Journal of Mining and Environment (JME) Vol. 18, No. 4, 2026, 1429-1443

Shahrood University of Technology

Journal of Mining and Environment (JME)

Journal homepage: www.jme.shahroodut.ac.ir

Iranian Society of Mining Engineering (IRSME)

Improving the Copper Grade Estimation at the Chehel Kureh Copper Mine using Machine Learning Methods

Hamed Norouzi[1*], and Ali Akbar Daya[2]

1. Department of Mining Engineering, Isfahan University of Technology, Isfahan, Iran
2. Department of Mining Engineering, University of Sistan and Baluchestan, Zahedan, Iran

Article Info

Received 29 May 2025
Received in Revised form 5 July 2025
Accepted 1 August 2025
Published online 1 August 2025

DOI: 10.22044/jme.2025.16326.3177

Keywords

Machine Learning
Gaussian Process Regression
Chehel Kureh
Grade Estimation
Spatial modeling

Abstract

Estimating mineral reserves in exploration or extraction projects is a critical and challenging process. It must be conducted precisely, regardless of the mining scale and mineral type. With the growing significance of mineral resources in economic and industrial development, the importance of adopting advanced technologies in mineral assessment has also surged. Modern spatial grade modeling techniques can play a pivotal role in decision-making processes. This study aims to compare the performance and capabilities of two popular machine learning methods, including Gaussian Process Regression (GPR) and Multilayer Perceptron Artificial Neural Network (MLP-ANN) in spatial grade modeling of copper at the Chehel Kureh Copper deposit. The dataset comprises 42 drill holes with an average copper grade of 0.18%. Each core sample data point includes seven variables: three spatial coordinates (X, Y, and Depth), lead grade, zinc grade, lithology and copper grade, which serves as the target variable. The Gaussian Process Regression (GPR) and Multilayer Perceptron (MLP-ANN) neural network were employed for copper grade estimation. To make a better assessment, the hyperparameters of both models were optimized using the Bayesian Optimization algorithm. The results showed that the Gaussian Process Regression outperformed MLP-ANN, achieving an RMSE of 0.04 and a coefficient of determination (R^2) of 0.89 compared to an RMSE of 0.05 and a coefficient of determination (R^2) of for MLP-ANN, suggest the superiority of the Gaussian Process Regression method in estimating copper grade spatial variability.

1. Introduction

Machine learning is an important complement to traditional techniques like geostatistics [1]. The concentration of minerals is a function of the location, geological settings, and structural characteristics of the ore deposit [2]. Machine learning methods can provide more accurate predictions in this domain without resorting to specialized expert knowledge [2]. The estimation problem is especially challenging in porphyry deposits [2]. Recently developed data mining and machine learning techniques allow one to identify patterns in large multivariate data sets and make predictions [3]. Overcoming these challenges requires breakthroughs that significantly transform intelligent systems while greatly benefitting geosciences [4]. However, recent advances in computer algorithms have allowed researchers to explore the potential of machine-learning techniques in mineral resource estimation [5]. Machine learning improves resource estimation in the following ways. For example, samples rejected in conventional resource estimates because they do not satisfy all quality control requirements can be used, provided the geological descriptions and measurements are reliable. Resource estimation block models can be constructed using fewer assays and more geology, reducing operational costs [6]. In recent years, machine learning techniques have emerged as a viable alternative to traditional geostatistical methods for addressing challenges in Mineral Resource estimation [7]. The synergy between traditional principles and modern

Corresponding author: Hamed.Norouzi@alumni.iut.ac.ir (H. Norouzi)

AI-driven techniques holds immense promise and will shape the trajectory of geoscience in the upcoming years [8]. Machine learning algorithms can provide a rich spectrum of approaches that directly learn from available data without making assumptions about the data [9]. Artificial neural networks (ANNs) have gained popularity for resource estimation in recent years due to their ability to model complex relationships in sample data [10]. Artificial Neural Networks (ANNs) are a better alternative to geostatistical techniques since they take less processing time to create and apply and do not require experimental variogram calculations with small input data [11]. A study was conducted to explore the effectiveness of the Gaussian process regression technique. This study compared various machine learning methods, including neural networks (NN), random forests (RF), and Gaussian processes (GP), with traditional geostatistical techniques like ordinary kriging (OK) and indicator kriging (IK) for estimating copper ore grades in the Sarcheshmeh porphyry copper deposit in Southeastern Iran. The research emphasized the importance of realistic testing protocols, ensuring training and test data were from different drill holes to avoid interpolation bias. Key findings revealed that Gaussian processes achieved the highest predictive accuracy, particularly when incorporating symmetric standardization of spatial inputs and an anisotropic kernel. Including rock type as an additional predictor further improved results. Neural networks and random forests performed well but were less accurate than GP and IK, especially for high-grade ore regions. The study highlighted the significance of geological information and spatial anisotropy in enhancing ore grade estimation. Overall, the results demonstrated the superiority of Gaussian processes over other methods, providing a robust framework for mineral grade prediction in complex deposits [2]. Another study evaluates various methods for estimating ore grades in structurally complex vein deposits, focusing on gold and other minerals. The study compares classical methods, including geostatistical techniques (such as kriging), and Artificial Intelligence (AI) approaches, particularly Artificial Neural Networks (ANNs), for ore grade estimation. The study focuses on gold deposits and resources, and other minerals such as iron, copper, lead, zinc, and bauxite in structurally controlled vein deposits. The study recommends AI techniques, particularly ANNs, for grade estimation in structurally complex vein deposits due to their flexibility, ability to handle nonlinear trends, and reduced reliance on restrictive assumptions. These methods offer a viable alternative to traditional geostatistical approaches, especially in deposits with erratic grade distributions [12]. This study applied an Artificial Neural Network (ANN) to predict copper ore grades at the Jaguar mine in Western Australia. The study compared the ANN with classic machine learning methods, including extra trees regressor, random forest regressor, light gradient boosting machine (LGBM), K-neighbors regressor, and linear regression. The ANN outperformed all these methods, with linear regression showing the poorest performance. Feature importance analysis using Shapley values revealed that lithology had the highest influence on grade prediction, while eastings had the least impact. The results highlight the ANN's superiority over traditional and other machine learning techniques for copper ore grade estimation, offering a robust tool for mine planning and resource evaluation [13]. Another study employed machine learning techniques, including Multilayer Perceptron Artificial Neural Networks (ANN-MLP), Random Forests (RFs), Extreme Gradient Boosting (XGBoost), and Support Vector Regression (SVR), to predict copper ore grades in the Peruvian copper deposit. The study concluded that XGBoost was the most effective for copper grade prediction, highlighting its potential to enhance accuracy in mineral resource estimation [14]. This study employed a hybrid machine learning approach to categorize mineral resources in a copper deposit in Peru. The methodology integrated the K-prototypes clustering algorithm for initial classification and the Random Forest (RF) model as a spatial smoother. Compared to traditional geostatistical methods, the RF-based approach improved classification objectivity, spatial continuity, and reproducibility, minimizing abrupt transitions between categories. This research highlights the effectiveness of machine learning (Random Forest) in enhancing mineral resource categorization, outperforming conventional techniques like OK in terms of accuracy and geological coherence [15]. Focusing on iron ore estimation, this study evaluates ore grade uncertainty in the Rezvan iron mine using Sequential Gaussian Simulation (SGS) and Ordinary Kriging (OK). SGS generated multiple realizations to capture grade variability, while OK provided a single smoothed estimate. Results showed SGS better replicated exploration data distributions and yielded higher net present value (NPV) in mine planning compared to OK. The SGS-based pits reduced deviation from production targets, demonstrating lower risk. The study

