ISERDAR International Science and Engineering Reviews: Development, Analysis and Research

Review Article

A Review of AI for Efficient Mineral Identification

Hooman Dadashzadeh Ahari [1,2]

[1] *Geomine Consulting Company,*

[2]*Member of Australian Institute of Geoscientists (MAIG), hooman.d.ahari@gmail.com, ORCID:0000-0002-1721-3606*

ARTICLE INFO

Article history:

Received Jul 12, 2024
Received in revised form Aug 26, 2024
Accepted Aug 30, 2024
Available online Aug 31, 2024

Keywords:

Artificial intelligence (AI), Machine learning (ML), Deep learning (DL), Automated mineralogy, Intelligent mineral identification, Mineral classification

Doi: 10.5281/zenodo.13631172

* Corresponding author

ABSTRACT

Precise and efficient identification of minerals is essential in a wide range of scientific and engineering disciplines. This research examines the growing impact of artificial intelligence (AI) in transforming mineral identification. We explore the latest progress in AI, specifically focusing on artificial neural networks, machine learning, and deep learning, and how they are being used in this field. Using visualization analysis, we examine the progression of mineral identification driven by artificial intelligence. This allows us to identify areas of active study and newly emerging keywords. By using trend and keyword analysis, we suggest potential directions for future study, which will facilitate continued progress in this captivating topic. This abstract circumvents explicit reference to the field of computer science or duplicating the original framework. The article specifically examines the use of AI in mineral identification, emphasizing the progress made and potential future developments.

1. Introduction

The integration of Artificial Intelligence (AI) across diverse domains has witnessed a significant surge in recent years, leading to groundbreaking advancements in image recognition, natural language processing, autonomous vehicles, and malware detection. Notably, the geosciences field has seen substantial progress in incorporating AI methodologies, particularly in addressing traditional challenges such as the identification of rocks and minerals. This fusion of AI with conventional geological research is paving the way for novel solutions and innovative approaches to longstanding issues. Conventional mineral identification techniques frequently demand considerable resources, including time, energy, and specialized equipment, to achieve precise results. Although early experiments have shown promise for intelligent mineral identification using Artificial Intelligence (AI), its adoption and progress have been slow due to implementation challenges. However, recent advancements in AI, such as improvements in deep learning and the availability of more user-friendly toolkits, have renewed interest in AI among geoscientists. Addressing the obstacles associated with applying AI methods to mineral identification is crucial for unlocking the full potential of this technology and fostering future advancements in the field.

The resurgence of interest in Artificial Intelligence (AI) among geoscientists can be attributed to recent progress in deep learning techniques and the accessibility of user-friendly toolkits. This renewed attention has led to a surge in studies focused on mineral identification – a critical aspect of mineral selection, exploration, separation, and archaeological artifact preservation. A prime example showcasing the significance of mineral identification is granite, a widely used material for monuments. In conservation activities like laser cleaning, the accurate identification of surface mineral deposits is essential for preserving these structures. As AI continues to advance, its
potential applications in geoscience, particularly for mineral identification, are expected to grow, ultimately contributing to more effective preservation strategies and a deeper understanding of our geological environment. Addressing the varying effects of minerals on granite can enhance processing techniques and prevent potential damage. This study provides an overview of Artificial Intelligence (AI)-driven intelligent mineral identification methods and introduces a novel classification of these approaches. By employing visualization techniques to examine development trends, the research enables mineral researchers to quickly discern appropriate discriminative routes and methods for diverse

scenarios. As AI technology continues to advance, its integration into mineral identification processes will likely yield more precise and efficient techniques, ultimately benefiting geological research and conservation efforts. This paper serves as a valuable resource for researchers seeking to leverage AI's potential in addressing various geological challenges and furthering our understanding of Earth's complex mineral compositions. By doing so, they can effectively address challenges in different settings and optimize mineral identification processes. This research aims to help AI researchers better understand current applications and identify potential challenges in developing AI technologies for intelligent mineral identification. The identification of mineral species is critical, with two primary approaches: *Expert Systems:* Computer programs simulating human experts for domain-specific problem-solving. Mineral identification expert systems contain specialized knowledge but are beyond this paper's scope**Hata! Başvuru kaynağı bulunamadı.**. *Artificial Intelligence Methods:* The focus of this paper, is on AI techniques that offer promising solutions for challenges in traditional mineral identification. *Identification method based on artificial intelligence model:* This paper focuses on an AI-based mineral
identification method that develops models using large amounts of mineral data. These models learn to identify minerals directly from the data and can recognize minerals not previously present in the system, improving identification accuracy. Key aspects of this approach include *Model Development:* Using AI and large mineral datasets to create models for mineral identification. *Data Input:* Feeding mineral data into the model for category discrimination. *Model Learning:* The AI-driven model "learns" from mineral data, enhancing its identification capabilities. *Accuracy Enhancement:* This AI-based method can effectively identify minerals not existing in the system, greatly improving identification accuracy and contributing to the advancement of mineral identification techniques. In recent years, the model identification method has gained popularity among researchers for intelligent mineral identification in geological studies. AI-driven intelligent mineral identification has seen significant progress and growing interest from researchers. By learning characteristic patterns of mineral samples, AI-based methods have simplified and improved the mineral identification process. Traditional manual identification methods, while simple and cost-effective, suffer from low accuracy, time-consuming processes, and require expert knowledge. Data-based identification methods like X-ray diffraction, electron microprobe, and Raman spectroscopy improve accuracy but still demand advanced instrumentation and identification knowledge. AI-based intelligent mineral identification methods provide solutions for handling big data and various data types while achieving high accuracy. These methods significantly reduce labor consumption during the identification process and enable accurate identification of simpler data types, such as photo-type data of ores. This reduces the reliance on specialized instruments for data acquisition. Some notable photo-type data-based mineral identification methods include: [14]: Rock and thin sections were segmented using Goodchild and Fuente's edge detection algorithm. A three-layered feedforward neural network with backpropagation error correction and a genetic algorithm was employed to find near-optimal solutions. [15]: Captured images were median-filtered for noise reduction and histogram-equalized for contrast enhancement. Adaptive thresh holding segmented rock and mineral images, followed by extraction of 11 shape-based features for classification using an artificial neural network. [16]: Researchers acquired images and marked random points on them, recording each point's position (XY coordinates) and classification. Pattern recognition methods (NN, KNN) and artificial neural network algorithms (multilayer perceptron—MLP) were used to define a multidimensional feature space for the automatic classification of structures. These studies demonstrate the potential of AI-based methods in improving mineral identification using photo-type data, reducing the need for specialized instruments, and simplifying the identification process. In the first set of experiments, RGB pixel values were used. The second series of experiments converted RGB images to HSV space for better alignment with human color perception. A feedforward MLPNN with a backpropagation training algorithm was employed, utilizing a tangent sigmoid activation function in the hidden layer and a logarithmic sigmoid function in the output layer. The neural network was implemented using MATLAB's neural network toolbox. [16] collected images and marked random points on them, recording

