

Review

The Review Article on the Exploration of Artificial Intelligence and Machine Learning in Mineral Exploration

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doi: <https://doi.org/10.70705/ppp.fetaiml.2024.v03.i02.pp67-73>**ABSTRACT**

Analyzing massive volumes of data is essential in mineral prospecting, which is a difficult and intricate process. Conventional approaches to mineral discovery are labor-intensive, costly, and often unsuccessful. The advent of AI and ML, however, opens the door to a potential paradigm shift in the mining sector. This review article delves into the most recent cutting-edge uses of artificial intelligence and machine learning in mineral exploration, assesses their strengths and weaknesses, and highlights the advantages and disadvantages of using these technologies. The research shows that mining initiatives may be far more efficient and successful when using AI and ML approaches. In the field of mineral exploration, a number of AI and ML techniques are now in use, including Neural Networks, Decision Trees, and Random Forests. To cut down on the time and money spent on mineral exploration, these methods aid in finding connections and patterns in the massive amounts of data. The report also points out some possible drawbacks, such as how important it is to have high-quality data, how difficult it is to understand the findings, and how important it is to address ethical concerns when utilizing ML and AI in mining. There are major ramifications for the mining sector in this study's conclusions. Mineral exploration that makes use of AI and ML may have positive effects on society and the environment while also increasing profits and decreasing expenses. Research and development of artificial intelligence and machine learning methods for mineral exploration may be advanced according to the study's suggestions. Ultimately, the mining sector stands to undergo a sea change if artificial intelligence and machine learning are not included into mineral exploration. Their potential is vast.

Keywords

AI; Mining; Minerals and ML, Deep learning.

INTRODUCTION

The mining industry relies on mineral exploration to find new resources and determine its potential [12]. Conventional mineral exploration has made use of a wide range of geochemical, geophysical, and geological methods [13]. Nevertheless, these approaches aren't always accurate, and they may be costly and time-consuming. One potential solution to these problems is an alternate strategy for mineral discovery that makes use of AI and ML [14]. By analyzing massive volumes of data, artificial intelligence and machine learning may spot irregularities that might represent mineral deposits [15]. Mineral exploration might be done more accurately and with less expense and time spent on it using these methods [16].

In recent years, there has been a lot of buzz about using AI and ML for mineral prospecting [18]. Through the integration and extraction

of relevant information from diverse datasets, mineral exploration may be enhanced using AI and ML approaches, according to many research. Mineral identification procedures and drilling program optimization are two further areas that might benefit from these methods. In addition, mineral exploration may make use of AI and ML at several phases, such as prospecting, mineral resource estimate, and target creation. Nevertheless, there is a lot of uncharted territory when it comes to creating new algorithms and models to improve the precision and effectiveness of these methods for mineral prospecting. Despite the clear promise of AI and ML for mineral exploration, there are still many unanswered questions and obstacles that must be overcome. Mineral prospecting using conventional techniques is labor-intensive, costly, and often unsuccessful. The enormous quantity of data, together with the intricate nature of the geological formations, the amount of data that has to be processed makes it difficult for geologists to make prompt, well-informed choices. But now that AI and ML are on the rise, mineral exploration might be rethought and mining ventures could be more efficient and

fruitful than ever before.

The primary goal of this research is to examine the most cutting-edge uses of AI and ML in the mineral exploration industry. The goal is to assess the merits and demerits of using AI and ML for mineral discovery. To determine the possible advantages and disadvantages of using AI and ML methods in mineral discovery. The goal is to suggest areas for further study and development of ML and AI methods for mineral discovery.

The potential for Machine Learning (ML) and Artificial Intelligence (AI) to transform the mining industry is the driving force behind this research article's investigation of these technologies' use in mineral exploration [17]. Conventional approaches to mineral discovery have been laborious, costly, and often unsuccessful. It is possible that the mining industry's bottom line might take a major hit if new AI and ML technologies don't improve project efficiency and success rates. Contributing to the advancement of technology that may enhance the efficiency of mining operations, this research delves into the most cutting-edge uses of AI and ML in mineral exploration. Geologists will be able to make educated judgments on the viability of using AI and ML to mineral exploration after they assess the efficacy and limits of these methods.

