therefore, variations in composition and the crystal structure of these minerals can change this phenomenon. The yellow apatite is impregnated with iron oxide-hydroxides and contains metal cations in the lattice, as seen in the microprobe results, which can affect the crystal lattice and crystallinity degree. This might further be the case for the minor and trace elements as assayed by LA-ICP-MS, which might vary in orders of magnitude. The presence of iron-bearing species on the mineral surface probably enhanced the hydrophilicity of apatite, resulting in the reduction of the adhesion of collector molecules onto the mineral surface sites. ■

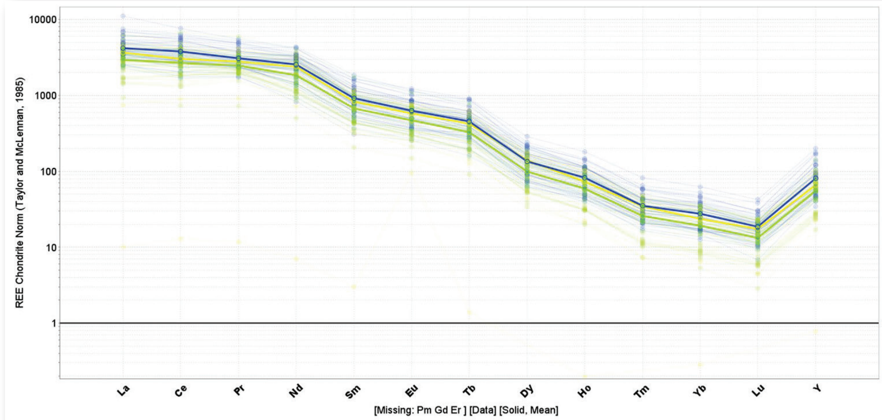

Fig. 2 Primitive-mantle-normalized spidergram showing relative concentrations of elements in apatite from Catalão. Primitive mantle data from Taylor and McLenman [4].

Selected references

1. Pufahl PK, Groat, LA (2017) Sedimentary and igneous phosphate deposits: formation and exploration. An invited paper. Economic Geology 112(3):483–516
2. Pasero M, Kampf AR, Ferraris C, Pekov IV, Rakovan J, White TJ (2010) Nomenclature of the apatite supergroup minerals. Eur J Mineral 22:163–179
3. Chakmouradian AR, Reguir EP, Zaitsev AN, Couëslan C, Xu C, Kynický J, Mumin AH, Yang P (2017) Apatite in carbonatitic rocks: compositional variation, zoning, element partitioning and petrogenetic significance. Lithos 274:188–213
4. Taylor SR, McClennan SM (1985) The continental crust: its composition and evolution. Blackwell, Oxford. 312 pp

Coal and rock classification with rib images and machine learning techniques

Yuting Xue
CDC NIOSH Pittsburgh Mining Research Division, Pittsburgh, PA, USA
*Corresponding author email: qcj1@cdc.gov

Full-text paper:
Mining, Metallurgy & Exploration (2022) 39:453–465, https://doi.org/10.1007/s42461-021-00526-4

Keywords: Rock classification, Image processing, Patch, Machine learning, SVM

Special Extended Abstract

The classification of rock and coal will assist in automated coal rib rating and shearer horizon control, and is studied with machine learning techniques in this work. A database of rock and coal images is created by filtering photographs taken by researchers from the National Institute for Occupational Safety and Health (NIOSH). The classifier was trained with patches extracted from the coal and rock images, and an accuracy score of 0.9 was obtained. The trained classifier was then applied to classify rock from a new coal rib image with three rock layers of different thicknesses, and good agreement was achieved. The results demonstrate that it is promising to use machine learning techniques and rib images for rock and coal classification.

Introduction

NIOSH researchers are currently developing a coal pillar rib rating (CPRR) technique to quantify the bearing capacity of coal ribs to eliminate injuries and fatalities due to rib falls [1]. The presence, location and thickness of rock partings affect the performance of coal ribs, and different adjustments are conducted for rib rating. Thus, one important step of coal rib rating is to classify rock from coal ribs. The classification of rock from coal ribs can also be applied for shearer horizon control at the longwall mining face. This enables a shearer to automatically track the interface between coal and rock, providing information for the shearer to adjust the cutting drum. In this work, machine learning techniques were applied to classify rock from coal rib images.

Database and method

Each image is made up of pixels. The pixel value represents the color intensity. For RGB images, there are three color channels: red, green and blue. An RGB image has three layers with each layer of a matrix of pixel values, and thus the image is represented as a three-dimensional array, which are features for machine learning.

The process to generate the databases is shown in Fig.1. During extensive field trips, NIOSH researchers took photographs to capture the failure mode of coal ribs. In order to capture the representative features of coal and rock, the photographs with fresh rock and/or coal surface were selected. Smaller images, or patches, were further extracted to generate a large database. The patches have the same size of 50 × 50 in pixels and potentially contain the same amount of information for coal and rock, and the feature extraction and classification are conducted on the patches. There are 10,500 and 14,500 patches extracted for coal and rock, respectively, making a total of 25,000 patches for model training and validation.

