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| RESEARCH ARTICLE

Estimation of Shadan Gold Deposit Lithology Based on Wells Coordinate Data Using Artificial Neural Network Method.

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| ABSTRACT

Machine learning today has become a more effective instrument to solve many particular problems where there are difficulties problems to predicted lithology. In other words, it is a great tool for describing non-linear phenomena. We tried to use this technique to improve the existing process of predicted lithology and reduce costs on site by applying computer leaded predictions on the basis of existing on-field collected data. The dissertation describes the usage of machine learning algorithms for predicted lithology modelling based on exploration wells coordinate data for Shadan Gold Deposit. We use core analysis and well testing to determine the lithology. Unfortunately, coring from each well in the Shadan gold deposit is very expensive. However, because of the importance of this information which is obtained from lithology, it is necessary to coring from some of the deposit wells. The purpose of this study is to give a prediction of lithology in the Shadan gold deposit using an artificial neural network with back propagation algorithm (BP) and Trainlm algorithm with Mat lab software from Exploration wells coordinate data. This method can reduce the requirement of coring and reduce the costs. The area we have studied consists of six lithologies, including Andesite, Granodiorite, propylitic Alteration, Silicated Andesite, Limestone and Silica Streak. The regression between the predicted and the real values of Train, Test and Validation are obtained, respectively, as 0.94, 0.93 and 0.93. And also, RMSE the Train, Test and Validation are obtained respectively, as 0.1000, 0.1252 and 0.1012. The results show that the neural network gives a reasonable estimation for lithology.

| KEYWORDS

Lithology Modelling, Shadan Gold Deposit, wells coordinate data, artificial neural network method

| ARTICLE INFORMATION

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1. Introduction

Iran is located in the central part of the Tethyan orogenic and metallogenic belt, and its diversity in magmatism, geodynamics and mineralization is a consequence of the subduction of various generations of Tethyan Ocean and the accretion of Gondwana-derived micro-continents to the southern margin of Eurasia (Stocklin, 1968; Berberian & King, 1981; Richards & Sholeh,2016). Numerous mineral deposits are known to be associated with the Neotethyan Ocean evolution (Richards, 2015). This subduction and subsequent collision have produced three main magmatic belts: (i) the Eastern Iranian Magmatic Belt (EIMB), (ii) Urumieh-Dokhtar Magmatic Belt (UDMB), and (iii) the Alborz-Azerbaijan Magmatic Belt (AAMB) (Berberian & King, 1981; Verdel et al., 2011; Pang et al., 2013; Omidianfar et al., 2020).

The Sistan suture zone is a branch of the Neotethyan Ocean with a complex tectonic history (Camp & Griffis, 1982; Tirrul et al., 1983; Pang et al., 2013). Magmatic activity in the Sistan suture zone and generally in the east of Iran occurred during a period mostly from Middle Eocene to the Late Oligocene (Pang et al., 2013). Subduction between the Lut Block and the Afghan Block is a controversial issue, and various tectonic-magmatic theories have been proposed. Verdel et al. (2011) ascribed the mineralization in Eastern Iran to an extensional rift basin, but most researchers believe that the subduction is an undeniable subject. Saccani et al. (2010), by studying the ophiolitic complex of Nehbandan, suggested that subduction has played a key role in the closure of the Sistan Ocean and the associated mineralization resulted from the eastward intra-oceanic subduction of the Sistan Ocean beneath the Afghan Block. In addition, Camp & Griffis (1982) and Tirrul et al. (1983) proposed that magmatic activity in the East of Iran resulted from the eastward subduction of the Sistan Ocean beneath the Afghan Block. On the other hand, Berberian & King (1981), Zarrinkoub et al. (2012) and Pang et al. (2013) proposed that subduction of the Sistan Ocean was westward beneath the Lut Block. Meanwhile, two-sided asymmetric subduction is another theory in the closure of the Sistan Ocean (Arjmandzadeh et al.,2011). Omidianfar et al. (2020) studied the Koudakan intrusive in EIMB and proposed delamination of thickened lithosphere after a collision between the Lut Block and Afghan Block.

The Tertiary plutonic and volcanic rocks are widely distributed in the southwest of Birjand. Recently, significant deposits have been reported in this area, including Maherabad, Khopik, Khunic and Hired. Mahdavi et al. (2020) stated that the Shadan area is a porphyry deposit. Richards (2012) determined the age of the Shadan gold (+copper) deposit as 37.26 ± 0.26 Ma. Malekzadeh & Karimpour (2011) reported the U-Pb zircon ages of 39 ± 0.8 Ma from monzonite rocks of the Maherabad Cu-Au deposit. Malekzadeh et al. (2014) attributed the formation of the Khopic porphyry copper deposit to Middle Eocene magmatism in eastern Iran. The Khunic area has been studied by Samiee et al. (2019), who believed that the hydrothermal breccia in the central part of the area is the main mineralization phase. As reported by Karimpour et al. (2007), the Hired gold-tin prospecting area is associated with S-type granites.