each point's position (XY coordinates) and classification
Pattern recognition methods (NN, KNN) and artificial neural network algorithms (multilayer perceptron—MLP) were employed to establish a multidimensional feature space for automatic classification of structures. These experiments showcase the potential of AI-based methods in improving mineral identification using photo-type data, ultimately simplifying the identification process and reducing reliance on specialized instruments. A feedforward [17] gathered sample image sets and processed them using photo-editing software for uniform adjustment, image segmentation, and annotation. Data enhancement techniques like mirror flipping and random cropping were applied to the images. A custom Unit convolutional neural network model was designed using Tensor Flow to extract deep feature information and enable intelligent recognition and classification of ore minerals. [18] collected large, diverse datasets and enhanced them through data augmentation techniques, including image flipping and scale transformation. ResNet-18 was chosen as the convolutional neural network, and SGD was used as the optimizer for implementing a deep-learning-based intelligent mineral recognition method. [19] selected important and common rock and mineral images, extracted internal square slices from raw images, and expanded the dataset with techniques like image flipping and rotation. The ResNet-50 model served as the base model, and a Python- and HTML5-based rock and mineral intelligence recognition tool was developed. This tool employs a clouded service model with front-end service for the user's browser and back-end service for the cloud server. These studies demonstrate the potential of AI-driven methods in enhancing mineral identification processes, making them more efficient and accurate. This paper attempts to introduce the research advances in this field, analyze the research methods and basic paths of identification of minerals based on artificial intelligence, show the existing specific research works, summarize these works, and provide an outlook on the research in this field in an attempt to provide

a reference for scholars to carry out relevant research. In this paper, artificial intelligence-based mineral identification models are classified into three categories. (1) Artificial neural network. Mineral identification models based on artificial neural networks are accurate and have a potential advantage over other methods when, for example, Raman spectroscopy datasets are used for mineral identification, without the need to remove fluorescence. However, artificial neural networks require too much mineral expertise and experience to avoid overtraining and undertraining. (2) Machine learning. In this paper, machine learning is divided into statistical-based machine learning and rule-based machine learning. The model is given the ability to identify minerals in the process of training the model. In the process of training the model, certain rules are adopted to improve efficiency by influencing the training of the model i.e., rule-based machine learning. Statistical-based machine learning, on the other hand, requires little mineral expertise, relies mainly on the quality of the dataset, and requires large amounts of data for training. (3) Deep learning. The emergence of deep learning breaks the deadlock of artificial intelligence and is an extension of artificial neural networks. Deep learning models have deeper hidden layers to achieve results that are as close to reality as possible; so, deep learning has more learning power and better performance. Deep learning models rely heavily on data, with larger datasets generally leading to improved accuracy.

This is due to their capacity for nonlinear function mapping, enabling them to recognize complex patterns within data. As data availability and computing power increase, the potential of deep learning models for mineral identification grows. Addressing data quality, bias, and interpretability is essential for fully leveraging these models in geoscience. Research on AI-driven mineral identification methods has gained attention in scholarly literature, with a focus on three main approaches. Keyword detection analysis identified key research areas and trends for each method, revealing a shared goal of achieving accurate identification results across diverse scenarios. Ongoing collaboration between geoscience and AI experts will likely lead to further progress in mineral identification techniques.

2. Fundamentals

2.1. Process of Intelligent Mineral Identification

The intelligent identification of minerals involves a consistent, four-stage process: (1) *Dataset Acquisition.* Instruments are used to gather mineral data, such as images and physical properties. Multi-image photographs, microscopic images of thin sections, and spectral images are important datasets for intelligent identification. (2) *Dataset Preprocessing.* Preprocessing techniques, like partitioning SEM images, dimensionality reduction, and noise reduction, are applied to improve the accuracy of the classifier. (3) *Model Training.* AI is used to train the mineral identification model. Despite the relatively short development of AI, significant milestones have been achieved in intelligent mineral identification. (4) *Model Validation.* The model discriminates the data to determine the mineral category. Various discriminative models are used based on different mineral datasets, resulting in a wide range of accuracy rates.

2.2.1. Artificial Neural Network (ANN)

In AI-driven research, ANNs have demonstrated their potential in various fields, thanks to their ability to approximate complex functions. By optimizing the weights of each layer, researchers can fine-tune these models for specific applications. The activation function's role in facilitating universal approximation ensures ANNs' continued relevance in cutting-edge AI research.

2.2.2. Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are deep-structured feedforward neural networks, that serve as key deep learning algorithms. Developed since the 20th century, CNNs excel in image recognition and object detection. Their unique ability to process grid-like data through convolution and pooling operations sets them apart from traditional neural networks. CNNs continue to be instrumental in AI-driven research across various domains. CNNs have evolved from early models like time-delay networks and LeNet-5. Technological progress and deep learning theory have led to their application in fields like natural language processing and computer vision. CNNs work by using convolutional kernels to extract spatial features from images, adjusting parameters through the backpropagation algorithm, and creating models that effectively process image information. CNNs comprise five main layers: input, convolutional, pooling, fully connected, and output. Their adaptability and efficacy make CNNs essential tools for AI-driven research, particularly in image-related tasks.

Input Layer: As convolutional neural networks use gradient descent algorithms for learning, their input data need to be normalized, which can effectively improve the learning efficiency of convolutional neural networks.

Hidden Layer: The hidden layer of the convolutional neural network mainly includes the convolutional layer, pooling layer, and fully connected layer. Among them, the convolutional layer is mainly used to extract the features of the image, the pooling layer is mainly used for feature selection and information filtering, and the fully connected layer is mainly used for classification.

