Automatic Classification of Sedimentary Particles for Insights into Past Climate Environment

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Abstract

This work presents early-stage research on the classification of sedimentary particles in microscope images from samples spanning different geological epochs. The overarching goal is to enable a quantitative assessment of past environmental changes using a fast and unbiased annotation method. Since particle labels are available for only a small subset of images, we focus on unsupervised learning. The workflow consists of two stages: first, particles are segmented using a combination of thresholding methods and the pre-trained SAM2 model (Ravi et al. [2024]); second, segmented particles are grouped through zero-shot classification using the pre-trained DINOv2 model (Oquab et al. [2023]). Initial qualitative results show that most particles are successfully segmented. However, the resulting clusters contain heterogeneous mixtures of particle types, highlighting the challenges of unsupervised classification in this domain. Future work will incorporate available labeled data to improve the classification results.

Keywords: Digital microscopy, self-supervised learning, geological imaging, zero-shot classification

1 Introduction

Understanding past environmental conditions is essential for studying climate evolution, mapping natural resources, and developing sustainable energy solutions. One of the key approaches for reconstructing such environments relies on the identification and classification of microscopic organic particles (palynofacies) preserved in rocks (e.g., Tyson [1995], Dybkjær et al. [1996], Dybkjær [2004], Dybkjær et al. [2019], Nøhr-Hansen et al. [2021]). Several common particle types are shown in Fig. 1, which in this work are grouped into eight categories.

The traditional workflow involves preparing microscope slides by removing rock minerals through acid and heavy-liquid treatments, mounting the remaining organic residue, and analyzing it under transmitted-light microscopy. During this process, particles are manually identified and assigned to predefined categories within a selected area. Typically, analysis continues until a target number of particles is counted (commonly around 300, out of the thousands

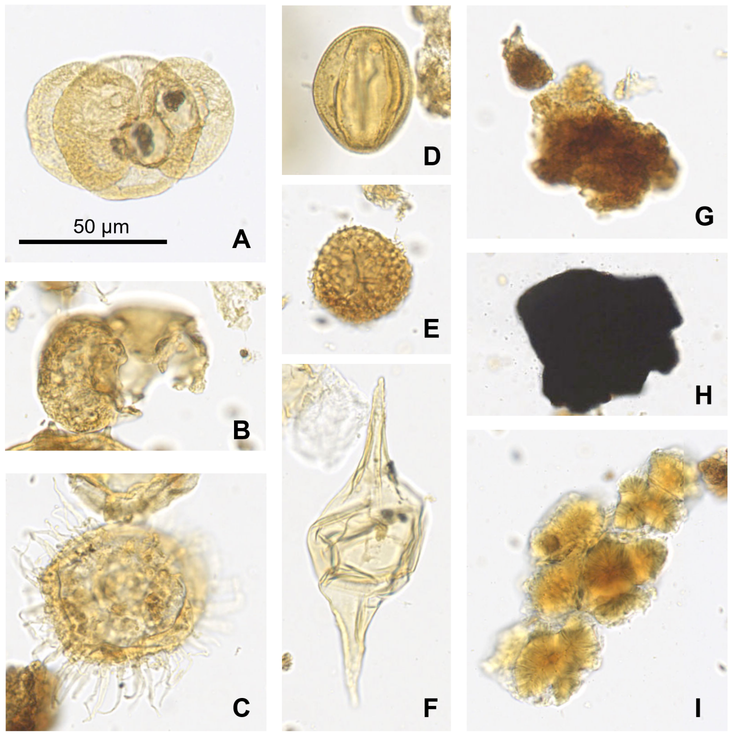

Figure 1: Examples of typical organic particles. A) Well preserved bisaccate pollen; B) Large fragment of a bisaccate pollen; C) Dinocyst; D) Non saccate pollen; E) Spore; F) Dinocyst; G) Amorphous organic matter; H) Phytoclast (fragment of black wood); I) Freshwater algae (Botryococcus). Note that particles C and F belong to the same category.

often present on a slide). However, the counting area is rarely precisely defined, making it difficult to reproduce the analysis or correct initial annotations without repeating the entire procedure. Furthermore, the accuracy of particle identification depends on the analyst's experience, which introduces variability and complicates data integration across different studies.

To address these limitations, our project introduces a digital, standardized workflow designed to enhance transparency, reproducibility, and efficiency in the analysis of sedimentary organic particles. This approach makes it possible to extract high-quality environmental information from complex microscopic data in a more consistent and scalable manner.

2 Related work

Automatic particle recognition and classification have become integral to a wide range of scientific disciplines, including biology, materials science, and the life sciences Roseman [2004], Timmins et al. [2012], Zhu et al. [2017], Sachs et al. [2023], Bals and Epple [2023].