Due to the ambiguities about the petrogenesis of magmatic systems in the Shadan area, the purpose of this study is to discuss and present the geochemical data to decipher the petrogenesis and petrology of the Shadan intrusive and subvolcanic rocks in the East of Iran in the context of geodynamics and metallogenic evolution of the system (Fig. 1).

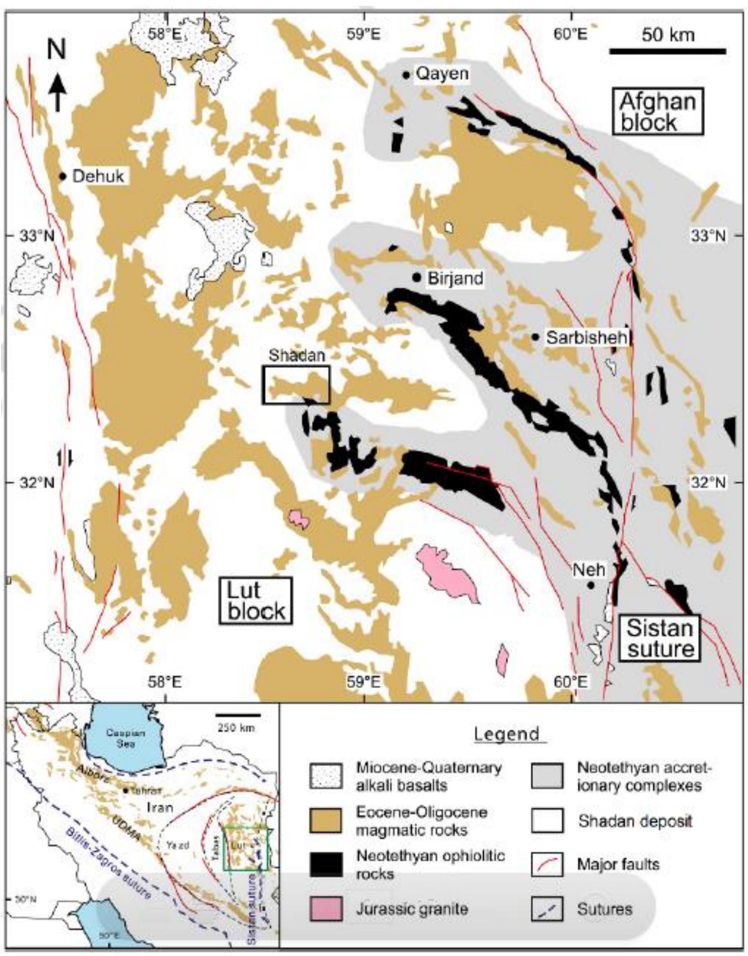


Figure 1. Geological map of Lut-Sistan region, east of Iran and location of the Shadan deposit in the Lut Block (Modified from Pang et al., 2013 and Modabberi et al., 2019)

2. Geology of the studied area

Shadan area is located 60 km southwest of Birjand, near Khousf town, in the Lut Block (32°23′ 42″-32°20′ 56″ N and 58°56′ 96″-58°59′ 57″ E) in the South Khorasan province, Iran. The Lut Block, with a length of 900 km, is one of the structural units of the Central Iran microcontinent, which is bounded to the west by the Nayband Fault, to the east by the Nehbandan Fault and Sistan suture zone, to the north by the Dorouneh fault and to the south by the Jazmourian depression (Berberian & King, 1981). The Lut Block is composed of a pre-Jurassic metamorphic basement, Jurassic sedimentary rocks and various generations of Late Mesozoic and Cenozoic volcanic-intrusive rocks (Camp & Griffis, 1982; Tirrul et al., 1983). The magmatic activity in the Lut Block was initiated in the middle Jurassic (165-162 Ma), and its peak was in the Tertiary (Karimpour et al., 2011). In terms of the geological situation, the Shadan gold (+copper) deposit is located in the 1:250000 Birjand geological map (Vahdati-Daneshmand & Eftekhar-Nejad, 1991) and in the northeast corner of the 1:100000 geological map of Sarchehe- Shoor (Vassigh & Soheyli, 1975).

