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Predicting gold grade using support vector machine and neural network to generate an evidence layer for 3D prospectivity analysis

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ABSTRACT

This paper uses support vector machine (SVM), back propagation neural network (BPNN), and Multivariate Regression Analysis (MLA) methods to predict the gold in the Dalli deposit situated in the central province of Iran. After analyzing the data, the dataset was prepared. Subsequently, through comprehensive statistical analyses, Au was chosen as the output element for modelling, while Cu, Al, Ca, Fe, Ti, and Zn were considered input parameters. Then, the dataset was divided into two groups: training and testing datasets. For this purpose, 70% of the datasets were randomly entered into the data process, while the remaining data were assigned for the testing stage. The correlation coefficients for SVM, BPNN, and MLA were 94%, 75%, and 68%, respectively. A comparison of these coefficients revealed that all used methods successfully predicted the actual grade of Au. However, the SVM was more reliable and accurate than other methods. Considering the sensitivity of the gold data and the small number in the exploratory database, the results of this research are used to prepare the main layer in the mineral prospectivity mapping (MPM) of gold in 2 and 3D.

Keywords: *Gold grade estimation; Support vector machine; Back propagation neural network; Dalli deposit, Iran..*

1. Introduction

Mineral exploration is a complex process integrating different methods, which can be costly and time-consuming [1]. Geochemical studies are one of the appropriate methods for prospecting and detailed exploration, which are used to identify areas with mineralization potential [2-6]. Geochemical studies generally are related to rock, soil, water, air, or plants. Examining soil and stream sediment samples taken from sediments is called sedimentary geochemistry. The primary goal of stream sediment geochemical discoveries is to identify areas enriched or depleted of elements indicative of the mineralization of a specific type of mineral. This recognition is conducted by applying pathfinder and indicator elements. Determining potential mineralization types and areas is facilitated by examining paragenetic relationships between elements and conducting correlation analyses [7-9]. For years, various methods have been used to predict pathfinders, indicators, and mineralizing elements in rocks and geochemical samples. Besides, statistical, geostatistical, fractal, and neural networks are the most common techniques to predict possible mineral elements [10-15].

Regression analysis is the process of using statistical techniques to quantify and understand the relationship between variables. Linear regression is a process of modelling a linear correlation between two variables [16]. Logistic regression is a process of modelling the probability of a discrete outcome given an input variable. Multivariate regression is a supervised machine learning algorithm involving multiple data variables for analysis. It attempts to find out a formula that can explain how factors in variables respond simultaneously to changes in others [17,1]. The type of regression depends on the obtained function. If the function is linear, the regression is called linear and if the function is nonlinear, it is called non-linear [16].

Over the last decade, the artificial neural networks (ANNs) method has been extensively used in different areas of mining engineering [18-27]. The quality of the suggested models in this technique depends on the relationship between the patterns used in training procedures and the expected patterns (prediction) with the lowest error. Apart from determining many parameters, such as the type of network, the number of layers, and the number of neurons in ANNs methods, there are other main issues, such as overfitting or finding comprehensive optimal points. For instance, if excessive training is applied to data, the ANN will eventually overfit, meaning that it will be fitted precisely to this set of training datasets, thus losing generalization. Also, the first relative optimal point is introduced as the best solution instead of finding optimal points [28]. The possibility of providing a premature and inappropriate answer, along with the high number of samples can be introduced as other problems for neural networks, which means that neural networks converge to one solution for each training dataset. There is no guarantee that the presented answer is the best model for the data. Moreover, with a small number of samples, it is not possible to provide a proper prediction [29, 30]. Due to the failure to offer suitable solutions for neural networks in many cases and considering the contradictions between the models and the limited availability of data to train these networks, support vector machine (SVM) was introduced in early 1990s by Vladimir Vapnik. Indeed, this technique has a high generalization ability in solving classification and prediction problems

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[31]. Among the advantages of vector machines over neural networks, we can mention the easy training process of this machine, not providing local optimal points as solutions, and exemplary performance in non-linear problems [32]. For this, this method has been widely applied in different areas of geochemical studies, such as multi-classification of prospective mineral areas, lithology classification, mineralization zones separation, and economic projects [33-39].

The chemical analysis related to gold element is generally complicated, sensitive, time- and cost-consuming. This decision-making procedure would be challenging, especially in the early stage of exploration in which limited data is available. Literature reviews revealed that little research had focused on predicting Au grade with artificial intelligence techniques. Considering that one of the advantages of the SVM method is its ability to predict and estimate well with a small amount of data, we used it in this study. Therefore, the main objective of this research was to predict Au grade by employing the SVM and BPNN, and comparing their results. For this purpose, the Dalli copper-gold deposit was selected as a case study and 16 main elements were selected after collecting and analyzing the required samples. The main innovation of this research is the use of the SVM method in predicting the Au grade and comparing the obtained results with the regression and BPNN in the Dalli deposit.

2. Geology of the study area

The Dalli Au-Cu porphyry deposit is located in the Central province of Iran. This deposit is located about 70 km northeast of Arak city. From a geological prespective, the Dalli deposit is located in the central part of the Urumieh-Dokhtar magmatic belt between the Sanandaj-Sirjan zone and Central Iran (Fig 1.). The Dalli deposit is part of the 1:100000 Salafchegan-Khorhe geological sheet of Iran, positioned between 50^0 and 50^0 30' E longitudes and 34^0 to 34^0 30' N latitude.