Various machine learning techniques from the Scikit-Learn package were used [2]. Principal component analysis (PCA), a dimensionality reduction technique, was applied to extract meaningful features by projecting the data onto the principal axes and measuring the importance of each feature. The goal is to represent the data in a suitable lower dimension and retain essential features. Support vector machine (SVM) was used as the classifier. It is a discriminative classifier formally defined by a set of hyperplanes in a high- or infinite-dimensional space. The PCA preprocessor and SVM classifier could be further packaged into a pipeline. When there are new data, the pipeline preprocesses them and feeds the processed data into the classifier for prediction. Furthermore, a grid search cross-validation method was used to tune the model hyperparameters controlling the model performance. Finally, the database was randomly split into a training set (75 percent) to train the classifier, and a testing set (25 percent) to evaluate the model performance.

Results and discussions

Model performance. The performance of the trained SVM classifier was evaluated with the testing dataset. The evaluation shows there were 627 wrong predictions and 5,636 correct predictions, leading to an accuracy score of 0.900. At the same time, there were 295 false negative cases and 3,316 true positive cases, leading to a recall score of 0.918. The high accuracy score and recall scores demonstrate the capability of the classifier in classifying rock from coal.

Influence of patch size. Patch size affects the number of captured features, and different patch sizes, including 25 × 25, 50 × 50, 75 × 75 and 100 × 100 pixels, were used to study their influence on model accuracy. The learning curves, a tool to show how the model responds to increasing training data, show that the training and testing scores are converging to different values with increasing training data. The general trend is that larger patch size leads to higher testing score. However, the difference in testing scores decreases with increasing patch size. The testing curves for patch sizes of 75 × 75 and 100 × 100 almost overlap with any training size, indicating that, for the rock and coal image database, a size of 75 × 75 pixels is representative to include essential rock and coal features.

Application. A new rib image was used to show the application of the technique (Fig. 2). Part of the image with fresh surface was cropped and imported. A sliding window function was used to extract 50 × 50 patches from the input image. A total of 5,106 patches were extracted and fed into the pipeline for dimensionality reduction and prediction. The predicted rock patches are marked with a red border. It shows the approximate locations of the three rock layers. However, the accuracy depends on patch size and rock layer thickness. The top layer has the maximum thickness, and the whole layer is accurately predicted by overlapping patches. When the thickness reduces, there is less overlapped rock patches, resulting from the lesser contribution of the rock layer to the patch.

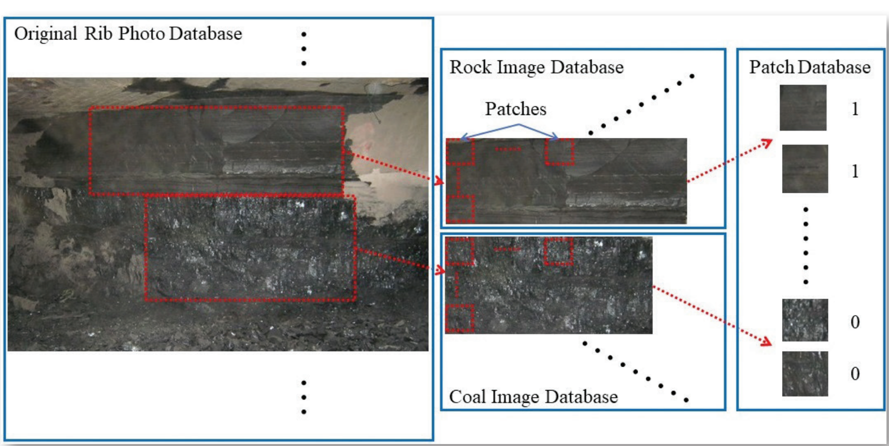

Fig. 1 Image-processing procedures to generate the database.

Conclusions

Machine learning techniques were used to classify rocks from coal rib images in gateroads. The trained SVM classifiers show good performance with an accuracy score of 0.90. It was then used to classify rock patches from a coal rib image. The highlighted rock patches illustrate the approximate location of the three rock layers. However, the accuracy depends on the rock layer thickness and patch size. ■

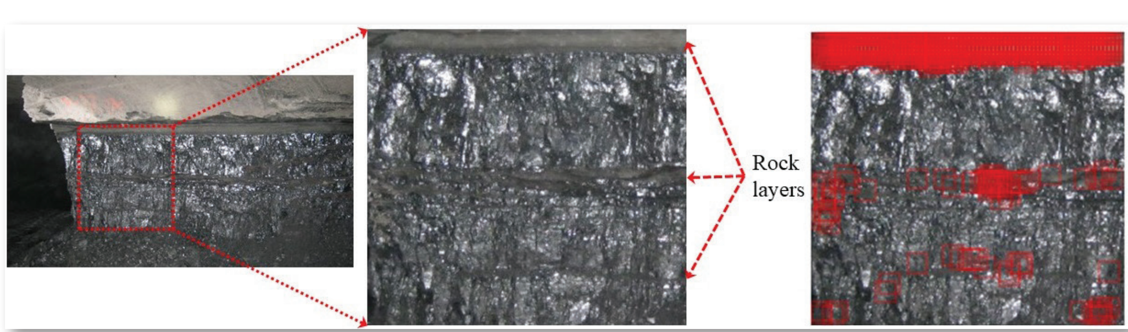

Fig. 2 Model application with SVM classifier.

