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AI-Driven Mineral Exploration: Enhancing Geochemical Anomaly Detection with Generative adversarial Networks and Transfer Learning, A Case Study from Janja polymetallic deposit, SE Iran

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Abstract

This research endeavor concentrates on minerals exploration within the context of a hydrothermal polymetallic vein deposit environment. Stream sediment sampling was executed to acquire geochemical signatures pertinent to mineralization zones. The mineralization nature is classified as epithermal, predominantly involving polymetallic sulfides. The geochemical analyses yielded multi-element concentration maps, facilitating the identification of anomalies and the establishment of zoning. Although recent developments underscore the efficacy of machine learning, notably deep learning techniques, in the detection of geochemical anomalies, the majority of preceding studies were predicated on univariate statistical methodologies. To address this constraint, a multivariate approach was implemented, incorporating spatial characteristics such as shape, overlap, and zoning within anomalies and halos. Considering the limited availability of validated mineralized samples, unsupervised and semi-supervised methodologies—most notably Generative Adversarial Networks (GANs)—were employed. GANs were trained using multi-element geochemical maps, applying transfer learning to mitigate the challenges posed by restricted deposit data, thereby facilitating the delineation of prospective exploration zones. Quantitative analyses have indicated that the approach utilizing GANs attained an accuracy exceeding 92% alongside a minimal cross-entropy loss of approximately 0.07, thereby surpassing conventional methodologies in detecting of weak anomalies. The model effectively corroborated previously recognized anomalies while simultaneously detecting new prospective mineralization areas, thereby augmenting exploration opportunities. This investigation illustrates that GANs enable a more thorough utilization of geochemical datasets, integrating a wide range of variables and intricate spatial characteristics. Although GANs demonstrate superior proficiency in modeling weak anomalies, conventional techniques continue to be effective for more pronounced anomalies. The integration of both methodologies may enhance the efficiency of mineral exploration endeavors. In summary, the results emphasize the promise of GANs and sophisticated machine learning frameworks in enhancing anomaly detection and expanding mineral exploration within hydrothermal polymetallic systems.

1. Introduction

Mineral prospectivity mapping and detecting anomalies are fundamental objectives within the realm of regional geochemical exploration. Anomaly detection pertains to the recognition of data points that significantly diverge from the greater part of samples [1]. This methodology is of paramount importance as it mitigates both risk and financial expenditures associated with exploration endeavors. Consequently, anomaly detection has evolved into a crucial component within various

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decision-making frameworks. In recent decades, a diverse array of methodologies has been developed for the identification of geochemical anomalies, encompassing statistical techniques [2], geostatistical methods [3-5], integrating principal component analysis and U-statistics [6], and fractal modeling approaches [6-9]. However, the emergence of machine learning (ML) and deep learning techniques has precipitated substantial enhancements in modeling applications within the Earth sciences [10-15]. These advancements indicate that ML-based methodologies for mineral prospectivity mapping utilizing geochemical data are more adept at revealing statistical correlations between observed geochemical patterns and mineralization trends compared to conventional non-ML approaches. Furthermore, these methodologies equip geoscientists to execute comprehensive multivariate geochemical analyses within a big data framework, thus facilitating the identification of geochemical anomalies [16-20].

It is vital to employ methods that can characterize mineral deposits and detect geochemical anomalies, as well as assess the reliability of geochemical data. These methods must have the ability to overcome survival bias to avoid incorrect evaluation. In this regard, several methods can be mentioned in previous studies. Exploration Information System (EIS), which was introduced in 2019 and published in Ore Geology Reviews, serves as an integrated analytical platform that synthesizes diverse datasets relevant to mineral exploration, including geological, geophysical, and geochemical information [21]. Its primary function is to enhance targeting accuracy for mineral deposits by providing a holistic assessment framework, thus supporting exploration strategies with higher confidence levels. The utilization of EIS allows for better integration of exploration data, leading to improved decision-making and resource prioritization in prospectivity analysis. Complementing this, the Confidence Index functions as a quantitative measure of the reliability and certainty associated with geochemical anomalies detected in exploration data [22]. This index employs probabilistic approaches, such as Bayesian inference, to evaluate the likelihood that identified anomalies are indicative of mineralization rather than false positives or data noise. By providing a statistical measure of data confidence, this tool helps mitigate uncertainties inherent in exploration datasets and facilitates a more robust ranking of targets. The combination of EIS and the Confidence Index within a comprehensive exploration workflow addresses key challenges related to data uncertainty and bias. This approach aligns with the overarching goal of employing advanced methods to improve the accuracy and reliability of mineral exploration outcomes. Additionally, such tools are instrumental in overcoming issues like survivorship bias, which can lead to overly optimistic assessments of exploration results. Their application ensures that resource estimates and exploration decisions are based on more realistic and statistically sound foundations. Furthermore, methods to address bias in exploration data, such as survivorship bias, are critical to avoid overly optimistic resource assessments. Overcoming survival bias leads to improve accuracy in targeting mineral deposits [23]. Recognizing and mitigating these biases ensures that exploration strategies are based on more realistic evaluations of mineral potential. Machine learning methods, given their capabilities, are well-suited to meet the aforementioned requirements. They can effectively analyze geochemical data, identify anomalies, and assess uncertainties, while also addressing biases such as survivorship bias. These approaches enhance the accuracy of exploration predictions and provide more reliable assessments of mineral deposit potential.

Recent empirical studies have elucidated that machine learning (ML) methodologies significantly enhance the amalgamation of multi-faceted geochemical datasets, thereby facilitating the proficient identification and extraction of geochemical anomalies that are concomitant with mineralization, which may have eluded detection by conventional non-ML approaches [24-28]. This observation suggests that numerous hydrothermal mineral deposits coexist with surrounding halos that exhibit anomalous elemental concentrations pertinent to mineralization—designated as pathfinders—stemming from the dispersion within stream sediments. Consequently, it is crucial to analyze the alterations in the spatial attributes of multivariate geochemical anomalies and their correlation with mineralization to pinpoint new regions for prospective mineral exploration and to explore additional mineral resources. Both machine learning and deep learning frameworks permit the formulation of sophisticated models or algorithms proficient in detecting anomalies associated with mineralization, a task that conventional (non-ML) methodologies frequently fail to achieve. This accentuates the potential of ML and deep learning techniques to augment the efficacy of geochemistry-oriented mineral

exploration. As the magnitude and intricacy of data managed by these methodologies increase, advanced learning algorithms have been proposed to address such complex datasets for anomaly detection. These encompass convolutional neural networks (CNN) [19], recurrent neural networks (RNN) [29], autoencoders (AE) [30], and generative adversarial networks (GANs) [31]. Generative models have surfaced as prominent instruments for anomaly detection due to their proficiency in fitting data distributions. Importantly, the variable autoencoder (VAE) [30] and GAN, along with their diverse adaptations, are frequently employed. VAE aims to minimize the lower bound of the logarithmic likelihood of the data, whereas GAN seeks to establish a balance between the generator and discriminator [32]. Empirical findings suggest that GAN surpasses VAE in yielding superior-quality and higher-resolution outputs [33]. As a result, GAN has garnered substantial attention since its inception, exhibiting an extraordinary capacity to generate realistic image samples. By exclusively training on a dataset composed of standard exemplars and acquiring latent-space feature representations, it can identify anomalous samples that do not reconstruct accurately. The generative capabilities of GAN mitigate challenges associated with limited anomalous sampling [34]. Moreover, GAN is particularly well-suited for anomaly detection tasks that involve intricate datasets and can proficiently represent the distribution of high-dimensional data. Thus, most contemporary GAN-based frameworks and concepts are well-equipped for anomaly identification.