Based on the 1:100000 sheet of Sarcheh-e-Shoor, the study area consists of dacite, altered andesite, tuff breccia and a number of subvolcanic to intrusive rocks. However, field evidence and petrographic studies indicated that most of the volcanic rocks in the Sarcheh-e-Shoor geological map are subvolcanic and intrusive rocks. According to the 1:1000 Shadan geological map (Karand Sadr-e-Jahan Co. 2022) and field studies (Fig. 2), Mineralization in Shadan region befalls in two separate areas, respectively, in oxide and sulfide regions. The main metallic minerals in these regions include pyrite, chalcopyrite, chalcocite, bornite, magnetite, pyrrhotite, hematite, colitis, malachite, and iron hydroxides. Lithological units can be divided into three units:

1) Eocene volcanic-pyroclastic rocks with intermediate to mafic composition, which has undergone quartz-carbonate, argillic and propylitic alteration,

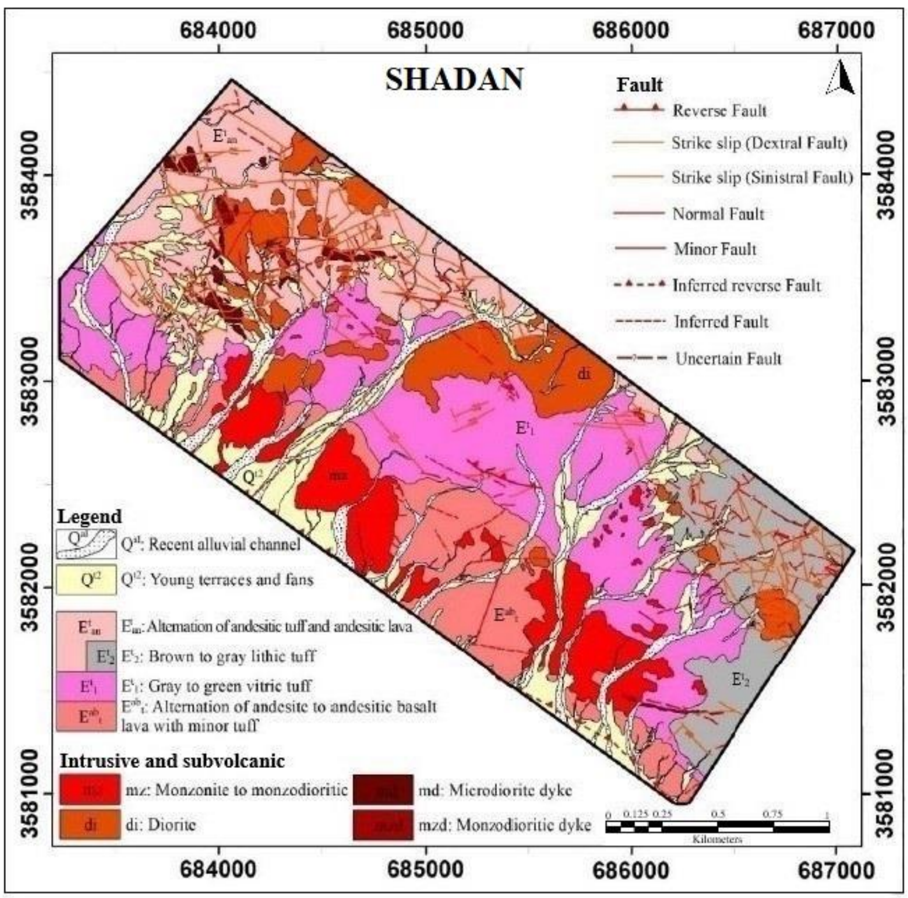


Figure 2. Simplified geological map of the Shadan area (Karand Sadr-e-Jahan Co. 2022)

2) Eocene-Oligocene subvolcanic and intrusive rocks with a northwest-southeast trend and intermediate to felsic composition, which intruded into the volcanic-pyroclastic rocks. These rocks consist of granodiorite to gabbro-diorite with potassic, sericitic, argillic, quartz-carbonate and propylitic alteration,

3) Quaternary unit, consisting of young and old terraces, recent alluvium and debris. Based on the tectonic studies, faults, especially strike-slip faults, are major structures in the Shadan area. Approximately, faults have been formed in all directions in the study area;

3. Materials and methods

The estimation of lithology is one of the most key and complicated aspects in the valuate of deposits. The complication of that is due to scientific uncertainty. In the last years, due to the most dependency on mining projects for the most exact determination of lithology, different methods have existed for the estimation of lithology, of which we can point to geometric roles, distance based and geostatistics. But every one of these methods has limitations and weaknesses that affect the estimate accuracy.

