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ECOLOGICALLY ORIENTED MINERAL EXPLORATION: THE SYNERGY OF REMOTE SENSING AND MACHINE LEARNING

Annotation. The article explores the prospects of integrating remote sensing (RS) and machine learning (ML) in mineral exploration. The combination of these advanced technologies opens new horizons for geological research, enabling more efficient and accurate identification of mineralization, mapping of lithological units, and analysis of structural features and alteration zones. The paper examines current methods of processing remote sensing data using various machine learning algorithms, including deep neural networks and clustering methods. Special emphasis is placed on practical examples demonstrating the successful application of RS and ML synergy in geological exploration. The main challenges and future research prospects in this area are also discussed, highlighting the potential to significantly enhance the efficiency and sustainability of mineral exploration processes.

Keywords: Remote sensing; geological mapping; satellite imagery; mineral exploration; optical; hyperspectral.

Introduction

Geology is the science of Planet Earth. It deals with the study of the materials that make up the planet, the phenomena that affect those materials, the resulting products, as well as the history of the planet and the life forms that have existed on it since its inception [1]. Remote sensing is the art or science of obtaining information about an object without direct contact, often defined in various ways [2]. This concept has been defined by many scientists, including Lintz and Simonett [3], Curtis [4], and Colwell [5]. In general, remote sensing involves acquiring information about the Earth's land and water surfaces through images captured from above, using electromagnetic radiation in one or more ranges of the electromagnetic spectrum reflected or emitted from the Earth's surface [6]. Geological remote sensing, therefore, can be defined as the study of geological structures and surfaces, both on Earth and beyond, using technologies that analyze their interaction with the electromagnetic spectrum, without direct contact with the objects of study.

In the early days of geological work, a series of Landsat satellite images were used extensively. These images were particularly valuable for geologists conducting regional surveys, as the multiple coverages provided by Landsat data allowed them to assess changes in vegetation and the angle of sunlight, which are important for understanding the physical history and formation conditions of the Earth [7]. Y. Isachsen, an employee of the Geological Survey of the State of New York, used space images measuring 100 by 100 miles to create mosaics of the state and its neighboring regions. These mosaics clearly revealed the geological connections of New York's diverse landscape, including basic rock units, glacial features, major linear structures, and circular formations (Figure 1). Isachsen visited these areas to verify the existence of many features identified in the Landsat mosaic and demonstrated how satellite images could be used to detect features not observed in large-scale studies [8].

