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Mineral interpretation results using deep learning with hyperspectral imagery

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Minerals are key resources for several industries, such as the manufacturing of high-performance components and the latest electronic devices. For the purpose of finding new mineral deposits, mineral interpretation is a task of great relevance in mining and metallurgy sectors. However, it is usually a long, costly, laborious, and manual procedure. It involves the characterization of mineral samples in laboratories far from the mineral deposits and it is subject to human interpretation mistakes. To address the previous problems, an automatic mineral recognition system is proposed that analyzes in real-time hyperspectral imagery acquired in different spectral ranges: VN-SWIR (Visible, Near and Short Wave Infrared) and LWIR (Long Wave Infrared). Thus, more efficient, faster, and more economic explorations are performed, by analyzing in-situ mineral deposits in the subsurface, instead of in laboratories. The developed system is based on a deep learning technique that implements a semantic segmentation neural network that considers spatial and spectral correlations. Two different databases composed by scanned drilled mineral cores from different mineral deposits have been used to evaluate the mineral interpretation capability. The first database contains hyperspectral images in the VN-SWIR range and the second one in the LWIR range. The obtained results show that the mineral recognition for the first database (VN-SWIR band) achieves an 86% in accuracy considering the following mineral classes: Actinolite, amphibole, biotite-chlorite, carbonate, epidote, saponite, whitemica and whitemica-chlorite. For the second database (LWIR band), a 90% in accuracy has been obtained with the following mineral classes: Albite, amphibole, apatite, carbonate, clinopyroxene, epidote, microcline, quartz, quartz-clay-feldspar and sulphide-oxide. The mineral recognition capability has been also compared between both spectral bands considering the common minerals in both databases. The results show a higher recognition performance in the LWIR band, achieving a 96% in accuracy, than in the VN-SWIR bands, which achieves an accuracy of 85%. However, the hyperspectral cameras covering VN-SWIR range are significantly more economic than those covering the LWIR range, and therefore making them a very interesting option for low-budget systems, but still with a good mineral recognition performance. On the other hand, there is a better recognition capability for those mineral categories with a higher number of samples in the databases, as expected.
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