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Machine Learning-Based Mineral Prospectivity Mapping of the Shadan Porphyry Copper-Gold Area

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Abstract

Accurate identification of prospective mineral zones is a critical step in detailed exploration programs, particularly for porphyry copper-gold deposits where drilling is expensive and spatially limited. This study applies two supervised machine learning algorithms, Support Vector Machine (SVM) and Random Forest (RF), to produce a mineral prospectivity map for the Shadan porphyry copper-gold area in South Khorasan Province, eastern Iran. Multiple exploration datasets, including geological, structural, geochemical, remote sensing, geomagnetic, and drilling data, were integrated in a GIS-based framework. Eleven evidential layers were prepared and normalized, and borehole data were used to label training and testing samples. The performance of the models was evaluated using Accuracy, Sensitivity, ROC-AUC, and prediction–area plots. The results show that both algorithms performed effectively; however, SVM achieved better predictive performance, with Accuracy of 0.92, Sensitivity of 0.88, and AUC of 0.93. The SVM model identified approximately 13% of the study area as highly prospective for future drilling.

Keywords:

Mineral prospectivity mapping; Porphyry copper-gold; Support Vector Machine; Random Forest; Shadan area

1. Introduction

Mineral exploration requires systematic methods to reduce uncertainty and identify the most promising targets before costly field operations and drilling. In porphyry copper-gold systems, mineralization is controlled by complex interactions among lithology, structures, hydrothermal alteration, geochemical anomalies, and geophysical responses. Conventional knowledge-driven and statistical methods are useful but may not adequately capture nonlinear spatial relationships among multi-source exploration datasets. Machine learning methods provide an effective alternative because they can model complex patterns and improve prediction accuracy. The main objective of this study is to compare the efficiency of SVM and RF algorithms for mineral prospectivity mapping in the Shadan area and to identify favorable zones for supplementary drilling.

2. Methodology

The Shadan area is located about 65 km south of Birjand, in South Khorasan Province, and lies within the eastern margin of the Lut Block and the Flysch–Ophiolite Belt of eastern Iran. The area contains volcanic and intrusive rocks, including andesite, granite, granodiorite, microdiorite, and porphyritic units, accompanied by hydrothermal alteration and copper-gold mineralization.

Several datasets were used in this research. Geological and structural information was extracted from a 1:1000 geological map. Geochemical data included 300 rock samples analyzed for 46 elements by ICP-OES, while gold was analyzed by Fire Assay. Ground magnetic data were obtained from 547 stations along 35 profiles in a regular 70 × 70 m grid. ASTER satellite imagery was used to map alteration zones. Drilling information from 27 boreholes was used to define favorable and unfavorable mineralization classes.

Eleven evidential layers were prepared: lithological units, distance from faults, Cu anomaly, Au anomaly, Mo anomaly, the first mineralization-related factor from robust factor analysis, total magnetic field, reduction-to-pole magnetic map, argillic alteration, propylitic alteration, and iron oxide alteration. Because these layers had different units and ranges, they were normalized before modeling. A 5 m cell size was selected, and integration of the evidential layers produced 44,708 eleven-dimensional feature vectors.

Boreholes were classified into two classes based on weighted Cu and Au grades and an N-S fractal diagram. Class 1 was considered favorable and class 2 unfavorable. From the generated feature vectors, 535 vectors were labeled using borehole locations. Of these, 70% were randomly assigned to model training and 30% to model testing. The SVM model was trained using optimized parameters, including C = 10 and gamma = 0.01, while the RF model was optimized using 1000 trees and a minimum of 5 samples per node. Cross-validation was applied to improve parameter selection and reduce overfitting. Model performance was assessed using confusion matrices, Accuracy, Sensitivity, ROC curves, AUC values, and prediction–area plots.

3. Discussion and Results

The results demonstrate that both SVM and RF are capable of mapping prospective porphyry copper-gold zones in the Shadan area. However, SVM showed stronger predictive performance. The SVM model achieved Accuracy of 0.92, Sensitivity of 0.88, and AUC of 0.93, whereas the RF model achieved Accuracy of 0.88, Sensitivity of 0.79, and AUC of 0.88. These values indicate that SVM was more successful in distinguishing favorable mineralized zones from unfavorable areas.

Prediction–area analysis further confirmed the superiority of SVM. The final performance value of SVM was 0.40, compared with 0.29 for RF. This means that SVM identified mineralized targets more efficiently while assigning a smaller proportion of the total area to the high-potential class. The SVM model classified about 13% of the study area as prospective, whereas the RF model identified a larger area with lower selectivity.

The high-potential zones detected by SVM are spatially associated with andesitic, granitic, and granodioritic units, strong structural deformation, fault density, argillic and phyllic alteration, and significant Cu, Au, and Mo geochemical anomalies. These relationships are consistent with the conceptual model of porphyry copper-gold systems. The RF feature-importance results also showed that the mineralization-related geochemical factor, Cu anomaly, and argillic alteration were among the most influential predictors. In contrast, lithological units had lower importance, probably because several rock units in the area have relatively similar compositions.

The better performance of SVM can be attributed to its ability to define an optimal separating boundary between classes and model nonlinear relationships through kernel functions. This characteristic is particularly useful in mineral exploration, where the boundary between mineralized and barren zones is often complex and controlled by multiple interacting factors.

4. Conclusions

This study confirms that supervised machine learning algorithms can improve mineral prospectivity mapping in porphyry copper-gold exploration. Although both SVM and RF produced acceptable results, SVM provided higher predictive accuracy and better spatial selectivity. The SVM-based prospectivity map is therefore recommended as a more reliable guide for future exploration in the Shadan area. The most favorable targets are mainly located in structurally active zones with strong geochemical, alteration, and magnetic evidence. Future drilling should focus on the high-potential zones identified by the SVM model, especially in the northwestern part of the area where drilling has not yet been conducted. It is also recommended that new drilling results be incorporated into the database and used to retrain the models, allowing continuous improvement of the prospectivity map.

5. References

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