Disclaimer

The findings and conclusions in this report are those of the author and do not necessarily represent the official position of the National Institute for Occupational Safety and Health, Centers for Disease Control and Prevention.

References

1. Mohamed KM, Xue Y, Rashed G, Kimutis R (2021) analyzing rib stability and support using a coal pillar rib rating. In the Proceedings of the 40th International Conference on Ground Control Mining, Canonsburg, PA, USA
2. Pedregosa F, Varoquaus G, Gramfort A, Michel V, Thirion B, Grisel O. Scikit-learn (2011) Machine learning in Python. J Mach Learn Res 12:2825–2830

Efficient separation and recovery of vanadium, titanium, iron and magnesium and synthesizing of anhydrite from steel slag

Jinrong Ju[1,2,3], Yali Feng[1,*], Haoran Li[2,3,*], Chenglong Xu[1] and Yi Yang[1]

[1]Civil and Resource Engineering School, University of Science and Technology Beijing, Beijing, China

[2]Key Laboratory of Biochemical Engineering, Institute of Process Engineering, Chinese Academy of Sciences, Beijing, China

[3]University of Chinese Academy of Sciences, Beijing, China

*Corresponding author emails: ylfeng126@126.com, hrli@ipe.ac.cn

Full-text paper:
Mining, Metallurgy & Exploration (2022) 39:733–748, https://doi.org/10.1007/s42461-022-00552-w

Keywords: Steel slag, Sulfuric acid leaching, Solvent extraction, Selective stripping, Oxalic acid precipitation

Special Extended Abstract

Steel slag is an industrial byproduct of steelmaking that is mainly composed of calcium, iron, silicon and magnesium. In addition, depending on the different raw materials entering the furnace, steel slag contains a certain amount of vanadium that is the main source of vanadium production, accounting for 69 percent of the species of the total vanadium raw material [1]. From experience, the production of one ton of steel will generate 1.0 to 1.5 tons of steel slag [2]. However, the utilization efficiency of steel slag is less than 30 percent, and a large amount of steel slag is identified as waste and stacked in tailings. The random stacking of steel slag not only wastes large amounts of limited steel and land resources but also exerts pressure on the environment [3], making it imperative to research the effective utilization of steel slag and recycling of metal resources.

Background

In the study, the process of leaching vanadium, titanium, iron and magnesium from steel slag and synthesizing of anhydrite at the same time is explored. The influences of acidity, temperature and time on metal leaching efficiency and slag phase composition are investigated. The separation process and mechanism of metals in the leaching solution are systematically studied, and the optimal separation conditions determined. The feasibility of recovering magnesium from solution to obtain magnesium oxide by oxalic acid precipitation method is researched, and the optimal conditions of precipitation explored.

Method

The steel slag used in the study was sourced from Pansteel & Iron Co. Ltd., located in the city of Panzhihua in Sichuan province in China. The leaching experiments of steel slag with sulfuric acid (H_2SO_4) solution were carried out with an electrically heated magnetic stirrer. After adding 100 mL of prepared H_2SO_4 solution of known concentration to a 250-mL Erlenmeyer flask and heating to the specified temperature, the steel slag was added while maintaining stirring. After the reaction was complete, a filtrate containing vanadium, titanium, iron and magnesium and leaching residue as calcium sulfate products were obtained by filtration.

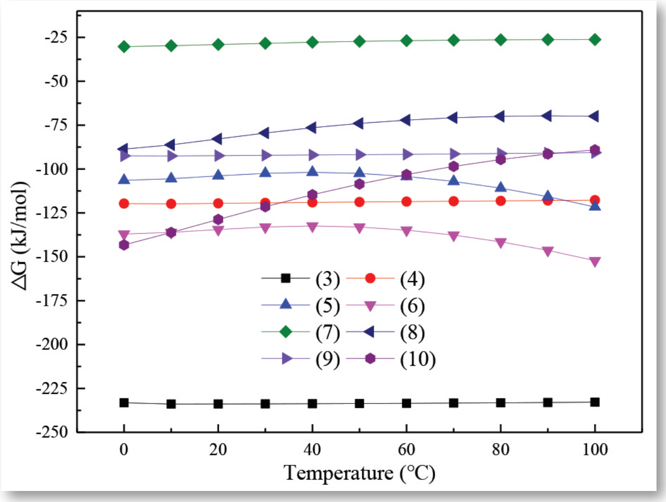

Fig. 1 Relationships between ΔG and temperature for the main reactions in the leaching process.

Results and discussion

The reactions of the compositions in steel slag with H_2SO_4 solution are given in Eqs. (1) to (8), and their thermodynamic diagrams are shown in Fig. 1.