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SHORT COMMUNICATION

Application of Artificial Neural Networks in Mineral Resource Evaluation

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Abstract. This paper explores the novel technique of artificial neural networks and their application to mineral resource evaluation. The primary objective of this exploratory work is concerned with cost minimization, especially in drilling. The objective is to reduce investment costs on projects before decisions on further development of a mineralization are made. A data set consisting of 163 sample locations for a bauxite deposit was collected and used for training and testing an artificial neural network model using the back propagation technique. This trained network was then used to predict known point values at specified locations. Results between actual and predictions were then compared for validation purposes. Same results are also compared with estimates obtained from a geostatistical technique (kriging). These results indicate that the ANN-based model predictions were in close agreement with actual results within the main zone of mineralization than at the boundaries. Finally, the validated model was used to predict values at unsampled locations in order to determine the feasibility of drilling in these locations. The investigation on the bauxite deposit shows that artificial neural networks can be used as a complementary decision tool in mining and earth sciences, not so much at an early stage of exploration as in the later stages of exploitation.

Introduction

The inhomogeneity of the earth's subsurface is so immense that an alleged mineral discovery is only seen as a mineralization, until and unless sufficient study has been carried out, and its content evaluated to be in sufficient quantity and quality upon which when mined will yield a profit, before such a 'find' could be considered to be an ore deposit.

The significant role played by data in terms of quality and quantity in the evaluation of a mineral deposit stands foremost in the minds of evaluators and miners. There is no substitute yet for data, neither is it being envisaged that there would be one in the near future. In the circumstance highlighted, data precedes any model or technique used in the evaluation of mineral resources. Data is constantly assembled right from the initial stage of reconnaissance study, through the delineation of the orebody through drilling and trenching, and on to the actual exploitation of the deposit which is, in turn, phased into short-term, medium-term, and long-term planning. With each new set of data, the drilling grid, mining plans, sections, and knowledge of the resource are correspondingly updated, taking into account the new information.

While a lot of effort is required to be put into the analysis of earth science data, it is just as frustrating as it is fraught with difficulties. The above notwithstanding, a representative enough data set still remains the mainstay of the entire mining operation together with knowledge about its degree of variability. The question then is, at what stage of the project do we limit our expense on data collection? Obtaining data is usually a very expensive experiment. The cost of drilling a single bore hole could run into a huge amount of money, with no guarantee of the operation being successful before a decision on whether or not to proceed with the development of the orebody is made, especially at the exploration stage. This inevitably calls for caution, besides the natural limitation on the budget constraints. Under such conditions, alternative approaches of maximizing our knowledge on the limited data set has to be explored to, at least, boost our confidence in, for instance, a planned drilling program to ensure that it would not be wasteful.

Within the past two decades, techniques for predicting attributes $Z(X)$ in unsampled areas have been constantly under development. Prominent amongst these are the geostatistical approaches ranging from the distribution dependent to the nonparametric ones, and spatial imaging(simulation). Although these techniques have met a fair amount of success, there are still some inherent difficulties as more orebodies with different levels of variability and complex structural phenomena are encountered, thus opening an avenue for other techniques which may be found to be adaptable to specific environments or, at the very least, complement or improve on the existing ones.

In recent years, considerable attention has been given to developing estimation and forecasting models based on artificial intelligence techniques such as artificial neural networks (ANNs) and expert systems. These techniques have been successfully applied to a wide range of engineering applications by many authors reporting higher accuracy compared to classical estimation methods. Artificial neural networks (ANNs) are computer models that are designed to emulate human information processing capabilities such as knowledge processing, speech, prediction, and control. The ability of ANN systems to handle a large number of variables with complex relationships, spontaneously learn from examples, reason over inexact and fuzzy data, and to provide adequate and quick responses to new information has generated increasing acceptance of this technology in different engineering fields. As a result of numerous applications in engineering, this new tool has demonstrated remarkable success. Artificial neural networks are relatively new to the area of mining engineering and earth sciences, and it has only been sparsely demonstrated in this field. In this work, an attempt is made to use this novel approach to reduce exploration costs in terms of drilling, improve our data-base, and provide a basis for eventual evaluation of the mineral resource.