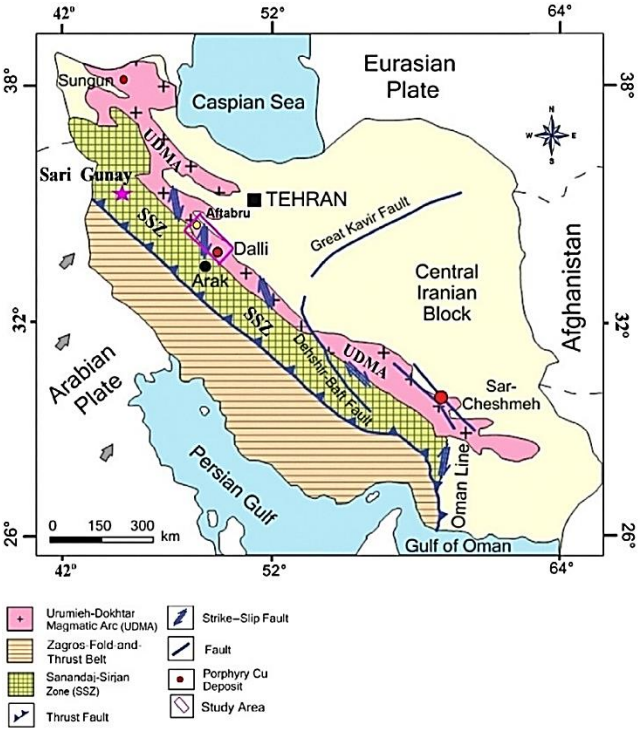

Fig 1. The location of the Dalli deposit (study area) on the structural geology of Iran and main zones (modified after [40]).

The Dalli deposit lithology includes andesite rocks, andesite breccias, porphyritic andesites, diorite, and quartz diorite porphyry (Fig 2.) [41]. Hydrothermal solutions have led to potassic, sericitic (phyllic), propylitic, silicification, and argillic alterations in the area [42-45]. The outcrops around the mineralized intrusions are all igneous intrusions and hornblende lavas with propylitic alteration. The Dalli deposit has several characteristics: erosion has led to the disappearance of most alteration in the mineralization area and intrusive masses are exposed. Mineralization in the Dalli deposit is gold-rich copper mineralization associated with a quartz-magnetite stock-work within the quartz diorite intrusive mass. In addition, copper carbonate mineralization (malachite and azurite) and iron oxides can be seen almost throughout the intrusive mass [42, 40, 46]. Therefore, in this deposit, we do not have pathfinder and indicator elements expected foe gold mineralization, such as As, Sb, and Bs. The pathfinder elements in this deposit are associated with intrusive mass compositions and ore minerals, the most significant of which are copper and iron. Alterations and mineralization evidence are presented in Fig 3., for instance.

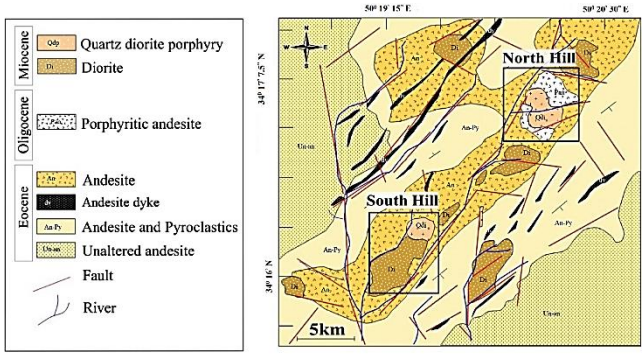

Fig 2. The geological map of the Dalli porphyry deposit (modeified after [41]), and the location of study area, in this study we investigated in north Hill area.

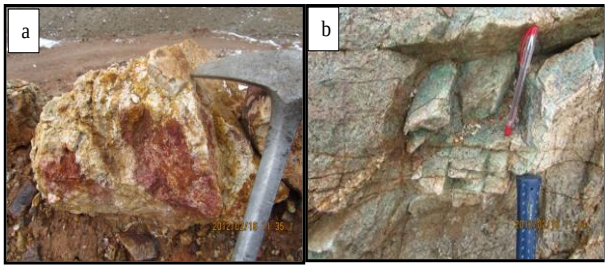

Fig 3. The sericitic alteration with quartz, hematite, and pyrite (a), Copper mineralization as malachite and azurite (b).

3. Materials and Methods

The Dalli deposit is divided into northern and southern regions, and this research was done in the northern zone. First, including 345 required samples were collected by digging six trenches in the area, TR04, TR05, TR06, TR07, TR3940, and TR4080. Then, the collected samples were tested by the ICP-MS for 34 elements, performed at the ALS Chemex Lab in Canada.

Since gold analyzes are time-consuming, costly, and need precise equipment, this study aims to examine and present a new method for predicting gold grade by collecting a few samples. As a result, the dataset was built based on fifty data collected from only two trenches, TR07 and TR3940, considered for the testing procedure. After the dataset construction, the SVM and BPNN methods were applied to predict Au grade, described in the following sections.