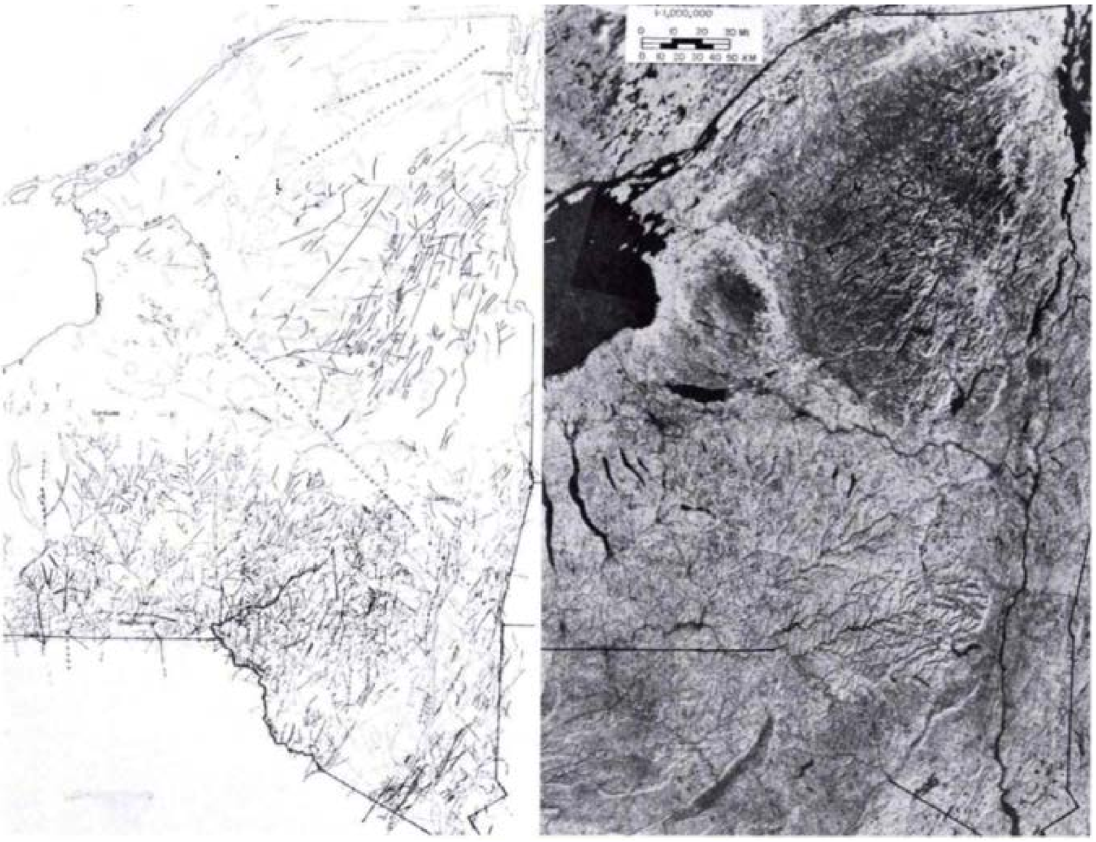

Figure 1 - LANDSAT mosaic and lineament map of eastern New York State (after Isachsen, 1973).

The next significant advancement came with the launch of the ASTER satellite (Advanced Spaceborne Thermal Emission and Reflection Radiometer). Launched in December 1999, the TERRA spacecraft orbits the Earth in a sun-synchronous orbit with an inclination of about 98.2°, an altitude of 705 km, and a repeat cycle of 16 days. The TERRA platform hosts the advanced multi-spectral imaging system ASTER, which is part of the Earth Observation System (EOS). ASTER measures visible reflected radiation in three spectral bands (VNIR 0.52 to 0.86 µm, with a spatial resolution of 15 m) and infrared reflected radiation in six spectral bands (SWIR 1.6 to 2.43 µm, with a spatial resolution of 30 m). Numerous geological studies have utilized the ASTER multispectral system [9]. For example, [10] the study used data from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) to clarify the geological structure of the Precambrian basement of the Proterozoic inlier at Igherm, located in the Central Anti-Atlas region of Morocco. The interpretation of the digitally processed data in this study was complemented by geological field data collected through an exploration and mapping program in the Central Anti-Atlas. The use of ASTER data for mapping the lithological composition of rocks through the spectral information of thermal channels has been applied in studies such as the investigation of rock composition at Mountain Pass, California, USA [11]. Another example is the rock mapping in the Bodie region of California, USA [12], where gold and silver deposits were identified due to hydrothermal alterations in volcanogenic complexes. Attempts were made to quantify the SiO2 content in rocks using spectral analysis of satellite images. Research was conducted in the Hiller Mountains, Nevada, USA, and in Virgines-La Reforma, Baja California Sur, Mexico [13]. As a result of the work on spectral data, maps of the quantitative SiO2 content in rocks were created. In Nevada, USA, the feasibility of mapping minerals and rocks containing ammonium using spectral methods was demonstrated [14]. Copper-porphyry deposits are among the most commonly studied objects, characterized by naturally varying contrasts in the mineral composition due to hydrothermal alterations. A spectral map of porphyry deposits was developed for the Silver Belt region, specifically in areas such as Arizona, USA [15], Collahuasi in northern Chile [16], and others [17]. The study identified propylite, clay, and phyllite zones of hydrothermal-metasomatic changes in the bedrock. Hyperspectral images, widely used in geological exploration and environmental monitoring, provide detailed information about the spectral characteristics of various materials on the Earth's surface. Unlike multispectral images, which cover several broad spectral ranges, hyperspectral data consists of hundreds of narrow spectral bands, allowing for more precise identification and differentiation of minerals, soils, and vegetation. This data is particularly useful for mapping mineralization, analyzing areas of change, detecting geochemical anomalies, and monitoring soil degradation. Due to their high spectral resolution, hyperspectral images enable researchers to identify hidden geological features and analyze them with exceptional accuracy, opening up new opportunities for effective exploration and development of mineral resources. [18] in this study demonstrates that high-resolution AISA hyperspectral images (2 m) provide a more accurate representation of mafic and ultramafic rocks in the Subarctic region compared to EnMAP images (30 m). Van der Meyer et al. [19] utilized hyperspectral images for detailed mapping of lithological units, significantly enhancing the understanding of the geological structure of the studied area. In Clark's study [20], hyperspectral data were used to analyze the mineral content of the surface in arid regions, where traditional mapping methods were challenging due to the lack of vegetation. This approach enabled the identification of new potential mining sites. Kruse [21] also noted that hyperspectral images can effectively identify minerals associated with hydrothermal alteration zones, which is particularly important for mineral deposit exploration. Additionally, laboratory studies conducted by Graham Hunt have made a significant contribution to specialists working with optical remote sensing data [22]. Graham Hunt and John Salisbury systematically analyzed the diagnostic absorption features of all major groups of minerals and rocks. Their work was published in the journal "Modern Geology" [23]. Figure 2 presents a spectral signature diagram illustrating the effects of electronic and vibrational processes observed in different minerals under laboratory conditions [22].