The exercitation of abilities method in the estimation of lithology has an important role in reducing errors and estimation limitations. These reduced errors and limitations can reason for improved reservoir estimation and therewith can be design improvement and economic planning in the mine. As for errors existent in field use from normal roles for estimation of lithology in gold mines, in this research, the efficiency of intelligence estimators, like artificial intelligence, purposeful to estimation lithology of the Shadan gold deposit. The present research, including the first item of estimation of lithology, is used from wells coordinates, which, fortunately, the result gets acceptable.

The most important property of neural networks, non-linearity and ability is removing noise. Neural networks don't need clear instructions and specific mathematical models, and to solve problems that their formulas are unknown and or ambiguities, it's not seen there; it's applicable where minerals complicate data and non-linearity. Therefore, artificial neural networks can be an effective technique to solve this problem. One of the uses of neural networks in earth science issues, it's an estimation of lithology. In the issues of estimation of lithology by neural networks, network input is wells coordinates data and lithology at those coordinates (network output) network training by this data. Then for each coordinate provided to a learned neural network, the corresponding output in those coordinates is the estimated lithology, estimated by the network.

4. Preparation of used data

For every research faced by artificial intelligence neural networks, we need the data. In this research, we use the term exploratory data of the well coordinates (X, Y, Z) and the nature of lithology exist of these wells in the Shadan gold deposit. Now Wells are drilled vertically, so these coordinates it's available to use. and not important to make new coordinates (x, y). Alone part of lithology, which it's considered as output data, we must change it to qualitative data to be understandable for the MAT lab program, input and output data defined like a Matrix and then all data made normal in intervals of (0 - 1) in finally inserted input and output data to the network for training.

5. Network input data

In this research, input data include the wells coordinates (X Y Z), prepared sixteen wells to complement Related to Shadan gold deposit that gives in total 2490 coordinates; the network is designed programming in MAT lab to select this data randomly 70% for training 20% for test and 10% for validation. The network is trained with input and output data; if the network is best trained, finally network can estimate lithology.

6. Network output data

Network output is all of the lithology which exists in sixteen wells from the Shadan gold deposit, consisting of Andesite, Granodiorite, propylitic Alteration, Silicated Andesite, Limestone, and Silica streak rocks; these lithology's are qualitative data.

So that we can change qualitative data to quantity, we must consider code for lithology to can them insert into the network, so respectively for them choose numbers (1, 2, 3, 4, 5, 6) as a code shows in (Table.1).

Table 1. Lithology code for inserted data to network

Lithology code	Type of lithology
1	Andesite
2	Granodiorite
3	propylitic Alteration
4	Silicated andesites
5	Limestone
6	Silica streak

7. Back propagation network (BPN)

An Artificial Neural Network (ANN) is a simplified simulation of biological neural networks in human brains. ANN is capable of "learning"; that is, it can be trained to improve its performance by either supervised or unsupervised learning. The back-propagation network (BPN) and the supervised learning, i.e., learned by samples, are chosen in this study. After learning (or training), the trained weight can be used for future prediction of debris flow occurrence. The BPN is an ANN using a back-propagation algorithm and is one of the popular ANNs, which has been widely applied to many scientific and commercial fields for non-linear analysis and prediction. The structure of BPN contains three layers: input, hidden, and output layers, as shown in Fig. 3. Each layer contains *I*, *J*, and *K* nodes denoted respectively by circles. The node is also called a neuron or unit. The circles are connected by links, denoted by arrows in Fig. 1, each of which represents a numerical weight. The *wij* is denoted as numerical weights between input and hidden layers, and so is *wjk* between hidden and output layers, as also shown in Fig. 3. The processing or computation is performed in each node in the hidden and output layers. The back propagation learning algorithm is composed of two procedures: (a) feed-forward and (b) back propagation weight training.

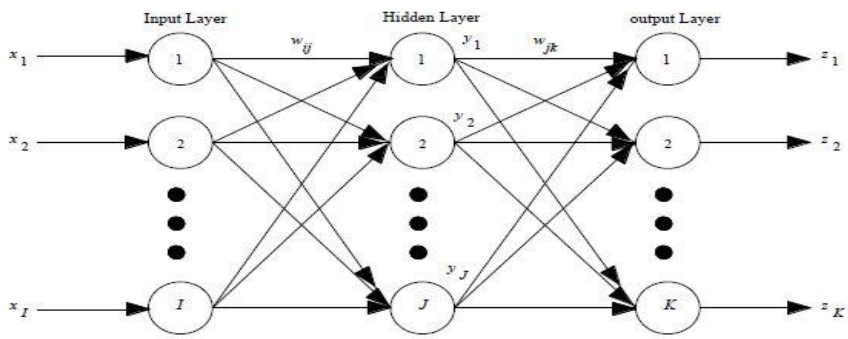


Figure 3. Neural network structure back propagation (baolong zhu. 2011)

7.1. Training samples and results

A total of 20 records used for training were selected from Shadan Gold deposit. This study utilized these records to feed into the ANN model for training. The learning rate and momentum term were 0.01 and 0.87, respectively. The stop criterion of the error function was set to 0.001, and the maximum number of iterations was 2000. The initial weights were random numbers generated by the computer. After 878 times were trained, a single study sample error of less than 6%, which shows the convergence of the network.