Convolutional Layer: As the central layer of the convolutional neural network, the convolutional layer extracts different features of the input data by convolutional operations, and it also reduces the number of parameters to prevent overfitting caused by too many parameters. The convolutional layer can have multiple convolutional kernels, and each element of each convolutional kernel also has corresponding weight coefficients and deviations. When the convolutional kernel slides to each position, it operates with the input image and projects the information in its field of perception onto the feature map. The parameters of the convolution layer mainly consist of the convolution kernel size, padding, and step size. The size of the convolution kernel needs to be smaller than the size of the input image, and as the convolution kernel gets larger, the input features that can be extracted become more and more complex. The padding process is to artificially increases the size of the feature map before it passes through the convolution kernel to counteract the negative effects of size shrinkage during the computation. The step size of the convolution mainly defines

the distance between two adjacent positions of the convolution kernel during the scanning of the feature map. When its value is 1, the convolution kernel scans every element of the entire feature map; when its value is n, it skips n-1 pixels after each scan to continue scanning. The dimensionality of the convolution layer can be calculated from the filter of size (K1, K2, C), the input image of fixed size (H, W, C), the step size Zs, and the number of zero padding Zp. The calculation formula is as follows:

$$\mathrm{Dim}_c(H\,1,\ W\,1,\ D\,1) = \left(\frac{H + 2Zp - k1}{Zs} + 1\right),\ \left(\frac{W + 2Zp - k2}{Zs} + 1\right) \quad (1)$$

The convolutional layer usually has an activation layer, which is usually combined with the convolutional layer and called the "convolutional layer". The activation layer is a nonlinear mapping of the output of the convolutional layer, and the activation function used is usually the ReLU function.

Pooling Layer: The pooling layer is in the middle of the successive convolutional layers, which is mainly used for feature selection and information filtering. Feature selection is mainly used to reduce the number of training parameters, thus reducing the dimensionality of the output feature vector of the convolutional layer, while information filtering is performed to retain only useful information, to reduce The two main pooling methods are Max Pooling, which picks the maximum value of the sliding window, and Average Pooling, which picks the average value of the sliding window. The dimensionality of the pooling layer can be calculated as;

$$Dim_p(H_2, W_2, D_2) = \frac{H1 - k}{Z_s} + 1,\ \frac{W1 - k}{Z_s} + 1,\ D_n \quad (2)$$

Fully Connected Layer: The fully connected layer is located in the last part of the implicit layer of the convolutional neural network and only passes signals to the other fully connected layers. The role of the fully connected layer is to perform a nonlinear combination of the extracted features to obtain the output for classification, i.e., the features obtained from the convolutional and pooling layers are classified by the fully connected layer mainly obtains the weight of each neuron feedback based on the weights, and then adjusts the weights and the network to obtain the final classification results. *Output Layer:* The output layer has a loss function similar to the categorical cross-entropy, which is used to calculate the error of the prediction. Once the forward propagation is completed, the backward propagation starts updating the weights and biases to reduce errors and losses. For image classification problems, the output layer uses a logistic function or a normalized exponential function to output the classified labels. For the image semantic segmentation problem, the output layer can directly output the classification results for each pixel. function or a normalized exponential function to output the classified labels. For the image semantic segmentation problem, the output layer can directly output the classification results for each pixel.

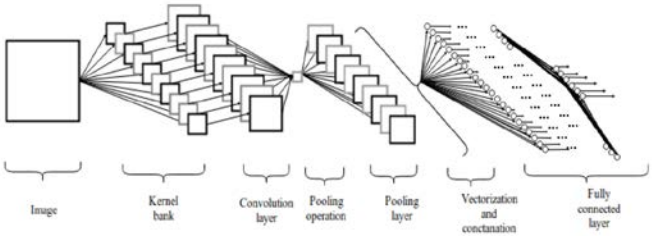

Figure 1. The structure of a CNN network is shown in the following

4. Utilizing AI for Automated Mineral Classification

The progression of artificial intelligence, propelled by the central role of machine learning, is poised to catalyze a fresh era of industrial and technological innovation. By discerning complex patterns and relationships from empirical data, machine learning empowers the extraction of latent insights, thus promoting the ability to draw inferences and drive informed decision-making. Over the years, scientists have leveraged machine learning techniques in attempts to address the challenge of intelligent rock and mineral identification. Although initial experimental outcomes suggest potential in utilizing machine learning for this purpose, widespread adoption of these methods for intelligent mineral identification has been gradual. Recent rapid advancements, including significant progress in deep learning techniques and the development of increasingly accessible and user-friendly toolkits, have rekindled geoscientists' interest in machine learning. Consequently, an expanding array of exploratory studies centered on intelligent mineral identification methods has surfaced. This paper aims to provide a concise overview of machine learning methodologies employed in intelligent mineral identification. By offering this resource, we aspire to enable mineral researchers to swiftly discern the distinct approaches and techniques available for implementation and to discover the most effective solutions across various scenarios. Moreover, we aim to help machine learning researchers comprehend the diverse scenarios where existing methods are applied, thereby identifying possible issues and challenges that may emerge due to advancements in the field. This paper classifies artificial intelligence techniques for intelligent mineral identification into three primary categories: artificial neural networks, machine learning, and deep learning. Machine learning is further subdivided into statistical-based and rule-based machine learning, as depicted in Table 1. Mineral identification primarily employs rule-based machine learning techniques, which involve using accessible training data class labels (classification) or target predicted values (regression) to generate models for anticipating new observation classes or values. Intelligent mineral identification employs several key machine learning techniques: principal component analysis (PCA), partial least squares regression (PLS), decision trees, random forests (RF), and distance metric models. PCA reduces data complexity while preserving vital information, while PLS manages highly correlated variables in mineral exploration. Decision trees and random forests classify and predict using tree-like

structures. Lastly, distance metric models evaluate mineral sample similarity based on a defined distance measurement.