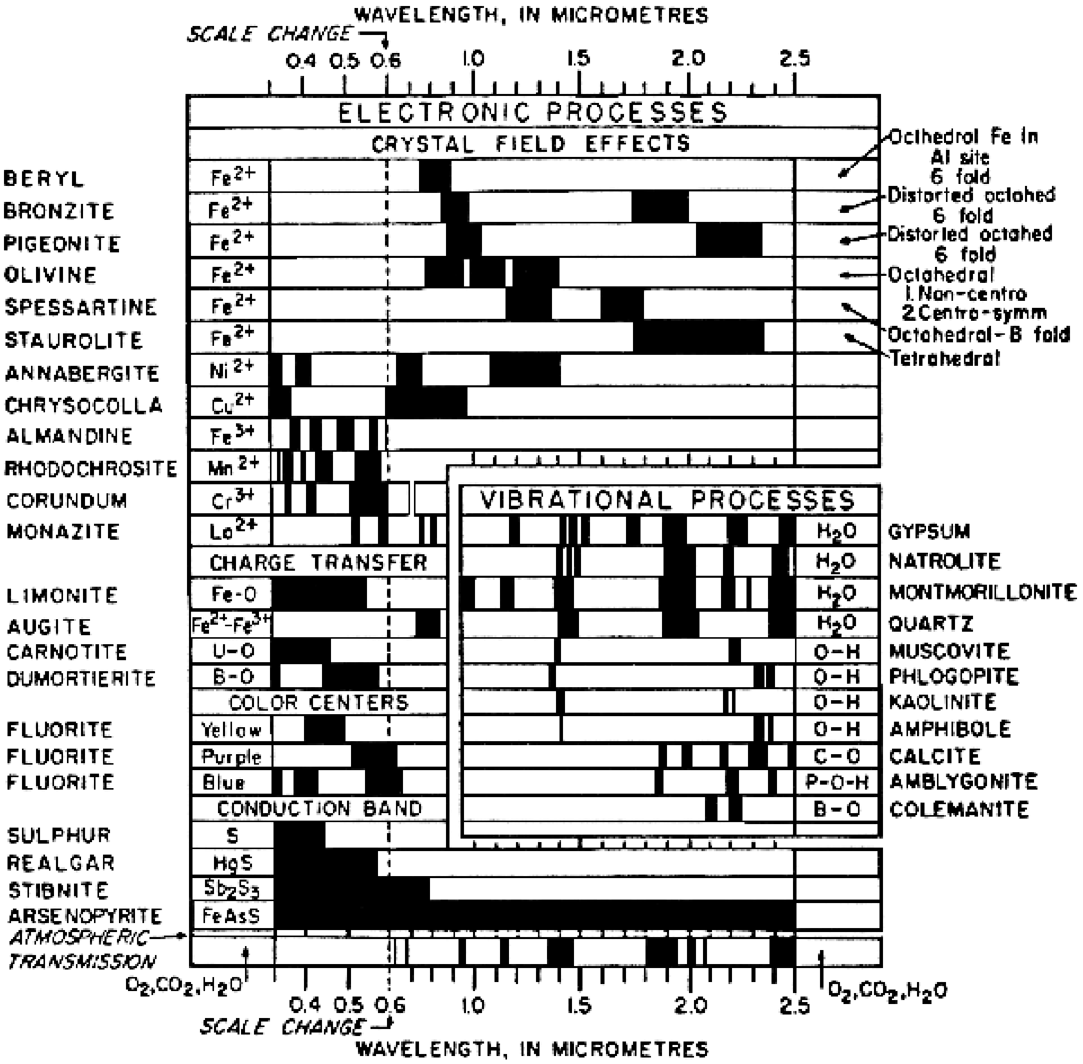

Figure 2 - Spectral signature diagram

Fundamentals of machine learning in remote sensing data processing. Classification is the process of categorizing input data into target classes using a discriminative function, $y=f(x)$. In machine learning, a classification model f' is created, which, along with the operator, approximates this function and assigns inputs to the target classes [24, 25].

The classification process is divided into three stages: (1) data preprocessing, (2) model training, and (3) predictive evaluation. Preprocessing involves preparing and transforming the data to ensure its relevance [26, 27]. Model training includes setting algorithm parameters using methods such as cross-validation. Evaluation is performed on test data to assess the model's ability to classify new samples accurately [25, 28]. To assess the performance of models, indicators such as overall accuracy and the kappa coefficient are often used, particularly in remote sensing applications [29].