This research addresses a critical gap in the existing literature by integrating advanced machine learning approaches, in particular generative adversarial networks, into the framework of anomaly detection in mineral exploration. This is a critical area where conventional techniques often struggle to produce satisfactory results. While previous studies focused mainly on univariate and simple multivariate analyses, this research takes advantage of the benefits of deep learning to explore complex, high-dimensional geochemical data sets, which provide a more nuanced understanding of mineralization trends and geochemical anomalies. The importance of closing this gap is underlined by the increasing complexity and volume of available geochemical data, together with the demand for improved exploration techniques that reduce risk and optimize resource extraction. The aim of the study is not only to advance the identification of mineral deposits but also to provide a methodological framework that can be adapted to different geological environments and ultimately shape future exploration strategies. This study proposes a new approach that combines GANs with the analysis of geochemical data to improve the detection of small anomalies and to increase the overall efficiency of mineral prospectivity mapping.

2. The study area

Iran is divided into several areas according to its mineral and geological resources [35-40]. In this section, the Flysch Basin in eastern Iran is considered to be one of the geological states of origin [35]. The eastern boundary of this area is found at Iran's eastern edge, western Pakistan, and the Sistan block (Harirud fault), while the western boundary is marked by the Nehbandan fault, and to the south, it is bordered by the Makoran zone and the Bashagard fault. The Janja region is situated in the Flysch basin in eastern Iran, 30 km northwest of Sefidabeh. The position of this area and the ways to access it are illustrated in Figure 1. The study focuses on a hydrothermal polymetallic vein deposit, primarily consisting of polymetallic sulfides associated with epithermal mineralization. The selection of elements—Ag, Zn, Cu, Pb, and Au—is driven by their significance as pathfinder elements and indicators of mineralization processes in such deposits. Silver (Ag), zinc (Zn), copper (Cu), and lead (Pb) are commonly associated with polymetallic sulfide mineralization, often co-occurring with gold (Au), which is a valuable target for exploration. These elements serve as geochemical proxies, enhancing the detection of mineralization zones and providing essential information for prospective exploration.

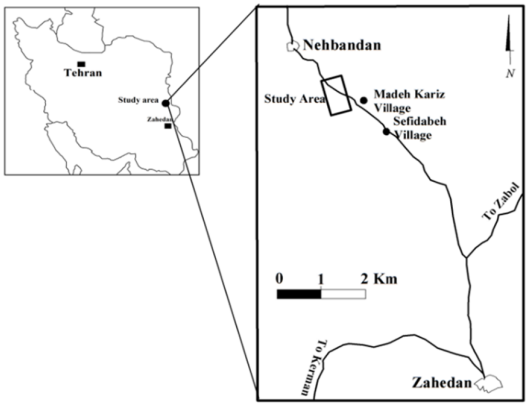


Figure 1. The location of the study area

As mentioned, the geological formations of Janja consist primarily of sedimentary units (Figure

2). The basin consists of extensive beds of flysch facies, which contain shale, sandstone, and limestone, with ophiolite-bearing strata attached to the oceanic crust. The most ancient sedimentary formations in the region are composed of rocks with Cretaceous intrusive units. Sedimentary units in the area were affected by magma activity, including infiltration and outflow [41]. In the study area, a series of porphyry dykes, likely of diorite to granodiorite composition, intersects the sedimentary formations of the Flysch facies. Evidence of gold and copper mineralization is visible in these units, probably stemming from these dikes.

The bedrock of the Janja Mountains is mainly slate, accompanied by sandstone beds. In the higher regions, tough rocks exhibiting a hornfels appearance are seen, which consist of shales and siltstones that have undergone minor metamorphism and considerable alteration. The cause of this transformation and change is the intrusion of various diorite dykes within them. The general orientation of sedimentary and metamorphic rocks is primarily northwest-southeast, although this order is broken by dike intrusion. In general, the Flysch sequence was disrupted by several dykes showing an eastern and northeast-southwestern orientation, characterized by porphyry diorite hornblende composition. Radiometric data indicate that its age ranges from the middle to late Miocene epoch [42]. These intrusive rocks have created dark, weathered hornfels and metamorphic halos in the surrounding rock that are visible.

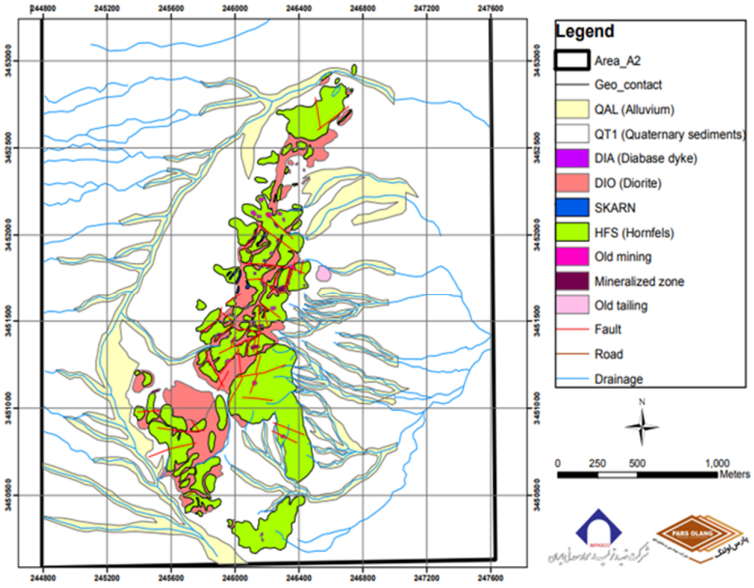


Figure 2. Geological map of the study area

3. Materials and Methods

The data used in this study were obtained as part of the Janja initiative for geological exploration. In total, 154 stream sediment geochemical samples were collected in a network covering 144 km2 (Figure 3). The density of the sampling network for the geochemical samples is estimated at approximately 1.3 samples per square kilometer.

All samples were analyzed for 48 elements using the ICP-AES method. It should be noted that the technique of preparation of the fire assay was used for the gold analysis. The results of the statistical analysis of the stream sediments geochemical data from the Janja area are presented in Table 1.

Table 1. Statistical analysis of geochemical data from the Janja area

Element	Concentration				
	Min	Max	Median	Mean	Standard deviation
Au (ppm)	0.003	0.04	0.0038	0.0045	0.0037
Ag (ppm)	0.12	0.42	0.27	0.25	0.07
Cu (ppm)	19	103	26	26.64	6.9
Pb (ppm)	9	544	19	24.88	43.9
Zn (ppm)	46	538	68	72.63	39.84

The geochemical data obtained were used to create maps of the distribution of the elements. This study then uses GANs to identify potential areas for gold exploration using multi-element geochemical maps, combining different spatial features, and using transfer learning to address the gap in known deposits. Figure 4 summarizes the research methodology.