4.1. Artificial Neural Network

Artificial Neural Networks (ANNs) consist of multiple interconnected simple processing units, mimic key characteristics of the human brain or biological neural networks. Neural network theory contributes fresh perspectives to machine learning research and has proven effective in intelligent mineral identification applications. Artificial neural networks excel over decision tree classifiers for mineral species identification by drawing out data features and emulating biological neural networks. They yield an average accuracy of 83% for group-based mineral classification and 73% for individual mineral classification. This technique is advantageous when using Raman spectroscopy for mineral identification, as it eliminates the need for fluorescence removal and even improves classification performance with its presence. However, ANN implementation necessitates user expertise to avoid overtraining and undertraining issues. Additionally, ANNs require retraining for data from different spectrometers due to variations in noise, background/fluorescence levels, Raman peak line shape, and spectrometer resolution, which can be a significant inconvenience. Furthermore, any new spectra added to the database also necessitate retraining. The models of artificial neural networks involved in the intelligent identification of minerals are perceptron, Autoencoder, BP neural network, Kohonen (also called SOM) network, multilayer perceptual neural network (MLP), and feedforward network structure. Each of them is described below and shown in Table 2. *Perceptron:* Ref. [7] trained a multilayer perceptron based on single polarized and orthogonal polarized image texture features to identify 23 test minerals in igneous rocks. Compared with other networks, artificial neural networks [14] are ideal for applications requiring repetitive identification of a limited number of minerals because they are less susceptible to changes such as lighting. This approach achieves 90% accuracy for identifying colored and colorless minerals, with improved performance when utilizing larger training datasets. Ramil, A. etal [1] implemented a backpropagation algorithm with mean square error minimization to optimize a traditional three-layer perceptron for identifying minerals within granite images. Experimental results demonstrated that a 10-neuron hidden layer artificial neural network yielded the best performance as a granite mineral recognition model, attaining a 90% success rate. In [16], two artificial-intelligence-based approaches are compared. One is based on the pattern recognition method—more precisely, on the nearest neighbor (NN) method; the other is based on the artificial neural network (multilayer perceptron—MLP) algorithm. The results from the experiments show that both AI methods have a high correct classification rate and that the pattern recognition method has great potential to be applied to the identification of coal micro fraction groups, and the results of the study also show that the best results can be obtained with the most classical pattern recognition method, i.e., the neural network method. López,A.etal. [2] proved the ability of a laboratory-scale hyperspectral reflectance imaging system combined with an artificial neural network to accurately identify the constituent minerals of Hessian granites in Haixi. *Autoencoders:* have been effectively utilized to address the common geological occurrence of nonlinear mineral mixing. Zhou Qiu et al. [24] developed a self-coding neural network incorporating dropout noise reduction and sparse strategies, culminating in a sparse fully connected neural network. This innovative approach contributes to the range of spectral unmixing methods aimed at mineral identification and quantitative analysis. *BP Neural Network:* The method of interpretation of stratigraphic elements is based on optimization algorithms that use core analysis data to identify minerals by determining a mineral model that reflects the distribution of mineral content. However, mineral identification in coreless wells becomes very difficult, and artificial neural networks can solve this problem with their unique sample learning capability. Tang, D.G. etal. [13] trained and optimized a BP neural network for mineral identification, and a BP neural network trained from a known well successfully predicted another unknown well; however, due to the diversity of elements in the XRF measurements, elemental analysis had to be performed before training the BP neural network. Qiang, Z.etal [25] used the spectral angle mineral mapping method for identification and BP neural network technique for different iron ores, both of which have their own advantages. Tang, D.G. etal [13] used XRF to analyze the elemental content of rock chips and the BP neural network (BPNN) model to identify the rocks to construct a neural network evaluation system based on accuracy, kappa, recall, and training speed, and the improvement made the model have significant advantages in recognition performance

and training speed. Hizhen, H. etal [26] designed a multilayer perceptron, applied 5-fold cross-validation, and performed artificial neural network identification for each image after clustering mineral pixels using the properties of RGB and HSI color spaces of mineral pixels and the proposed clustering algorithm of the new ART algorithm design. This intelligent system has high accuracy and precision for mineral identification. Table 1. Comparison of different artificial neural network models for intelligent identification of minerals.

4.2. Machine Learning

Machine learning, a subset of artificial intelligence, focuses on recognizing and interpreting data patterns and structures for learning, reasoning, and decision-making without human intervention. In essence, machine learning enables users to input substantial data amounts into computer algorithms, allowing data-driven recommendations and decisions based solely on the input data. Algorithms integrate corrected information for improved future decisions.

Table 2. summarizes intelligent mineral identification methods utilizing machine learning techniques.

Algorithm	Pros	Cons
Statistical Learning [27]	Simple and stable	The iteration speed is slow, the number of iterations is high, and it is easy to fall into the local optimum.
Clustering [8,28,29]	Simple, direct, and efficient. Fast convergence. Strong interpretability of results. Good clustering effect	The mean value must be defined. The number of clusters needs to be specified. The value of the number of clusters affects the clustering effect. High impact on outlier

Statistical-based machine learning will be introduced first. Statistical-based machine learning is machine learning based on data rules, which includes *statistical learning and clustering. (1) Statistical Learning:* Statistical learning is used to discriminate the class of a mineral by calculating the magnitude of the probability of the measured mineral. Aligholi et al. [27] selected seven mineral optical properties in the CIELab color space, calculated the probability that the test sample was a specific class, and used a majority voting scheme to determine the class of the mineral. *(2) Clustering:* Clustering is employed for unsupervised mineral detection, grouping similar spectral features into one mineral class. Unsupervised learning extracts valuable information from unlabeled data, with clusters categorized as soft or hard. Hard clustering assigns each data point to one cluster, whereas soft clustering allows points to belong to multiple clusters with varying membership degrees. Prabhavathy, P etal [8] utilized principal component analysis (PCA) for dimensionality reduction and hard/soft clustering algorithms for hyperspectral data classification. Mi, Z. etal [28] applied KSOM for training with clustering centers as input, facilitating the identification of six mineral classes and their occurrence frequencies. Jiang, G. etal [29] implemented the K-means clustering algorithm for classification and the FCC-K-means method for unsupervised mineral identification, significantly enhancing performance. Prabhavathy, P etal [8] combined unsupervised training with the PCA algorithm for dimensionality reduction of HSI dimensions. Hard clustering (K-means) and soft clustering (PFCM) algorithms were employed for data classification, with PFCM outperforming K-means for both original HSI images and reduced bands based on DBI values. ***Rule-based*** machine learning is introduced in the following. Rule-based machine learning is a statistical machine learning based on rules, which includes *principal component analysis (PCA), partial least squares regression (PLS), decision tree, random forests (RF),*