Machine learning algorithm theory. Naive Bayes is one of the simplest and most effective machine learning algorithms, widely used in various scientific fields, including geology. This method is based on Bayes' theorem and assumes that all features used for classification are conditionally independent of each other (figure 3). Despite its simplified assumptions, the Naive Bayes classifier demonstrates high accuracy and efficiency in solving various classification problems in geological research [30]. In geology, Naive Bayes is used for tasks such as predicting rock types, identifying mineralization zones, and classifying spectral data obtained through remote sensing. For example, in the work by Elrasheed and Szabó [31], this method was used to classify lithological units based on spectral data obtained from hyperspectral images. The results showed that the Naive Bayes classifier can effectively utilize spectral features to distinguish between different rock types, demonstrating high accuracy and robustness to parameter variations.

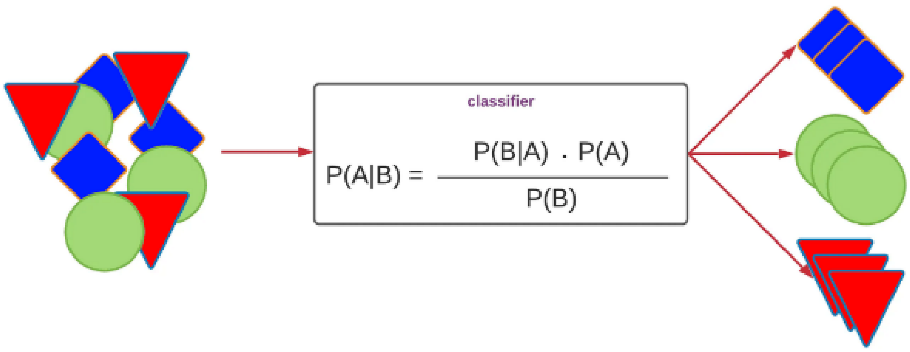

Figure 3 - Naïve Bayes Classifier

Forson, E. D., and Amponsah, P. O. [32] used Naive Bayes to identify mineralization zones in the Copper Mines area based on geochemical data. The authors noted that this method is effective for processing large datasets to identify significant geological patterns, which in turn improved the efficiency of mineral exploration. Additionally, the Naive Bayes classifier has been successfully applied in avalanche forecasting problems. Chen W. et al. [33] applied the Naive Bayes method to assess the risk of landslides based on geological and climatic data. The study demonstrates that Naive Bayes can be a valuable tool for evaluating the likelihood of landslides and implementing appropriate risk management measures.

Thus, the Naive Bayes classifier has proven to be an effective tool in geology, particularly for classification and forecasting based on large datasets. Its simplicity, high computational speed, and ability to handle high-dimensional data make it an attractive choice for geological research.

The k-Nearest Neighbors (kNN) method is a simple and efficient machine learning algorithm commonly used in remote sensing for classification and regression tasks. This algorithm falls under the category of lazy learning methods, which do not create explicit models but instead analyze the nearest neighbors of an object in the feature space to make decisions [34].

In geological research and remote sensing, the kNN method is used to classify soil types, vegetation, and geological formations, as well as to map minerals and other resources. This is made possible by the algorithm's ability to adapt to various data types and handle multidimensional feature spaces, which is particularly valuable when analyzing satellite images.

A study by Zhang et al. [35] demonstrated the successful use of the kNN algorithm for mineral classification based on spectral characteristics obtained from hyperspectral data. The classification accuracy reached 90% when the k parameter was appropriately selected and data preprocessing methods were applied to reduce noise [35].

One of the main advantages of the k-NN method is its simplicity and ease of interpretation. The algorithm does not require complex hyperparameter tuning and is easily adaptable to various tasks. Additionally, kNN performs well with small training samples that have a high degree of heterogeneity (figure 4).

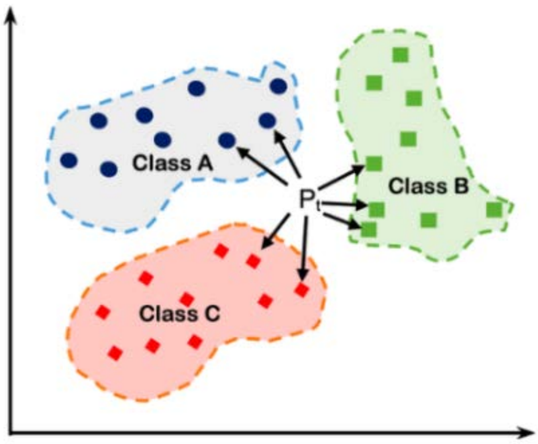

Figure 4 - The k-Nearest Neighbors

However, this method has some limitations. Firstly, the algorithm's performance heavily depends on the size of the training sample; as the number of objects increases, the need to store data in memory can become a bottleneck when working with large datasets [36]. Secondly, the choice of the distance metric and the parameter k significantly affects classification results, necessitating further research and experimentation.