At first, the model was run once, and point-by-point lithology estimation was tested after comparing the actual lithology with the predicated lithology by the network of obtained regression values for training '0,94 for test 0,93 for validation 0,93 and also mean square error values for training '0,1000 for test 0,1252 and for validation 0,1012 was obtained, These outcomes demonstrate that the well coordinate data and lithology in those coordinate are stable and reliable for estimated lithology.

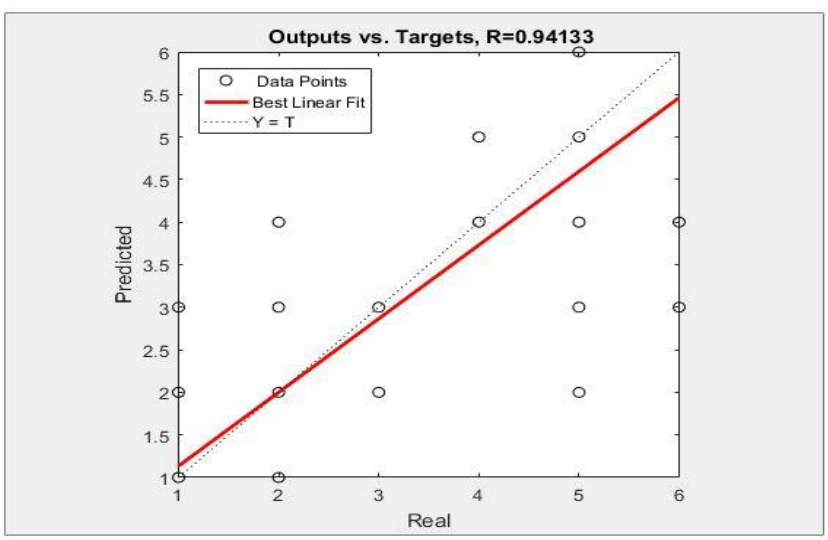
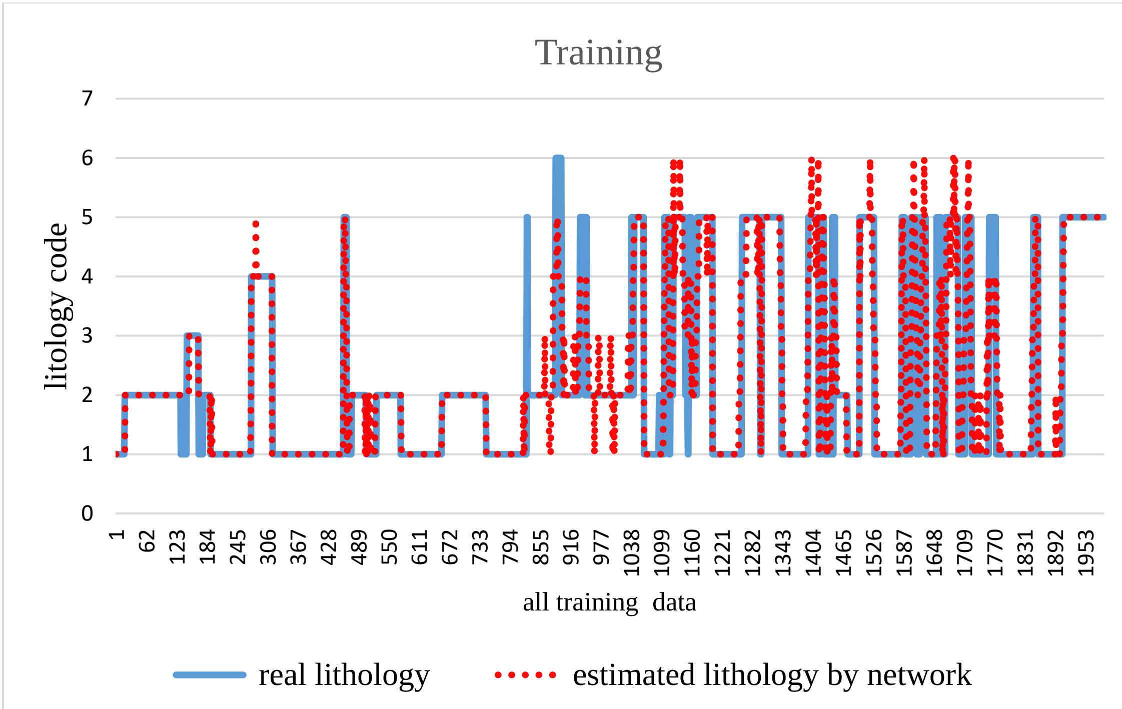


