemical data	PCA [83]	Unsupervised RF [83]
Determining mineralogical spatial distribution of the different components in a concentrate sample	Near-infrared hyperspectral image	-	k-NN [71]
Determining type of rock texture	Rock images	-	k-NN [89]
Discrimination of lithologic domains	Hyperspectral data	MNF [61]; OTVCA [61]	SVM [61]
Drill-core mapping	Hyperspectral data	PCA [67]	RF [64,67,68]; SVM [68]
	Hyperspectral short-wave infrared (SWIR); scanning electron microscopy-based image analyses using a mineral liberation analyzer (SEM-MLA); visible/near-infrared (VNIR); long-wave infrared (LWIR)	OTVCA [65]	RF [63]; SVM [63]; [65]; FF-ANN [63]
Estimating the mineralogical compositions	Elemental data acquired using X-ray fluorescence (XRF) instruments	-	ANN [84]
Finding association between imaging and XRF sensing	Images of rock samples	-	LR [101]; SVM [101]
Generating 2D mineral map of chromite samples	Optical micrograph images	-	RF [90]
Geochemical anomaly detection; prospectivity for future exploration	Geochemical exploration data; concentration of major and trace elements	Feature elimination with cross-validation based on random forest [47]; unsupervised deep belief networks (DBNs) [54]; MMML [55]; hierarchical clustering [56]; SDAE [56]; PCA [56]	VAE [45]; RF [47]; CNN [51]; SVM [54]; ACE [55]; IF [56]
	Litho geochemistry of sandstones obtained from drill cores	PCA [82]	LDA [82]; RF [82]
	Geochemical assay (ppm Cu); total magnetic intensity; isostaticresidual gravity	-	SVM [52]
	Spatial proxies	-	ANN [58]; RF [58]

Table 3. Cont.

Application	Dataset	Feature Engineering Method	ML Technique
Geochemical imaging	Qualitative LIBS spectral data	PCA [48]	K-means [48]; agglomerative hierarchical clustering [48]; GMM [48]
Geological and Geophysical Mapping for mineral exploration, mine planning, and ore extraction	Multispectral, RGB, and hyperspectral data	OTVCA [62]	SVM [62]
Geological texture classification	Images of drill cores	GLCM [66]; LBP [66]	RF [66]; SVM [66]; k-NN [66]; ANN [66]
Identifying and mapping geology and mineralogy on a vertical mine face	Hyperspectral data	-	GP [60]
Mapping of gold deposits and prospects	Lithogeochemical major oxide data; spatial data	PCA [49]; WOE [49]	RBFNN [49]; SVM [49]
	Geoscience data	-	CNN [50]
	Geological, geochemical, structural, and geophysical datasets	-	RBFLN [81]
Mineral identification	Reflected light optical microscopy (RLOM) images	-	CNN [80]
	μCT images	-	CNN [72]
	Multispectral images	-	LDA [70]; FF-ANN [70]
	Reflectance spectra	-	Bayes nets [100]
	X-ray spectrum data	PCA [95]	ANN [95]
	X-ray microtomography scans	-	Fuzzy inference system (FIS) [74]
	Images of microscopic rock thin section (RGB pixels)	-	k-NN [77]; DT [77]
Optical identification of minerals	Mineral properties such as color, hardness, pleochroism, anisotropism, and internal reflections	Cramer's Vand Pearson correlation coefficient (PCC) [75]	DT [75]
Prediction of concentrate yield and modal mineralogy	Bulk chemistry data from the mining company open pit database	-	ANN [79]
Predicting rock type and mine face, detecting hydrothermal alteration	Physical properties of rocks	-	SVM [59]
	Hyperspectral data	-	GP [53,86]; SVM [86]; SAM [86]
	Multi-element geochemistry	K-means++ [93]	RF [93]
	Images of the rocks	-	ANN [94]
Reducing noise in hyperspectral data	Hyperspectral imagery from vertical mine faces	-	GP [88]
Regolith landform mapping	Gamma-ray spectrometry data; derivatives of the SRTM elevation model, Landsat, and polarimetric radar	-	ANN [99]

Table 3. Cont.

Application	Dataset	Feature Engineering Method	ML Technique
Segmenting hyperspectral images	Hyperspectral data	-	SVM [87]; RF [87]; ANN [87]; k-NN [87]; DT [87]; NB [87]
Segmenting mineral phases	μ CT dataset	-	K-means [73]; FCM [73]; RF [73]; k-nearest neighbors [73]

¹ Feature engineering methods are not used/mentioned in the corresponding works.