highlights SGS's superiority over OK for iron ore grade estimation under uncertainty, enabling more reliable pit designs and economic outcomes [16]. Expanding the application to copper deposits. This study evaluates grade uncertainty in an underground copper vein deposit using Sequential Gaussian Simulation (SGS) and ordinary kriging (OK). Fifty SGS realizations were generated and compared with OK to assess ore reserve variability and economic impacts. Results revealed significant discrepancies: SGS predicted ore reserves between 453,000–799,000 tonnes (95% confidence), while OK yielded a single estimate of 644,525 tonnes. Economic values ranged $6.7M–$30.7M (SGS) versus $15.6M (OK), highlighting OK's smoothing effect and underestimation of uncertainty. The heuristic-based SLO3D algorithm optimized stope layouts, demonstrating SGS's efficacy in risk-aware mine planning [17]. Moving to artificial intelligence approaches. This study proposes a hybrid artificial intelligence approach combining Extreme Learning Machine (ELM) and Particle Swarm Optimization (PSO) for iron ore grade estimation in the Choghart deposit, Iran. ELM, a single-layer feedforward neural network, was optimized via PSO to minimize the mean absolute error (MAE) between estimated and actual grades. Results demonstrated enhanced accuracy with PSO-ELM compared to standalone ELM, particularly in central boreholes, though marginal boreholes showed extrapolation limitations. The method leverages drill-hole data (location, depth, and assays) and highlights the efficacy of metaheuristic-optimized neural networks in complex mineral grade estimation [18]. Building on AI applications, this study introduces a Python-based AI framework for estimating iron ore (Fe_2O_3) grades in the Choghart deposit, Iran, combining Mean Shift clustering, Random Forests, and Gradient Boosting. Mean Shift segmented drill-hole data spatially, Random Forests predicted clusters, and Gradient Boosting regressed grade values. Results achieved 91% accuracy in ore-block detection, with low errors (training MSE: 0.001, MAE: 0.029; testing MSE: 0.002, MAE: 0.03). Validation on excluded boreholes revealed marginal extrapolation limitations (max MAE: 0.2). The hybrid method outperformed individual models, demonstrating robustness against sparse, noisy data. This approach highlights AI's potential to reduce exploration costs while maintaining precision in complex mineral systems [19]. Shifting focus to copula methods. This study evaluates the effectiveness of Gaussian copula (GC) for copper grade estimation in the Sungun porphyry deposit (Iran), comparing it with ordinary kriging (OK) and indicator kriging (IK). The methods were assessed using cross-validation (Jackknife test), focusing on global accuracy, precision, error statistics (MBE, MSE), and variability. Results showed that GC outperformed OK and IK, producing globally accurate and precise estimates with acceptable error metrics, while IK exhibited excessive smoothing and OK suffered from conditional bias. The study highlights GC as a robust alternative for spatial grade estimation in mineral resource evaluation [20]. Examining estimation challenges more broadly, this study examines discrepancies between estimated and actual grades in an Iranian iron open-pit mine, analyzing uncertainties from orebody variability, random errors, and systematic biases. A probabilistic model quantified each factor's contribution, revealing systematic errors as the primary reconciliation issue, followed by geological complexity and random variability. The findings highlight the need for improved grade estimation techniques, such as advanced geostatistics or machine learning, to enhance accuracy in iron ore mining. The results underscore the economic implications of poor reconciliation and suggest methodological refinements to minimize uncertainty in mineral resource evaluation [21]. Continuing with reconciliation analysis, this study investigates grade reconciliation discrepancies between exploration estimates and blast-hole data in an Iranian iron open-pit mine. The methods include analyzing inherent variability, statistical uncertainty (from sparse sampling), and systematic uncertainty (measurement biases) in grade estimation. Correction factors were applied to mitigate these errors. Results showed systematic uncertainty as the dominant factor, followed by inherent variability and statistical uncertainty. Implementing corrections improved reconciliation from 10% to 50%, demonstrating enhanced accuracy in resource modeling. The findings underscore the importance of addressing exploration-stage uncertainties for reliable grade estimation in iron ore deposits [22]. Finally, returning to kriging limitations, this study evaluates the limitations of kriging, particularly its smoothing effect, in grade estimation for the Sungun copper deposit, Iran, and proposes sequential Gaussian simulation (SGS) as an alternative. SGS better reproduces the spatial variability and statistical distribution of raw exploration data compared to kriging. Results show that SGS increases mineable ore reserves and

improves net present value (NPV) by 40%, demonstrating its superiority in minimizing estimation bias and optimizing economic outcomes in open-pit mining. The findings highlight the efficacy of stochastic simulation over traditional kriging for accurate resource modeling [23]. In this study, we differentiate ourselves from previous works by focusing specifically on the application of two advanced machine learning techniques, Gaussian Process Regression (GPR) and Multilayer Perceptron Artificial Neural Network (MLP-ANN) for the spatial grade modeling of copper at the Chehel Kureh copper deposit. Unlike earlier studies that predominantly employed traditional geostatistical methods or single machine learning approaches, we explicitly compare the performance of these two methods in estimating copper grade, providing a direct evaluation of their effectiveness in this specific geological context. Additionally, our research emphasizes the optimization of hyperparameters using Bayesian Optimization, which has not been extensively explored in past studies, thereby enhancing the accuracy and robustness of the results. This comprehensive approach aims to highlight the superiority of modern machine learning techniques in mineral resource estimation and offer insights into best practices for future applications in the field.

2. Methodology

The fundamental assumption in conducting this research is the variability of most geological phenomena in a nonlinear, complex, and multi-origin manner, and intelligent machine learning methods also have a high ability to detect these complex nonlinear behaviors. Therefore, identifying these behaviors requires the use of intelligent and data-based methods. The research method is as follows: based on the statistical analysis of the data, the data were composited to the appropriate length. Outlier data were corrected using the GESD method [24], and proper values were replaced to prevent the false convergence of copper grade estimation. The original data were divided into training, validation, and testing groups to compare the methods used in copper grade estimation better and more closely. Different methods were then trained using the training data and evaluated using the test data. The Bayesian optimization method also optimized the parameters of the methods used. In the following, the performance of each of the methods is also evaluated using the RMSE objective function. At the end of the work and after examining the quantitative and qualitative accuracy of the training and also their performance on the test data, the appropriate method for estimating the copper grade was introduced. Therefore, the best performance was related to the Gaussian Processes method. Figure 1 shows the path this research took for spatial modeling of copper grade in the studied area.

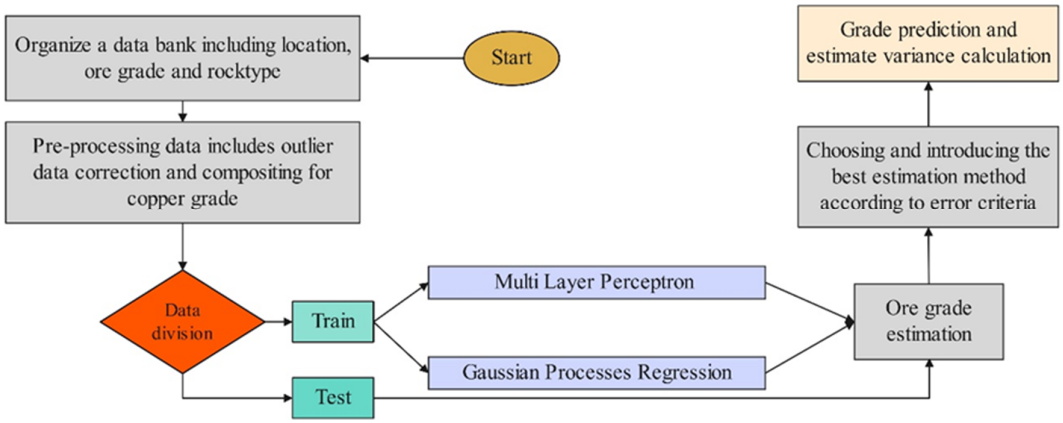

Figure 1. Spatial modeling workflow for copper grade estimation at the Chehel Kureh deposit.