Much of the existing research in automatic particle classification has relied on task-specific supervised models, designed for particular datasets or narrow application domains. While successful in controlled settings, these models often struggle to generalize to new or unseen sample types.

In this context, self-supervised learning methods Chen et al. [2020], Radford et al. [2021], Oquab et al. [2023] hold particular promise. By learning transferable feature representations directly from large collections of unlabeled images, they reduce the dependence on extensive manual annotations. Applied to palynofacies, such approaches could enable robust classification of organic particles across diverse geological samples, paving the way for more scalable and reproducible paleoenvironmental reconstructions.

3 Workflow

Stage 1: Particle Segmentation and Extraction

The first stage focuses on the automatic detection and extraction of individual particles from digitized microscope slides. We employ classical image processing techniques, including Gaussian smoothing of grayscale-converted images, contrast enhancement, and Otsu's thresholding. For particles that cannot be confidently segmented using thresholding alone, we leverage the Segment Anything Model v2 (Ravi et al. [2024]) to generate instance masks. This hybrid approach successfully isolates single particles in most cases, although overlapping particles occasionally cannot be fully separated. The output of this stage is a set of individual particle images suitable for further analysis.

Stage 2: Feature Extraction and Unsupervised Classification

In the second stage, each segmented particle is represented as a high-dimensional embedding using the DINOv2 vision transformer model (Oquab et al. [2023]). Since particle labels are available for only a small subset of images, we focus on unsupervised learning. To this end, we use pre-trained DINOv2 features as-is, i.e., with a frozen backbone, no fine-tuning, and no learned classification head. The resulting embeddings are then clustered using k-means, an unsupervised algorithm that partitions the feature space into a predefined number of clusters McQueen [1967]. Each cluster serves as a pseudo-label, grouping visually similar particles together. This produces a structured dataset in which images are organized according to intrinsic visual properties, enabling further analysis in the absence of ground-truth annotations.

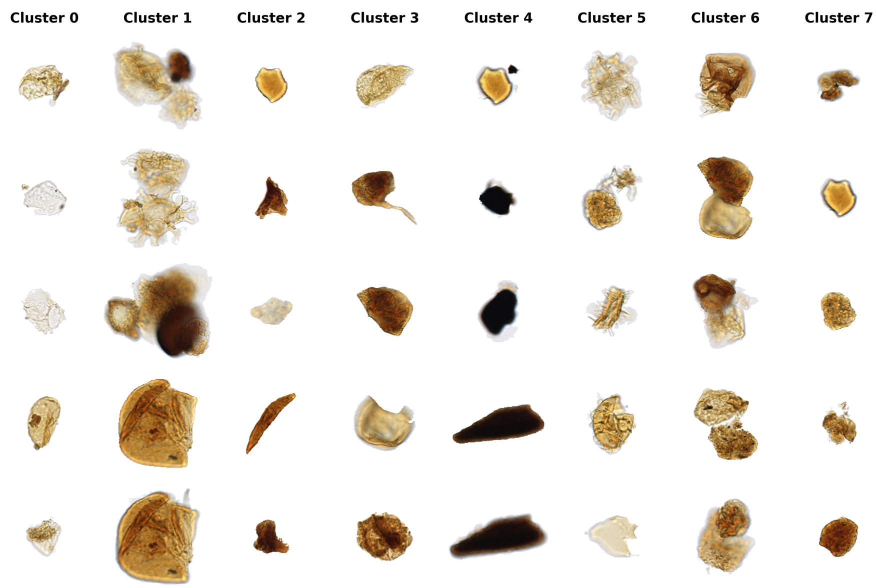

Figure 2: Examples of particle classifications using the DINOv2 model.

An implementation of the particle segmentation and classification workflow is publicly available at `https://github.com/nikolai-andrianov/palynofacies`.

Preliminary Results and Outlook

Initial clustering demonstrates that visually similar particles are generally grouped together, but each cluster still contains a mixture of particle types. Some particles were assigned to multiple clusters, though they ideally belong to a single category. For example, Cluster 4 effectively identified black wood particles but also included particles from other types. Clustering appears to be influenced primarily by color and shape, resulting in certain clusters dominated by rounded or darker particles regardless of their true classification. Cluster 6 grouped overlapping particles that should ideally have been treated as separate entities.

These observations highlight both the potential and current limitations of unsupervised, feature-based clustering for palynofacies analysis. While this approach provides a rapid and unbiased method to organize particles, further refinement—such as incorporating semi-supervised learning with available labeled data or adding additional morphological descriptors—could improve cluster purity and better reflect true particle categories. Overall, our results demonstrate the feasibility of constructing structured, visually informed datasets without extensive manual annotation, paving the way for scalable and reproducible studies of past environmental conditions.

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