3.1. Support Vector Machine (SVM)

The SVM can be used in two-class to multi-class prediction and classification problems [31]. The purpose of such problems is to create a classification criterion that can be used well for unseen samples and simultaneously has good generalization capability. The linear separating

plane with the maximum margin, the distance between the separating plane and the closest points, is called the optimal hyperplane, which is expected to extend the obtained boundary to all possible ranges [47]. Generally, in linear separation problems, a weight like 'W' should be considered for a vector-like 'X' so that this weight can classify the vectors well in their respective class. Equation (1) is considered for the optimal separator plate [47,48].

$$w^T x + b = 0 \quad (1)$$

where:

w: weight matrix

T: matrix transpose

x: vector

b: constant

The relationship between the vector 'x' and a weight such as 'w' is expressed as internal multiplication. In addition, the symbol T indicates the output of the weight matrix. Based on the stated conditions, a set of points is optimally separated by a plane when:

1) They have been placed in their respective class without any mistake.
2) The distance between the closest points of each data class to the separating plane is the maximum (Fig 4.) [49, 50].

Based on this, parameters ' w' and ' b' should be calculated to meet the two mentioned conditions. To solve this problem and control the data's separability, equation (2) is expressed for the margin [50].

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$$w^T x + b \begin{cases} x \le 1 & for \;\; y_i = -1 \\ x \ge 1 & for \;\; y_i = 1 \end{cases} \quad (2)$$

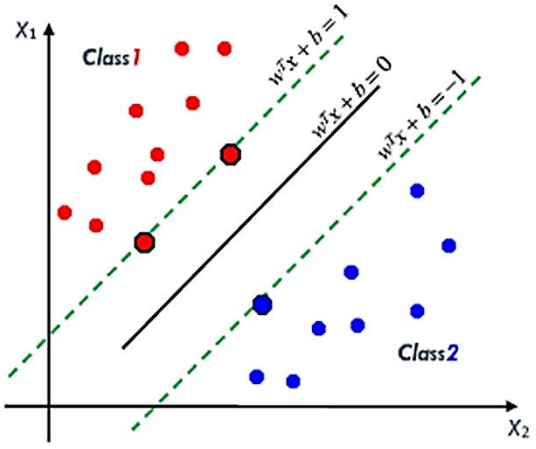

Fig 4. The optimal separator plate and margins modified after [51].

In order to introduce the separation screen with the largest margin, it is tried to maximize the distance between two considered margins. Equation (3) calculates and maximizes the distance between these two margins [31].

$$d(w,b;x) = \frac{|(w^T x+b-1)-(w^T x+b+1)|}{\|w\|} = \frac{2}{\|w\|} \quad (3)$$

where:

‖w‖ is called a soft function.

The desired margin will be maximized based on the output calculated from equation (4) if it is maximized [47, 52].

Sometimes in the linear system, there are situations where several data are not included in their respective classes (Fig 5.). In such situations, a function called the penalty function must be introduced to achieve the super plane separator. This function is represented by equation (4) [53, 54].

$$F(\xi) = \sum_{i=1}^{N} \xi_i \quad (5)$$

where:

ξ_i shows the amount of classification error.

The noteworthy point in Figure 4. is the data placed on the margins. These data are the same support data that the vector machine uses to classify the data correctly [55, 53].

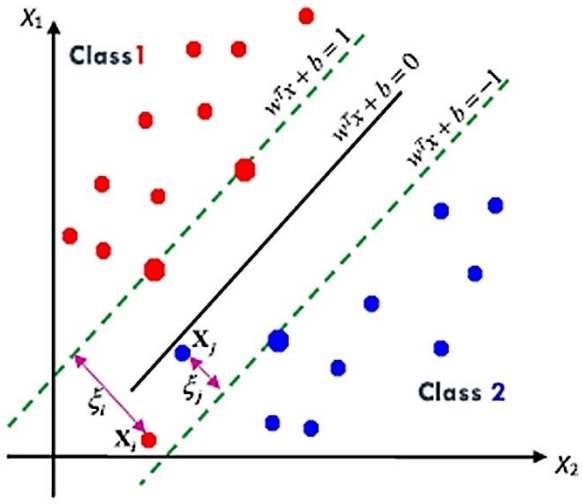

Fig 5. An integral linear system with an error rate of ξ_i modified after [51].

Therefore, the convex optimization problem in non-separable linear systems is written as equation (5). The hypersurface of the generalized optimal separator is determined by the vector W for minimizing, as follows (Eq. (5)) [53].

$$M\,in_{w,b} = \frac{1}{2} w^T w + C \sum_{i=1}^{N} \xi_i \;,\; S.t \quad y_i\,(w^T w + b) \ge 1 - \xi_i \quad (5)$$

where:

C is the trade-off coefficient to maximize the margins and minimize the function error.

As mentioned before, in situations like this, Lagrange coefficients are used, which in the recent relation considering α, β as Lagrange coefficients (Eq. (6)) [53].

$$L_p(w,b,\xi,\alpha,\beta) = \frac{1}{2} w^T w + C \sum_{i=1}^{N} \xi_i - \sum_{i=1}^{N} \alpha_i \{y_i [w^T x_i + b] - 1 + \xi_i\} - \sum_{i=1}^{N} \beta_i \xi_i \quad (6)$$

Dual classical Lagrange can transform the original problem of equation (6) into its dual problem. The dual problem of this relationship is defined by equation (7).

$$M\alpha xW\,(\alpha,\beta) = M\alpha x_{\alpha,\beta}\,(M\,in_{w,b,\xi} L(w,b,\alpha,\xi,\beta)) \quad (7)$$

If equation (7) is taken for w, b, and the derivative, and set equal to zero, the values of equation (8) are obtained.