Figure 4. The regression coefficient (R) training shows the between network outputs and the real output.



Graph 1. Comparison of training data, real lithology & estimated lithology by network

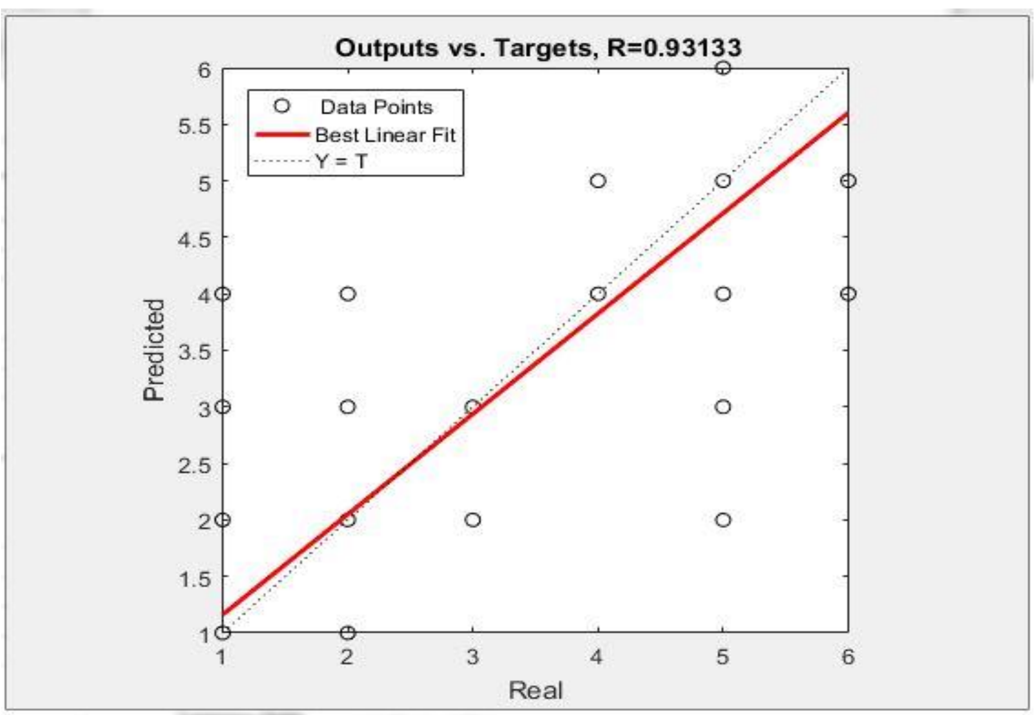
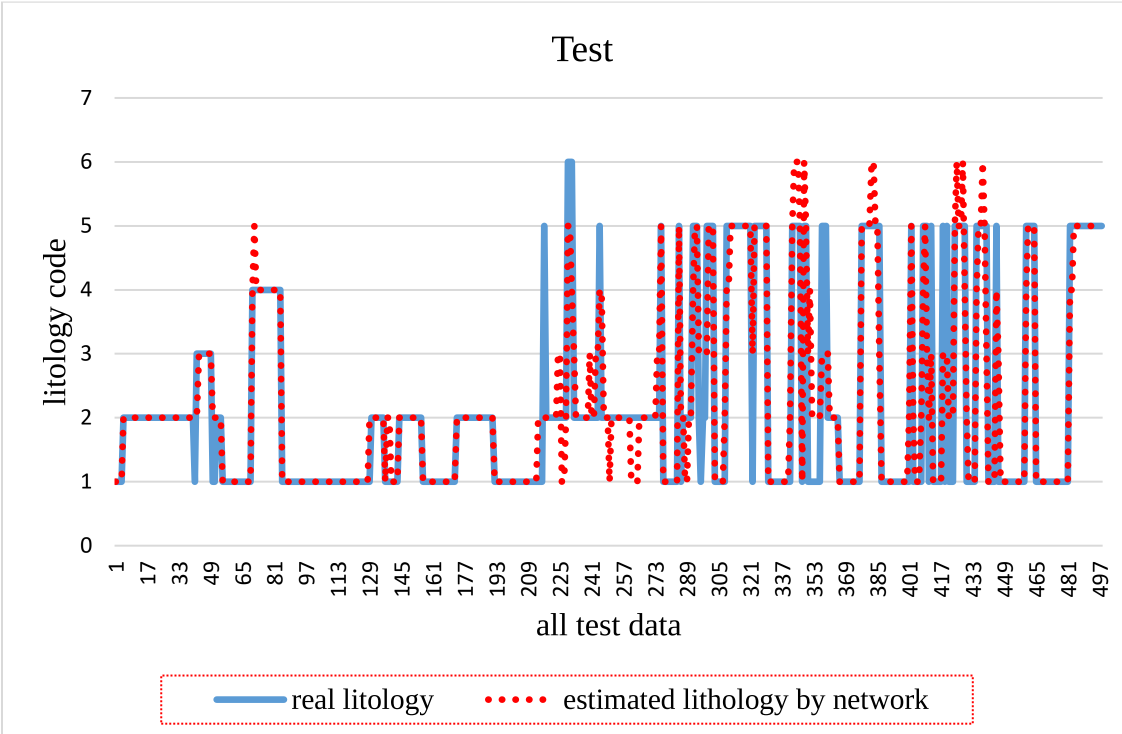