Algorithm	Pros	Cons
Perceptron [1,2]	The model is simple and easy to implement	Cannot handle linearly indistinguishable training data perfectly. The final number of iterations is strongly influenced by the hyperplane results as well as the data in the training set. The goal of the loss function is only to reduce all misclassified points with the hyperplane. Eventually, some of the sample points will likely be very close to the hyperplane; in a way, such a classification effect is not particularly good, and this problem will be well-solved in the support vector machine.
Auto encoder [24]	Generalization is strong and it is unsupervised learning, so no data labeling is required	It is a loss, and the decompressed output is degraded compared with the original input. It is data-dependent and can only compress those data that are similar to the training data
BP Neural Network [13,25]	Strong nonlinear mapping capability. Highly self-learning and self-adaptive capabilities. With some generalization ability. Fault-tolerance capability	With local miniaturization problem. Slow convergence rate. Structure selection varies. Paradoxical problems with application examples and network size. Paradoxical problems with predictive and training abilities.
Multilayer perceptual networks [26]	High parallelism. High nonlinear generic effect. Good fault tolerance and associative memory function	The number of parameters makes training difficult. The spatial information between pixels is lost and only vector input is accepted

and distance metric models, as shown in Table 3. Table 3. Comparison of different rule-based machine learning algorithms for intelligent identification of minerals

Algorithm	Pros	Cons

Principal component analysis [29]	Greater ease of use of datasets. Reducing the computational overhead of the algorithm. Removing noise. Making the results easier to understand. Complete absence of parameter restrictions.	If the user has some a priori knowledge of the observed object and has mastered some features of the data, but is unable to intervene in the processing process through methods such as parameterization, the expected results may not be obtained and the efficiency may not be high. The decomposition of eigenvalues has certain limitations. In the case of non-Gaussian distribution, the resulting principal elements may not be optimal.
Partial least squares regression [30–32]	The regression of multiple dependent variables on multiple independent variables can be performed simultaneously, which is also applicable when the sample is small, and the exact regression equation can be obtained. The degree of influence of independent variables on dependent variables can be quantified when the number of variables is suitable. It is possible to control and predict more effectively.	The regression coefficients are difficult to interpret. Not applicable when the number of independent variables is small.
Decision Tree [33]	Easy to understand and simple to explain the mechanism. Can be used for small datasets. Less time complexity. Can handle numbers and classes of data. Can handle multiple output problems. Insensitive to missing values Can handle uncorrelated feature data. High efficiency, requiring only one construction and repeated use, with the maximum number of calculations per prediction not exceeding the depth of the decision tree.	More difficult to predict for continuous fields. Prone to overfitting. When there are too many categories, the error may increase faster. Does not perform too well when dealing with data with strong feature correlation. For data with inconsistent sample sizes in each category, the information gain results in favor of those features with more values in the decision tree.
Random Forest [10,34]	Training can be highly parallelized. When the sample features are of high dimensionality, the model can still be trained efficiently. After training, the importance of each feature for the output can be given. Due to the use of random sampling, the variance of the trained model is small and the generalization ability is strong. The implementation is relatively simple. insensitive to partial missing features.	On certain sample sets with more noise, it is easy to fall into overfitting. Features that take more divided values tend to have a greater impact, which affects the effectiveness of the fitted model

Principal Component Analysis (PCA): PCA is frequently employed to reduce dataset dimensionality while preserving the features contributing most to variance. Jiang, G. etal [29] utilized the K-means clustering method with hue saturation value (HSV) PCA to group mineral regions into different classes. *Partial Least Squares (PLS):* PLS addresses the challenges of variable multicollinearity in system modeling and considers input-output correlations. PLSDA is a widely-used chemo metric technique for high-dimensional data regression. Remus et al. [49] applied PLS to identify obsidian provenance with over 90% accuracy in California, USA. El Haddad et al. [32] employed PLS, specifically MCR-ALS, on SEM/EDS and LIBS data for mineral analysis, yielding less than 10% root mean square error compared to quantitative mineral analysis (QMA) results. PCA and PLS extract latent variables representing a system's physical properties. PLS performs regression on expected system response, while PCA solely extracts variables. For classifying high-dimensional data, PCA and PLS do not require data downscaling before classification [31]. *Decision Trees:* Decision trees are predictive models representing the mapping relationship between object attributes and values. Data are classified top-down based on attribute distinguishability, with leaf nodes signifying specific categories and the paths from root to leaf nodes forming classification rules. Decision trees are easily interpretable, handle numerical and categorical data, and exhibit robustness in large or noisy datasets. Yousefi, B. etal. [33] used decision trees to extend applications in the optical identification of common opaque minerals. *Random Forest:* A random forest (RF) is a classifier comprising multiple decision trees. During learning, a random subset of candidate features is selected to train the decision trees, and the output class is determined by the plurality of output classes from the multiple trees. RFs handle numerous input variables, yield accurate classifiers, and reduce classification errors in imbalanced datasets. Xuefeng Liu et al. [50] applied RF models for SEM grayscale anomaly image segmentation classifier training. Chen, Z. etal [10] utilized linear discriminant analysis (LDA) to project data into a space with fewer dimensions and maximum separability between classes. RFs introduce modifications by constructing a collection of n trees (without pruning) or using only a subset of m descriptors. A comparison of LDA, SVM, and RF methods revealed similar performance, with RF demonstrating slightly higher accuracy. Khajehzadeh, N. etal [34] employed RF-based models to classify various stages of kerogen (organic component) and minerals (inorganic component). *Distance Metric Model*: The distance metric model assesses the similarity of test data to other minerals using a distance function (metric) between elements in a set. While simple and scalable, this model requires highly distinguishable classification features. Baklanova et al. [51] classified datasets based on similarity through K-means clustering analysis for mineral identification, utilizing distance calculations like Euclidean distance. Yalçın, C. [52] examined the use of machine learning theory in mineral exploration, emphasizing its capacity for improved and influential prediction compared to conventional approaches, hence increasing the complexity of the process.

