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# The application of "transfer learning" in optical microscopy: The petrographic classification of opaque minerals

**Yi-Wei Cai[1], Kun-Feng Qiu[1,*], Maurizio Petrelli[2,†], Zhao-Liang Hou[3,*], M. Santosh[1,4], Hao-Cheng Yu[1], Ryan T. Armstrong[5], and Jun Deng[1,6]**

[1]Frontiers Science Center for Deep-time Digital Earth, State Key Laboratory of Geological Processes and Mineral Resources, School of Earth Sciences and Resources, China University of Geosciences, Beijing 100083, China
[2]Department of Physics and Geology, University of Perugia, Perugia 06100, Italy
[3]Department of Geology, University of Vienna, Vienna 1090, Austria
[4]Department of Earth Science, University of Adelaide, Adelaide, South Australia 5005, Australia
[5]School of Minerals and Energy Resources Engineering, University of New South Wales, Sydney, New South Wales 2052, Australia
[6]Geological Research Institute of Shandong Gold Group Co., Ltd., Jinan 250013, China

## Abstract

The analysis of optical microscopic image data is crucial for the identification and characterization of mineral phases and, thus, directly relevant to the subsequent methodology selections of further detailed petrological exploration. Here, we present a novel application of Swin Transformer, a deep learning algorithm to classify mineral phases such as arsenopyrite, chalcopyrite, gold, pyrite, and stibnite in images captured by optical microscopy. To speed up the training process and improve the generalization capabilities of the investigated model, we adopt the "transfer learning" paradigm by pre-training the algorithm using a large, general-purpose image data set named ImageNet-1k. Furthermore, we compare the performances of the Swin Transformer with those of two well-established Convolutional Neural Networks (CNNs) named MobileNetv2 and ResNet50, respectively. Our results highlight a maximum accuracy of 0.92 for the Swin Transformer, outperforming the CNNs. To provide an interpretation of the trained models, we apply the so-called Class Activation Map (CAM), which indicates a strong global feature extraction ability of the Swin Transformer metal mineral classifier that focuses on distinctive (e.g., colors) and microstructural (e.g., edge shapes) features. The results demonstrate that the deep learning approach can accurately extract all available attributes, which reveals the potential to assist in data exploration and provides an opportunity to carry out spatial quantization at a large scale (centimeters-millimeters). Simultaneously, boosting the learning processes with pre-trained weights can accurately capture relevant attributes in mineral classification, revealing the potential for application in mineralogy and petrology, as well as enabling its use in resource explorations.

**Keywords:** Swin Transformer opaque mineral classifier, microscopy images, transfer learning, deep learning, class activation map