Figure 5. The regression coefficient (R) test shows the between network outputs and the real output.



Graph 2. Comparison of test data, real lithology & estimated lithology by network.

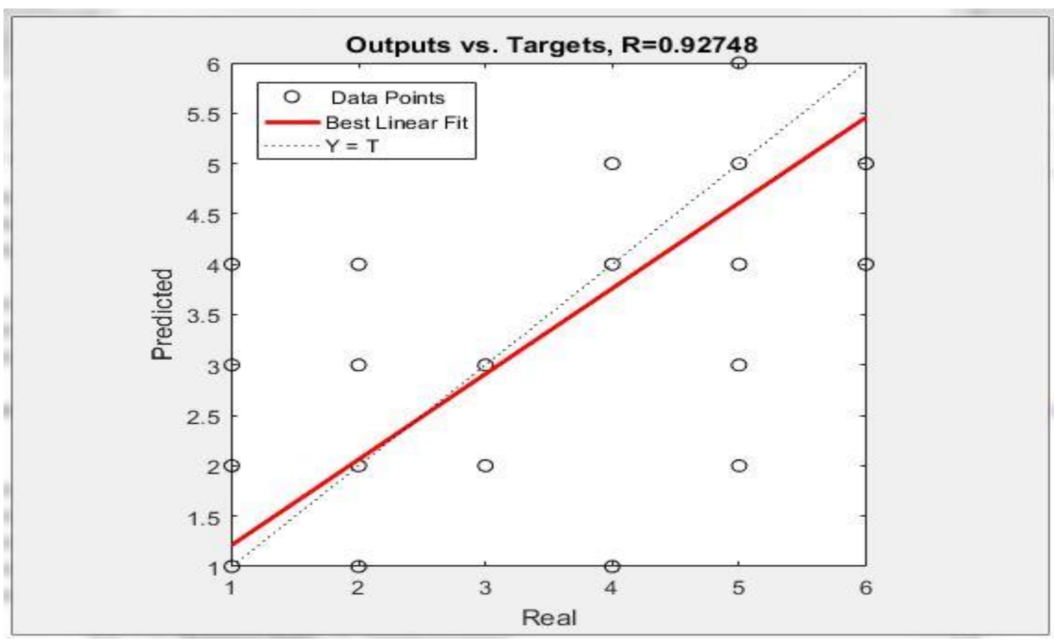
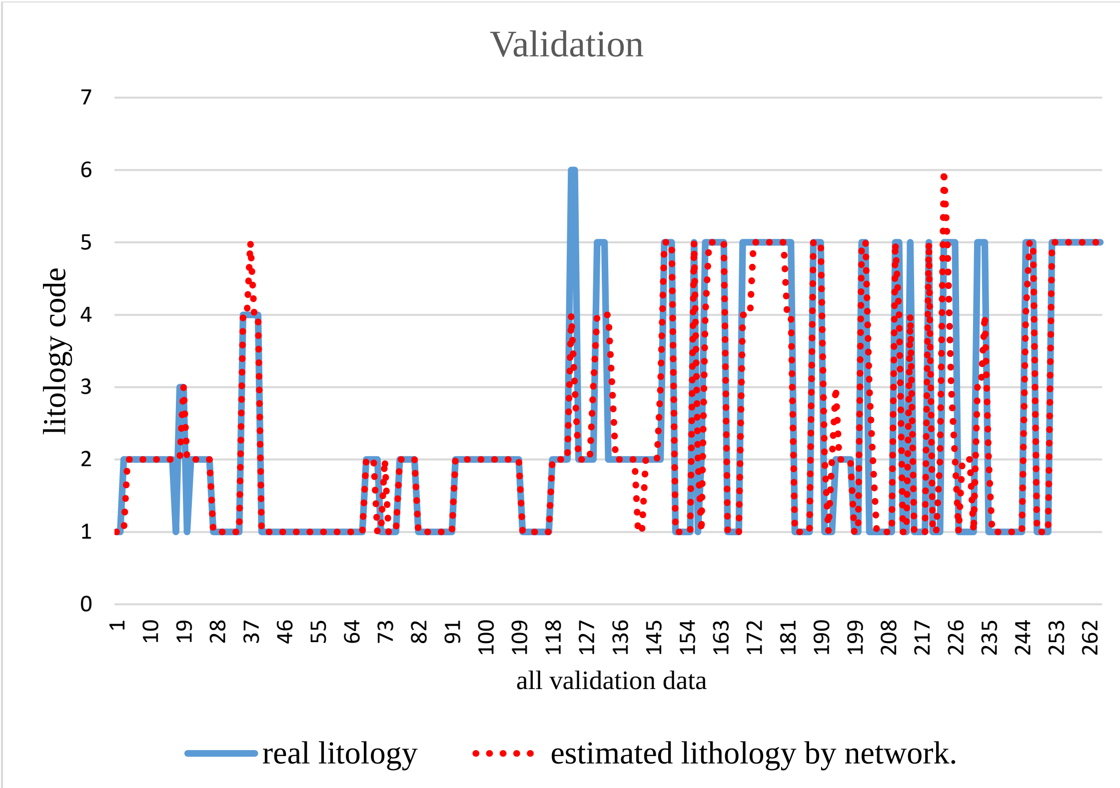