$$\frac{\partial L}{\partial w} = 0 \rightarrow w = \sum_{i=1}^{N} \alpha_i \beta_i x_i$$

$$\frac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^{N} \alpha_i y_i = 0 \quad (8)$$

$$\frac{\partial L}{\partial \xi} = 0 \;\rightarrow \alpha_i + \beta_i = C$$

By inserting these relations in equation (7), the fundamental equation

of the vector machine in the inseparable linear situation is obtained, which is in the form of equation (9) [53].

$$Max\ L_d(\alpha) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2}\sum_{i=1}^{N} y_i y_i \alpha_i \alpha_i x_i^T x_i \quad (9)$$

$$S.t \begin{cases} 0 \le \alpha_i \le c \\ \sum_{i=1}^{N} \alpha_i y_i = 0 \end{cases}$$

As seen, the objective function of the linear inseparable system resembles that of the linear separable system. The only difference between the two is the modification of the limits of Lagrange coefficients. Parameter c, which determines the additional capacity of the classifier, must be determined in these systems [56,51]. Generally, a vector-like x in a higher space is written as a linear vector machine in a higher space (often called a feature space) and is visualized as Fig 6., while its input space remains non-linear.

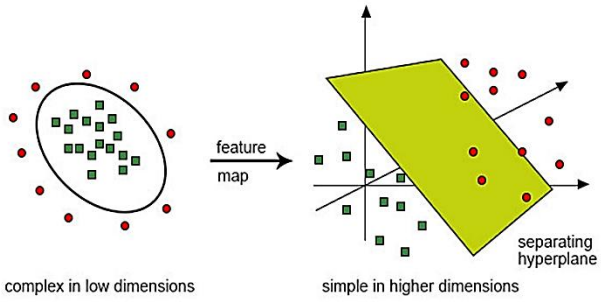

Fig 6. Classified data in high space modified after [56,51].

3.2. Back Propagation Neural Network

The neural network is a computing method connecting several processing units (neurons). This network consists of a certain number of neurons that connect the input to the output. This network can learn from different real, vector, or discrete functions [58, 59]. A neural network can be considered a machine for building a model made of electronic parts or simulated through software. These networks are used to solve problems whose solution formula is unknown, and there is no cause-and-effect model for them. Because of the similarity of the network to the human brain's neural network, it is called a neural network. The primary purpose of using a neural network is to provide a model for data for which a specific function cannot be defined [60, 61].

Neural networks are divided into different types based on the relationships between the input and output functions. The BPNN is a type of neural network whose name is derived from how the weights are applied and adjusted based on the error [59]. Minsky and Papert established this method to solve classification problems in perceptron [63]. This type of neural network structure has at least one feedback loop. In the ANNs, it is tested after training the network (i.e., the free parameters of the network adapt to the placement environment by employing the simulation process).

4. Dataset

Sixteen elements were chosen for statistical analyses based on chemical studies' results and the elements' enrichment status. Then, the data homogenization process was carried out after substituting the censored data values. It should be noted that regardless of the source of pollution, the non-homogeneities in the data may occur due to the involvement of various physical and chemical factors. As a result, the dataset was divided into different groups and homogenized to better reveal their anomalies. For this purpose, the median value of each group was considered as the background value because it is not affected by border values, and the value of each element was deducted from the relevant background. Afterward, all group's obtained values formed a general community. In many statistical techniques, we assume that the errors are normally distributed, in other words, we assume the data distribution is a normal distribution. Considering that our data in this research is not normal, the data distribution should be normalized. Transforming our variables can improve the predictive power of our models [64,16]. There are many transformation methods to convert data into a normal distribution, which are used in different situations [65]. According to the goal of this research (prediction) and the data used, as well as its simplicity and commonness, we chose the Cox-Box method for transformation. The Cox-Box transformation is a type of power transformation that converts non-normal dependent variables into data with a normal distribution. This transformation also helps improve the predictive power of models [16,17]. The general form of the used transformation is as follows:

$$z = \frac{x^{\lambda}-1}{\lambda}(\lambda = 0), x > 0 \quad (10)$$

where:

λ: is the value of the data to be normalized, and z is the transformed value.

After normalization, the data were converted to the standard normal. Because the minimum data was not known correctly, and there were censored values among a series of data, the values were standardized and converted between zero and one, using the formula $\frac{x_i}{x_{max}}$, where xi was considered as the value of each data. Also, x_{max} and z_i were considered the maximum and standard data values, respectively.

Before applying the SVM and ANN to the dataset, the dataset was analyzed by the principal component analysis (PCA) to find the elements most correlated with gold used for this data processing. This analysis confirmed that copper, aluminium, calcium, iron, titanium, and zinc positively correlate with gold (Table 1.). It should be mentioned that elements were selected whose correlation level was more than 0.5.

Fig 7. shows a three-dimensional diagram of the components. As the figure shows, the mentioned elements are placed in the same plane as gold and very close to the gold element which the primary statistical diagrams of these elements are shown in Fig 8. (box plot) and Fig 9. (Frequency diagram).

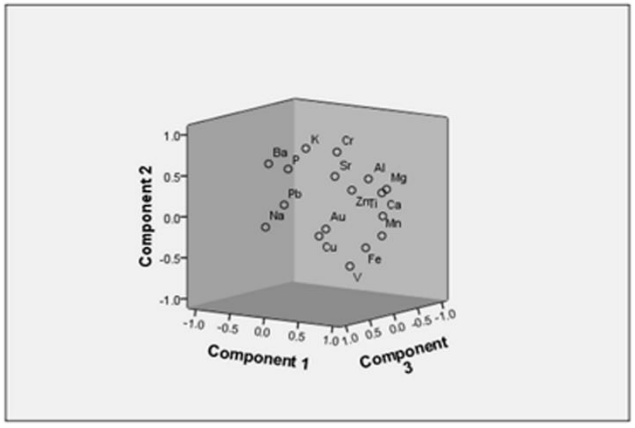

Fig 7. Three-dimensional diagram of the components for the samples taken from the study area.

