Journal of Mineral Resources Engineering, 10(2): 71-89, (2025)

Imam Khomeini International University
Vol. 10, No. 2, Summer 2025

نشریه مهندسی منابع معدنی
Journal of Mineral Resources Engineering
(JMRE)

Research Paper

Improving the 3D Estimation of Copper Grade in Sarcheshme Copper Deposit using Deep Learning Methods

Norouzi H.[1], Fathianpour N.[2*]

1- M.Sc, Dept. of Mining Engineering, Isfahan University of Technology, Isfahan, Iran
2- Associate Professor, Dept. of Mining Engineering, Isfahan University of Technology, Isfahan, Iran

Received: 16 Aug. 2024 **Accepted: 22 Dec. 2024**

Abstract: Minimizing grade estimation errors through modern methods is crucial for optimizing mining operations and mitigating the risk of economic failure in mining projects. The current research is an attempt to enhance the three-dimensional estimation of copper grades in the Sarcheshmeh copper deposit by employing advanced deep-learning techniques and comparing their outcomes with those of traditional geometric methods. The Sarcheshmeh copper deposit is among the largest porphyry copper deposits located within the Urmia-Dokhtar volcanic belt, south of Kerman in central Iran. In this study, data from a number of 526 boreholes containing 38,006 core samples assayed for total copper were deployed. The average copper grade in the samples is 0.54 percent, with a maximum value of 3.43. Prior to grade estimation, preprocessing steps were performed, including outlier correction and data compositing. The anisotropy ellipsoid of the copper grade was determined using the covariance matrix. Two methods were applied for grade estimation: a deep learning algorithm based on the ResNet-50 architecture and the inverse distance weighting (IDW) method, a conventional geometric approach. Validation results indicated that the ResNet-50 algorithm, with an RMSE of 0.45, outperformed the IDW method, which had an RMSE of 0.6.

Keywords: Grade modeling, Neural networks, Deep learning methods, Inverse distance weighting method, Grade estimation.

How to cite this article
Norouzi, H., and Fathianpour, N. (2025). *"Improving the 3D estimation of copper grade in Sarcheshme copper deposit using deep learning methods"*. Journal of Mineral Resources Engineering, 10(2): 71-89.
DOI: 10.30479/jmre.2025.20784.1712

*Corresponding Author Email: *fathian@iut.ac.ir*

COPYRIGHTS
©2025 by the authors. Published by Imam Khomeini International University.
This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution 4.0 International (CC BY 4.0) (https://creativecommons.org/licenses/by/4.0/)

INTRODUCTION

One of the most critical steps in evaluating the quality of mineralization in mineral deposits is estimating the grade of the deposit. The challenge associated with this issue lies in estimating the mineral grade within the deposit. The mineral concentration throughout a deposit is influenced by a number of factors, including the spatial dependency among samples and geological and structural settings of the sought mineralization [1]. Deep learning is one of the subsets of the machine learning class of methods that has made significant achievements in many areas in recent years. Unlike other machine learning methods, deep learning methods automatically benefit from discovering data features and patterns in models with complex structures [2]. Considering that most geological phenomena occur in the space-time domain and have heterogeneity, the variability of the behavior of these phenomena is usually nonlinear and often complex. Therefore, due to the powerful intelligent methods to reveal complex nonlinear behaviors, it is necessary to use these methods to identify nonlinear behaviors in geological phenomena [3].

METHODS

This research assumes that the variability of most geological phenomena is nonlinear, and intelligent methods can also reveal these complex nonlinear behaviors. To better guide the modeling methods, the primary data were divided into three groups tagged as training, validation, and test, which were trained using the training data and different methods, followed by evaluating their performances through test data. The performance of the methods was also evaluated using the RMSE objective function. By evaluating the results, the ResNet-50 convolutional neural network demonstrated the best performance, while the inverse distance weighting method showed the weakest performance. The inverse distance weighting method is one of the geometric interpolation methods in which the estimation weights are determined based on the inverse of the distance of the points entered in the estimation concerning the center of the estimated block. Microsoft introduced the ResNet convolutional neural network. ResNet is an abbreviation for two words: Residual Network [4]. This architecture solved the problem of training deep networks using residual structure. This residual structure is known as the residual block, the main task of which is to connect the primary inputs to the output of the next layer [5]. Figure1 shows the flowchart used in the spatial modeling of the grade in current research.