3. Research methods

The limited availability of information compared to the unknowns in the spatial modeling process of copper grade is the reason for using estimators. The estimators are commonly classified based on various criteria. One of the most general criteria is the classification of methods based on whether they are geostatistical or non-geostatistical. The methods that fall into this classification are among the most widely used. Nowadays, with the expansion and development of methods based on deep learning and machine learning, another classification based on whether

the estimation methods are intelligent or non-intelligent has been added to these classifications, which are considered in this research. The theoretical background of the methods used in current research is presented in what follows.

3.1. Gaussian Process Regression (GPR)

Estimation methods aim to define a function **f** for a limited training dataset **D** and utilize it to estimate all possible input values. To achieve this, assumptions must be made about the properties of the target function; otherwise, any function consistent with the training data is valid. Several methods have been introduced to address these issues, among which two are more common. The first method involves restricting the considered functions, and the second involves using a prior probability for all possible functions. The first method has a fundamental problem: the suitability of the considered functions must be determined. For example, we will not have a reasonable estimate if we use a model based on a specific class of functions (linear functions) and the target function is not well modeled by this class. One way to overcome this problem is to increase the flexibility of the function class. The probability of overfitting the data should be seriously considered in this case. The second method also has a fundamental problem. There are infinitely many possible functions, and using these functions for calculations in a limited time is impossible. Gaussian Processes (GPs) have been introduced for this purpose. A Gaussian process is a generalized form of Gaussian probability functions. While the probability distribution describes the properties of random variables, a stochastic process encompasses the properties of target functions [25]. Since the Gaussian process is not a parametric model, we do not have to worry about whether the model can fit the data. This can be important if we use a linear model for nonlinear data [26]. The problem of training Gaussian processes is the problem of finding the appropriate properties for the covariance function. There are various methods for interpreting Gaussian process (GP) models. A Gaussian process can be considered a definition of functions, and inference can occur directly in the function space. The simple linear regression model, whose output is a linear combination of inputs, has been widely used and studied. The main feature of this method is its ease of implementation and interpretability. The main disadvantage of this model is its limited flexibility. Weak models are presented if a linear function cannot approximate the relationship between input and output. A Gaussian process is a set of random variables such that any finite set has a joint Gaussian distribution [26]. The mean function and the covariance function completely determine a Gaussian process. A Gaussian process is a set of random variables. Therefore, this definition automatically conveys the stationarity concept, sometimes called the marginal property. In other words, examining a larger set does not change the distribution of the smaller set. Gaussian process regression is a linear smoother [27]. One of the standard methods for solving nonlinear problems is to use kernel functions, which are defined based on the inner product of the given data. The design of regression methods based on Gaussian processes also includes the use of the concept of the kernel function. The role of the kernel function and the local model used in other models is combined in the covariance function. Like the kernel function, the covariance function is also a function of the model inputs, specifying the covariance between the inputs. In Gaussian processes, it is assumed that the output of each set of data has a multivariate Gaussian distribution, the covariance of which is determined by the covariance function. Predictions can be made using the covariance between the test data and all the training data, and the test output function can be obtained. Each of these kernel functions has its kernel-specific parameters, which are called hyperparameters. The use of kernel-based modeling methods requires the creation of appropriate user-defined parameters, as the accuracy of this regression method is highly dependent on the selection of these parameters [28].

3.2. Multilayer perceptron neural network

Neural networks are currently used to model complex functions and nonlinear phenomena. In theory, neural networks can model any nonlinear function from the input. Neural network models are highly flexible and can adapt to the existing features in the data and update the parameters accordingly. Theoretically, neural networks are well-resistant to input data distribution and can model incomplete, noisy, and ambiguous data. Multilayer Perceptron Neural Networks are feedforward neural networks with multiple or a single hidden layer. If the number of nodes in this neural network is chosen appropriately, then this network can approximate any function. If the input vector is **X**, then the output of the multilayer perceptron neural network with one hidden layer

and **H** nodes in the hidden layer is equal to (Formula 1):

$$\hat{Y}(x) = \sum_{j=1}^{H} v_j f(w_j^T x + w_{bj}) + v_b \quad (1)$$

X - Input vector

H - Number of nodes in the hidden layer

W_j -Network weight matrix

W_b - Weight bias matrix

V_i -Weights of connections between neurons and the output layer

When the network weight matrix between the nodes of the input layer and the nodes of the output layer is equal to W(W_1,W_2, … , W_H), then $\{w_{bj}\}_{j=1}^{H}$ represents the biases of the hidden layer neurons, and $\{v_i\}_{j=1}^{H}$ represents the weights of the connections between the neurons and nodes in the output layer [29].

This research introduces novel aspects by utilizing a dataset comprising 42 drill holes from the Chehel Kureh copper deposit, characterized by an average copper grade of 0.18%. This specific focus on the Chehel Kureh deposit is crucial, as it addresses the challenges of estimating copper grades in this geological context. Furthermore, our application of Gaussian Process Regression (GPR) is particularly innovative, as it has not been extensively employed in similar spatial modeling tasks within this region. Additionally, the incorporation of a systematic hyperparameter optimization strategy using Bayesian Optimization enhances model performance, providing a rigorous framework for improving accuracy in mineral resource estimation. This combination of unique dataset characteristics, focused application of GPR, and advanced optimization techniques significantly contributes to the existing body of knowledge and sets a precedent for future studies in mining and mineral exploration.

4. Geological area

The Chehelkureh copper deposit is 120 km northwest of Zahedan, at 29° 07' 06" N and 60° 29' 14" E. This deposit is one of the ancient mines of Iran and is located in Sistan and Baluchistan province. [30]. The Chehelkureh deposit is a vein-type copper-lead-zinc deposit with Eocene sedimentary host rocks. In the Chehelkureh area, several granitoid bodies have played a role in the deposit formation [31]. This is confirmed in terms of the relative age of mineralization and field geological evidence. One of the characteristics of hydrothermal deposits is the presence of alterations associated with mineralization, and sometimes alteration halos on the surface of the earth are the only sign of hidden mineralization at Depth [30]. Therefore, the study of alteration halos is essential in various aspects. This area is bounded west by an ophiolitic mélange and east by middle Eocene limestones. [30]. The intrusive rocks at Chehelkureh are calc-alkaline and have chemical features typical of I-type granitoids. The geotectonic environment of Chehelkureh granitoid is an intracontinental volcanic arc, the same setting as that in the multiphase granitoid batholiths of Zahedan, located southeast of Chehelkureh. Granitoids of the Chehelkureh area have moderate REE (rare-earth element) contents [31] [32]. From a structural geology point of view, the Sistan zone and the Chehelkureh area in which it is located are highly tectonic, and most of its formations are cut by significant north-south and northwest-southeast faults. The formations in this area in the western part have north-south trends, and the direction of its significant faults, which are branches of the Nehbandan fault, also has the same north-south direction. Parallel horsts and grabens with north-south to northwest-southeast trends along the faults form the structural geological feature of the region [30]. [31]. There are two periods of primary Cu-Zn-Pb mineralization that crosscut each other. The first stage includes quartz, calcite, dolomite, ankerite, siderite, ilmenite, rutile, molybdenite, pyrrhotite, arsenopyrite, pyrite, and chalcopyrite. The second stage consists of quartz, dolomite, ankerite, siderite, chalcopyrite, sphalerite, pyrite, galena, selenian galena, marcasite, nevskite, and paraguanajuatite. The gangue minerals are dominated by quartz and various carbonates, locally associated with chlorite. Hypogene alteration consists of silicification, carbonatization (ankerite, magnesite, siderite, and dolomite), chlorination, kaolinization, sulfidation, and, less commonly, sericitization [32]. Copper-zinc-lead mineralization has occurred at the faults and is of the vein type with turbidite host rock. The Chehelkureh deposit has a complex shape and consists of numerous veins and lenses. The overall mineralization trend is SE-NW and has been displaced by approximately W-E faults. From the extensive workings on the surface of the region, it can also be seen that the mineralization is discontinuous. Brecciation is observed in many places on the Earth's surface and in the drill cores. [30] [31]. [32].