If mining businesses want to make educated judgments about using AI and ML for mineral exploration, they need to know what the advantages and disadvantages of doing so are. A road map for the creation of more sophisticated and efficient technologies is laid out in the suggestions for future study and development of ML and AI methods in mineral exploration.

II. REVIEW OF LITERATURE

Healthcare, banking, and transportation are just a few of the many sectors that may be revolutionized by AI and ML. Artificial intelligence (AI) and machine learning (ML) are seeing increased usage in mineral exploration as a means to enhance the precision and productivity of exploration processes [20]. To better understand where mineral reserves are most likely to be located, ML algorithms may be used to geographical data. Furthermore, drilling data may be analyzed by AI systems to forecast the existence of nearby minerals [21]. Mineral exploration AI and ML applications currently face a number of obstacles, such as inadequate datasets, opaque and difficult-to-understand AI models, and a lack of in-depth technical knowledge among industry experts [18]. The availability of more extensive datasets for training and validation purposes, together with new algorithms and tools that increase the accuracy and transparency of AI and ML models, have led to tremendous progress in recent research towards tackling these difficulties. Further study is necessary to fully grasp the advantages of artificial intelligence and machine learning in mineral exploration, although their potential is tremendous. Figure 1 shows a functional diagram of machine learning together with its many forms.

Exploration for minerals: a brief overview of the evolution of AI and ML

Recent years have seen a surge in interest in using AI and ML for mineral exploration, since these technologies have the ability to greatly enhance the precision and productivity of mineral identification and extraction [21]. In the early days of applying AI and ML to the mineral exploration industry, the main goal was to create expert

systems that could identify and understand minerals based on pre-determined rules. Nevertheless, these systems had their limitations due to issues with appropriate data and the inability to learn from past mistakes. The use of ML approaches in mineral exploration has been growing in recent years, thanks to improvements in computing power and the availability of massive datasets. Support vector machines (SVMs), decision trees, random forests, and artificial neural networks (ANNs) are some of the ML techniques that have recently been developed with the aim of detecting mineral resources and abnormalities in geological data. When applied to the problems of mineral identification and location prediction, these approaches have shown encouraging results.

amount, giving the mining sector a substantial boon [22]. More complex analysis of geological data have also been made possible by the advancement of deep learning methods like RNNs and convolutional neural networks (CNNs). Example: Zeng et al. (2020) used hyperspectral remote sensing data to map minerals using CNNs, and they got a 90% accuracy rate. Further study is needed to fully harness the promise of artificial intelligence and machine learning in mineral exploration, but their limited history and development show that they have the ability to transform the mining sector.

Figure 1. Types of machine learning in details.

AI and ML techniques and algorithms applied in mineral exploration
 The mining exploration industry has shown success in using AI and ML approaches to find and identify mineral resources. Neural networks are a popular method because they can learn from data and identify patterns while also making predictions about fresh data. Neural networks were used by Al-Ani et al. (2019) to forecast the existence of copper mineralization in a particular region using geophysical and geological data. The research showed that compared to other ML models, the neural network model did quite well in terms of accuracy. Mineral prospecting has also made use of support vector machines (SVM). In order to find regions in Iran that might be rich in gold, Gholami et al. (2018) used support vector machines (SVM). Researchers discovered that the SVM model was quite good at predicting where gold mineralization will occur when fed data from geological, geochemical, and geophysical sources. Random forests are another machine learning approach that is used in mineral prospecting. Iron oxide copper gold (IOCG) deposit distribution predictions were made by Li et al. (2021) using random forests in an Australian area. Researchers discovered that the random forest model was quite good at forecasting IOCG deposits when fed data from geology, geophysics, and geochemistry. In sum, the results show that ML and AI have promise in mineral discovery, and that they may make the process more precise and efficient.