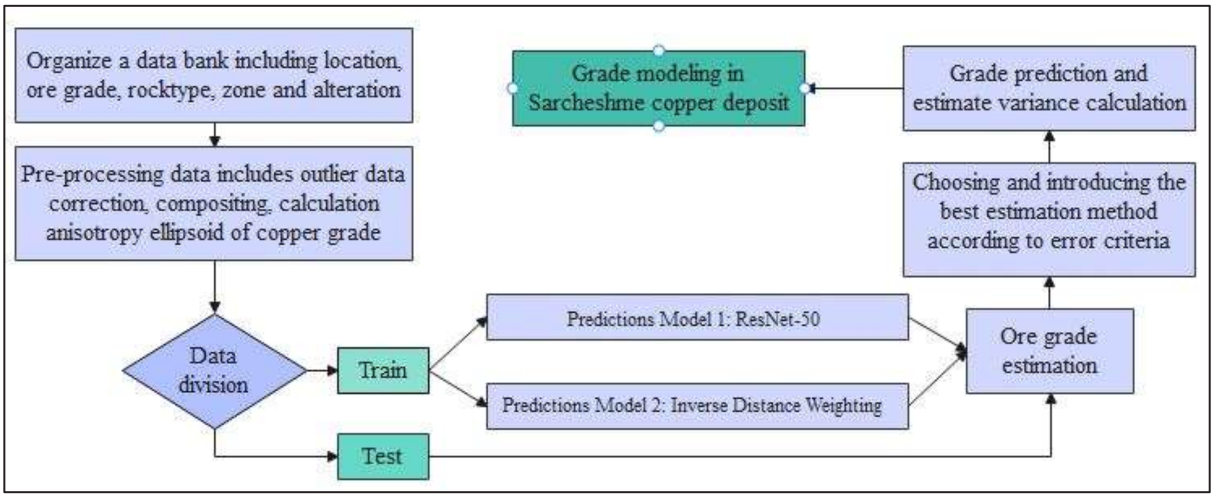
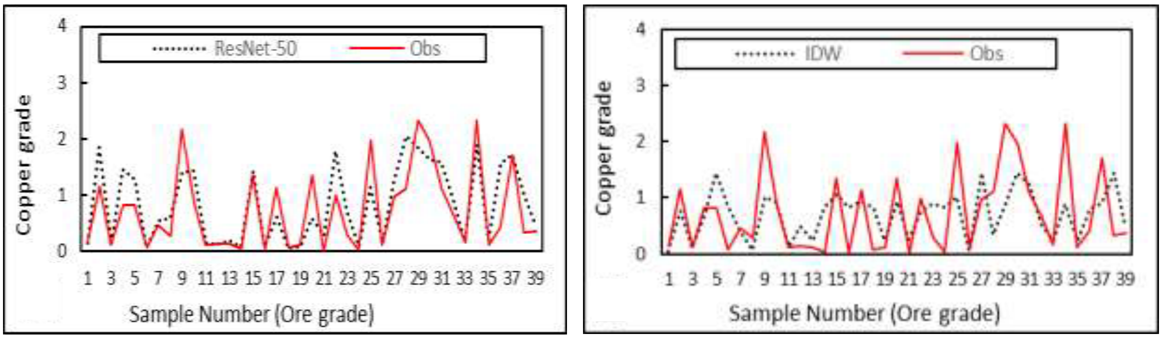


Figure 1. The workflow of the grade estimation process in the study area

FINDINGS AND ARGUMENT

Local-scale surveys were conducted to evaluate and compare the performance of each estimation method during both the training and testing phases of the network using the corresponding stage data. Next, their results were evaluated both quantitatively and qualitatively. It was found that in the training phase, the ResNet-50 method with an RMSE value of 0.3 has the lowest error, representing a method based on convolutional neural networks. Among the geometric methods, the inverse distance weighting method with an RMSE value of 0.57 has the highest error. Therefore, it can be concluded that in the training step, among all the methods used in copper grade estimation, the ResNet-50 architecture with the lowest amount of error has the best performance, and the inverse distance weighting method with the highest amount of error has the weakest performance. Quantitative checks were made for the test data, and it was found that ResNet-50 with RMSE equal to 0.45 has the lowest amount of error, and the inverse distance weighting method with RMSE equal to 0.6 has the highest error. Therefore, through considering both the training and test steps, the best performance belongs to the ResNet-50 method, while the weakest performance is related to the inverse distance weighting method. Figure 2 shows the results of qualitative visual evaluation of model performances on test data.



(A) **(B)**

Figure 2. The results of the qualitative evaluation of the network performance of the test data for the methods **A:** ResNet-50 and **B:** IDW

CONCLUSIONS

To assess the effectiveness of the methods used for copper grade estimation in this research, the training phase included evaluating the performance of deep convolutional networks based on residual structures, recognized as one of the most efficient deep neural network architectures. Quantitative and qualitative comparisons revealed that the ResNet-50 convolutional neural network achieved the best performance with an RMSE of 0.36, while the inverse distance weighting method had the weakest performance with an RMSE of 0.57 during the training stage. Following the evaluation of each method's training quality, their performance was further analyzed through testing scenarios. These evaluations were done according to qualitative and quantitative criteria and on a local scale. Finally, it is concluded that the ResNet-50 convolutional neural networks demonstrate the capability to learn complex spatial and nonlinear relationships within the data while effectively generalizing across different scales, from local to broader field extents. Their performance surpasses that of traditional geometric methods.

REFERENCES

[1] Bishop, C. M. (1995). *"Neural networks for pattern recognition"*. Clarendon Press, Oxford University Press, Oxford, pp. 482.

[2] Krizhevsky, A., and Sutskever, I., and Hinton, G. E. (2012). *"ImageNet classification with deep convolutional neural networks"*. In: Pereira, F., Burges, C. J. C., Bottou, L., and Weinberger, K. Q. (Eds.), Advances in Neural Information Processing Systems, Vol. 25, Curran Associates, Inc., Red Hook, NY, 1097-1105.

[3] Rendu, J. M. (2017). *"Risk Management in Evaluating Mineral Deposits"*. Society for Mining, Metallurgy, and Exploration, Inc., May 22, pp. 320.

[4] He, K., Zhang, X., Ren, Sh., and Sun, J. (2016). *"Deep Residual Learning for Image Recognition"*. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 770-778. DOI: https://doi.org/10.1109/CVPR.2016.90.

[5] Waterman, G. C., and Hamilton, R. L. (1975). *"The Sar Cheshmeh porphyry copper deposit"*. Economic Geology, 70(3): 568-576.