5. Results and Discussions

5.1. Multivariate linear regression analysis

This study investigates the relationship between Au and other elements using the multivariate regression method. Au was considered the output, while Cu, Al, Ba, Ca, Cr, Fe, K, Mg, Mn, Na, P, Sr, Ti, V, and Zn were considered dependent. Therefore, the gold grade was obtained based on other elements with a linear relationship. In the suggested relationship, the gold grade was considered a dependent variable, and

Table 1. The correlation matrix of the elements in the samples collected from the study area.

	Au	Cu	Al	Ba	Ca	Cr	Fe	K	Mg	Mn	Na	P	Pb	Sr	Ti	V	Zn
Au	1																
Cu	0.777	1															
Al	0.542	0.208	1														
Ba	-0.465	-0.530	-0.279	1													
Ca	0.605	0.157	0.379	-0.548	1												
Cr	0.218	-0.015	0.380	0.171	0.298	1											
Fe	0.578	0.532	0.537	-.0761	0.515	-0.128	1										
K	0.124	0.283	0.472	0.332	-0.135	0.588	-0.104	1									
Mg	0.189	0.187	0.871	-0.471	0.484	0.375	0.460	0.296	1								
Mn	0.124	0.033	0.253	-0.494	0.596	-0.154	0.471	-0.361	0.502	1							
Na	0.189	0.453	-0.123	0.021	-0.302	-0.236	0.078	0.260	-0.489	-0.455	1						
P	-0.418	-0.383	0.023	0.569	-0.386	0.170	-0.355	0.342	-0.139	-0.457	0.037	1					
Pb	0.000	-0.086	-0.199	0.322	-0.476	0.000	-0.264	0.053	-0.271	-0.181	-0.028	0.141	1				
Sr	0.004	0.237	0.498	0.120	0.241	0.136	0.190	0.502	0.301	0.222	0.066	0.023	-0.073	1			
Ti	0.518	0.401	0.701	-0.499	0.646	0.475	0.548	0.354	0.864	0.409	-0.241	-0.239	-0.487	0.302	1		
V	0.440	0.463	0.204	-0.685	0.233	-0.242	0.798	-0.239	0.275	0.401	-0.040	-0.348	-0.191	-0.211	0.303	1	
Zn	0.535	0.321	0.300	-0.320	0.586	0.651	0.197	0.290	0.414	0.277	-0.101	-0.337	0.023	0.150	0.551	0.056	1

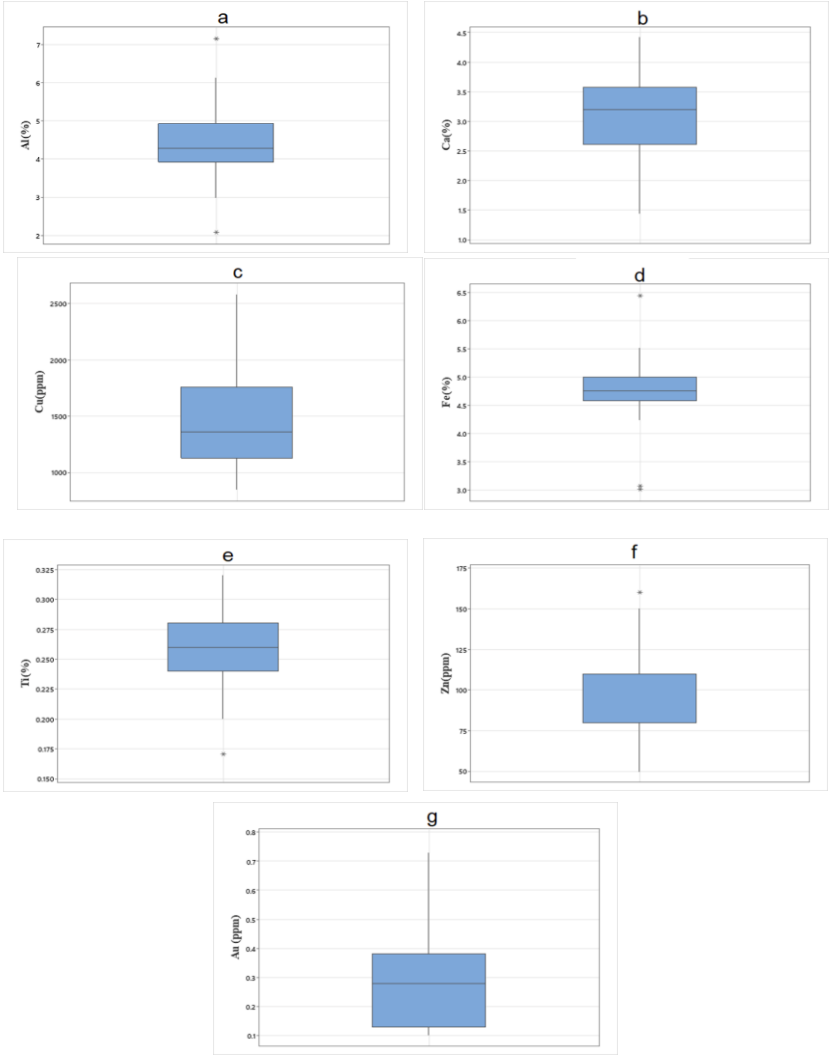

Fig 8. Box-plots of selected elements: a) Al; b) Ca; c) Cu; d) Fe; e) Ti; f) Zn and g) Au.