3.1. GAN networks

A Generative Adversarial Network (GAN) consists of two parts: a generator (G) and a discriminator (D) [43] (Figure 5). The generator input is random noise that follows a specific distribution. The generator learns the distribution of the real data from the latent space and generates new examples. The discriminator is a classical classification system structure that tries to classify examples as real (from the domain) or fake (generated). The two models are trained together in a zero-sum game. That is, they are adversarial until the discriminator can distinguish whether the example is a generated or real example, which indicates that the generator model can produce acceptable examples.

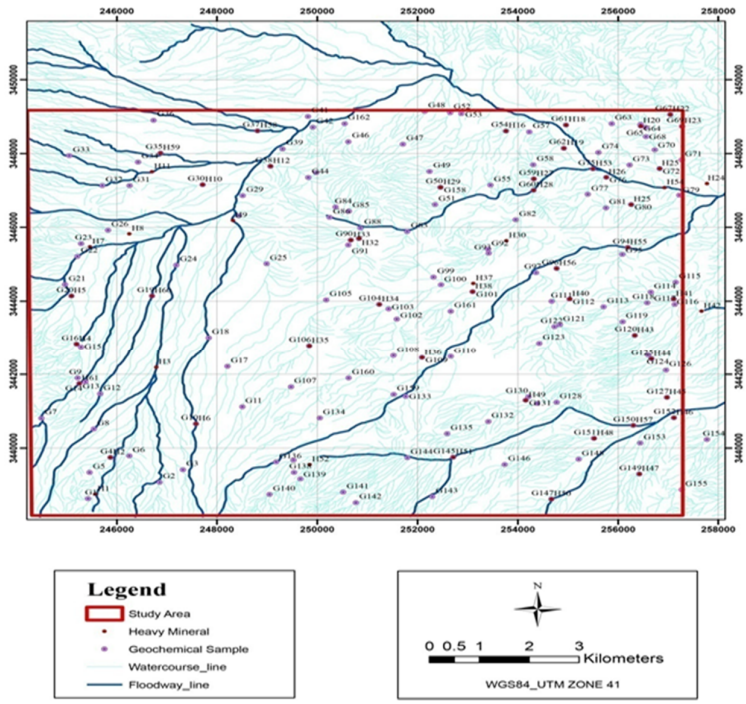


Figure 3. Geochemical sampling network of the study area

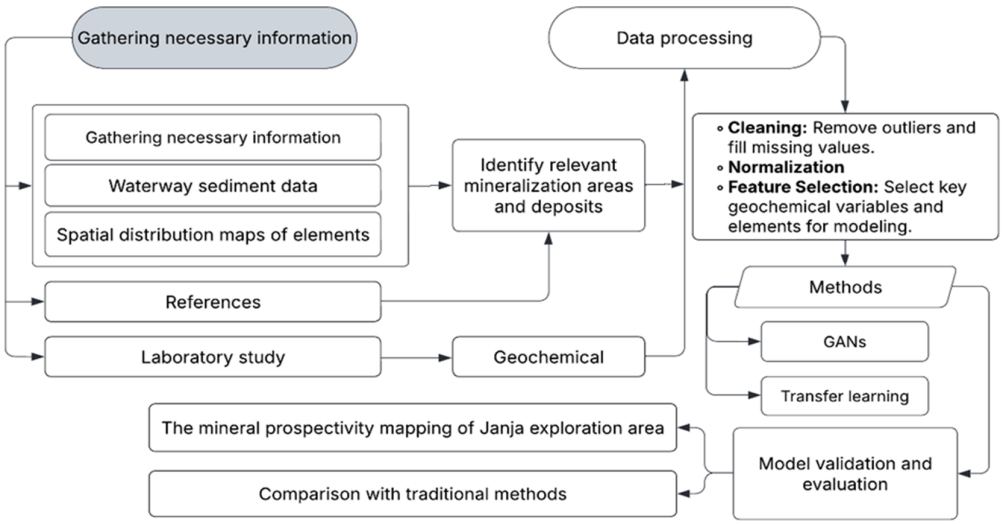


Figure 4. Research Methodology

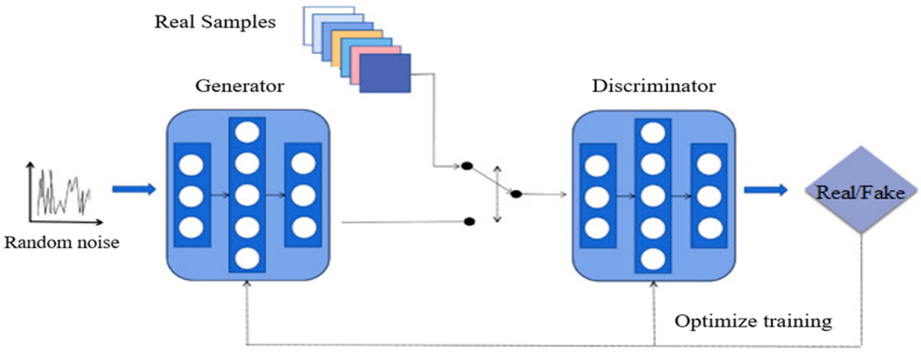


Figure 5. Architecture of deep generative adversarial networks [43]

GANs is a generative algorithm that has its roots in deep learning paradigms. GANs exhibit remarkable capabilities. In image synthesis applications, the generator uses random noise (z) as its input to produce visual outputs, denoted by G(z). The discriminator's function is to assess whether an image is genuine or fake [43]. During the training phase of GANs, the goal is to ensure that the images produced by the generator network G closely resemble real images, thereby confounding the discriminator network D. Conversely, the discriminator aims to accurately discriminate between the artificial outputs of the generator and authentic images [43]. For the GAN framework, its value function V(G,D) is as follows (equation 1 to 3):

$$L_{real}(D) = \mathbb{E}_{y \sim Pdata(y)}[\log D(y)] \quad (1)$$

$$L_{fake}(G,D) = \mathbb{E}_{z \sim Pz(z)}[\log(1-D(G(z)))] \quad (2)$$

$$\min_G \max_D V(D,G) = L_{real}(D) + L_{fake}(G,D) \quad (3)$$

Where are:

y – the real image,

G – the trained generation network that can be used to generate "fake" images.

3.2. Transfer learning

Effective deployment of generative adversarial networks (GANs) as an unsupervised deep learning framework requires a significant amount of training data [28]. However, exploration at an early stage is usually in regions with only a limited number of known deposits or mineral occurrences. These few examples often serve as the labeled training data needed to model geochemical anomaly detection and mineral prediction, which significantly hampers the convergence and accuracy of neural network training. To address the issues resulting from the absence of sample labels, the study will implement transfer learning.

Transfer learning is a machine learning approach that utilizes pre-trained models for distinct but related tasks. It aims to reduce the manual effort required in sample annotation by migrating models from a source domain—where labeled data exists—to a target domain that lacks extensive labeled datasets [44]. Moreover, research indicates that transfer learning can bridge discrepancies in input data across different models and effectively mitigate overfitting issues [45]. The rapid advancements in neural network architectures have spurred considerable research interest in transfer learning [46-48].