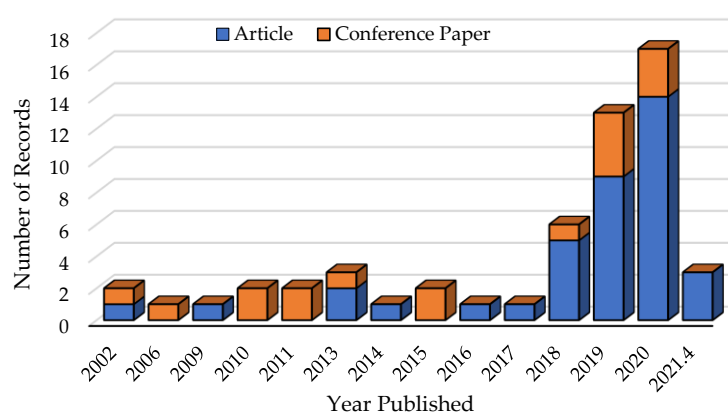


Figure 5. Yearly distribution of the number of selected papers (January 2000–April 2021).

For the sake of providing a general insight into the scope of the reviewed papers, Figure 6 illustrates the word frequency map of their titles, where the more popular words are represented with a bigger font size. As depicted, aside from the common keywords, namely *using*, *machine*, *learning*, and *mineral*, we can generally infer the main trends discussed in the previous sections considering the relatively high frequency of the words *hyperspectral*, *mapping*, and *classification*. Complementary to this, Figure 7 presents the word frequency map for the authors' keywords as well as index keywords, where aside from the familiar words, the terms *exploration*, *geochemical*, and *mapping* are perceptible. These, in line with the findings presented previously, represent the current trends in the application of ML for processing large datasets comprising mainly hyperspectral and geochemical data for anomaly detection and mapping of minerals in exploration studies.

Based upon our review of the selected works, we noticed the lack of high-quality data for applying ML in the mining and mineral studies. This issue, in many cases, is not simply related to not storing the data, but the unavailability of accurate and reliable labels for the data, which is required for training the supervised learning models. In many cases, the required labels need to be generated manually, thereby it is not only time consuming but also prone to biases and human errors. Unfortunately, since most of the works lack economic studies about the practical value of leveraging ML in the proposed applications, investing in providing reliable datasets seems to be challenging. Thus, a potentially valuable research avenue is the economic evaluation of using AI and ML in mining and mineral industry.



Figure 6. Word frequency map of the title of the reviewed records.



Figure 7. Frequently used words in the author and index keywords of the reviewed papers.

Considering the case dependency of the ML models and lack of sufficient training data, potential benefits of the *transfer learning* concept can be evaluated in the future works to curb such issues. It is worth emphasizing that in the reviewed works, we found examples of using transfer learning, yet they are limited to utilizing the models trained for general applications such as conventional image classifiers in special domains, e.g., geochemical anomaly identification [51]. However, the possibility of benefiting from a model trained on a specific dataset in a different case, e.g., using a model trained for mapping gold deposits in an area to facilitate the development of a new model for another geographic location, needs further evaluation.

Another point that is typically overlooked in the studied literature is the importance of feature engineering, especially in the case of conventional ML techniques, and hyperparameter setting. As the success of ML methods is highly sensitive to the selection of the input features as well as hyperparameters of the models [10], it is always beneficial to assess different sets of input features as well as hyperparameters to reach a more accurate model.

In addition, to the best of our knowledge, the application of semi-supervised techniques and reinforcement learning is missing in the existing literature on the application of ML in exploiting mineralogical data in mining and mineral industry. Such techniques can prove valuable especially in the reviewed applications where the judgement of specialists is always required considering the criticality of the tasks and that the frequency of unexpected cases where the ML models cannot generalize well may be relatively high. In this regard, a potential solution could be the application of a semi-supervised learning method on top of the current supervised techniques to decide whether the outcomes are reliable or further analysis and evaluations need to be carried out for specific samples.

4. Conclusions

In this paper, a systematic review of the works carried out on the application of machine learning for innovative use of mineralogical information in mining and mineral studies was presented. The search strategy resulted in a total of 145 records from which

55 publications were carefully chosen following the presented selection criteria. The selected papers were then thoroughly investigated to answer the main research questions involving (1) the types of problems in the area under study for which applying ML techniques are advantageous, (2) the specific complexities that favor ML over traditional approaches in such problems, (3) the most common type of datasets and output variables employed in the existing literature, (4) the ML algorithms leveraged, and (5) general trends in the area under investigation.

The review results revealed that the ML techniques have been used in a wide range of applications including geochemical anomaly mapping, mineral prospectivity, drill-core mapping, mineral processing, segmentation of μ CT images, prediction of material properties, and calculating the amphibole formula, to name but a few. Analyzing massive and complex datasets with nonlinearities and hidden underlying interdependencies and patterns among different features, automating manual operations to improve productivity via enhancing speed and reducing human errors, cost reduction, and dealing with the problems caused by high noise are among the most significant reasons behind using ML in such studies. The main datasets used in these studies comprise hyperspectral images, μ CT images, optical microscopic images, geochemical data, litho-geochemical data, data collected by the electron probe microanalyzer, as well as spatial, geophysical, geological, total magnetic intensity, and isostatic residual gravity data. In addition, support vector machine, random forest, and artificial neural networks are concluded to be the most frequently used supervised learning algorithms, whereas K-means clustering and hierarchical clustering are among the unsupervised learning models used more in the selected literature.

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