Data Preparation

The data set used in this application is from a bauxite deposit. Sampling is on a random stratified grid at an average sampling interval of 100feet. The assays are for thickness (TH_i) as a continuous variable, percent alumina ($\%Al_2O_3$), and percent silica ($\%SiO_2$); hence, the accumulations can be easily calculated:

$$\text{accumulation} = \text{percent (metal)} \times \text{thickness}$$

The data set consists of 163 sample locations, each with its X and Y coordinates (no missing values). The distribution of the borehole locations are shown in Fig. 1. A preliminary statistical analysis of the data set indicates that the data set is reasonably isotropic, and is skewed to the right with a few extreme values as outliers as shown by Fig. 2.

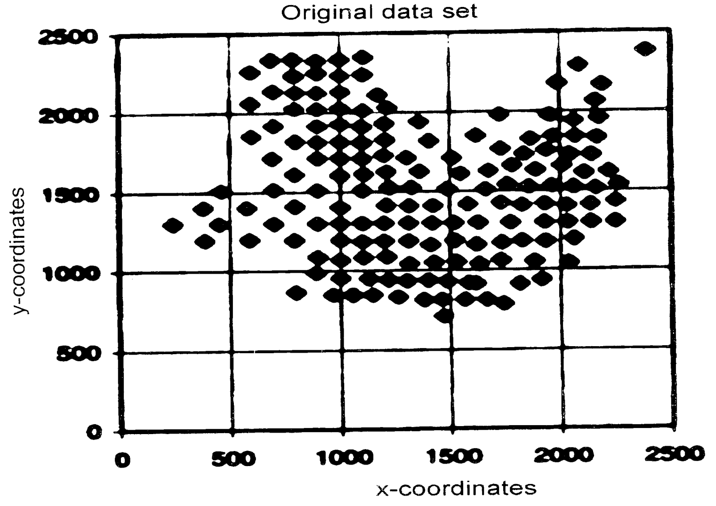

Fig. 1. Distribution of the borehole locations.

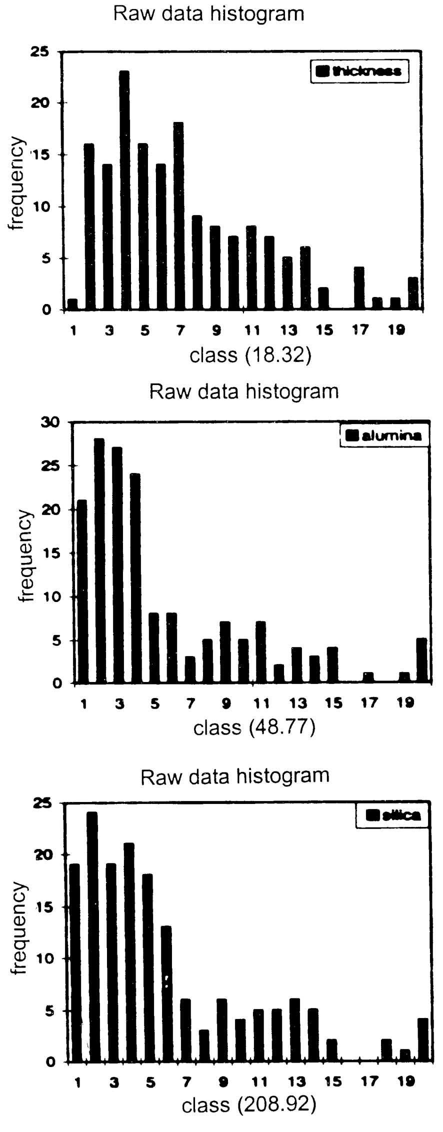

Fig. 2. Data distribution.

From this data, a set of input-output patterns was first prepared. The set was developed by using the actual values for thickness (TH_i), feet percent alumina (FT-%AL_2O_3), and feet percent silica (FT-%SiO_2) from the drilling programme results and the corresponding coordinates (X_i) and (Y_i) in a given grid. Figure 1 shows a typical drilling programme to evaluate the thickness of the orebody and the percentage metals (alumina and silica) in a given location. This information is used to generate the different training patterns to develop the model. It is also used for cross validation of the model results.

ANN Architectural Design

As illustrated by Fig. 3, the network architecture is composed of many simple processing elements that are organized into a sequence of layers. These are the input layer, the hidden layer, and the output layer. The neurons in the input layer receive two input signals representing the coordinates (X_i) and (Y_i) in a given grid; hence, two neurons are used for input in the ANN architecture.