In this study, we use Google Inception-v3 convolutional neural network template for the training process. Unlike the conventional GAN structure, characterized by a generative network and a discriminative network [43], the Inception-v3 model has several generative and discriminative layers. These additional layers increase the model's ability to extract the image features more efficiently and allow for the accurate identification of the geochemical anomaly. The Inception-v3 architecture contains approximately 25 million parameters and can perform fast image classification on standard computers without the need for a GPU. The structure of the Inception-v3 template is shown in Figure 6.

This methodology uses pre-trained models derived from large data sets originally developed based on large training sets, which require significant time and computing resources. Given the uncertain characteristics of the study area, we implement a transfer learning strategy in combination with the pre-trained Inception-v3 model to enhance network convergence for foresight modeling applications. This transfer learning approach is specifically utilized to explore geochemical anomaly detection. Although we maintain the fundamental structure of the Inception-v3 model, modifications are made by substituting its dropout, fully connected, and

softmax layers with entirely new components. This innovative modification is a new strategy for detecting geochemical anomalies. By incorporating modified softmax layers and utilizing the cross-entropy loss function, we retrain the model by evaluating the error between the outputs of the softmax layer and the corresponding class labels of the samples. This retraining process yields an improved model capable of effectively identifying geochemical anomalies, thereby mitigating the challenges posed by the limited number of known sediments and occurrences.

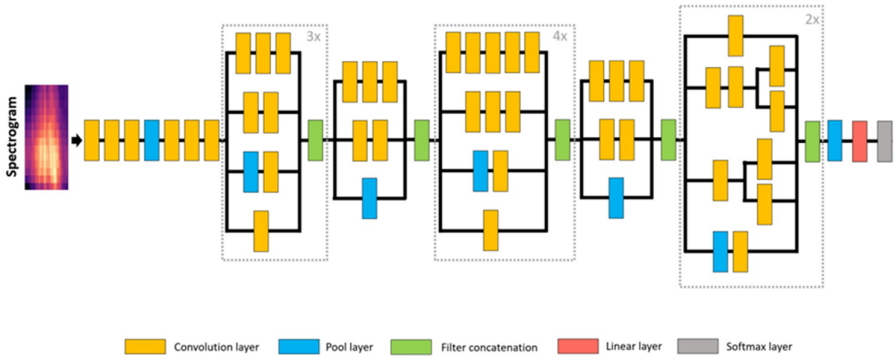


Figure 6. Inception-v3 model's architecture [49]

In our approach, the inputs to the Inception-v3 model consist of maps representing the spatial distribution of geochemical elements. The subsequent phase of modeling involves the replacement of the dropout, fully connected, and softmax layers in the pre-trained Inception-v3 model with completely new layers designed for our specific task. Following this modification, we retrain the model by calculating the discrepancies between the output of the softmax layer and the provided sample class labels; weight parameters are adjusted accordingly using a cross-entropy loss function. This comprehensive process ultimately leads to a more accurate training model. The overall workflow of this simultaneous neural network modeling using the Inception-v3 architecture is illustrated in Figure 7.

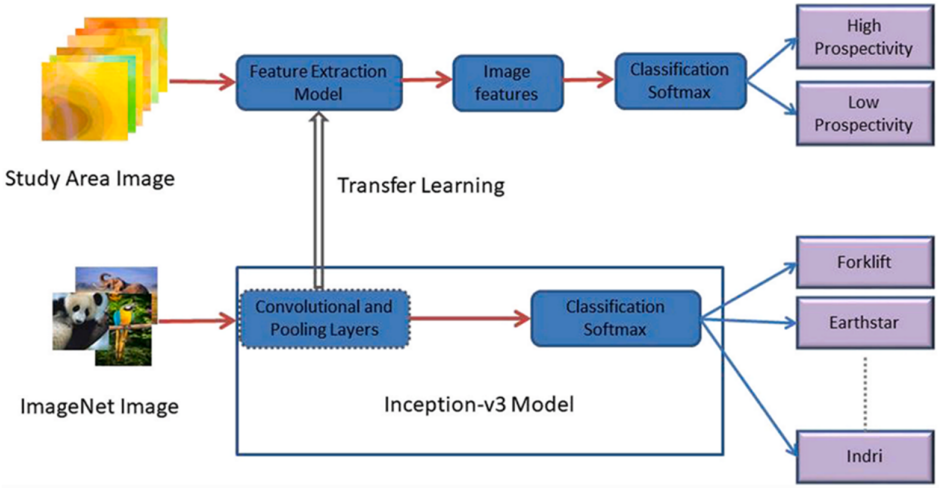


Figure 7. The main GAN neural network process flow of the modeling undertaken during this study

4. Results and analysis

4.1. Data Preparation

Ordinary kriging functions are the most effective unbiased linear estimator for interpolating spatially variable data [50, 51]. This method utilizes variograms to assess the geometric properties, scale, and spatial connections among the samples in a specific dataset. In this study, ordinary kriging was applied to interpolate the data related to the five elements analyzed from the samples gathered in the research area, resulting in the development of the spatial distribution maps presented in Figure 8.