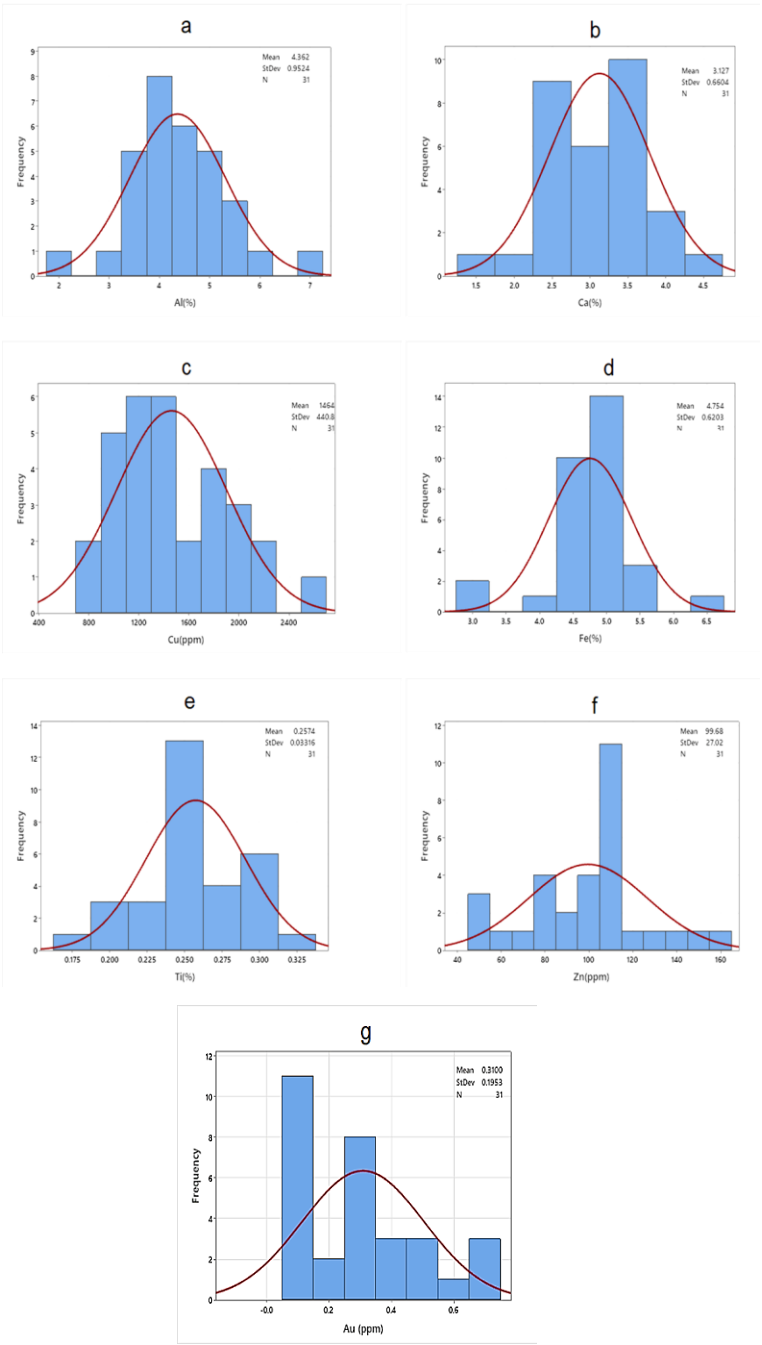

Fig 9. The Frequency distribution diagrams for the selected elements a) Al; b) Ca; c) Cu; d) Fe; e) Ti; f) Zn, and g) Au.

the other elements were considered as independents variables. The relationship between variables (in this study, gold with different elements) is shown by coefficients.

The suggested relationship is as follows (Eq. (11));

Au (ppm) = 0.242 + 0.000335 Cu - 0.0077 Al + 0.000365 Ba + 0.0253 Ca - 0.00033 Cr + 0.0071 Fe - 0.321 K + 0.044 Mg + 0.000012 Mn - 0.079 Na + 0.000233 P - 0.00117 Sr + 0.46 Ti - 0.00181 V + 0.00127 Zn (11)

Where: R-Sq = 80.6% R-Sq (adj) = 61.2%

Due to the importance of other related elements such as Fe, Cu, Al, Ti, and Zn to Au, the relationship between them was given in equation (12).

Au (ppm) = - 0.145 + 0.0504 Ca (%) - 0.0408 Fe (%) + 0.000235 Cu (ppm) - 0.0299 Al (%) + 0.471 Ti (%) + 0.00118 Zn (ppm) (12)

R-Sq = 74.8% R-Sq(adj) = 68.5%

The results will be obtained by comparing equations (11) and (12). As seen, the R-Sq of eq. (12), at 74.8%, is less than 80.6% in eq. (11). Also, the number of variables in eq. (11) was greater than in eq. (12), presenting the limitation of the MLRA (multivariate linear regression analyses) method. Indeed, the values of R-sq increaseby adding more variables, even if they have no geological and geochemical relation with the target element. In other words, the number of variables is crucial role in this method. Because the R-sq shows how many percent of the changes in the dependent variable are explained by the independent variables. Therefore, the R-sq assumes that each independent variable observed in the model explains the changes in the dependent variable. Therefore, the percentage shown by this index assumes the influence of all independent variables on the dependent variable. The percentage

shown by the R-sq adjusted is only the result of the actual effect of the independent variables of the model on the dependent (not all independent variables).