4.3. Deep Learning

Deep neural networks extend traditional neural networks, incorporating multiple hidden layers to extract complex structured data features. Deep learning encompasses various network architectures, including convolutional neural networks, residual networks, and Siamese networks. Numerous deep learning frameworks exist, each offering unique capabilities. Tables 5 and 6 summarize intelligent mineral identification methods leveraging deep learning techniques. Deep learning's ability to capture intricate patterns in data has led to its widespread adoption across numerous domains, revolutionizing the field of artificial intelligence and enabling more accurate and efficient solutions to complex problems. As research in this area continues to progress, we can expect further advancements and innovative applications in the field of mineral identification and beyond. *Convolutional Neural Networks (CNNs):* CNNs comprise one or more convolutional layers and a fully connected layer at the top. This architecture leverages the two-dimensional structure of input data, yielding superior results in image and speech recognition. When applied to semantic segmentation of spectral images, CNN models encounter resolution reduction in feature maps due to repeated convolution and pooling operations, leading to loss of detailed structural and edge information. Tian et al. [43] addressed this issue by introducing dilated convolution, proposing a mineral spectral classification method based on a one-dimensional dilated convolutional neural network (1D-DCNN). This approach extracts spectral features using a null-dilated convolutional neural network, adjusts model parameters with a backpropagation algorithm and stochastic gradient descent optimizer, and outputs spectral classification results for end-to-end detection of mineral categories. Tiwary, A.K etal [38] applied the simple linear iterative clustering (SLIC) method to SEM images of mineral particles smaller than 50 µm for high-quality segmentation. They employed a convolutional neural network-based model, ResNet, to overcome gradient disappearance problems in deep learning networks with hundreds or thousands of layers, improving performance and reducing training errors. Cai Y. et al. [42] constructed a multiscale expanded convolution attention network for Raman spectroscopy to identify unknown minerals. Expanding convolution was used to extract multiscale features from mineral spectra, broadening the field of perception for feature extraction. A channeled attention mechanism was formed by combining a squeeze-and-excitation block (SE block) and a multiscale expanding convolution module, increasing the convolutional network's sensitivity to informative features. Zeng, X. et al [44] proposed a mineral identification method combining mineral photo image features and mineral hardness features, utilizing the deep convolutional neural network EfficientNet-b4 for image feature extraction. Okada, N. etal [5] introduced an automatic mineral identification system combining hyperspectral imaging and deep learning to identify mineral types before the mineral processing stage. Liu, X. etal [41] developed a new automated mineral identification method integrating measurements from two complementary spectroscopic techniques, employing CNN for

Raman and VNIR and cosine similarity for LIBS. Reference [45] applied convolutional neural network techniques for the automatic extraction of optical mineral features for mineral identification. Loao, A etal [11] explored the use of CNN as a tool to accelerate and automate micro phase classification, employing migration learning based on a robust and reliable CNN model trained on numerous non-geological images. In summary, CNNs have shown remarkable potential in advancing mineral identification methods by extracting complex features from various data sources and overcoming challenges encountered in traditional approaches. *Inception-v3:* Zhang et al. [46] employed the Inception-v3 architecture to extract four mineral image features: potassium feldspar, feldspar, plagioclase, and quartz. They utilized machine learning methods such as logistic regression (LR), support vector machine (SVM), random forest (RF), k-nearest neighbor (KNN), multilayer perceptron (MLP), and Gaussian Naive Bayes (GNB) to develop identification models. LR, SVM, and MLP emerged as prominent single models for high-dimensional feature analysis, with LR serving as the metaclassifier in the final prediction. Model fusion effectively enhanced the overall performance. Peng et al. [47] studied 16 common mineral crystal images to construct a mineral identification Inception-v3 model, achieving an overall accuracy of approximately 86% and a top-5 accuracy of 99%, demonstrating robust performance. Cochrane, C etal [35] selected Inception-v3 as a pre training model for rock mineral image identification, capitalizing on its ability to extract and classify complex image features. Inception-v3 has shown promising results in mineral identification tasks, offering efficient feature extraction and strong classification capabilities for high-dimensional data analysis in geological contexts. *ResNet:* Guo et al. [18] utilized the ResNet-18 neural network model as a basis to train a more accurate mineral identification model on five mineral images: quartz, hornblende, black mica, garnet, and olivine. This approach achieved an accuracy of 89%, enabling intelligent mineral identification based on deep learning. Ren et al. [48] attained the highest accuracy when employing the ResNet-50 model as the base model for intelligent identification of rock mineral image samples, demonstrating its effectiveness in extracting features and classifying mineral images Tiwary, A.K etal [38] reported a validation accuracy of 90.5% using a 47-layer ResNet-2 architecture, showcasing its robust performance in rock mineral image classification tasks ResNet has proven to be a valuable tool in deep learning-based mineral identification, providing accurate classification results by efficiently learning complex mineral image features and addressing challenges faced in traditional methods. Transfer Learning: Lou, W. etal [53] proposed a multiproduct coal image classification method combining convolutional neural networks and Transfer Learning. They constructed a deep learning model based on the Inception-v3 convolutional

neural network within the TensorFlow and Keras frameworks. By applying the Transfer Learning method to train and test different coal product image datasets, they achieved convergence in loss values and accuracy during the training process, resulting in a test accuracy and validation accuracy

exceeding 90%. Lou, W. etal [53] employed a combination of Transfer Learning and Siamese neural networks to enhance the extraction of multielement geochemical anomalies. By incorporating multiscale geochemical data, they improved model performance, achieving an accuracy of 85%. This demonstrated that the enhanced deep learning approach significantly bolsters anomaly identification capabilities. El Haddad, J. etal [36] leveraged Transfer Learning techniques, utilizing pretrained parameters from a larger ImageNet dataset to initialize the network. This strategy enabled high accuracy and low computational costs, as the network could capitalize on knowledge gained from previous training. Loao, A etal [11] explored CNNs for accelerating and automating microphase classification, employing Transfer Learning based on a robust and reliable CNN model trained on numerous non-geological images. This allowed the model to

Algorithm	Pros	Cons
Inception-v3 [35,46,47]	Fast calculation speed. Increased network depth. Increased network width. Decomposing into small convolutions is effective in reducing the number of parameters, mitigating overfitting, and increasing the expressiveness of the network nonlinearity. Making spatial structured, transforming spatial information into higher-order abstract feature information. Having higher expressiveness of the rich network.	The problem of information loss due to information compression cannot be solved without an increase in computational volume. It is not possible to increase the topology of the model to improve its expressiveness without increasing the computational volume.
ResNet [18,38,48]	Enables feedforward/feedback propagation algorithms to proceed smoothly and with a simpler structure. Constant mapping increase does not degrade the performance of the network.	Long training time.

adapt its existing knowledge to a new domain, improving classification performance. Transfer Learning has proven effective in various mineral identification and classification tasks, as it allows models to harness knowledge from previous training, resulting in enhanced performance and reduced computational costs Wen, L. et al. [24] introduced a research approach combining neural networks with physical models to tackle the challenge of learning from limited samples in hyperspectral remote sensing geological investigations. They employed a domain-knowledge-based data augmentation method, integrating the Hapke radiative transfer model with a small number of ground truth points for training label data augmentation. Subsequently, they utilized a sparse, fully connected neural network for mineral content assessment, effectively leveraging domain knowledge to improve classification performance with limited data. Int. J. Coal Geol [39] proposed hierarchical spatial-spectral feature extraction with long- and short-term memory (HSS-LSTM) to explore the correlation between spatial and spectral features. This method obtained hierarchical intrinsic features for mineral identification, demonstrating the potential of integrating spatial and spectral information for enhanced classification results. These innovative approaches highlight the importance of leveraging domain knowledge and integrating complementary information sources to overcome challenges in mineral identification, particularly when dealing with limited data or complex, multidimensional datasets.