5. Exploratory Data Analysis

The data used in this study include 42 exploratory boreholes with a total drilling length of 11,373 meters. The average copper grade in the analyzed data is 0.18%. The data used in this research include seven main variables, three of which are related to the location (longitude, latitude, Depth) of each sample. The fourth variable is related to lead grade, and the fifth is related to zinc grade. The sixth variable is lithology, and these six variables have been used as predictors, and the seventh is copper grade, the target variable. These variables estimate the copper grade in the Chehelkureh copper deposit. Among these seven variables, six are recorded quantitatively, and one (lithology) is recorded qualitatively, which was converted to quantitative values before being used in intelligent methods. The lithology variable used as predictors are Siltstone ، Shalet Sandstone, Quartz monzonite, Granodiorite, Alluvial, Lamprophyre, Serpentine, Quartzite, Hornblende diorite dyke and Hematite. The distribution of copper grade values shows that these data have a strong positive skewness (Figure 2). The location of the boreholes used is shown in Figure 3.

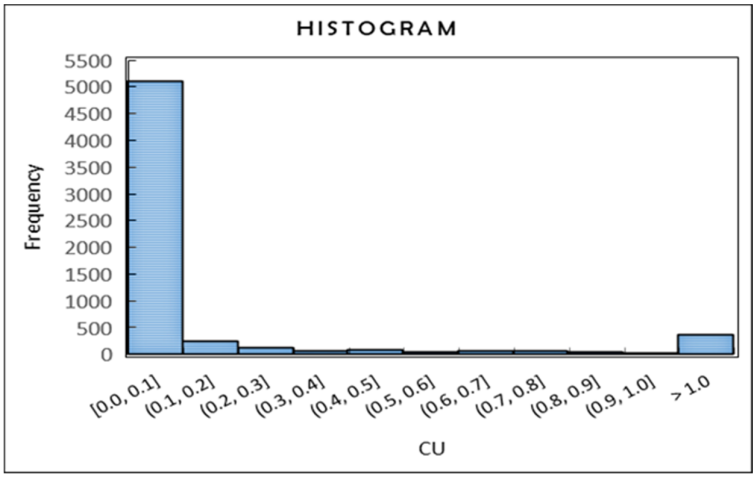

Figure 2. Histogram of Copper Grade Frequency

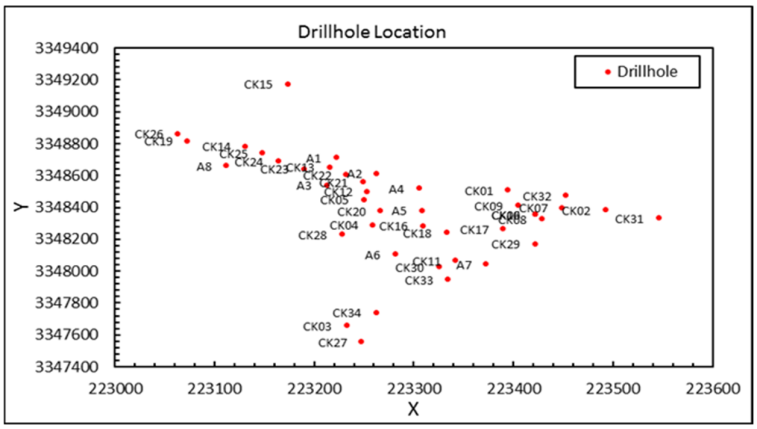

Figure 3. Location of Exploration Boreholes in the Chehelkureh Copper Mine

5.1. Data

All data were partitioned into training, validation, and test sets. 70% of the data was allocated to the training set, while 15% was assigned to the validation and test sets [33]. Stratified random sampling was employed for data partitioning. This method, while maintaining the randomness of the sampling process for data division, maximizes the transferability of the statistical characteristics of the original data to the validation and test data spaces [34]. Details and statistical information of the data after partitioning are presented in Tables 1 and 2.

Table 2 also shows the descriptive statistical information of the data. Based on the analysis of the statistical information of the data, they were finally composited over a length of 1 meter.

Table 1. Specifications of the Number and Percentage of Data Partitioning

Data Group	Percentage	Count
All Data	100	6253
Training Data	70	4377
Test Data	15	938
Validation Data	15	938

Table 2. Statistical Information of Main Data Before and After Division into Three Groups: Training, Test, and Validation

Data Group	Count	Kurt	Skew	Mean	STD	Range	Min	Max
All Data	6253	19.5	4.2	0.18	0.56	4.11	0	4.11
Training Data	4377	18.9	4.19	0.18	0.56	4.11	0	4.11
Test Data	938	20.7	4.37	0.17	0.55	3.92	0	3.92
Validation Data	938	18	4.06	0.18	0.57	3.92	0	3.92

5.2. Data preprocessing and Optimization of estimation parameters

Preprocessing steps, including outlier correction, data normalization, and integration, were performed to better identify and accurately evaluate the data characteristics used in this study. The optimal length for compositing was considered to be 1 meter. The GESD method was used to correct outliers. Failure to preprocess the data may severely affect the convergence of the computational algorithm. Therefore, normalization is usually performed on the data before applying the model to the network. In this research, normalization is done by subtracting the data value (X) from the minimum data and then dividing by the difference between the maximum and minimum data (Formula 2).

$$Z = \frac{X - Min(x)}{Max(x) - Min(x)} \quad (2)$$

X- Data value

To achieve the desired result in Gaussian process regression and multilayer perceptron neural network methods, the values of the parameters and hyperparameters of these functions must be chosen correctly because the final accuracy of these methods depends heavily on the values considered. For this purpose, the hyperparameters of the mentioned methods were optimized using the Bayesian Optimization method, and their appropriate values were determined to achieve the desired result in the mentioned methods. The result of solving the optimization problem for Gaussian process regression methods is shown in Figure 4, and for the multilayer perceptron neural network method in Figure 5. Bayesian Optimization is a model-based optimization technique. This technique is commonly used in machine learning and hyperparameter optimization. The main idea of this optimization method is to use a probabilistic model to represent the objective function and then use this model to decide on the next point where the function should be evaluated. This process repeatedly creates a probabilistic surrogate model of the function and uses it to suggest the next point to consider [35]. The objective function is a tool to examine the performance of a network that should be minimized. In this study, the root mean square error (RMSE) objective function has been used as a criterion to evaluate the network's performance. This function is the most common objective in nonlinear regression problems, as shown in Formula 3.

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{n}=1}^{N}[\mathrm{y}^{(\mathrm{n})} - \mathrm{O}^{(\mathrm{n})}]^2} \quad (3)$$

N - The number of data points under consideration

$y^{(n)}$ – Represents the estimated values

$\mathrm{O}^{(n)}$ - Represents the observed values

Where N equals the number of data points under consideration, $y^{(n)}$ represents the estimated values, and $\mathrm{O}^{(n)}$ represents the observed values. By minimizing the objective function, the weights and other parameters of the network can be calculated.

Table 3 presents the range of values considered for hyperparameter optimization in the Gaussian process regression method. In Table 4, the results obtained for this method are shown.

Like the Gaussian process regression method, the multilayer perceptron neural network was optimized using the Bayesian method. Table 5 shows the range of values considered for hyperparameter optimization, and Table 6 shows the results obtained for the optimized values.