However, by checking R-sq (adjusted), 68.5% in eq. (12) versus 61.2% in eq. (11), it can be found that all elements are not related to the target element, but this description of the relationship is not sufficient.

5.2. SVM and BPNN

The BPNN and SVM techniques have been applied for more accurate Au grade prediction. The dataset should be divided into training and testing sets. Five elements, Fe, Cu, Al, Ti, and Zn, were the input data, while Au was the output. The network was trained by different modes, and training as well as testing data ratios, ranging from 90/10 to 50/50. The results are given in Table 2. As found, the best modes occurred when 70% of the data was for training and 30% for testing.

Table 2. The different selection ratio of testing/training data and its effect on the SVM and BPNN algorithms.

Model	Training/Testing (%)	R^2 (Train)	R^2 (Test)	RMSE (Train)	RMSE (Test)
BPNN	90/10	0.997	0.72	0.44	2.21
SVM		0.999	0.89	0.42	0.89
BPNN	80/20	0.997	0.74	0.43	2.03
SVM		0.999	0.91	0.41	0.85
BPNN	70/30	**0.997**	**0.75**	0.40	1.94
SVM		**0.999**	**0.94**	0.40	0.77
BPNN	60/40	0.990	0.67	0.54	2.91
SVM		0.991	0.87	0.45	1.02
BPNN	50/50	0.974	0.51	0.68	4.29
SVM		0.982	0.76	0.53	2.16

As mentioned before, five elements, Fe, Cu, Al, Ti, and Zn, were used in the primary statistical analyses (Table 1) for Au grade prediction. In the following section, various datasets with different numbers of elements were tested by applying the BPNN and SVM algorithms (Table3). The table shows that dataset (11) with Fe, Cu, Al, Ti, and Zn input parameters has the best results (maximum R^2 and minimum RMSE). Hence, this dataset was selected for further prediction procedures. It is worth mentioning that these elements (Cu, Al, Ca, Fe, Ti, and Zn) are highlighted in red color in different datasets for better visualization.

Based on (Tables 2) and (3) Au grade prediction was made by two following selected datasets: in the first dataset, Cu, Al, Ca, Fe, Ti, and Zn were the input data, and Au grade was the output. In the second one, the ratio of 70/30 was selected for training/test datasets. In both models, 70% of the data were randomly assigned to the training and 30% to the test sets. The modelling validation process was based on the Leave One Out (LOO) method, because this type of validation does not impose any bias on the modelling [52]. For choosing a suitable kernel for implementation, the Gaussian kernel was selected as the best kernel [58]. The one-out method was used to determine the value of the sigma kernel Gaussian parameter and the Ɛ penalty parameter. The best values for Sigma and Ɛ were 0.13 and 0.08, respectively.

The differences between the actual and predicted data reveal that the first method is unsuitable for prediction. The correlation diagram between the actual and predicted Au grades is presented in Fig 10. The correlation coefficient between them is 75%.

Fig10. The prediction model of Au grade and the correlation level obtained by the BPNN technique

Although the result of the BPNN for the Au grade prediction had an acceptable level, it could be enhanced. Therefore, the SVM technique was applied. The correlation between the actual and predicted data using the SVM technique is also demonstrated in Fig 11.

The results revealed that the SVM method could predict Au grades more precisely than the BPNN technique, which was close to reality. Based on the Fig11 and the high correlation coefficient value of 94%, it is found that the predicted data corresponded well with the actual data by employing the SVM technique.

Table 3. Various dataset selection and its effect on the accuracy of the SVM and BPNN algorithms.

Model	Dataset	Input parameters	R^2 (Train)	R^2 (Test)	RMSE (Train)	RMSE (Test)
BPNN	Dataset 1	Cu, Al, Ba, Ca, Cr, Fe, K, Mg, Mn, Na, P, Pb, Sr, Ti, V and Zn	0.901	0.34	0.91	5.95
SVM			0.932	0.60	0.80	3.12
BPNN	Dataset 2	Cu, Al, Ca, Cr, Fe, K, Mg, Mn, Na, P, Pb, Sr, Ti, V and Zn	0.911	0.35	0.86	5.91
SVM			0.938	0.61	0.75	3.04
BPNN	Dataset 3	Cu, Al, Ca, Fe, K, Mg, Mn, Na, P, Pb, Sr, Ti, V and Zn	0.941	0.39	0.65	5.18
SVM			0.973	0.65	0.51	2.90
BPNN	Dataset 4	Cu, Al, Ca, Fe, Mg, Mn, Na, P, Pb, Sr, Ti, V and Zn	0.964	0.44	0.53	4.90
SVM			0.981	0.70	0.48	2.70
BPNN	Dataset 5	Cu, Al, Ca, Fe, Mn, Na, P, Pb, Sr, Ti, V and Zn	0.979	0.49	0.50	4.61
SVM			0.987	0.74	0.47	2.42
BPNN	Dataset 6	Cu, Al, Ca, Fe, Na, P, Pb, Sr, Ti, V and Zn	0.981	0.54	0.49	4.29
SVM			0.989	0.78	0.48	2.11
BPNN	Dataset 7	Cu, Al, Ca, Fe, P, Pb, Sr, Ti, V and Zn	0.984	0.58	0.47	3.91
SVM			0.991	0.83	0.46	1. 82
BPNN	Dataset 8	Cu, Al, Ca, Fe, Pb, Sr, Ti, V and Zn	0.985	0.59	0.46	3.80
SVM			0.992	0.84	0.45	1.70
BPNN	Dataset 9	Cu, Al, Ca, Fe, Sr, Ti, V and Zn	0.992	0.67	0.43	2.91
SVM			0.997	0.85	0.42	1.08
BPNN	Dataset 10	Cu, Al, Ca, Fe, Ti, V and Zn	0.995	0.73	0.41	1.99
SVM			0.999	0.93	0.40	0.79
BPNN	Dataset 11	Cu, Al, Ca, Fe, Ti, and Zn	**0.997**	**0.75**	0.40	1.94
SVM			**0.999**	**0.94**	0.40	0.77