Table 4. Intelligent mineral identification methods based on Transfer learning and convolutional neural networks

Algorithm	Pros	Cons
Transfer learning [5,11,35,36]	Requires less training data and can make more efficient use of existing data. Better generalization of the model by migration learning. The training process is more stable and easier to debug, increasing the robustness of the model. Makes deep learning easier. Enables customization.	Although it can be quantified, it has an upper limit and is not suitable for solving all problems
Convolutional Neural Network [5,9,12,37–45]	Shared convolutional kernel, which can handle high-dimensional data. No manual feature selection and good feature classification.	Need to normalize the dataset; difficult to train with different sizes mixed. No memory function. Physical meaning is not clear enough. Need to tune the reference; need many samples; training is best to use GPU. Natural language processing capability for video speech.

Table 5. Intelligent mineral identification methods based on Inception-v3 and ResNet

5. Conclusion

Intelligent mineral identification is a critical task in geology, mining engineering, and related fields. The integration of computer science and earth science has gained significant attention, with artificial intelligence applications in deep-time digital earth science contexts demonstrating immense potential. While there is still a significant gap between geology and artificial intelligence domains, the lack of interpretability in AI identification processes, criteria, and

unified benchmark mineral datasets necessitates progressive foundational work. This paper offers a comprehensive and in-depth summary of intelligent ore recognition, presenting three types of taxonomies. We visualize relevant domain literature and conduct trend analysis through keyword detection to better explore the field's development. Several suggestions are provided for potential future research directions. We aim to guide researchers in computing and earth sciences studying intelligent mineral identification. Although the dataset preprocessing methods, various scenarios, scientific questions, data, and applications corresponding to different objectives are not fully analyzed due to the study's scope limitations, these aspects will be addressed in future work. Overall, this study highlights the importance of interdisciplinary collaboration and the need for further research in addressing challenges and advancing intelligent mineral identification techniques to meet the needs of both scientific research and industrial demands.

6. References

[1] Ramil, A.; López, A.; Pozo-Antonio, J.; Rivas, T. A computer vision system for identification of granite-forming minerals based on RGB data and artificial neural networks. Measurement 2018, 117, 90–95.

[2] López, A.; Ramil, A.; Pozo-Antonio, J.; Fiorucci, M.; Rivas, T. Automatic Identification of Rock-Forming Minerals in Granite Using Laboratory Scale Hyperspectral Reflectance Imaging and Artificial Neural Networks. J. Nondestruct. Eval. 2017, 36, 52.

[3] DeTore, A.W. An introduction to expert systems. J. Insur. Med. 1989, 21, 233–236.

[4] Folorunso, I.; Abikoye, O.; Jimoh, R.; Raji, K. A rule-based expert system for mineral identification. J. Emerg. Trends Comput. Inf. Sci. 2012, 3, 205–210.

[5] Okada, N.; Maekawa, Y.; Owada, N.; Haga, K.; Shibayama, A.; Kawamura, Y. Automated identification of mineral types and grain size using hyperspectral imaging and deep learning for mineral processing. Minerals 2020, 10, 809.

[6] Mishra, K.A. AI4R2R (AI for Rock to Revenue): A Review of the Applications of AI in Mineral Processing. Minerals 2021, 11, 1118.

[7] Izadi, H.; Sadri, J.; Bayati, M. An intelligent system for mineral identification in thin sections based on a cascade approach.

[8] Prabhavathy, P.; Tripathy, B.; Venkatesan, M. Unsupervised learning method for mineral identification from hyperspectral data. In Proceedings of the International Conference on Innovations in Bio-Inspired Computing and Applications, Gunupur, India, 16–18 December 2019; Springer: Cham, Switzerland, 2019; pp. 148–160.

[9] Chen, Z.; Liu, X.; Yang, J.; Little, E.; Zhou, Y. Deep learning-based method for SEM image segmentation in mineral characterization, an example from Duvernay Shale samples in Western Canada Sedimentary Basin. Comput. Geosci. 2020, 138, 104450.

[10] Lobo, A.; Garcia, E.; Barroso, G.; Martí, D.; Fernandez-Turiel, J.L.; Ibáñez-Insa, J. Machine-learning for mineral identification and ore estimation from hyperspectral imagery in tin-tungsten deposits. Remote Sens. 2021, 13, 3258.

[12] De Lima, R.P.; Duarte, D.; Nicholson, C.; Slatt, R.; Marfurt, K.J. Petrographic microfacies classification with deep convolutional neural networks. Comput. Geosci. 2020, 142, 104481.

[13] Tang, D.G.; Milliken, K.L.; Spikes, K.T. Machine learning for point counting and segmentation of arenite in thin section. Mar. Pet. Geol. 2020, 120, 104518.

[14] Wang, Q.; Zhang, X.; Tang, B.; Ma, Y.; Xing, J.; Liu, L. Lithology identification technology using BP neural network based on XRF.

[15] Acta Geophys. 2021, 69, 2231–2240.

[16] Thompson, S.; Fueten, F.; Bockus, D. Mineral identification using artificial neural networks and the rotating polarizer stage.

[17] Comput. Geosci. 2001, 27, 1081–1089.

[18] Baykan, N.A.; Yılmaz, N. Mineral identification using color spaces and artificial neural networks. Comput. Geosci. 2010, 36, 91–97.

[19] Mlynarczuk, M.; Skiba, M. The application of artificial intelligence for the identification of the maceral groups and mineral components of coal. Comput. Geosci. 2017, 103, 133–141.

[20] Xu, S.T.; Zhou, Y.Z. Artificial intelligence identification of ore minerals under microscope based on deep learning algorithm. Acta Petrol. Sin. 2018, 34, 3244–3252.

[21] Guo, Y.J.; Zhou, Z.; Lin, H.X.; Liu, X.H.; Chen, D.Q.; Zhu, J.Q.; Wu, J.Q. The mineral intelligence identification method based on deep learning algorithms. Earth Sci. Front. 2020, 27, 39–47.

[22] Ren, W.; Zhang, S.; Huang, J.Q. The rock and mineral intelligence identification method based on deep learning. Geol. Rev. 2021, 67, 2.