The output layer, on the other hand, consists of three output neurons representing the thickness of mineralized lengths of the deposit, the corresponding content of alumina and silica respectively with a given thickness. Between the input and output layers, generally, there is one or more hidden layers.

Determining the number of hidden layers to use and the appropriate number of neurons to include in each hidden layer is not an exact science. Research in this area [5,6] proved

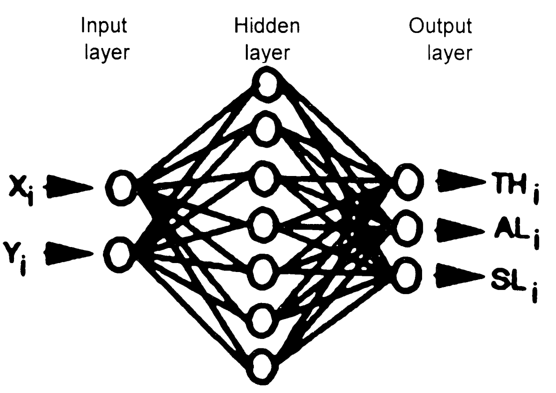

Fig. 3. The proposed ANN architecture.

that one or two hidden layers with an adequate number of neurons is sufficient to model any solution surface of practical interest. Furthermore, recent research findings show that the number of neurons to include in the hidden layer is a function of the number of training pairs available [7]. A large number of hidden layer nodes has a large number of associated parameters, and if the number of training pairs are small, the network will then tend to memorize rather than generalize. The author offered the following formula for calculating the appropriate number of hidden nodes to use in a single hidden layer network if the number of training pairs are known:

$$N = [Hn\ (In+1) + On\ (Hn+1)] \tag{6}$$

where,

N = number of training pairs available
= a constant greater than 1.0
Hn = number of hidden nodes to be used in a network that has only one hidden layer
In = number of input nodes
On = number of output nodes

Using the above formula, Hn = 6.52 resulted from the calculation. This result indicates that 6 or 7 hidden nodes can be used in the hidden layer. This finding is validated by evaluating a number of hidden node configurations and computing the root mean square error for both the design points and the test points. As a result of this evaluation, it was found that a network with 6 to 8 nodes on the hidden layer would be a good choice. The network containing 7 hidden nodes, however, yielded the smallest error over the region of interest. Based on these results, one hidden layer containing seven neurons was used to develop the ANN architecture.

Network Training

The multilayer feedforward networks developed in this work were trained using the backpropagation (BP) paradigm developed in reference [8]. The BP algorithm uses the supervised training technique. In this technique, the interlayer connection weights and the processing element thresholds are first initialized to small random values. The network is then presented with a set of training patterns, each consisting of an example of the problem to be solved (the input) and the desired solution to this problem (the output). These training patterns are presented repeatedly to the ANN model and weights are adjusted by small amounts that are dictated by the general delta rule [8]. This adjustment is performed after each iteration when the network's computed output is different from the desired output. This process continues until weights converge to the desired error level or the output reaches an acceptable level. The system of equations that provides a generalized description of how the learning process is performed by the BP algorithm is shown in Simpson [9].

For the present work, the training process was performed using the NeuroShell™ simulator. After several adjustments to the network parameters, the network converged to a threshold of 0.0001. Predictions from this trained model were in agreement with the actual data, thereby producing an R^2 value of 0.72 for TH_i, 0.78 for Al_2O_3 and 0.82 for SiO_2. These results indicate that, for the data set used in this study, 72 percent of the variability in the thickness, 78 percent in the alumina, and 82 percent in the silica can be explained by the ANN model developed in this work.

Having trained the network successfully, the next step is to test the trained network, using the test data set, in order to judge its performance.

Network Testing and Validation

The generalization capability of the models was tested by presenting 35 patterns that were excluded from the data set prior to network training. Figures 4 (a), (b), and (c) provide the results and illustrate the relationship between actual results and estimates obtained from the ANN-based model for the thickness, alumina and silica for ten (10) randomly selected sample locations.