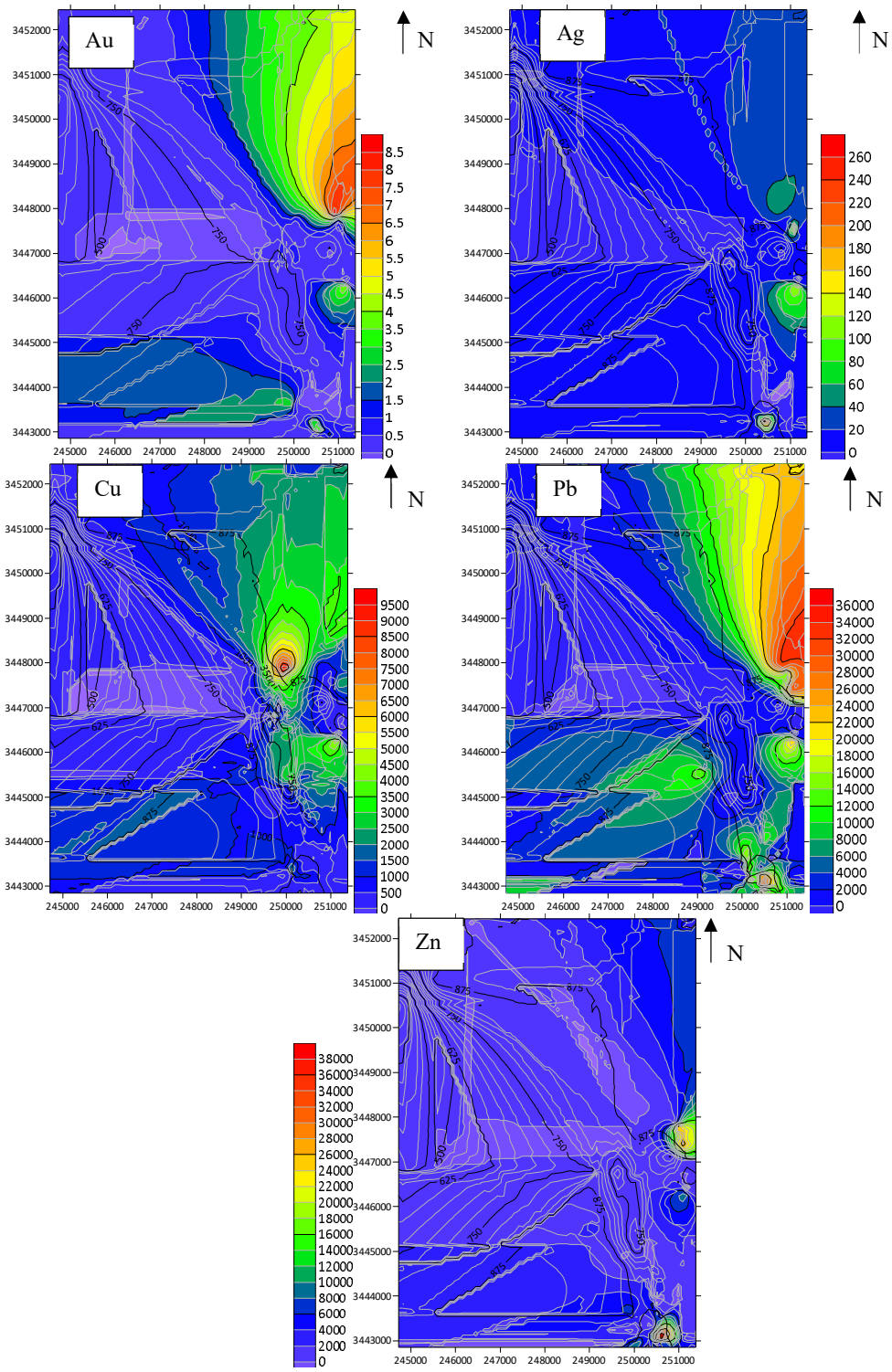


Figure 8. The maps illustrate the spatial distribution of the five elements examined in this study, with gold expressed in ppb and the other elements represented in ppm

4.2. Model Training and Evaluation

This study is distinguished by its innovative use of a Generative Adversarial Network (GAN) combined with transfer learning techniques, effectively tackling the issue of limited data availability. This integration significantly improves the detection of geochemical anomalies. To assess the predictive accuracy of the GAN neural network and the transfer learning model utilized in this research, we aimed to investigate whether

enhancing the model with additional geochemical spatial distribution maps would lead to better predictive outcomes. Consequently, we analyzed four distinct subgroups of spatial distribution maps, which included one element (Au), three elements (Au, Ag, Cu), four elements (Au, Ag, Cu, Pb), and five elements (Au, Ag, Cu, Pb, Zn). Each of these elements is directly linked to mineralization in the study area or acts as a pathfinder indicative of various mineralization zones.

The spatial distribution maps were systematically subdivided into 264 uniform grid cell images, each covering an approximate area of 0.22 km². These grid images served as the basis for selecting data to create training datasets for model development. Within the datasets, positive samples represent highly prospective areas, while negative samples denote regions of lower prospectivity. The classification into positive and negative samples was based on the spatial location of identified ore deposits or occurrences. Specifically, if a cell was located within or near a known deposit boundary, it was classified as a positive sample, indicating a high prospectivity area. In the resulting images, these areas were visually indicated by red and orange shading. Conversely, cells characterized by low gold concentrations, which do not serve as reliable indicators of mineralization, were designated as negative samples and depicted in blue and purple shades within the images (Figure 9). This classification generated a dataset consisting of a total of 14,859 positive grid cells and 158,726 negative grid cells, forming the foundation for training and validating the model throughout this research. For data preparation, we randomly selected 80% of the positive sample data, alongside the entirety of the negative sample data from each subgroup, to serve as the training dataset. The remaining data within each subgroup was then allocated for validation purposes. Table 2 summarizes the distribution of datasets, training data, and validation data for each subgroup, providing a comprehensive overview of the data utilized in this analysis.

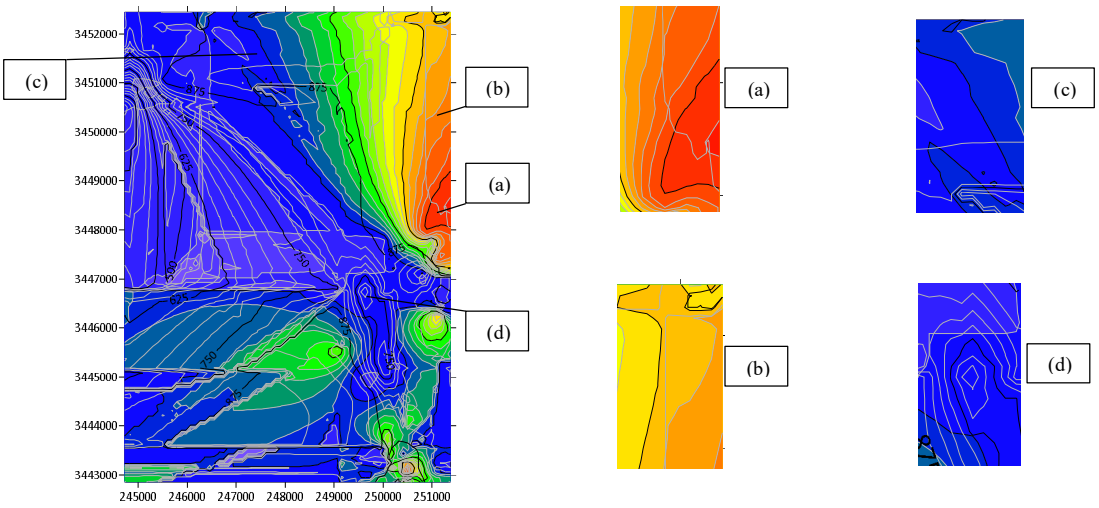


Figure 9. Map showing the distribution of gold in part of the study area, positive examples include (a, b) and negative (c, d)

Table 2. The numbers of data sets, training data, and verification data of each subgroup

Subgroups	data set	training data	verification data
One-elements	173585	170613	2972
Three-elements	173585	170613	2972
Four-elements	173585	170613	2972
Five-elements	173585	170613	2972

To improve the efficacy of models operating with limited training datasets and to expedite the convergence of neural networks, transfer learning was employed. After preparing the datasets, training data for each subgroup were generated by combining the GAN neural network with the pre-trained Inception-v3 model. These datasets were instrumental in training the model and subsequently assessing its accuracy. Throughout the training process, accuracy metrics were meticulously documented to evaluate the model's performance, with particular attention paid to

variations in accuracy as a measure of model quality. Following the training phase, a validation set was introduced to assess the model's predictive capabilities and to quantify its prediction accuracy. To enhance the model's performance, various hyperparameters were evaluated during the training process. The first hyperparameter, layers_count, specifies the number of additional dense layers included in the model, with considerations for values of 1, 2, and 3. Moreover, the dropout_rate hyperparameter was established to reduce overfitting, with evaluations for values of 0.3, 0.5, and 0.7. The learning_rate hyperparameter, which affects the speed at which the model adjusts its parameters, was set to 0.0001, 0.001, and 0.01 during training. Furthermore, the optimizer_type hyperparameter was defined to determine the optimizer selection, with options such as 'adam' and 'sgd' (Stochastic Gradient Descent). The activation_function hyperparameter, which relates to the type of activation function used in the Dense layers, included choices like 'relu', 'tanh', 'sigmoid', 'leaky_relu', and 'elu'. Lastly, the batch_size hyperparameter, which indicates the number of samples processed in each training iteration, was assessed using values of 16, 32, and 64. These hyperparameters were incorporated as inputs into the create_model function, which was responsible for constructing the appropriate model architecture. K-Fold cross-validation was employed to determine the most effective combination of hyperparameters, as outlined in Table 3.