[23] recognizing minerals from multispectral data. Analyst 2021, 146, 184–195.

[24] Wen, L.; Jia, M.; Wang, Q.; Fu, Q.; Zhao, J. Automated mineralogy part I. advances and applications in quantitative, automated mineralogical methods. China Min. Mag. 2020, 341–349.

[25] Qiang, Z.; Runxin, Z.; Junming, L.; Cong, W.; Hezhe, Z.; Ying, T. Review on coal and rock identification technology for intelligent mining in coal mines. Coal Sci. Technol. 2022.

[26] Huizhen, H.; Qing, G.; Xiumian, H. Research Advances and Prospective in Mineral Intelligent Identification Based on Machine Learning. Editor. Comm. Earth-Sci.-J. China Univ. Geosci. 2021, 46, 3091–3106.

[27] Murugan, P. Feed forward and backward run in deep convolution neural network. arXiv 2017, arXiv:1711.03278.

[28] Mi, Z.; Kai, Q.; Ling, Z.; Yuechao, Y. Deep Learning Method for Mineral Spectral Unmixing. Uranium Geol. 2022.

[29] Jiang, G.; Zhou, K.; Wang, J.; Cui, S.; Zhou, S.; Tang, C. Identification of iron-bearing minerals based on HySpex hyperspectral remote sensing data. J. Appl. Remote. Sens. 2019, 13, 047501.

[30] Izadi, H.; Sadri, J.; Mehran, N.A. Intelligent mineral identification using clustering and artificial neural networks techniques. In Proceedings of the 2013 First Iranian Conference on Pattern Recognition and Image Analysis (PRIA), Birjand, Iran, 6–8 March 2013; pp. 1–5.

[31] Aligholi, S.; Khajavi, R.; Razmara, M. Automated mineral identification algorithm using optical properties of crystals. Comput. Geosci. 2015, 85, 175–183.

[32] Anigbogu, P.; Odunayo, D.; Okwudili, S.; Olanloye. An Intelligent System for Mineral Prospecting Using Supervised and Unsupervised Learning Approach. Int. J. Eng. Tech. Res. (IJETR) 2015, 3, 200–208.

[33] Yousefi, B.; Castanedo, C.I.; Maldague, X.P.; Beaudoin, G. Assessing the reliability of an automated system for mineral identification using LWIR Hyperspectral Infrared imagery. Miner. Eng. 2020, 155, 106409.

[34] Khajehzadeh, N.; Haavisto, O.; Koresaar, L. On-stream and quantitative mineral identification of tailing slurries using LIBS technique. Miner. Eng. 2016, 98, 101–109.

[35] Cochrane, C.J.; Blacksberg, J. A fast classification scheme in Raman spectroscopy for the identification of mineral mixtures using a large database with correlated predictors. IEEE Trans. Geosci. Remote Sens. 2015, 53, 4259–4274.

[36] El Haddad, J.; de Lima Filho, E.S.; Vanier, F.; Harhira, A.; Padioleau, C.; Sabsabi, M.; Wilkie, G.; Blouin, A. Multiphase mineral identification and quantification by laser-induced breakdown spectroscopy. Miner. Eng. 2019, 134, 281–290.

[37] Domínguez-Olmedo, J.L.; Toscano, M.; Mata, J. Application of classification trees for improving optical identification of common opaque minerals. Comput. Geosci. 2020, 140, 104480.

[38] Tiwary, A.K.; Ghosh, S.; Singh, R.; Mukherjee, D.P.; Shankar, B.U.; Dash, P.S. Automated coal petrography using random forest.

[39] Int. J. Coal Geol. 2020, 232, 103629.

[40] Liu, C.; Li, M.; Zhang, Y.; Han, S.; Zhu, Y. An enhanced rock mineral recognition method integrating a deep learning model and clustering algorithm. Minerals 2019, 9, 516.

[41] Liu, X.; Song, H. Automatic identification of fossils and abiotic grains during carbonate microfacies analysis using deep convolutional neural networks. Sediment. Geol. 2020, 410, 105790.

[42] Anderson, T.I.; Vega, B.; Kovscek, A.R. Multimodal imaging and machine learning to enhance microscope images of shale.

[43] Comput. Geosci. 2020, 145, 104593.

[44] Latif, G.; Bouchard, K.; Maitre, J.; Back, A.; Bédard, L.P. Deep-Learning-Based Automatic Mineral Grain Segmentation and Recognition. Minerals 2022, 12, 455.

[45] Zhao, H.; Deng, K.; Li, N.; Wang, Z.; Wei, W. Hierarchical Spatial-Spectral Feature Extraction with Long Short Term Memory (LSTM) for Mineral Identification Using Hyperspectral Imagery. Sensors 2020, 20, 6854.

[46] Tanaka, S.; Tsuru, H.; Someno, K.; Yamaguchi, Y. Identification of alteration minerals from unstable reflectance spectra using a deep learning method. Geosciences 2019, 9, 195.

[47] Jahoda, P.; Drozdovskiy, I.; Payler, S.J.; Turchi, L.; Bessone, L.; Sauro, F. Machine learning for pp. 1–5.

[48] recognizing minerals from multispectral data. Analyst 2021, 146, 184–195.

[49] Cai, Y.; Xu, D.; Shi, H. Rapid identification of ore minerals using multi-scale dilated convolutional attention network associated with portable Raman spectroscopy. Spectrochim. Acta Part A Mol. Biomol. Spectrosc. 2022, 267, 120607.

[50] Qing-Lin, T.; Bang-Jie, G.; Fa-Wang, Y.; Yao, L.; Peng-Fei, L.; Xue-Jiao, C. Mineral Spectra Classification Based on One-Dimensional Dilated Convolutional Neural Network. Spectrosc. Spectr. Anal. 2022, 42, 873–877.

[51] Zeng, X.; Xiao, Y.; Ji, X.; Wang, G. Mineral identification based on deep learning that combines image and mohs hardness.

[52] Yalçın, C. (2023). Advantages of Applying Machine Learning Theory in the Investigation of Mineral Deposits. General Topics in Geology and Earth Sciences 1. Pehlivanlı, B.Y. (ed.), BIDGE Publications. p.56-72. ISBN: 978-625-6645-64-6. 25.12.2023.

[53] Lou, W.; Zhang, D.; Bayless, R.C. Review of mineral recognition and its future. Appl. Geochem. 2020, 122, 104727.

.