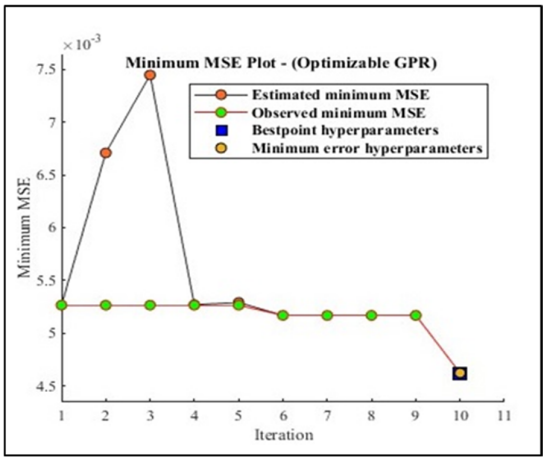

Figure 4. Optimization Result for Gaussian Process Regression Method

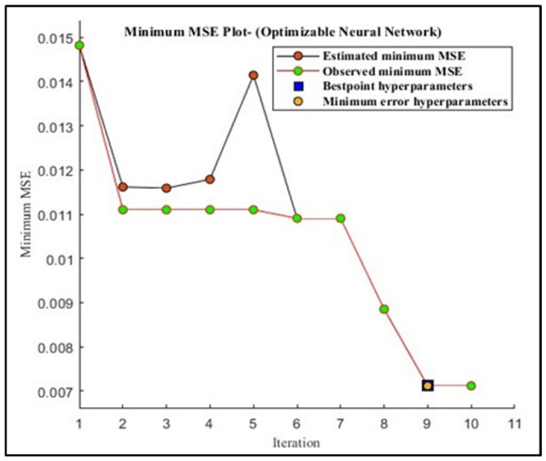

Figure 5. Optimization result for the MLP neural network method

Table 3. The Ranges of Hyperparameters Considered for the Gaussian Process Regression Method

Hyperparameter	Search Range
Sigma	0.0001 – 1.392
Basis Function	Constant, Zero, Linear
Kernel Function	Nonisotropic Exponential, Nonisotropic Matern 3/2, Nonisotropic Matern 5/2, Nonisotropic Rational Quadratic, Nonisotropic Squared Exponential, Isotropic Exponential, Isotropic Matern 3/2, Isotropic Matern 5/2, Isotropic Rational Quadratic, Isotropic Squared Exponential
Kernel Scale	0.001 - 1000
Standardize Data	True, False

Table 4. Bayesian Optimization Result for Gaussian Process Regression Method

Hyperparameter	Value
Sigma	0.2881
Basis Function	Linear
Kernel Function	Isotropic Exponential
Kernel Scale	0.050835
Standardize Data	No

Table 5. Hyperparameter Ranges Considered for Multilayer Perceptron Neural Network Method Optimization

Hyperparameter	Search Range
Number of fully connected layers	1-3
Activation	ReLU, Tanh, Sigmoid
Standardize Data	Yes, No
Regularization strength (Lambda)	2.5536 e-09 – 25.5363
First layer size	1 - 300

Table 6. Bayesian Optimization Result for Multilayer Perceptron Neural Network Method

Hyperparameter	Value
Number of fully connected layers	3
Activation	ReLU
Standardize Data	Yes
Regularization strength (Lambda)	2.9185 e-04
First layer size	284
Second layer size	3
Third layer size	32

6. Evaluating the Performance of the Methods Used in Estimation

After obtaining the optimal hyperparameter values for the methods used in copper grade estimation, with the aim of a more detailed study and evaluation of the methods' capabilities, the results obtained for the two training and testing stages were examined and compared. These examinations and comparisons were performed in both quantitative and qualitative forms. Table 7 presents the calculated error results for the training and test data used in the estimation methods. By conducting the examinations, it was found that in the training stage, the Gaussian process regression method with an RMSE value of 0.06 had the lowest error, and the second method, the multilayer perceptron neural network, with an RMSE value of 0.08 had the highest error. The qualitative evaluation results of network training for the estimation methods used are shown in Figure 6. Therefore, it can be said that in the training stage, among the methods used in copper grade estimation, the Gaussian process method with the lowest error rate has the best performance, and the multilayer perceptron neural network method with the highest error value has the weakest performance. For the test data, quantitative studies were also conducted, and it was found that the Gaussian process regression method with an RMSE value of 0.04 had the lowest error value, and the multilayer perceptron neural network method with an RMSE value of 0.05 had the highest error. Figure 7 shows the qualitative evaluations for the test data. In both the training and testing stages, the best performance is related to the Gaussian process method, and the weakest performance is associated with the multilayer perceptron neural network method.

Table 7. Error of the Methods Used in Estimation for Training and Test Data

Method	RMSE Test	RMSE Train
Gaussian Processes Regression	0.04	0.06
Multilayer Perceptron	0.05	0.08

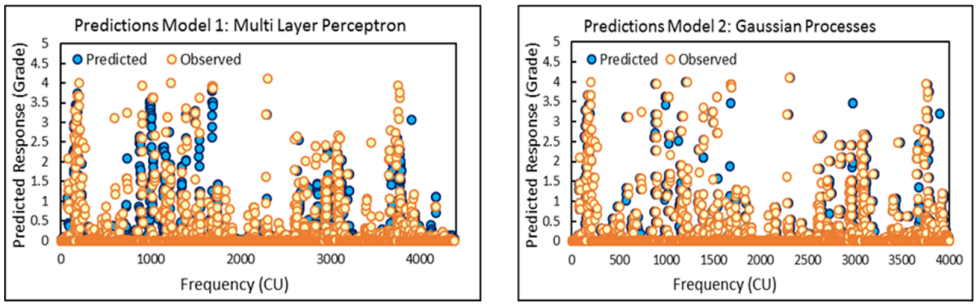

Figure 6. Qualitative evaluation results of network performance on training data for the methods used in copper grade estimation.

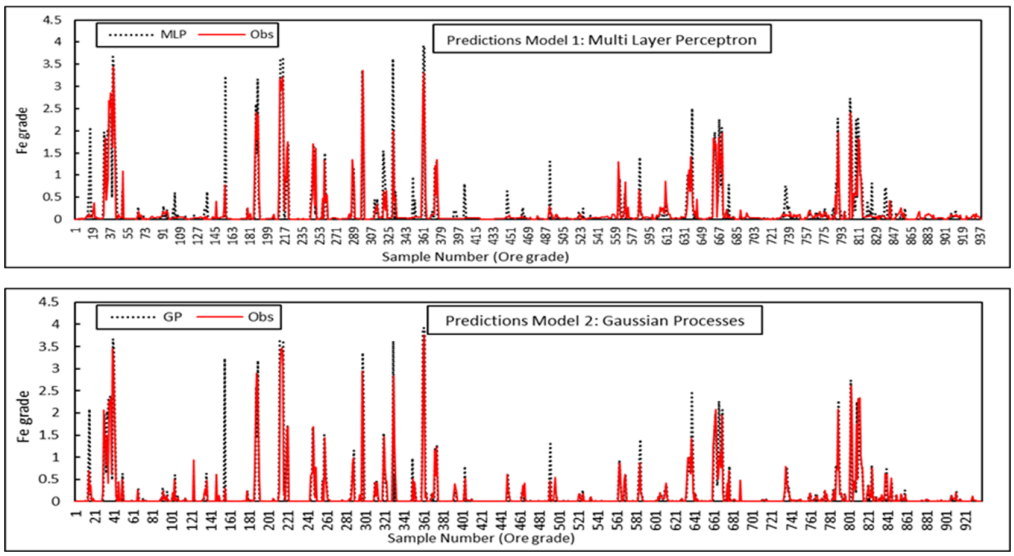

Figure 7. Qualitative evaluation results of network performance on test data for the methods used in copper grade estimation

To qualitatively evaluate the estimates by different methods, a copper grade variation map was drawn for the 1470-meter depth of the deposit (Figure 8). The reason for choosing this depth is that it has more mineralization. Therefore, the trend of grade variations in different parts of this depth is better separated than in other depths. The assessments related to this section are qualitative, and the copper grade variation map in the original data was used as a guide to control and evaluate the results.

6.1. Cross-Validation

To evaluate the efficacy of each method in copper grade estimation, their performance was assessed using cross-validation. This approach compares the test data estimated by different methods against their corresponding original values. Subsequently, using linear regression, the degree of correlation between these two data groups is measured. Figure 9 illustrates the cross-validation results for the Gaussian process regression and multilayer perceptron neural network methods. These results are presented in Table 8.

