



-INTRODUCTION -

The analysis of light and SEM microscopy images of thin rock sections, while informative, is currently dependent on a significant investment of human time, which implies a limited number of processed images, thereby compromising conclusions at larger scales.

In recent years, advances in artificial intelligence have taken image analysis to a new level by automating human interpretation, allowing a greater number of samples to be processed.

Our study aims to perform automatic compositional analysis of micro-petrological features across many SEM images of thin rock sections for the robust characterization of volcanic deposits.

STEPS:

Automatic Image Segmentation: Segment SEM images to clearly delineate distinct "objects" within the samples.

Object Identification: Machine-learning (ML) to identify these "objects" based on quantitative morphological data and elemental composition mappings derived from Energy Dispersive Spectroscopy (EDS).

In this poster we present results on image segmentation and Linear Discriminant Analysis (LDA)



- Three backscattered SEM images of thin sections of two volcanic rocks that correspond to pyroclastic density current deposits of the Fumarole Bay Formation of Deception Island (Antarctica).
- Fragments consist of a glassy groundmass bearing plagioclase, olivine and pyroxene phenocrysts and microcrysts, and abundant vesicles, however, the clasts are highly altered, with some even lacking sideromelane.
- A collection of objects (e.g., vesicles, minerals) was interactively outlined in the SEM images to serve as a training and validation set.

APPLIED VOLCANOLOGY TEAM

Al-driven analysis of SEM images of thin layers of volcanic rocks: a test with Segment Anything for Microscopy

https://diapiro.geo3bcn.csic.es/alobo/blog/microsam_test_SEMGEO_nb.html

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METHODS

Image Segmentation:

- We utilize the Segment Anything Model (SAM)^{1, 2}, as implemented in Segment Anything for Microscopy (micro-SAM)^{3,4}, to conduct image segmentation.
 - This involves testing both the original SAM models and fine-tuned variants.
 - A grid search was performed to find the best values of the essential parameters of SAM.

Linear Discriminant Analysis:

- LDA to assess the consistency of our taxonomy with the elemental composition obtained from EDS mappings.
 - The LDA was applied to our training set of SEM features, overlaid on the EDS mappings.

Software: napari⁵, micro-SAM^{3, 4}, R packages (terra⁶, ggplot2⁷, MASS⁸). Hardware: Dell Precision 3660, Intel i9, 62.5 GiB RAM, NVIDIA RTX A4000 GPU.

IMAGE SEGMENTATION



Selected results resulting from SAM models vit_b and vit_h (pred_iou_th=0.7, stab_score_th=0.9 and box_nms_th=0.1), and automatic instance segmentations resulting from micro-sam fine-tuning with our own images and training sets.

Element Mappings from EDS-SEM -





PRELIMINARY FINDINGS -

Fine-tuning in microSAM increased accuracy (CD) in DI17 images, but added few new objects. DI18A did not improve; further tests with more images and parameters are ongoing.

The original SAM vit_h model, with grid-searched parameters, yielded a useful result with many polygons and with a high (CD+OS)/(US+M) ratio. Subsequent ML classification can be applied to both well- and over-segmented objects.

LDA reveals a general alignment between our initial taxonomy and element composition, highlighting some necessary modifications to ensure class uniformity across both morphological and chemical data spaces. This consistency is a sine-qua-non condition for the effective identification by ML methods.

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Deep-learning techniques heavily rely on large training datasets. The creation of such datasets can be significantly enhanced through collaborative projects between institutions, potentially utilizing federated learning strategies.

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²https://arxiv.org/abs/2304.02643 ³Archit, A., Freckmann, L., Nair, S. et al. Segment Anything for Microscopy. Nat Methods 22, 579–591 (2025) https://computational-cell-analytics.github.io/micro-sam/micro_sam.html#segment-anything-for-microscopy ⁵napari contributors (2019). napari: a multi-dimensional image viewer for python. ⁶R Core Team (2024). _R: A Language and Environment for Statistical Computing_. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/ ⁷Hijmans R (2025). _terra: Spatial Data Analysis_. R package version 1.8-30, commit 5712294aac31f7c45aca2868d709f1435bb1d7d0, https://github.com/rspatial/terra ⁸H. Wickham. ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York, 2016 ⁹Venables, W. N. & Ripley, B. D. (2002) Modern Applied Statistics with S. Fourth Edition. Springer, New York.

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