Table 3. The tuning of model hyperparameters

GAN Model Hyperparameters	Search Range	Optimal Value After Tuning
Layers_count	{1,2,3}	1
Dropout_rate	{0.3,0.5,0.7}	0.5
Learning_rate	{0.0001,0.001,0.01}	0.0001
Optimizer_type	{adam,sgd}	adam
Activation_function	{relu, tanh, sigmoid, leaky_relu, elu, softmax}	softmax
Batch_size	{16,32,64}	32

The model's training procedure consisted of 2000 iterations with a learning rate set at 0.0001. Throughout this process, both the training accuracy and the variations in cross-entropy loss were assessed. Training accuracy indicates the proportion of images accurately classified by the model using the designated training dataset. Conversely, the cross-entropy loss function measures the difference between the actual probability distribution and the predicted probability output. A decrease in cross-entropy values signifies a closer match between these distributions, indicating enhanced output accuracy. As the training iterations advanced, the model exhibited a significant learning effect, culminating in an accuracy of 94%. Initially, the cross-entropy loss experienced a substantial decline with each iteration, reflecting a reduction in the gap between actual and expected outputs, which aided in the convergence of the network. Over time, as the number of iterations increased, the cross-entropy loss values kept diminishing, ultimately dropping below 0.7. This benchmark indicates that the actual outputs closely align with the expected outputs, suggesting that the network has reached an optimal state, thereby demonstrating the model's efficacy and predictive power.

Furthermore, this research explored the impact of dataset selection on the training model and the accuracy of its predictions. To examine this factor, the modeling process was replicated ten times for each subset, with random selections for the training sets, and the prediction accuracy was computed for each instance. Figure 10a depicts the prediction accuracy for each model, indicating that most achieved accuracies exceed 70%, with several models surpassing 90%. This finding implies that the neural network model utilized in this study effectively predicts the locations of unknown mineralization areas based on the available geochemical data, despite the choice of a dataset having a minimal effect on the training process of the model.

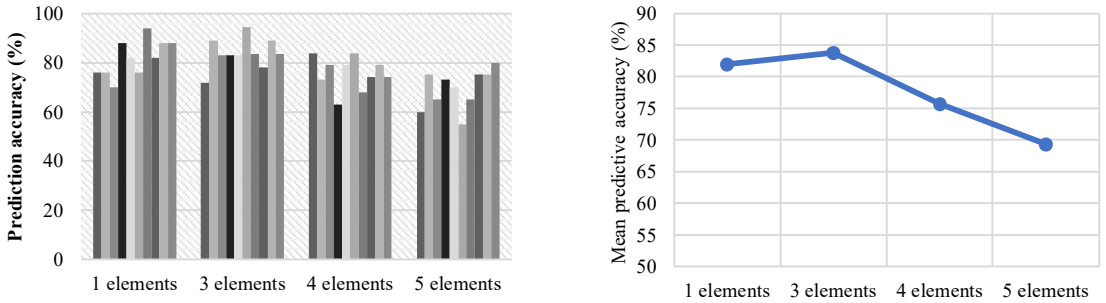
To further quantify the performance, the average prediction accuracy for each subgroup was calculated using Equation (4), based on the prediction accuracies obtained from the ten models. The average prediction accuracy for each subgroup is depicted in Figure 10b, providing a comprehensive overview of the model's consistency across different dataset selections.

$$\text{Mean\_acc}=\frac{\sum_1^{10} \boldsymbol{pre\_acc(model\_n)}}{\mathbf{10}} \quad (4)$$

Where are:
pre_acc – the prediction accuracy of model_n for nϵ(1,10),

Mean_acc – the mean prediction accuracy for a subgroup.

The model trained with the one-element subgroup exhibited the lowest average prediction accuracy, whereas the model utilizing the three-element subgroup achieved the highest average prediction accuracy (Figure 10b). This discrepancy suggests that incorporating additional elements in the geochemical data from the study area enhances the predictive capabilities of the neural network model employed in this research. However, it is important to note that adding more elements does not uniformly guarantee improved performance. The model's success can be compromised by data scatter and low correlation coefficients among the target elements and the other variables. This phenomenon was also observed in the models trained with four and five elements, which did not consistently yield better predictive accuracy despite the increased complexity of the input data.



(a) (b)

Figure. 10. (a) A graph illustrating the prediction accuracy of all models generated in this study. (b) A graph depicting the average prediction accuracy across the four subgroups analyzed in this research

4.3. Prospectivity modeling and mapping

The enhanced predictive accuracy demonstrated by the neural network model, which incorporates three elements, suggests that the final model was developed using a robust dataset that includes all positive and negative samples (n=173,585). This comprehensive training enables the model to accurately identify promising areas for upcoming gold exploration. Figure 11 depicts the model's training accuracy alongside the variations in cross-entropy loss throughout the training duration. The results indicate that repeated training significantly improves the accuracy of the training dataset, achieving values that surpass 90%. This achievement underscores the model's high precision and its capability to fulfill the predetermined standards for recognition rates. Furthermore, the initial cross-entropy loss showed a marked decline during the training process, indicating a narrowing of the disparity between actual and expected outputs, which is a sign of network convergence. Importantly, by the 500th training iteration, the cross-entropy loss stabilized at around 0.6. This point of convergence implies that the actual outputs are in close agreement with the expected outputs, confirming that the network has attained an optimal condition. Collectively, these results reinforce the assertion that the developed model is both effective and appropriate for identifying potential areas for gold exploration.

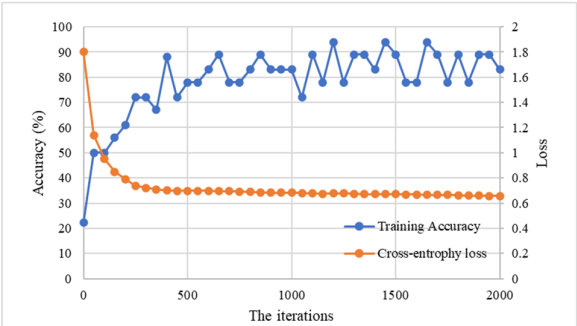


Figure 11. Graph depicting the changes in accuracy and cross-entropy loss for the training model throughout the iterative enhancement of the GAN neural network and the transfer learning-based model utilized in this study

Figure 12 presents the potential regions identified by the final model. This map indicates that the Inception-v3 deep learning framework, in conjunction with the transfer learning techniques utilized in this research, successfully recognized the majority of known mineral deposits and occurrences within the region. The outcomes derived from the neural network modeling demonstrate a more thorough identification of established mineralization zones compared to the

reliance on spatial distribution maps for individual elements such as gold, silver, copper, lead, and zinc. Solely depending on spatial distribution maps for a single element frequently fails to accurately identify geochemical anomalies. Specifically, regions with known deposits may not display clear positive geochemical anomalies when evaluated through single-element maps. The results imply that the integration of a broader range of geochemical data enhances predictive capabilities, facilitating the development of more precise models for mineral prospectivity mapping utilizing the GAN neural network. Furthermore, the modeling process has underscored several regions for prospective gold exploration, particularly Areas II and VII, while Areas I, III, IV, V, and VI are associated with polymetallic mineralization. By incorporating multiple elements, the GAN neural network is more adept at revealing hidden anomalous information, thus improving the reliability of its predictions. The identification of these high-prospectivity regions by the neural network model signifies that it has recognized important features related to the spatial distribution of the target elements, including aspects such as the shape, overlap, and zoning of multivariate geochemical anomalies and halos linked to mineralization in the area. These findings suggest that neural network modeling is a valuable method for identifying highly prospective regions, which should be prioritized for future gold exploration.