Random Forests—using advanced mapping tools, remote scientists can help locate rare metals and other valuable resources. However, the vast amount of map data and the complex variability of Earth's layers make precise resource identification challenging. Traditional methods often fall short due to limited data, so advanced mathematical tools are needed to improve predictions. Random Forests excel in handling large datasets and reducing errors, making them ideal for predicting the locations of these metals, leading to more accurate resource identification.

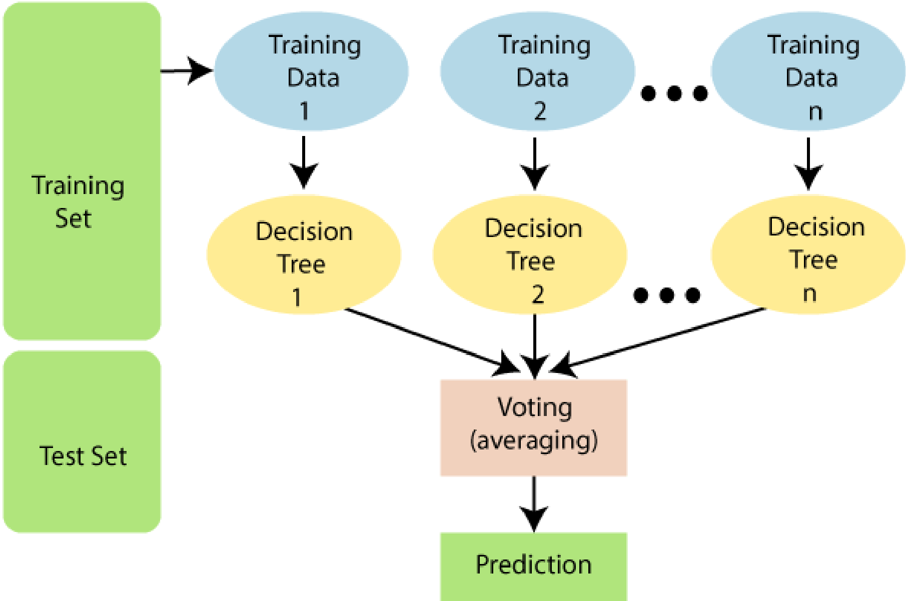

Figure 5 - Random Forest

Random Forests are widely utilized in earth science for detecting patterns in mineral deposits. They facilitate the development of models that handle complex data with multiple variables. A key advantage of using Random Forests is their ability to integrate different types of data. For instance, combining satellite imagery with ground surveys enhances the accuracy of predictions. In mineral exploration, using semi-automatic methods with Landsat-TM imagery can distinguish between active mining sites and areas containing mining waste. This approach provides crucial information for exploring large regions, such as Slovakia and Romania [37]. By combining satellite images with existing knowledge of known mining features, the strengths of both methods are leveraged, improving the quality of data for predictions. This multi-layered approach has demonstrated successful outcomes in mineral exploration.

The group learning plan of Random Forests improves figuring out by putting together many choice trees by different input info. This tactic lessens the risk of over-learning, a result common in earth datasets that are often fairly rocky and changing, making it impossible to get dependable predictions. Meanwhile, combining results from many trees allows staying tough to info irregularities. Moreover, this way is good for mineral searching as it allows for a bunch of info kinds, including spectra and geological things. Finally, the coming of far sensing tech has allowed making a great amount of high space and spec resolution satellite photos [38].

The large number of features in remote sensing data makes it easier to figure out what minerals are present because Random Forests are good at picking out the important features. This helps choose the most helpful spectral bands for finding minerals. Getting more accurate results in geological assessments and mineral maps depends on using the right features. Since these models don't overfit, they aren't limited to the training data and can be used with other datasets. Better understanding of mineral extraction locations and waste areas can help with managing mining waste. Remote sensing methods like semi-automated principal component analysis provide more detailed pictures and can tell the difference between mineral extraction and waste locations [37].

In short, using Random Forests together with location data has boosted guesswork about mineral locations. The bunching-up learning method cuts down on the risk of wonky results in the study of rocks and leads to more reliable and exact outcomes. Also, the ability to handle high-detail pictures from space has amped up the accuracy of mineral finding, which is key for searching for new deposits. The arrival of this cool machine learning method has definitely changed how we find minerals, opening up fresh ways and making how earth scientists hunt for resources totally different. Considering our society's growing need for vital minerals, we need to adopt cool tech like Random Forests to help the future of resource searching. Combining these breakthroughs alongside Random Forests definitely shows how machine learning can be used by mineral experts and shows how to solve problems in new ways.

Support vector machines (SVMs) have become a key way of looking at and understanding info in jobs like earth science, rock science, and space picture taking. SVMs are useful because earth science info has gotten complicated due to new technology. Structural earth science, which talks about earth structures like plate movement and breaks in the earth, is a vital use of this way of doing things. Other areas where SVMs are important include checking on the environment and managing natural resources, and finding and sorting minerals based on earth science and physics info to guess where deposits are. This way of doing things has become important due to the huge amount of info made through research.