To validate these results, three of the more common techniques that are generally used to determine the model's accuracy and performance are used. These techniques are: mean absolute deviation (MAD), mean squared error (MSE), and mean absolute percentage error (MAPE). MAD is the average of the absolute differences between the estimated values and the observed or experimental values. MSE is the average of the squared differences between estimated and observed values, and MAPE is the absolute differences between the estimated and observed values expressed as a percentage of the observed values. Statistical analysis of the results, shown in Table 1, indicate that the R^2 values for the testing set were 0.72 for THi, 0.81 for Al_2O_3, and 0.83 for SiO_2. The results show that approximately 79 percent of the variation in the dependent variable estimates can be explained by the independent variables selected and the data set used. These results demonstrate that the ANN-based model developed in this work can predict the grades at unsampled locations with reasonable accuracy. To verify the ANN-based model's results, attempts are being made to develop geostatistical-based models using the same data and to compare the results.

Table 1. Statistical analysis of the models

	TH_i	Al_2O_3	SiO_2
MSE	807.2	12746.3	178645.5
MAD	21.22	58.59	253.135
MAPE	25.82	33.72	35.74
SD	15.00	41.43	178.99
R^2	0.876	0.755	0.792

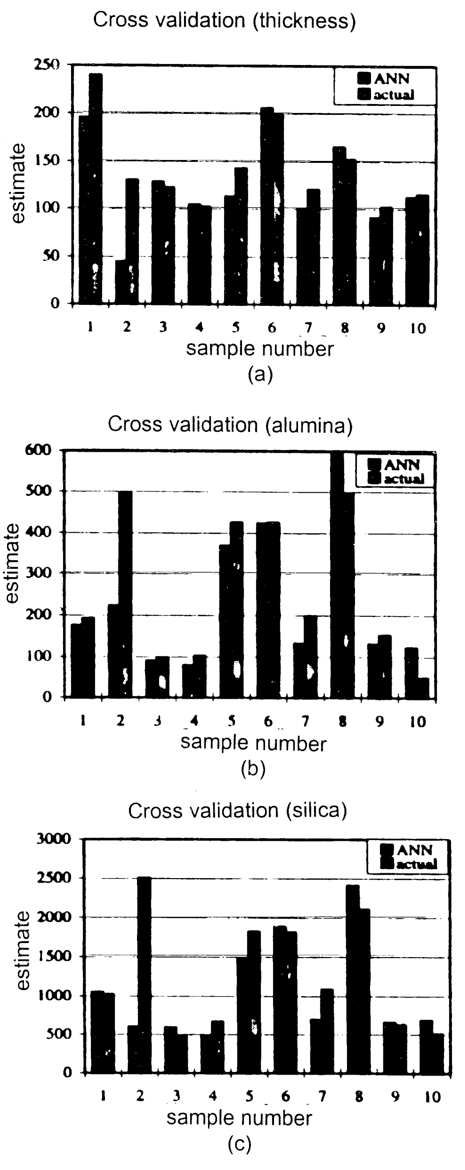

Fig. 4. ANN estimations compared to actual results for (a) thickness (b) alumina (c) silica.

To demonstrate the effectiveness of the proposed approach, the validated model was used to estimate the accumulation of silica and alumina at the same location and to predict thickness in 87 additional locations on the given grid. Coordinates of specific points on the grid were selected as shown by Figure 5a. An estimate was then obtained from the model based on the given coordinates. An example of these estimates is shown in Table 2 and their corresponding locations shown in Figure 5b.

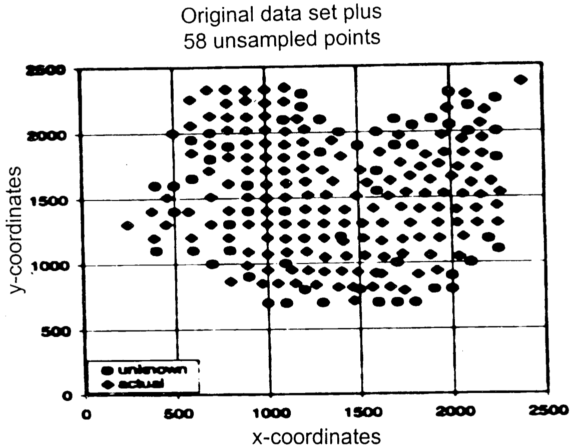

Fig. 5a. Additional locations selected on the grid.