Two criteria were employed to compare the cross-validation results of the estimation methods: the coefficient of determination of regression and the RMSE value associated with each method. The first criterion, the coefficient of determination of regression, is denoted by R^2 in regression equations. This coefficient indicates the degree of correlation between the two categories and represents the quality of copper grade estimation in each method. Based on this criterion, the Gaussian process regression method with a coefficient of determination equal to 0.89 has the best performance, and the multilayer perceptron neural network method with a coefficient of determination of 0.82 has the weakest performance. Based on the second criterion, namely the RMSE value for the estimated values, it can be said that the lowest RMSE, i.e., the value of 0.04, is related to the Gaussian process regression method, and the highest value, i.e., 0.05, is associated with the multilayer perceptron neural network method. Based on the cross-validation results, the best performance is related to the Gaussian process regression method, and the weakest performance is associated with the multilayer perceptron neural network method.

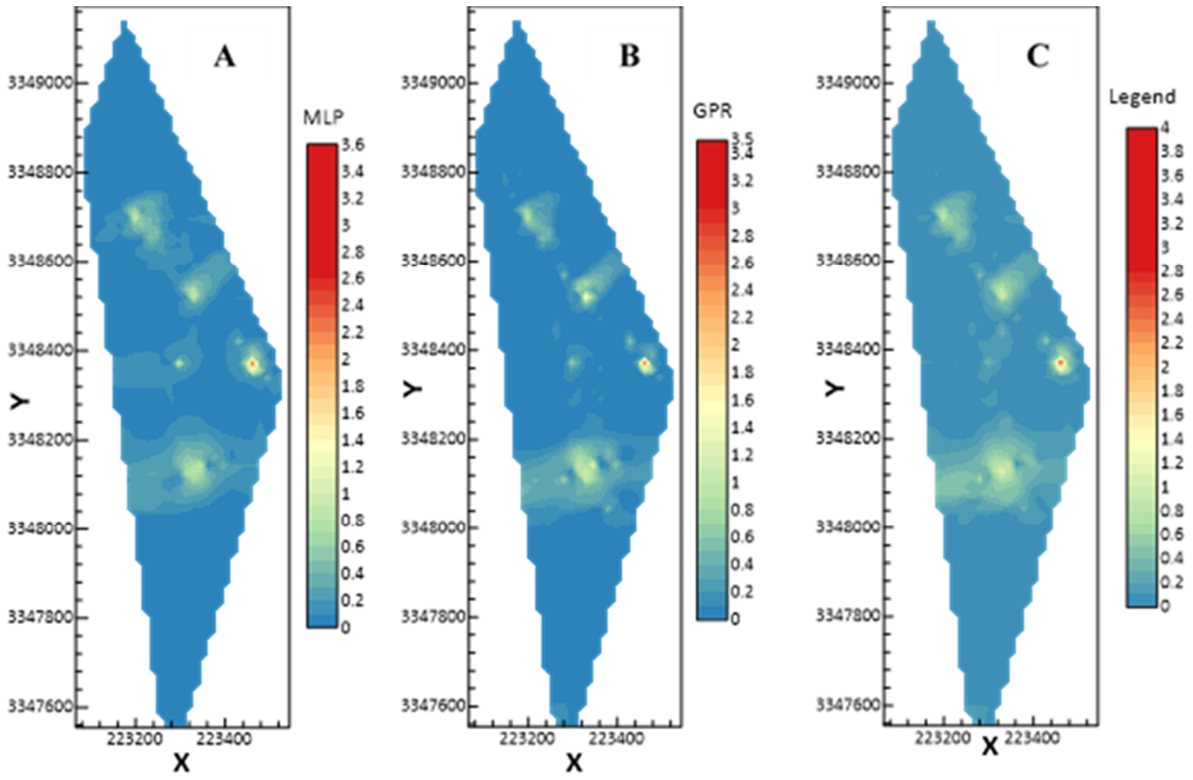

Figure 8. Map of copper grade at a depth of 1470 meters for A: MLP method, B: GPR method, and C: Original data

Table 8. Statistical Information Along with Calculated Error for Different Estimation Methods in Cross-Validation

Method	Min	Max	Mean	RMSE	R Squared
Gaussian Processes Regression	0	3.76	0.16	0.04	0.89
Multilayer Perceptron	0	3.4	0.17	0.05	0.82

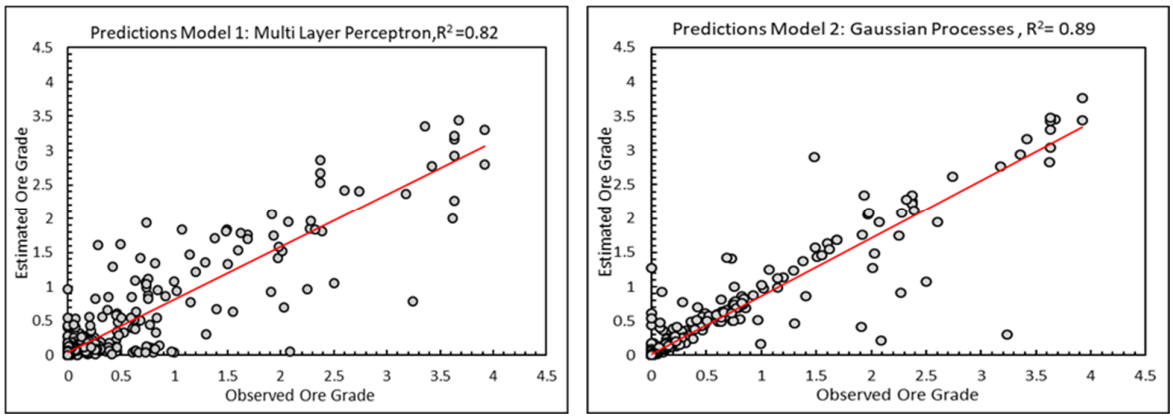

Figure 9. Cross-validation for the methods used in copper grade estimation

6.2. Residual Error

Another criterion for controlling and evaluating the performance of the methods in copper grade estimation is the residual error of the methods. The residual error is obtained from the difference between the actual value of copper grade and the estimated value by each method. By considering this criterion and then plotting the histogram of the residual error of each method and examining the three features of the degree of symmetry, the degree of elongation, and the amount of standard deviation, it can be concluded that the best performance is related to Gaussian process regression. Statistical information related to the residual error is shown in Figure 10 and Table 9.

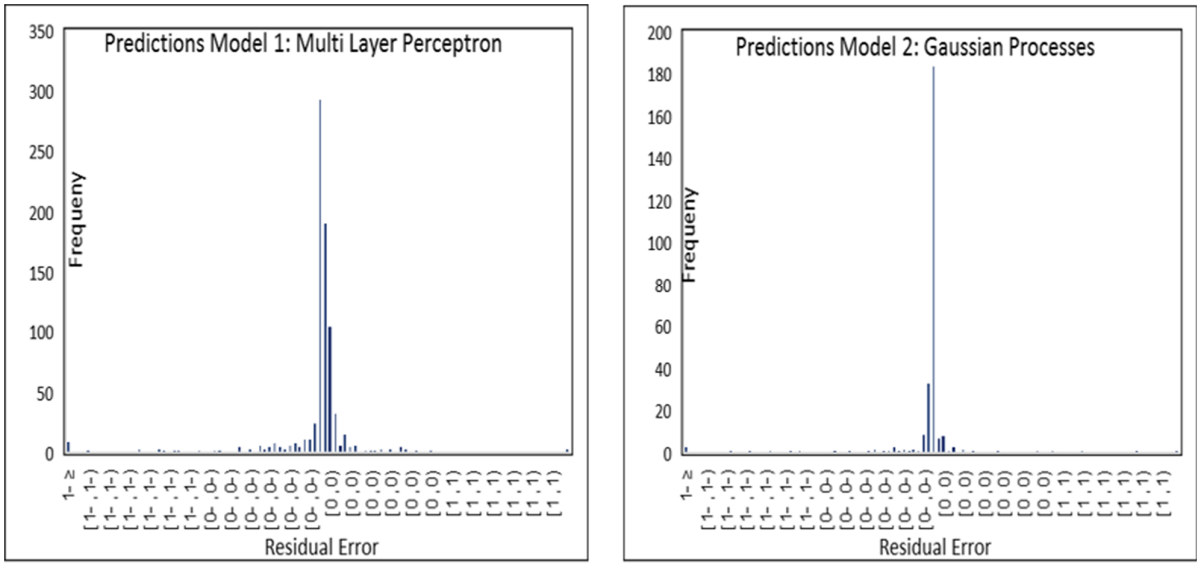

Figure 10. Histogram of Residual Error for the Methods Used in Estimation

Table 9. Statistical Characteristics of Residual Error for the Methods Used in Estimation