Support Vector Machine (SVM) methods have been shown to work well in dealing with massive amounts of data in earth science research. They effortlessly discover patterns from large spatial data and perform well, even with few examples for learning [39]. SVMs help researchers understand tectonic movement and fault lines through predictive modeling. The practical use of SVMs in satellite data is clear in geologic mapping and mineral exploration, where their performance matches that of traditional classifiers. It is possible to work with varying degrees and sizes of examples because SVMs adjust easily to real-world conditions.

Support Vector Machine (SVM) plans greatly increase the rightness of land cover sorting by looking at bulk facts got from grouped pictures. They enable better sorting results without needing earlier feature picking steps, as the Hughes rule does with old sorting plans [40]. This is especially useful in case of time change finding, as such changes can be watched and managed (e.g., deforestation, urbanization and other key ecological systems). The rightness of SVM sorting guesses helps with good care of natural things, as this way allows an adequate answer to fast ecological change caused by people's actions.

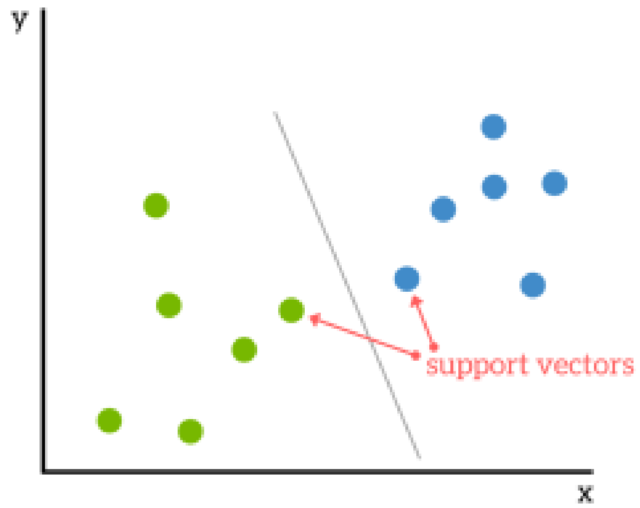

Figure 6 - Support Vector Machine (SVM)

Support Vector Machine (SVM) is a key part of handling tons of information to find patterns in earth science data. It uses a method based on stats to make predictions about where minerals are found more reliable. For instance, in side-by-side tests, SVM did a better job of putting alteration zones into groups than other ways of doing things [41]. As finding minerals relies more on data, SVM's talent for sorting through complicated information will be very important for finding and following minerals.

The use of support vector machines has dramatically changed the geosciences. In connection with the subject of this paper, this suggests that support vector machines have improved the study of geological formations and thus the knowledge of the forces shaping the earth's surface. On a related note, SVM-based applications have boosted land cover classification in remote sensing, which has implications for the management of natural resources. Lastly, SVMs have enhanced mineral exploration. The use of support vector machines in mineral exploration involves data classification with superior accuracy. In conclusion, the use of advanced computational methods is key for the advancement of the fields of geology, mineralogy, and remote sensing.

Artificial Neural Networks – computer brains have been used as a tool that attempts to build change in several fields. They have been widely used in taking pictures from space. Computer brains have powerful skills for breaking down hard-to-understand facts related to rocks. They have affected how rock experts tell what different rocks are by letting them deal with oddities in rock identification. They help in using many-color and super-color facts, thus making it easier to tell the rise in data worth for telling what different rocks are. Computer brains have space-picture uses in finding rock piles.

To start, computer brain systems greatly improve finding oddities. For instance, they let you take a look at mind-boggling geological data patterns, which is crucial for finding mineral treasures. The huge amount of info fed in leads to better accuracy when finding mineral treasures and lower costs for looking for them. One example is the work on air reading methods [42]. In this case, the computer brain learns the real connection between the readings of the light signal. Thus, there is no need to make complicated plans, as they might introduce errors in the dealing with the data, resulting in less trustworthiness.

Fake brain systems can figure out what minerals are in colorful pictures. Using different kinds of information, like land measurements, rock types, and chemical details, can make finding rocks and resources better. Finding rocks and resources needs understanding of how different rock features work together, which is especially important when looking for minerals because complex relationships affect where they are found [43]. Real-world examples show that using fake brain systems to combine information improves rock studies.

Fake brains proved to be a true jump forward in dealing with complex information given by remote sensing tools, boosting the accuracy of spotting mineral bits. The given programs are able to work through a huge amount of information in a significantly shorter time than old methods, which usually need manual analyzing and lots of site visits. A possible way to use this ability is shown by remote sensing research in Slovakia and Romania, which included a semi-automatic main component analysis (PCA) on geo-referenced Landsat-TM full scenes to improve the separation of mineral extraction and bad mining zones and compare them with old maps [37]. These studies show that the use of neural networks can make mineral analyses in geology studies easier and give quick data regarding mining actions.