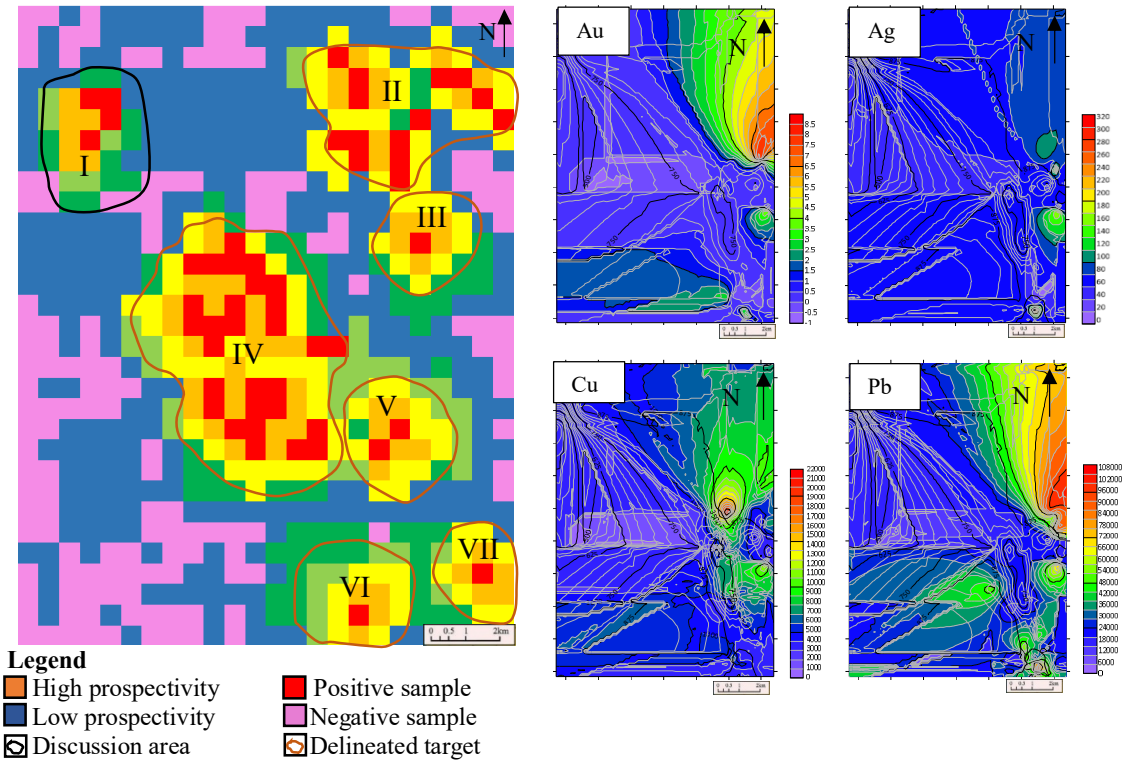


Figure 12. The predictive findings for the entire study area indicate both high and low prospectivity regions, thereby identifying potential targets for future exploration efforts

5. Discussion

This research highlights the effectiveness of combining Generative Adversarial Networks (GANs) with transfer learning strategies for geochemical anomaly detection and mineral exploration. The findings indicate that the GAN-based methodology not only improves the detection of geochemical anomalies but also significantly surpasses conventional methods in identifying subtle and complex spatial relationships among various geochemical variables. A key strength of the GAN approach is its capacity to learn complex data distributions through adversarial training, which allows the model to recognize intricate patterns and subtle anomalies that may be missed by standard techniques. Conventional methods, often based on univariate analyses or basic statistical approaches, may fail to adequately capture the interactions among multiple geochemical variables. In contrast, GANs are particularly effective in handling multivariate datasets, providing a thorough

understanding of geochemical patterns. Additionally, the GAN framework is inherently flexible, making it well-suited for modeling a variety of data environments. This flexibility is particularly advantageous in situations where indicators of mineralization are not clearly defined, enabling the identification of weak anomalies that conventional methods might overlook. Moreover, the integration of transfer learning enhances learning efficiency, especially in the context of sparse datasets, thereby significantly improving the model's accuracy.

While GANs offer notable benefits, conventional anomaly detection techniques retain significant advantages, particularly in recognizing distinct and prominent geochemical anomalies. These established methods are often grounded in solid statistical principles that effectively measure substantial data discrepancies. In cases where strong anomalies are present, conventional techniques may surpass GANs in performance, as they are tailored to identify major geochemical changes. Furthermore, conventional approaches typically reduce the complexity of geochemical data, which can lead to an oversimplification of intricate variable interactions. Although this simplification can enhance clarity, it risks overlooking important subtle characteristics inherent in mineralization patterns. Consequently, relying exclusively on conventional methods in certain contexts may result in missed exploration opportunities.

The findings presented in Table 4 of this research illustrate a comparative evaluation of various anomaly detection methodologies, revealing the unique benefits of the Generative Adversarial Network (GAN) approach. The data indicate that while conventional statistical techniques are proficient in detecting prominent, clearly defined anomalies, the GAN model excels in identifying subtle anomalies and revealing intricate, multivariate relationships. The experimental outcomes emphasize that the GAN approach achieved an accuracy rate exceeding 90%, showcasing its superior ability to detect geochemical anomalies in comparison to the performance metrics of conventional methods outlined in Table 4. This reinforces the idea that GANs significantly enhance the mapping of prospectivity, especially in underexplored areas where conventional techniques may be inadequate.

In conclusion, although conventional methods may perform well in certain situations, the combination of Generative Adversarial Networks (GANs) and transfer learning signifies a transformative advancement in the identification of geochemical anomalies. The results of this research strongly support the integration of sophisticated machine learning methodologies, particularly GANs, into mineral exploration frameworks. By utilizing complex, multidimensional geochemical data, this novel strategy enhances the accuracy of anomaly detection and aids in uncovering potential exploration sites that were previously hidden by standard analytical techniques.