Method	Min	Max	Mean	Median	STD	Kurt	Skew	Range
Gaussian Processes	-2.9	1.4	-0.01	0	0.18	98.68	-6.15	4.35
Multilayer Perceptron	-2.4	1.3	0	0.01	0.23	30.15	-3.31	3.79

The Gaussian process regression method exhibits the most symmetrical state, with a skewness of -6.18. It shows the most elongated state, with a kurtosis of 96.68. It also displays the lowest standard deviation with a 0.18.

7. Conclusions

To evaluate and investigate the capability of the methods used in copper grade estimation, the performance of the commonly used methods on the training data was evaluated in the network training phase. According to the quantitative and qualitative comparison of the estimation results, the Gaussian process method with an RMSE value of 0.06 has the best performance, and the multilayer perceptron neural network method with an RMSE of 0.08 has the weakest performance in the network training. After evaluating the training quality of each method, their performance on the test data was also assessed. These evaluations were based on qualitative and quantitative criteria. According to the evaluation results, the Gaussian process method with an RMSE value of 0.04 showed better performance compared to the multilayer perceptron neural network with an RMSE value of 0.05. In cross-validation, considering the two criteria of the regression coefficient of determination and the root mean square error, Gaussian process regression with an R^2 value of 0.89 compared to the Multilayer Perceptron Neural Network with an R^2 value of 0.82 has performed better overall. Considering the residual error as one of the essential criteria for analyzing and evaluating the performance of the estimation methods, examining the three criteria of symmetry, skewness, and standard deviation, and interpreting the statistical information of the residual error, this result is obtained that the Gaussian process has the best performance among the methods. Therefore, the Gaussian process regression method has performed better than the multilayer perceptron neural network in estimating copper grade. Future research should focus on expanding the scope of machine learning applications in mineral resource estimation, particularly by integrating additional geological variables and advanced algorithms. Investigating hybrid models that combine the strengths of Gaussian Process Regression with other machine learning techniques may lead to even more accurate grade estimations. Furthermore, conducting similar studies in diverse geological settings can enhance the generalizability of these findings and contribute to the development of standardized protocols in mineral exploration. By leveraging such techniques, the industry can not only achieve better resource assessments but also promote more sustainable mining practices. These future directions will not only affirm the findings of this research but also pave the way for innovations that can significantly impact the field of geosciences and mineral resource management. Finally, to improve the estimation accuracy further in future works, it is suggested to include the paragensis zoneation and mineral alteration types, should also be used as input and that the capabilities of other advanced deep learning approaches such as Long Short-Term Memory (LSTM) neural networks, Graph Neural Networks (GNNs), and Generative Adversarial Networks (GANs) predicting copper grade is evaluated.

References

[1]. Kanevski, M., Pozdnoukhov, A., & Timonin, V. (2008). Machine Learning Algorithms for GeoSpatial Data: Applications and Software Tools. *IEEE.*

[2]. Jafrasteh, B., Fathianpour, N., & Suárez, A. (2018). Comparison of machine learning methods for copper ore grade estimation. *Computational Geosciences*, 22(6), 1371-1388.

[3]. Caté, A., Perozzi, L., Gloaguen, E., & Blouin, M. (2017). Machine learning as a tool for geologists. *The Leading Edge*, 36(3), 64-68.

[4]. Gil, Y., Pierce, S. A., Babale, H., Banerjee, A., Borne, K., Bust, G., Cheatham, M., Ebert-Uphoff, I., Gomes, C., Hill, M., Horel, J., Hsu, L., Kinter, J., Knobloch, C., Krum, D., Kumar, V., Lermusiaux, P., Liu, Y., North, C., ... Shekhar, S. (2019). Intelligent systems for geosciences: An essential research agenda. *Communications of the ACM*, 62(1), 76–84.

[5]. Dumakor-Dupey, N. K., & Arya, S. (2021). Machine Learning—A Review of Applications in Mineral Resource Estimation. *Energies*, 14(14), 4079.

[6]. Zhang, S. E., Nwaila, G. T., Tolmay, L., Frimmel, H. E., & Bourdeau, J. E. (2021). Integration of machine learning algorithms with Gompertz Curves and Kriging to estimate resources in gold deposits. *Natural Resources Research*, 30, 39-56.

[7]. Mahboob, M. A., Celik, T., & Genc, B. (2022). Review of machine learning-based Mineral Resource estimation. *Journal of the Southern African Institute of Mining and Metallurgy*, 122(11), 655-664.

[8]. Zhao, T., Wang, S., Ouyang, C., Chen, M., Liu, C., Zhang, J., Yu, L., Wang, F., Xie, Y., Li, J., Wang, F., Grunwald, S., Wong, B. M., Zhang, F., Qian, Z., Xu, Y., Yu, C., Han, W., Sun, T., ... & Wang, L. (2024). Artificial intelligence for geoscience: Progress, challenges, and perspectives. *The Innovation*, 5(5), 100591.

[9]. Atalay, F. (2024). Estimating Fe Grade at an Ore Deposit Using Extreme Gradient Boosting Trees (XGBoost). *Mining, Metallurgy & Exploration*, 41(3), 2119–2128.

[10]. Battalgazy, N., Valenta, R., Gow, P., Spier, C., & Forbes, G. (2023). Addressing Geological Challenges in Mineral

Resource Estimation: A Comparative Study of Deep Learning and Traditional Techniques. *Minerals*, 13, 982.

[11]. Ismael, A. F., Embaby, A., Ali, F. A., Farag, H. A., Gomaa, S., Elwageeh, M., & Mousa, B. G. (2024). Prediction of Iron Ore Grade using Artificial Neural Network, Computational Method, and Geostatistical Technique at El-Gezera Area, Western Desert, Egypt. *Journal of Mining and Environment (JME), 15*(3), 889-905.

[12]. Abuntori, C. A., Al-Hassan, S., & Mireku-Gyimah, D. (2021). Assessment of Ore Grade Estimation Methods for Structurally Controlled Vein Deposits -A Review. *Ghana Mining Journal*, 21(1), 31-44.

[13]. Tsae, N. B., Adachi, T., & Kawamura, Y. (2023). Application of Artificial Neural Network for the Prediction of Copper Ore Grade. *Minerals*, 13(5), 658.

[14]. Marquina-Araujo, J., Cotrina-Teatiño, M., Mamani-Quispe, J., Noriega-Vidal, E., Vega-Gonzalez, J., & Cruz-Galvez, J. (2024). Copper Ore Grade Prediction Using Machine Learning Techniques in a Copper Deposit. *Journal of Mining and Environment (JME)*, 15(3), 1011-1027.

[15]. Cotrina-Teatino, M. A., Marquina-Araujo, J. J., Mamani-Quispe, J. N., Arango-Retamozo, S. M., Ccatamayo-Barrios, J. H., Gonzalez-Vasquez, J. A., Donaires-Flores, T., & Calla-Huayapa, M. A. (2025). Categorization of Mineral Resources using Random Forest Model in a Copper Deposit in Peru. *Journal of Mining and Environment*, 16(3), 947-962.