In short, computer brains have been used to make rock and gem study better. They've boosted the spotting of strange things for gem piles, joined multi-color and super-color info to give far-off sensing for gem finding more exact and quick. As the world keeps getting hungrier for Earth's goodies, using smart tech in the area of rock study is changing how we do it.

The following table shows a comparison of machine learning methods. The table provides data on methods, descriptions, pros and cons, as well as applications in geology (table 1).

Machine learning is changing many fields by looking at lots of info very fast and right. One of these fields is finding ways to get stuff out of the ground, which is important for making sure we can get things out of the earth. As the world runs out of stuff from the ground, making finding ways to get stuff out of the ground better is key as it helps find new places to get stuff from the earth. However, the cost of using new tech, teaching people how to use it, and getting good info are some problems these companies face. But the better and faster analysis of places to get stuff from the earth makes using these new tools worthwhile.

The use of computer learning in today's mineral searching will affect the money of the firms. Initially, the right setup and care of the software, including information gathering, will need companies to put a lot of dough into these new tools.

Table 1 – Comparison of machine learning methods

Method	Description	Advantages	Disadvantages	Application in geology
Support Vector Machines (SVM)	An algorithm that uses a hyperplane to separate classes in a multidimensional space.	- High accuracy on small samples - Effective for linearly separable data	- Sensitive to parameter selection - Slow on large datasets	Classification of minerals, recognition of structures, analysis of zones of changes.
Artificial Neural Networks (ANN)	A model that simulates the work of the human brain, capable of modeling complex nonlinear dependencies.	- Ability to learn from large datasets - Suitable for complex and non-linear tasks	- The need for a large amount of data - The risk of over-training and difficulty in interpretation	Mineralization forecasting, lithology mapping, anomaly recognition in remote sensing data.
k-Nearest Neighbors (k-NN)	An algorithm that classifies objects by the majority of votes of their nearest neighbors.	- Ease of implementation - Works well on small data	- Sensitive to noise - Slow performance on large datasets	Classification of rock types, identification of geological objects.
Random Forests	Multiple combination of decision trees to improve classification accuracy.	- High noise resistance - Effective when working with large datasets	- May require large computing resources - Difficulty in interpretation	Classification of lithological units, determination of zones of changes, analysis of geochemical data.

Naive Bayes	A classifier based on Bayes' theorem, assuming the independence of features.	- Speed and simplicity - Works well on small datasets and with text data	- Simplified assumptions about the independence of features - Not always suitable for complex dependencies	Mineralization identification, risk assessment of geological processes, basic classification of geological data.
Note-Compiled by the author				

Teaching workers how to use these new tools will also be needed to help the mining companies succeed. Some of the ways things are done in the current systems will have to be thrown out to make room for the computer learning ways of looking at information. Computer learning has been found to be good at mineral searching, but it also has its problems like any other tool. The beginning investment of resources will be needed if the companies would want to avoid upset reactions from the people being shown new information handling practices [44].

The worth of any machine-learning gizmo used for finding minerals will depend on how much good teaching data is around. This makes things tough, as mineral collections tend to be scattered and unusual, so making a full set of data is hard. So, with only a small set of data, gizmos get too focused on the teaching data, and finding minerals fails to reach the exactness needed. Using machine learning to look at current ways to do things needs a lot of money for data and teaching [45].

Since machine learning programs can look at huge amounts of info, they can find the layouts of mineral stashes that might be missed by old search methods. These programs use complicated methods to look at big sets of earth science data. At the same time, how well the programs work depends a lot on how good the data is. For example, machine learning needs top-notch, well-arranged, and labeled data sets to teach reliable programs [46]. Otherwise, its potential in finding minerals will be lost. As we have seen in successful cases, the programs can find mineral spots, giving a big boost to the mining field. Therefore, earth scientists need to change their ways.

The power of machine learning tools to rapidly review extensive geological records permits the finding of trends and weird things that are beyond the capacity of traditional ways. This edge is clear in mineral hunting, where the speed of real-time information processing can speed up smart decisions. Combining flawless information into a machine learning system improves geophysical modeling and reversal, subsequently making predictive models for mineral finding better. New ways in active mineral exploration places have certainly shown awesome accuracy, with one method making predictions for zinc amounts in boreholes with a 97% accuracy rate [44]. Such accuracy beats standard analysis methods, which rely on longer but less accurate lab tests.

In short, machine learning is changing how we look for minerals by making it easier to look at data, finding complex earth science details, and making our guesses about where minerals are better. Sadly, for this awesome tech to work well, we need lots of money, to teach people how to use it, and to find good data that tells us what's what. In the end, doing machine learning and the old ways of finding minerals together will help us find resources in a way that's good for the planet.