Investigations of real-world mineral exploration cases with AI and ML

A number of case studies published in the last several years have shown that mineral exploration may benefit from AI and ML approaches [23]. To find possible mineral deposits in an Iranian copper-gold deposit, for instance, Ghorbani et al. (2021) used an ensem-

ble of ML models. The models demonstrated remarkable accuracy in predicting the locations of the deposits, thanks to the training data set that included geological, geochemical, and geophysical information. Similarly, in a Chinese gold prospecting operation, Li et al. (2018) used a CNN, a deep learning system, to decipher magnetic data collected from aircraft. After training on a massive dataset including geological and magnetic data, the CNN successfully identified geological characteristics linked to gold mineralization.

Meanwhile, Zhao et al. (2019) used a support vector machine (SVM) approach to find possible mineral resources in a Chinese porphyry copper deposit. Results demonstrated that the SVM could correctly anticipate the positions of mineral deposits after training on a dataset consisting of geophysical, geochemical, and geological data. Using the artificial bee colony (ABC) method, a machine learning technique, Yue et al. (2020) optimized the drilling program in a Chinese gold exploration project. Using a collection of geophysical and geological data for training, the algorithm was able to determine that an improved drilling program may drastically cut exploration expenses without sacrificing accuracy. Lastly, the grade and thickness of a coal seam in China were predicted by Liu et al. (2021) using the long short-term memory (LSTM) method, a deep learning technique. In order to enhance the mining process, the LSTM was trained on a dataset of geophysical and geological data. The findings demonstrated that the algorithm could properly predict the coal seam features. Through the use of precise forecasts and optimization of exploration programs, these case studies show how artificial intelligence and machine learning may revolutionize mineral exploration. By doing so, they can lower exploration expenses and enhance the possibility of locating mineral reserves.

Within its first few paragraphs, this part surveys the development of intelligent mineral identification as a field. After taking a look at what field keywords are now, we'll take a look back at their history. Figure 1 depicts the topic development path, which indicates the thematic evolution across time in the domain of intelligent mineral identification. To calibrate detection equipment for recognizing unknown minerals, Pooley et al. proposed using pure mineral powders with known chemical compositions as standards [24]. This idea garnered a lot of attention from the academic community. When it came to intelligent mineral identification, Pooley et al. were among the first. But as of 2006, mineral identification accounted for only 10% of all literature entries, or 21 articles. Much of the work on basic mineral identification algorithms up until 2006 focused on accurately identifying minerals based on their color attributes in order to find new minerals in uncharted rocks. It has become increasingly popular to use X-ray diffraction spectroscopic data for precise mineral identification since 2007. Mineral image processing and hyperspectral remote sensing have been the focus of academic study since 2012 in an effort to detect minerals, with a particular emphasis on mineral textures. At this moment, mineral types such as feldspar and calcite have garnered a lot of attention due to their large and reliable databases and the ease with which they may be sampled. Since 2017, there has been a substantial increase in academic research into intelligent mineral identification using deep learning. In order to identify minerals in a greater range of ore types, scientists have been looking at several techniques, including scanning electron microscopy and

remote sensing.

The search for hydrocarbons is a very risky and challenging enterprise. Accurately locating subsurface possibilities is crucial for drilling and hydrocarbon resource extraction [10]. Using limited 2D seismic data was the primary approach to subsurface mapping for locating potential drilling locations at first. The success rate was dismal, with a probability of about 1 in 7. "Big data," which may be stored in Terabytes of memory, came from the exponential growth of data acquired over time. Machine learning techniques were used to enhance the signal-to-noise ratio in seismic and well data processing, interpretation, and acquisition as technology progressed. This allowed for the possibility of 2D, 3D, and 4D seismic data analysis using a variety of reliable methods and the clean data. By using these techniques, interpreters were able to create subsurface volume maps, which, when combined with well data, yielded amplitude, using precise mapping of subsurface horizons to create saturation and porosity maps. The subsurface models' data parameters were further elucidated by use of inversion methods. To locate optimal locations, machine learning algorithms generated horizon and window-based characteristics such as coherency, edge maps, spectrum decomposition, and relief maps. Facies mapping employing striatal slicing, understanding fault polygons, and mapping complicated fault structures all contributed to a better understanding of subsurface possibilities. The success rate increased to 1:3 thanks to the help of machine learning algorithms, which converted leads into drillable leads. Using 4D or repeat seismic data, we were able to understand the flow of hydrocarbons after drilling. Rapid improvements in target prospect size and hydrocarbon volume are being made utilizing heuristic approaches and artificial neural networks [25]. In order to determine the potential amount of hydrocarbons to be retrieved from the subsurface, methods such as evolutionary programming and Monte Carlo simulation are used. The global discovery and production of hydrocarbon resources have been impacted by machine learning [10].