[16]. Tahernejad, M. M., Khalokakaie, R., & Ataei, M. (2018). Analyzing the effect of ore grade uncertainty in open pit mine planning: A case study of Rezvan iron mine, Iran. *International Journal of Mining and Geo-Engineering*, 52(1), 53–60.

[17]. Sotoudeh, F., Ataei, M., Kakaie, R., & Pourrahimian, Y. (2020). Application of Sequential Gaussian Conditional Simulation into Underground Mine Design under Grade Uncertainty. *Journal of Mining and Environment*, 11(3), 695–709.

[18]. Fathi, M., Alimoradi, A., & Hemati Ahooi, H. R. (2021). Optimizing extreme learning machine algorithm using particle swarm optimization to estimate iron ore grade. *Journal of Mining and Environment*, 12(2), 397–411.

[19]. Ghasemitabar, H., Alimoradi, A., Hemati Ahooi, H., & Fathi, M. (2024). Intelligent borehole simulation with Python programming. *Journal of Mining and Environment*, *15*(2), 707–730.

[20]. Sohrabian, B., & Tercan, A. E. (2025). Grade estimation through the Gaussian copulas: A case study. *Journal of Mining and Environment*, 16(1), 1-13.

[21]. Parhizkar, A., Ataei, M., Moarefvand, P., & Rasouli, V. (2011). Grade uncertainty and its impact on ore grade reconciliation between the resource model and the mine. *Archives of Mining Sciences*, 56(1), 119-134.

[22]. Parhizkar, A., Ataei, M., Moarefvand, P., & Rasouli, V. (2012). A probabilistic model to improve reconciliation of estimated and actual grade in open pit mining. *Arabian Journal of Geosciences*, 5(6), 1279-1288.

[23]. Monjezi, M., Rajabalizadeh Kashani, M., & Ataei, M. (2013). A comparative study between sequential Gaussian simulation and kriging method grade modeling in open-pit mining. *Arabian Journal of Geosciences*, 6(1), 123-12

[24]. Rosner, B. (1983). Percentage Points for a Generalized ESD Many-Outlier Procedure. *Technometrics*, 25(2), 165-172.

[25]. Rasmussen, C. E., & Williams, C. K. I. (2006). Gaussian Processes for Machine Learning (Adaptive Computation and Machine Learning). *MIT Press*, 35, 42, 46, 49.

[26]. Hastie, T. J., & Tibshirani, R. J. (1990). Generalized Additive Models (Vol. 43). CRC Press, 48.

[27]. Irie, B., & Miyake, S. (1988). Capabilities of three-layered perceptrons. *In IEEE International Conference on Neural Networks* (pp. 641–648).

[28]. Torab, F. M., & Lehman, B. L. (2006). Iron oxide-apatite deposits of the Bafq district, central Iran: An overview from geology to mining. *World of Mining—Surface and Underground*, 58(6), 355–362.

[29]. Irie, B., & Miyake, S. (1988). Capabilities of three-layered perceptrons. *In IEEE International Conference on Neural Networks* (pp. 641–648).

[30]. Maanijou, M., Rasa, I., Lentz, D., & Alirezaei, S. (2008). Petrography and alteration of Chehelkureh copper deposit: Mass balance of elements and behavior of REE. *Journal of Earth Sciences,* 17(2), 165-182.

[31]. Movahhed Aval, M. (1974). Report on exploration of copper-lead-zinc deposits of Chehel-Kureh and Nasagh-e-Pourchangy Kuh-e-Lunka area. *Geological Survey of Iran (GSI)*, 80 p.

[32]. Maanijou, M., Rasa, I., & Lentz, D. R. (2012). Petrology, geochemistry, and stable isotope studies of the Chehelkureh Cu-Zn-Pb deposit, Zahedan, *Iran. Economic Geology*, 107(4), 683–712.

[33]. Laurent, O., Michael, M., & Ian, C. (2020). Estimating ore particle size distribution using a deep convolutional neural network. *IFAC*, 53(2), 12038–12043.

[34]. Neyman, J. (1934). There are two different aspects of the representative method: The method of stratified sampling and the process of purposive selection. *Journal of the Royal Statistical Society*, 97(4), 558–625.

[35]. Snoek, J., Larochelle, H., & Adams, R. P. (2012). Practical Bayesian Optimization of Machine Learning Algorithms. *arXiv preprint arXiv*:1206.2944.

نشریه مهندسی معدن و محیط زیست
نشانی نشریه: www.jme.shahroodut.ac.ir
انجمن مهندسی معدن ایران
دانشگاه صنعتی شاهرود

بهبود تخمین عیار مس در معدن مس چهل کوره با استفاده از روش های یادگیری ماشین

حامد نوروزی[1*]، علی اکبر دایا[2]

۱. گروه مهندسی معدن، دانشگاه صنعتی اصفهان، اصفهان، ایران
۲. گروه مهندسی معدن، دانشگاه سیستان و بلوچستان، زاهدان، ایران

اطلاعات مقاله

تاریخ ارسال: ۲۰۲۵/۰۵/۲۹
تاریخ داوری: ۲۰۲۵/۰۶/۰۵
تاریخ پذیرش: ۲۰۲۵/۰۸/۰۱

DOI: 10.22044/jme.2025.16326.3177

کلمات کلیدی

یادگیری ماشین
رگرسیون فرآیندهای گوسی
چهل کوره
تخمین عیار
مدلسازی فضایی

چکیده

تخمین ذخایر معدنی در پروژه های اکتشافی یا استخراجی، فرآیندی حیاتی و چالش برانگیز است که باید با دقت بالا و صرف نظر از مقیاس معدنکاری و نوع کانی زایی انجام شود. با افزایش اهمیت منابع معدنی در توسعه اقتصادی و صنعتی، ضرورت به کارگیری فناوری های پیشرفته در ارزیابی ذخایر نیز بیشتر شده است. در این میان، روش های جدید مدلسازی فضایی عیار می توانند نقش کلیدی در فرآیند تصمیم گیری ایفا کنند. این پژوهش به مقایسه عملکرد و قابلیت های دو روش رایج یادگیری ماشین، شامل رگرسیون فرآیند گاوسی (GPR) و شبکه عصبی مصنوعی پرسپترون چندلایه (MLP-ANN)، در مدلسازی فضایی عیار مس در کانسار مس چهل کوره پرداخته است. داده های مورد استفاده شامل ۴۲ گمانه اکتشافی با میانگین عیار مس ۰/۱۸ می باشد. هر نمونه مغزه شامل هفت متغیر است که سه متغیر آن مربوط به مختصات فضایی طول، عرض و عمق می باشند. دیگر متغیر ها عبارتند از عیار سرب، عیار روی، لیتولوژی و عیار مس (به عنوان متغیر هدف). برای تخمین عیار مس، از روش های رگرسیون فرآیند گاوسی (GPR) و شبکه عصبی پرسپترون چندلایه (MLP-ANN) استفاده شد. برای ارزیابی دقیق تر، هایپرپارامترهای هر دو مدل با استفاده از الگوریتم بهینه سازی بیزی تنظیم شدند. نتایج نشان داد که روش رگرسیون فرآیند گاوسی عملکرد بهتری نسبت به شبکه عصبی پرسپترون چندلایه دارد، به طوریکه مقدار RMSE=0.04 و ضریب تعیین (R^2)=0.89 برای رگرسیون فرآیندهای گاو سی در مقایسه با RMSE=0.05 و ضریب تعیین (R^2)=0.85 برای شبکه عصبی پرسپترون چندلایه به دست آمد. این نتایج برتری روش رگرسیون فرآیندهای گاوسی را در مدلسازی تغییرپذیری فضایی عیار مس تأیید می کند.

نویسنده مسئول مکاتبات: Hamed.Norouzi@alumni.iut.ac.ir (ح. نوروزی)