Table 2. Example of estimates for the locations selected

Co-ordinates X	Co-ordinates Y	TH_i	Al_2O_3	SiO_2
400.00	1000.00	57.44	43.04	223.16
400.00	1500.00	74.40	45.39	264.72
500.00	1300.00	55.29	44.04	222.47
500.00	2000.00	76.51	45.88	270.64
600.00	1500.00	47.73	44.14	207.36
600.00	1950.00	69.93	46.13	259.20
700.00	1600.00	36.55	44.46	184.55
800.00	1300.00	25.46	42.37	152.27
900.00	900.00	25.40	26.77	102.89
1000.0	700.00	4.00	3.00	41.00
1100.0	1400.00	74.79	119.06	569.64
1500.0	2200.00	113.24	128.65	763.68
1800.0	1900.00	195.38	174.27	1210.1

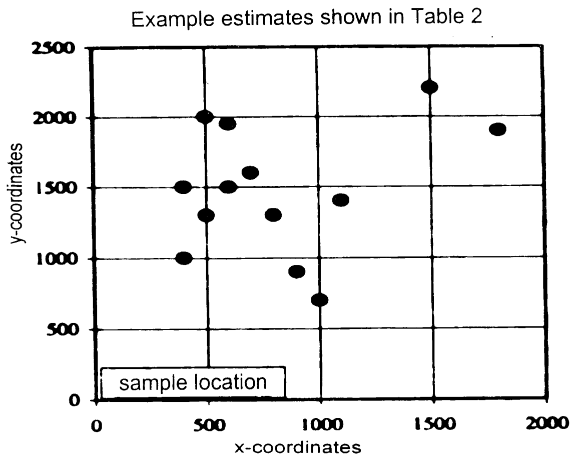

Fig.5b. Locations of example estimates.

The performance of ANN is further tested and compared with a known geostatistical technique (kriging), and since the paper addresses the direct application of ANN to mineral resource evaluation, only its performance against the technique is illustrated in Fig. 6. Even so, the results obtained by this comparison for the data set demonstrate that the ANN-based model can predict grade values with reasonable accuracy especially when there is sufficient data. Its performance at unsampled locations (usually at the edge of the mineralization) is somewhat limited when the additional 87 locations are considered, as the variations between predicted values and the actual and indeed kriged grades are a lot more pronounced. This finding tends to suggest that, ANN is best suited for predictions of grade values within the main mineralized zone with particular applications on specific block evaluations and size. At early stages of exploration, ANN applications need to complement other techniques in determining a suitable drilling pattern and an eventual reduction in cost.

Conclusions

In this work, an artificial neural network based model was developed for estimating point grades using actual data for 163 sample locations. The ANN receives the co-ordinate (X_i and Y_i) in a given grid, and based on the network connection weights formed at the end of the model training, predicts thickness, feet percentage alumina, and feet percentage silica for that co-ordinate. Prior to the training process, a training data set consisting of 163 sample borehole locations with its coordinates were obtained.