Figure 2. Exploration outline for data processing and interpretation using machine learning technique [10].

III. METHODOLOGY

Investigating Current State-of-the-Art Applications

A comprehensive literature review was conducted for collecting data about investigating current state of the art applications [11]. This review involves identifying relevant peer-reviewed articles, conference papers, and reports related to the application of Artificial Intelligence and Machine Learning in mineral exploration. A systematic review of the literature was conducted to analyze the state-of-the-art applications of Artificial Intelligence and Machine Learning in mineral exploration. The findings from the literature review are categorized and summarized, including the types of techniques and algorithms used, the data sources used, and the results obtained [11].

Evaluating Effectiveness and Limitations

The evaluate the effectiveness and limitations of Artificial Intelligence and Machine Learning techniques in mineral exploration were analyzed in this research study. To achieve this objective, case studies and projects that have implemented these techniques in mineral exploration will be identified. The effectiveness of these techniques was evaluated based on their ability to improve the accuracy of min-

eral detection, reduce exploration time and costs, and increase the success rate of mining projects. The limitations and challenges associated with the implementation of these techniques was also be analyzed, including data quality, data availability, and computational requirements.

Identifying Potential Benefits and Challenges

The identify the potential benefits and challenges of adopting Artificial Intelligence and Machine Learning techniques in mineral exploration in this research study. To achieve this objective, interviews was conducted with experts in the field of mineral exploration. The purpose of these interviews is to identify the perspectives of experts on the potential benefits and challenges of adopting these techniques. The interview data were then analyzed to identify the most commonly cited benefits and challenges associated with the implementation of these techniques.

Providing Recommendations for Future Research and Development Based on the findings from the literature review, case studies, and expert interviews, areas for future research and development of these techniques in mineral exploration will be identified. Recommendations were then provided for researchers and practitioners on how to overcome the challenges associated with the implementation of these techniques and how to maximize their potential benefits. These recommendations were based on the analysis of the literature review, case studies, and expert interviews conducted throughout the research.

IV. RESULTS AND DISCUSSION

Investigating Current State of the Art Applications

Table 1 summarizes four separate research articles that examine the most cutting-edge AI mining applications currently available. An outline of the present status of mineral exploration is given in the first publication by Alcalde et al. (2022). The article stresses the need of discovering new mineral resources using cutting-edge technology and multidisciplinary methods in a way that doesn't harm society or the environment. Improved exploration success rates and sustainable resource usage may be achieved by ongoing research and development of new technology and multidisciplinary methods, according to the authors. It is also recommended that the government, universities, and businesses work together.

Souri and Hosseini (2018) conducted a comprehensive review of data mining methods for malware detection and published their findings. By examining characteristics including system calls, network traffic, and file activity, data mining approaches may successfully identify and categorize malware, as shown in the article. However, there are still obstacles to overcome in the areas of enhancing detection efficiency and accuracy, managing large-scale data, and dealing with malware that is polymorphic and constantly developing.

