IDENTIFYING MINERAL PHASES IN METEORITES BY BSE-EDS IMAGES USING DEEP LEARNING MODEL

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Introduction: Hundreds of minerals have been identified in the meteorites, most of which are comparative to terrestrial minerals found in Earth environment. Common meteorite minerals include opaque minerals (Ilmenite, Magnetite, Chromite, Troilite, Sulfur, Carbon), and transparent minerals (Olivine, Pyroxene, Feldspar, Quartz, Spinel, Serpentine, Apatite).

The tranditional researches of meteorites require many state-of-art instruments, such as Scanning Electron Microscope (SEM) and Energy Dispersive Spectroscopy (EDS). SEM is a multifunctional electron microanalysis instrument, the main function of which is the morphological microanalysis of solid materials and the micro-area analysis of their elemental and structural properties. SEM can generate various images based on the interaction between electrons and samples, when the high-energy incident electron beam bombards the surface of the sample. When a high-energy incident electron beam bombards the sample surface, most of the incident electron energy is converted to thermal energy [1]. EDS can analyze the elemental compositions of samples, which is often used in combination with SEM or TEM. An electron beam bombards the surface of a sample under a vacuum chamber to excite the emission of characteristic X-rays from the sample. EDS can provide qualitative or semi-quantitative elemental analysis of micro-areas on the sample surface, as well as point, line scan, and mapping analysis of specific areas [2].

Meteoritics is a multidisciplinary field that requires the use of astronomy, geology, physics, chemistry, and biology for comprehensive studies. Nowadays, meteoritics can also cooperate and integrate with fields such as computer vision and deep learning. With the development of artificial intelligence and computer vision, deep learning models and trans-learning strategies can be used to quickly extract and quantify the mineralogical and elemental composition of meteorite slices, making it easier and faster for researchers to understand the basic information of the meteorite. improve the research efficiency.

The BSE (backscattered electron) images of meteorites can be equated to the target detection and semantic segmentation in the field of computer vision. Mask R-CNN, proposed by He et al. [3], is a general framework for object detection and instance segmentation. Mask R-CNN is a neural network which generates a series of candidate regions with potential targets, and then classifies, regresses, and segments each region, according to the characteristics of the candidate regions In this work, we performed Mask R-CNN analysis of mineral phases in the meteorite by BSE-EDS image.

Dataset and processing: The BSE images used for target detection and semantic segmentation are from the lunar meteorites Northwest Africa 10985 and Northwest Africa 11460. NWA 10985 is a prominent gabbro within a fragmental breccia and NWA 11460 has been classified as a polymict breccia, composed of feldspathic clasts, mafic-rich clasts (gabbroic and troctoliticfragments), granulites, and a wide range of impact melt breccias and dimict breccias [4-6]. Mask R-CNN was used to detect minerals in meteorite slices using SEM data and to implement instance segmentation of different minerals. The overall framework of meteorite mineral phase detection using Mask R-CNN is shown in Figure 1.
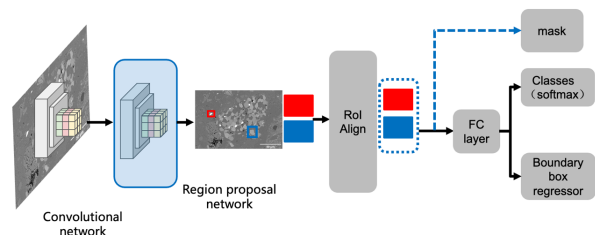

Figure 1: Mask R-CNN model structure diagrams. The Mask R-CNN is a two-stage framework, where the first stage scans the image and generates proposals , and the second stage classifies the proposals and generates bounding boxes and masks.

Result: The semantic segmentation model based on Mask- RCNN can well identify opaque minerals and translucent minerals in meteorite BSE images, including ilmenite, magnetite, chromite, troilite, sulfur, carbon, etc.. For a BSE photograph of NWA 11460, the ilmenitemineral can be effectively identified, and the identification results are shown in Figure 2.
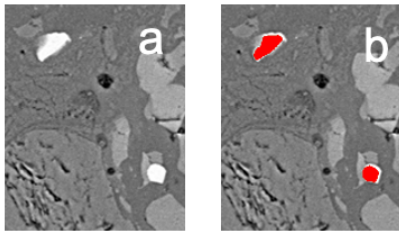
Figure 2: Identification results of ilmenite in NWA 11460

In a single BSE image, some minerals such as olivine, pyroxene and plagioclase have high similarity, and it is difficult to distinguish them directly by relying on a single data source. Therefore, we consider to combine BSE image and EDS elemental images and use image fusion method to detect and identify minerals with similar tones in BSE images. The resolution of EDS images is lower than that of BSE images, and cannot be directly fused. The image fusion strategy uses panchromatic sharpening, which is commonly used in the field of remote sensing to achieve the fusion of low-resolution multispectral images and high-resolution PAN images. [7]

We used the Gram-Schmidt variation algorithm to accomplish the data fusion and used noise filter to interpolate the low-resolution EDS elemental maps to achieve the resolution enhancement. The pyroxene can be identified in the fused NWA 10985 image.
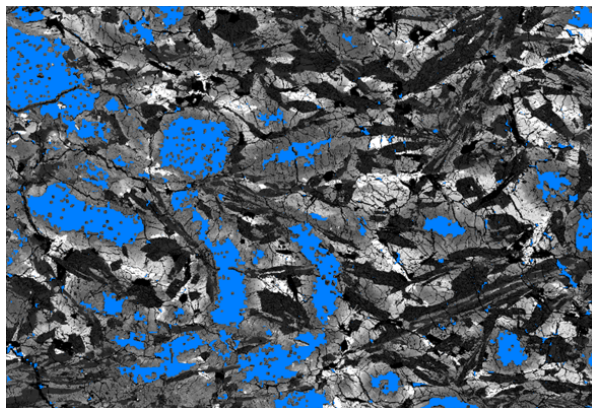

Figure 3: Pyroxene identification in the NWA 10985

Conclusion: The identification of major mineral phases is an important issue in meteorite research. In this paper, the Mask R-CNN network model is used to classify the image data of meteorite slices collected by SEM and EDS, and identify minerals. This is the first method to be applied to different meteorites for various size to extract populations of main mineral phases. We believe that the new methods could substantially deepen our understanding of cratering mechanism and crater chronology. The experimental results show that the established semantic segmentation   model has high accuracy..

The semantic segmentation network model proposed in this work greatly improves the recognition efficiency on the basis of ensuring the accuracy. In the face of more and more meteorites are collected and recorded in the database, the model will play its role better and provide help and reference for researchers in meteoritics.

On-going and future work: In future work, the model can also be used to identify porosity and mineral grain size in meteorite images[8]. By quantifying the bulk density, particle density and porosity of a meteorite sample, the evolution and physical processes of the meteorite and its parent body can be inferred. When compared with the densities of small solar system bodies, one can deduce the nature of asteroid and comet interiors, which in turn reflect the accretional and collisional environment of the early solar system.

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