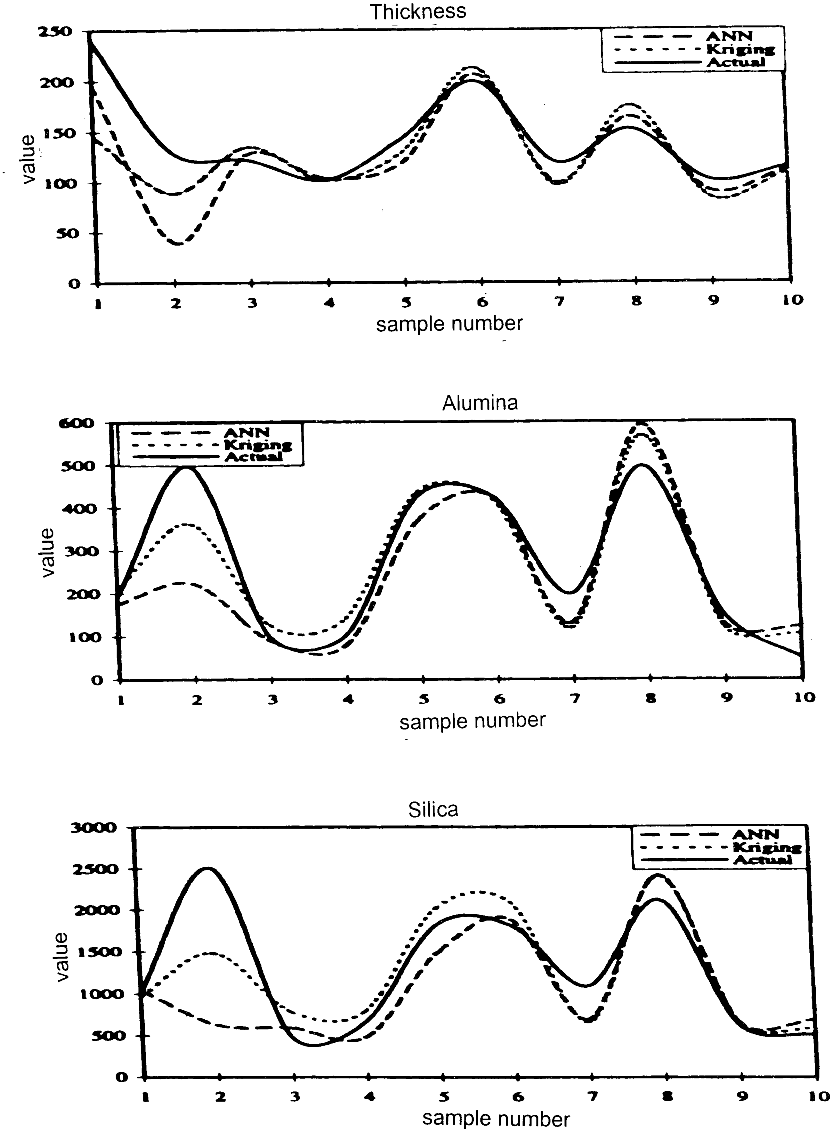

Fig. 6. Comparing ANN estimates against kriged and actual values.

These data were then used to train the network until a good agreement between estimated values and actual values was reached. Once the ANN model was adequately trained, the network was then tested to ensure that it could adequately predict the correct values. This testing was carried out by inputting new coordinates that were not included in the training data set into the model and obtaining the estimates. This testing process was conducted to ensure that the developed ANN models could adequately estimate the correct grades and thickness. Test results indicate reasonable accuracy with $R^2 = 0.72$ for TH_i, 0.81 for AL_i, and 0.83 for SL_i. The validated model was then used to estimate 87 unsampled points in order to determine the feasibility of drilling in these locations. A comparison of ANNs performance with the technique of kriging also showed encouraging results viewed against a background of it being an effective complementary tool.

ANN provides to the mining engineers and earth scientists a promising tool that can be used in assessing grade distribution based on sample points. Such a tool can help in determining a feasible drilling programme which results in extensive savings.

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تطبيقات الذكاء الاصطناعي باستخدام شبكات الأعصاب الاصطناعية في التنقيب عن مكامن الموارد المعدنية

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(أستلم في ١٣/٤/١٩٩٦م ؛ وقُبل للنشر في ٢٩/٣/١٩٩٧م)

ملخص البحث. يناقش هذا البحث تقنية جديدة للتنبؤ بتقدير مكامن الموارد المعدنية باستخدام تكنولوجيا الشبكات العصبية الاصطناعية. يهدف هذا البحث إلى خفض تكاليف عمليات الحفر الاستكشافي وترشيد تكلفة الاستثمار للمشروع عن طريق تقليل عمليات الحفر.

جمعت المعلومات المستخدمة في هذا البحث من ١٦٣ موقع حفر لمعدن البوكسايت. استخدمت هذه المعلومات في تطوير وصياغة واختيار نموذج الشبكات العصبية الاصطناعية، وبعد التأكد من صلاحية النموذج المصمم عن طريق اختباره تم استخدامه في التنبؤ بمواقع وجود خام البوكسايت. أظهرت مقارنة النتائج التخمينية مع النتائج الحقيقية تطابقاً جيداً، وبناءً على نتائج هذه الدراسة يمكن القول: إن شبكات الذكاء الاصطناعي يمكن استخدامها كطريقة جديدة مساعدة للتبوء بمكامن الموارد المعدنية في عمليات التعدين وعلوم الأرض.