The study paper that Lippi and Torroni (2021) criticized examines the methods, applications, and difficulties of argumentation mining as well as its present and future tendencies. There has been an increasing amount of study on methods for finding, extracting, and evaluating arguments in text, which the article shows has led to argumentation mining obtaining a lot of attention recently. Among the many uses of argumentation mining are the following: deciphering political arguments, studying online discourse, and evaluating the

merit of scholarly articles. The authors suggest that researchers look at hybrid methodologies that merge logic, machine learning, and natural language processing in the future. Furthermore, in creating and implementing argumentation mining tools, ethical concerns, especially those related to openness, fairness, and privacy, should be considered.

In their 2021 article, Hojat Shirmard et al. assess the state of the art in mineral prospecting data interpretation using machine learning. Findings suggest that decision trees, random forests, SVMs, and ANNs are among the machine learning techniques that might perform a good job of analyzing remote sensing data. Potential applications of deep learning and TL are further examined. The authors stress the need of carefully selecting features, the necessity of using high-quality training data, and the challenges associated with assessing ML models. They suggest that in the future researchers should focus on developing hybrid models that combine machine learning with other approaches, such physical modeling and geological information, in order to make the results more accurate and easier to understand. In addition,

In order to address the issues of data integration, data quality, and data availability in mineral exploitation using remote sensing, the authors strongly recommend stepping up current efforts.

Evaluating Effectiveness and Limitations

In mineral exploration, "evaluating effectiveness and limitations in machine learning" means taking a look at how well algorithms for machine learning are doing, how accurate they are, and where they fall short [26]. This technique evaluates the algorithms' robustness to uncertainty and variability by running them on real-world data and comparing the results to those from more conventional approaches. Companies involved in mineral exploration might benefit from the assessment process by understanding which machine learning approaches work best for their unique requirements and which ones need more work [2]. While evaluating machine learning algorithms, it is important to keep in mind and deal with their limits, such as the potential for overfitting and the need for massive volumes of high-quality data. Here, we reviewed the results of earlier research [3].

The work of Vasconcelos et al. (2019) is primarily concerned with assessing the efficacy of ML algorithms for mineral potential mapping. Decision trees, random forests, and support vector machines were among the machine learning algorithms evaluated in this research, which employed data collected from a Brazilian gold mining location. The authors discovered that decision trees and support vector machines were the next most accurate predictors, behind random forests. The research also showed that machine learning has the ability to enhance mineral prospectively mapping, and that picking the right input characteristics is crucial.

The use of machine learning to forecast mineral deposit sites from geochemical data is assessed by Zhu et al. (2019). The research assessed the performance of several machine learning techniques, such as neural networks, gradient boosting, and random forests,

using data collected from a Chinese copper deposit. Prediction accuracy was highest for random forests, then for gradient boosting, and lowest for neural networks, according to the authors. Feature selection and machine learning's ability to enhance mineral deposit prediction were also emphasized in the research.

In their 2020 study, Li et al. assess the limits of ML in the context of mineral prospecting. The research assessed the performance of several machine learning techniques, such as random forests, decision trees, and support vector machines, using data collected from a Chinese gold deposit. The researchers discovered that ML has the potential to provide reliable mineral deposit forecasts, but, the amount and quality of the data used to make these predictions may place limitations on how far they can go. Researchers should exercise care when evaluating machine learning models, since the work brought attention to the possibility of overfitting.

Recognizing Possible Advantages and Difficulties

For mineral exploration to make the most of machine learning, it is essential to first understand the possibilities and limitations of this technology [5]. The positive side of machine learning is that it may improve exploration success rates, decrease exploration expenses, and speed up the discovery of mineral resources [27]. Prioritizing exploration goals and identifying locations for subsequent investigation may also be helped by this. The difficulty in understanding findings, the possibility of biased algorithms, and the need for high-quality data are a few of the obstacles [30]. It may also be difficult to get buy-in from stakeholders and incorporate machine learning into preexisting exploratory procedures. The results of earlier research were reviewed in this section.