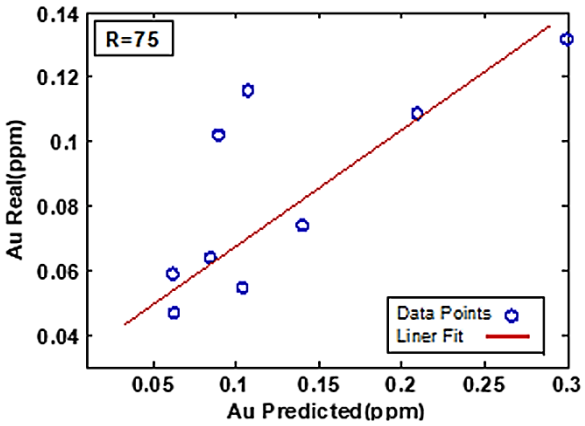

Fig10. The prediction model of Au grade and the correlation level obtained by the BPNN technique.

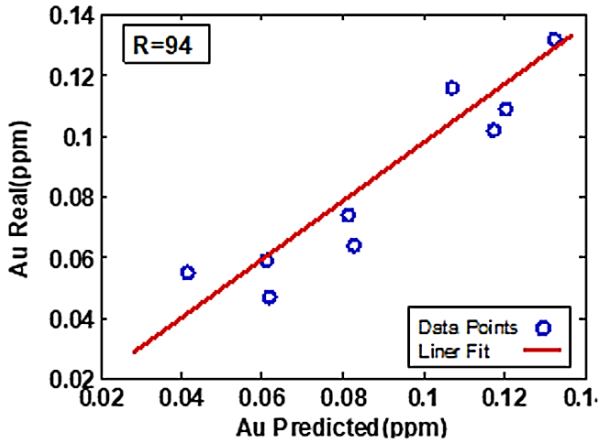

Fig 11. The Au grade prediction model and correlation obtained by the SVM technique.

Gold exploration studies pose challenges at all exploration stages Gold is a special metal whose amount is very low (ppm), in the early stages of reconnaissance, its amount may be about ppb. Its analyses are expensive and cannot be detected by analytical methods, so it may not be identified with usual geochemical studies, including sampling and analysis, like other elements. In the MPM of gold exploration, one of the main layers that we should use in gold exploration studies is the gold grade distribution map, accompanied by a challenge.

One way to overcome this problem is to obtain the relationship of gold with other elements, including trace elements and those associated with gold mineralization in the studied area. Based on the obtained relationship, it is possible to compensate for the lack of information and to predict the value of the layer of MPM with proper accuracy. It is worth mentioning that achieving accurate gold grade predictions enables the creation of 2D and 3D gold grade distribution maps for use in MPM.

There are various methods to check the relationship between elements. According to the mentioned conditions for the gold grade, the method that has the least error should be used. The purpose of this research is to investigate the different methods of relationship between elements and to predict the gold grade, especially in the case where there was a small amount of data. The SVM technique is one of the most powerful methods for predicting one variable according to several other variables. One of the main advantages of the SVM technique is its accurate prediction, particularly with a small dataset. According to the metioned items, the MLA, BPNN, and SVM were used.

Using the statistical analysis, related elements including Cu, Al, Ca, Fe, Ti, and Zn were selected for gold prediction. So, the gold grade was predicted by these elements and using the MLA, BPNN, and SVM methods. The results obtained from various methods were comared. The results showed that the SVM method was superior in predicting the gold grade. Therefore, in MPM studies for gold exploration, it is more efficient than other methods to prepare gold layer, especially with the use of other elements.

6. Conclusions

The gold distribution map is one of the main layers in the mineral prospectivity mapping (MPM) for gold exploration. Due to the unique nature of gold, preparing this layer is always challenging and comes with problems. The aim of this study is to provide a solution to overcome this challenge. For this purpose, we used the MLR, BPNN, and SVM techniques for predicting the gold grade using other elements.

Dalli copper-gold porphyry deposit was selected as a case study. After building a dataset, the gold was selected as the independent variable, and the Cu, Al, Ca, Fe, Ti, and Zn were determined as the independent variables based on the statistical results.

The dataset was then divided randomly divided into two categories, 70% for training, and 30% for testing data. The correlation coefficients of the MLR, BPNN, and SVM techniques were 68%, 75%, and 94%, respectively. The comparison between the results showed that although all mentioned techniques could reasonably estimate gold grades, the SVM method had better performance. Therefore, SVM would be more reliable than the others to predict the gold grades by considering a few data for the gold prospectivity mapping.

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