Table 4. Comparative Performance of Anomaly Detection Methods in Geochemical Analysis

Method	Accuracy (%)	Anomaly type	Reference
Disjunctive Kriging (DK)	63.4%	Metallic Anomalies	[52]
Random Forest (RF)	95	Metallic Anomalies	[53]
Restricted Boltzmann Machine (RBM)	91.9	Metallic Anomalies	[53]
Knowledge and Data-driven Methods	76	Metallic Anomalies	[54]
Support Vector Machine (SVM)	94.8	Lithological Mapping	[55]
Multi-Layer Perceptron (MLP)	94.8	Lithological Mapping	[55]
Concentration-Number Fractal (C-N)	72	Metallic Anomalies	[56]
Prediction-Area Fractal (P-A)	75	Metallic Anomalies	[56]
Fuzzy Ordered Weighted Averaging (FOWA)	77	Metallic Anomalies	[57]
Decision Trees (DTs)	91.7	Metallic Anomalies	[58]
Support Vector Machine (SVM)	82%	Metallic Anomalies	[58]
Analytic hierarchy process (AHP)	62.5	Metallic Anomalies	[59]
Fuzzy Logic	54.17	Metallic Anomalies	[59]
K-Nearest Neighbor (KNN)	85	Metallic Anomalies	[60]

Ultimately, to assess the effectiveness of the GAN-based model in detecting geochemical anomalies, a thorough comparison was performed between the model's forecasts and extensive field data obtained from established mineralization sites. The precision of the model's forecasts was evaluated using specific geochemical metrics, such as element concentrations and spatial distributions, which were validated by actual exploratory results. This meticulous validation process revealed a strong alignment between the model outputs and field data, highlighting the model's predictive accuracy. Furthermore, by successfully identifying promising regions for mineral exploration, the

GAN methodology offers considerable implications for reducing costs in exploratory activities. It can lower expenses by facilitating focused exploration initiatives, thus optimizing resource distribution and mitigating the risks linked to conventional exploration techniques. This advancement not only improves the economic feasibility of mineral exploration projects but also lays a solid foundation for future research in the realm of geochemical anomaly detection.

5. Conclusions

This research introduces a thorough methodology that successfully combines Generative Adversarial Networks (GANs) with transfer learning approaches to examine geochemical data obtained from stream sediments. The model has shown an accuracy rate surpassing 92% in identifying geochemical anomalies, with prediction accuracies consistently exceeding 90% across different configurations, while maintaining a cross-entropy loss below 0.7.

The conducted analysis indicates that the three-element model significantly outperforms single-element subgroup datasets, highlighting a marked enhancement in predictive accuracy through the integration of multivariate geochemical data. This approach has demonstrated effectiveness in accurately pinpointing areas linked to known mineral deposits and mineralization occurrences, thereby showcasing its ability to capture the spatial attributes and zoning characteristics of geochemical halos. From a practical standpoint, the incorporation of a wider array of geochemical variables into the training dataset not only improves the identification of geochemical anomalies but also aids in the creation of refined predictive models for mineral exploration. The findings of this study imply that leveraging extensive geochemical datasets can substantially lower exploration costs by enhancing the targeting efficiency of potential sites.

Furthermore, the model has identified several promising areas for elemental investigation within the Janja region, underscoring its practical relevance to real-world exploration scenarios. These results collectively affirm the transformative capabilities of advanced machine learning techniques, particularly the use of Generative Adversarial Networks (GANs) and transfer learning, in revolutionizing mineral exploration. Such methodologies enhance informed decision-making and strategic resource distribution within the industry. Looking ahead, future research should focus on broadening the dataset by integrating a diverse range of geochemical variables across various geological settings. Moreover, investigating the collaboration of additional machine learning methods alongside GANs may further enhance predictive models, thus refining exploration strategies within the mineral sector.

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اکتشاف مواد معدنی مبتنی بر هوش مصنوعی: بهبود تشخیص ناهنجاری‌های ژئوشیمیایی با شبکه‌های مولد تخاصمی و یادگیری انتقالی، مطالعه موردی از کانسار پلی‌متال جانجا، جنوب شرقی ایران

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روش‌های یادگیری انتقالی

چکیده

این تلاش تحقیقاتی بر اکتشاف مواد معدنی در چارچوب یک نهشته رگه‌ای پلی‌متالیک هیدروترمال متمرکز است. نمونه‌برداری از رسوبات رودخانه‌ای برای به دست آوردن اثرات ژئوشیمیایی مربوط به مناطق کانی‌سازی انجام شد. ماهیت کانی‌سازی به عنوان اپی‌ترمال طبقه‌بندی می‌شود که عمدتاً شامل نهشته‌های پلی‌متالیک است. تجزیه و تحلیل‌های ژئوشیمیایی منجر به تهیه نقشه‌های غلظت چند عنصری شد که شناسایی ناهنجاری‌ها و ایجاد پهنه‌بندی را تسهیل می‌کند. اگرچه پیشرفت‌های اخیر بر اثربخشی یادگیری ماشین، به ویژه تکنیک‌های یادگیری عمیق، در تشخیص ناهنجاری‌های ژئوشیمیایی تأکید می‌کند، اما اکثر مطالعات قبلی بر اساس روش‌های آماری تک متغیره انجام شده است. برای رفع این محدودیت، یک رویکرد چند متغیره پیاده‌سازی شد که شامل ویژگی‌های مکانی مانند شکل، همپوشانی و پهنه‌بندی در ناهنجاری‌ها و هاله‌ها بود. با توجه به محدودیت دسترسی به نمونه‌های کافی و معتبر، از روش‌های بدون نظارت و نیمه نظارتی - که مهم‌ترین آنها شبکه‌های مولد تخاصمی (GAN) هستند - استفاده شد. شبکه‌های عصبی مصنوعی (GAN) با استفاده از نقشه‌های ژئوشیمیایی چند عنصری آموزش داده شدند. همچنین از یادگیری انتقالی برای کاهش چالش‌های ناشی از داده‌های محدود از کانسار استفاده شد و در نتیجه، تعیین مناطق اکتشافی بالقوه را تسهیل کردند. تجزیه و تحلیل‌های کمی نشان داده‌اند که رویکردی که از GANها استفاده می‌کند، به دقتی بیش از ۹۲٪ در کنار حداقل اتلاف آنتروپی متقاطع تقریباً ۰.۰۷ دست یافته است، در نتیجه از روش‌های مرسوم در تشخیص ناهنجاری‌های ضعیف پیشی گرفته است. این مدل به طور مؤثر ناهنجاری‌های شناخته شده قبلی را تأیید کرد و همزمان مناطق جدید کانی‌سازی بالقوه را شناسایی کرد و در نتیجه فرصت‌های اکتشاف را افزایش داد. این بررسی نشان می‌دهد که GANها امکان استفاده کامل‌تر از مجموعه داده‌های ژئوشیمیایی را فراهم می‌کنند و طیف گسترده‌ای از متغیرها و ویژگی‌های مکانی پیچیده را ادغام می‌کنند. اگرچه GANها مهارت برتر در مدل‌سازی ناهنجاری‌های ضعیف را نشان می‌دهند، اما تکنیک‌های مرسوم همچنان برای ناهنجاری‌های برجسته‌تر مؤثر هستند. ادغام هر دو روش ممکن است کارایی تلاش‌های اکتشاف معدنی را افزایش دهد. به طور خلاصه، نتایج بر کارایی بالای GANها و چارچوب‌های پیشرفته یادگیری ماشین در افزایش تشخیص ناهنجاری و گسترش اکتشاف معدنی در سیستم‌های پلی‌متالیک هیدروترمال تأکید دارد.

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