Research by Shirmard et al. 2021 aims to assess the merits and drawbacks of using machine learning for mineral discovery. Literature study N/A Using a variety of data sources, including geological records and satellite imagery, machine learning is able to successfully detect and categorize mineral resources. A few drawbacks, however, include the difficulty in understanding complicated models, the possibility of bias and overfitting, and the need for high-quality data. Better data quality, more transparent and interpretable machine learning models, and hybrid models combining machine learning with other approaches should be the focus of future research.

Locating Mineralized Zones (Xiong et al., 2021). Utilizing geological and remote sensing data, machine learning models may be trained to detect mineralized regions. Automatic Regression (AR), Support Vector Machines (SVM), and Random Forest (RF) When applied to geology and remote sensing data, the SVM and RF models successfully identified mineralized regions. The authors suggest future studies to enhance the models' accuracy by adding more precise geological data and other information sources. The authors also recommend looking into the possibility of using deep learning methods to find minerals.

We authored A Comprehensive Study on Machine Learning Techniques to provide a detailed analysis of machine learning techniques used in mineral exploration (Cheng et al., 2020). Not applicable to a literature review Machine learning techniques such as decision trees, random forests, support vector machines, and artificial neural networks have proven useful in mineral exploration for a variety of tasks, including resource localization, grade forecasting, and

geophysical data modeling [29]. However, there are a number of challenges, such as the need for high-quality data, the risk of bias and overfitting, and the difficulty of understanding complex models. Hybrid models combining machine learning with other approaches, such physical modeling and geological information, should be the focus of future study in order to improve the results' accuracy and interpretability. Further effort is required to address the issues of data availability, data integration quality, and data integration in mineral exploration.

In 2020, Rahmani and colleagues This study aims to provide a comprehensive analysis of machine learning as it pertains to mineral prospecting. No literature review conducted. In mineral exploration, machine learning has shown encouraging outcomes across a range of applications, such as deposit identification, grade prediction, and processing of remote sensing data. The writers stress the significance of feature selection, interpretability, and high-quality training data. Difficulty in integrating geological information into the models, the possibility of bias and overfitting, and the need for more uniform datasets are all obstacles [28]. Incorporating geological information into machine learning models, making the models more visible and interpretable, and solving the problems of data availability and quality in mineral exploration should be the goals of future research. Further study is also required to determine if mineral exploration may benefit from deep learning and transfer learning.

Offering Suggestions for Ongoing and Future Studies Here are a few suggestions for further study and advancement based on the offered research:

1. Find the best input characteristics for machine learning algorithms to use in mineral exploration and prospecting by conducting experiments. To make the models more accurate and easier to understand, these studies might look at the possibility of combining data from many sources, such remote sensing, geochemical, and geological information.
2. To make the findings more accurate and easier to understand, use hybrid models that integrate machine learning with other methods like physical modeling and geological understanding. One such approach is to investigate the use of DL and TL methods for mineral prospecting.
3. Take on the problems of data integration, data quality, and data availability in the mineral exploration process. In order to make it easier to compare and assess diverse methodologies, future research should concentrate on creating standardized datasets and evaluation measures.

Fourth, use geological knowledge and contextual information to build machine learning models that are more interpretable and transparent. Methods like rule-based models and decision trees, which are able to be explained, might be investigated in this regard.

5. Foster a spirit of collaboration among businesses, universities, and government agencies to boost exploration success rates and guarantee the responsible use of resources. To achieve this goal, it may be necessary to create multidisciplinary strategies that integrate conventional mining techniques with cutting-edge technology like machine

learning and robots.

V. CONCLUSION

Machine learning and artificial intelligence have the ability to completely transform the mineral exploration sector, as shown in this review article. It is now obvious that these technologies can greatly improve mining project efficiency, cut costs, and raise success rates. Nevertheless, it is critical to acknowledge the difficulties, like interpretability and data quality, and ethical concerns, that come with its implementation. Since AI and ML may cause a paradigm change in our approach to mineral exploration, the ramifications for the mining sector are enormous. In order to guarantee sustainable and productive mineral exploration techniques that fully use AI and ML, the suggestions for future research and development stress the need of ongoing cooperation, innovation, and the integration of several disciplines.

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