Figure 6. The regression coefficient (R) validation shows the between network outputs and the real output.



Graph 3. Comparison of validation data, real lithology & estimated lithology by network

Then to ensure the efficiency and stability of the network, select twenty iterations and run the MAT lab program; the root mean square errors of training, test and validation results for every twenty iterations shows in (Table 2).

Table 2. Root means square error, training, test and validation.

RMSE Validation	RMSE Test	RMSE Train	iterations
0.1108	0.1288	0.1000	1
0.1050	0.0991	0.0999	2
0.0961	0.1113	0.1000	3
0.0997	0.1015	0.1000	4
0.1110	0.1111	0.1000	5
0.0965	0.1214	0.1000	6
0.1088	0.1150	0.1000	7
0.1146	0.1165	0.1000	8
0.1074	0.1312	0.0999	9
0.1034	0.1039	0.1000	10
0.1032	0.1216	0.1000	11
0.1045	0.1036	0.1000	12
0.0868	0.1013	0.1000	13
0.0988	0.1154	0.1000	14
0.1006	0.1155	0.1000	15

0.0896	0.1181	0.1000	16
0.0856	0.1145	0.1000	17
0.0929	0.1317	0.1000	18
0.1044	0.1149	0.1000	19
0.1044	0.1205	0.1000	20
0.1012	0.1252	0.1000	Avrage

From review (Table 2), the mean square error of training, test and validation of the network shows that the network has excellent stability for lithology estimation, and regressions obtained from this implementation were for training 0,94, for test 0,93 and for validation 0,93 which shows that the network is stable and reliable.

8. Conclusion

There are various methods for lithology estimation modeling based on the uncertainty that is in the traditional methods of lithology determination. An attempt was made to estimate lithology in order to avoid uncertainty as much as possible. Because lithology estimation is one of the most complicated parts of determining the mine, artificial intelligence has the ability to solve complex problems. In this research, the artificial intelligence method, back propagation network was used to estimate lithology; after running the MAT lab R2016a program and comparing the outputs predicted by the network with the actual output, the result of matching the outputs for the training phase is 94%, for the test 93% and for the validation 93%. and (RMSE) values for training 0.1000, for test 0.1252, and for validation 0.1012. The result of the comparison shows that the network has the best performance in lithology estimation; the results of this research are as follows:

- ✓ The proposed method is based on artificial neural networks, which have the ability to solve complex problems.
- ✓ Before using any type of neural network, quality control and normalization should be done on the available data.
- ✓ Neural network leads to accurate prediction of lithology, reduction of huge drilling expenses and accurate mine determination.

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