Conclusion

Mineral resources play a vital role in driving economic development, fostering technological progress, and promoting sustainable practices. As global demands change, it is crucial to adopt improved techniques for resource exploration. Traditional obstacles in mineral exploration, such as geological intricacies and technical constraints, can be mitigated through the use of remote sensing and machine learning. Satellite imaging offers a wealth of information for evaluating the Earth's surface, while machine learning uncovers intricate patterns within extensive datasets, facilitating immediate monitoring and rapid data analysis.

Remote sensing technologies enable real-time data gathering regarding geological shifts, improving awareness of the situation. Satellites from the Earth Resources Observation Satellite program assist in tracking land and mineral resources, allowing decision-makers to quickly respond to environmental changes through sophisticated data analysis driven by machine learning.

Machine learning techniques, including neural networks and decision trees, examine geological information by revealing underlying patterns. Neural networks effectively capture non-linear relationships to forecast mineral resources, whereas decision trees identify critical factors that affect mineral deposits. The combination of remote sensing data enhances geological forecasting further.

Improvements in remote sensing methods, such as satellite and aerial surveys, empower geologists to quickly gather information across vast regions, which is crucial for locating mineral deposits. Subsequently, machine learning analyzes these datasets to detect patterns and relationships, accelerating exploration and increasing precision.

The integration of space-based data collection with machine learning in mineral exploration has become essential for sustainable resource management. This collaboration supports real-time monitoring, enhanced data interpretation, and faster identification of valuable resources, transforming the landscape of geological exploration.

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ЭКОЛОГИЯЛЫҚ БАҒЫТТАЛҒАН ПАЙДАЛЫ ҚАЗБАЛАРДЫ БАРЛАУ: ҚАШЫҚТЫҚТАН ЗОНДТАУ МЕН МАШИНАМЕН ОҚЫТУДЫҢ СИНЕРГИЯСЫ

Аңдатпа. Мақалада пайдалы қазбаларды барлауда қашықтықтан зондтау және машиналық оқыту синергиясын қолдану перспективалары қарастырылады. Осы екі озық технологияның үйлесімі геологиялық зерттеулерге жаңа көкжиектер ашады, минералдануды тиімдірек және дәл анықтауға, литологиялық бірліктерді картаға түсіруге, құрылымдық ерекшеліктер мен өзгеру аймақтарын талдауға мүмкіндік береді. Жұмыста терең нейрондық желілер мен кластерлеу әдістерін қоса алғанда, машиналық оқытудың әртүрлі алгоритмдерін пайдалана отырып, қашықтықтан зондтау деректерін өңдеудің ағымдағы әдістеріне талдау жүргізіледі. Геологиялық барлауда арақашықтықтан зерделеу және машиналық оқыту синергиясын қолданудың жетістіктерін көрсететін практикалық мысалдарға ерекше назар аударылды. Болашақта пайдалы қазбаларды барлау процестерінің тиімділігі мен тұрақтылығын едәуір арттыруға мүмкіндік беретін осы саладағы әрі қарайғы зерттеулердің негізгі сын-қатерлері мен перспективалары талқыланады.

Кілт сөздер: Қашықтықтан зондтау; геологиялық картаға түсіру; спутниктік суреттер; пайдалы қазбаларды барлау; оптикалық; гиперспектрлік суреттер.

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ЭКОЛОГИЧЕСКИ ОРИЕНТИРОВАННАЯ РАЗВЕДКА ПОЛЕЗНЫХ ИСКОПАЕМЫХ: СИНЕРГИЯ ДИСТАНЦИОННОГО ЗОНДИРОВАНИЯ И МАШИННОГО ОБУЧЕНИЯ

Аннотация. В статье рассматриваются перспективы применения синергии дистанционного зондирования (ДЗ) и машинного обучения (МО) в разведке полезных ископаемых. Сочетание этих двух передовых технологий открывает новые горизонты для геологических исследований, позволяя более эффективно и точно выявлять минерализацию, картировать литологические единицы, а также анализировать структурные особенности и зоны изменений. В работе проводится анализ текущих методов обработки данных дистанционного зондирования с использованием различных алгоритмов машинного обучения, включая глубокие нейронные сети и методы кластеризации. Особое внимание уделено практическим примерам, иллюстрирующим успехи применения синергии ДЗ и МО в геологоразведке. Обсуждаются основные вызовы и перспективы дальнейших исследований в данной области, что позволит в будущем значительно повысить эффективность и устойчивость процессов разведки полезных ископаемых.

Ключевые слова: Дистанционное зондирование; геологическое картографирование; спутниковые снимки; разведка полезных ископаемых; оптические; гиперспектральные снимки.