Enhancing Ceramic Petrography Through Deep Learning

Ashley Rutkoski [1] Nicolas Gauthier [1,2] Neill Wallis [1] Andrea Torvinen [1] Ann Cordell [1]

[1]Florida Museum of Natural History, University of Florida [2]Department of Geography, University of Florida

Background

Ceramic petrography has long been instrumental in shedding light on key manufacturing techniques, identifying unique mineralogical signatures, and assessing patterns of cultural exchange among diverse communities [1]. Even with the integration of bulk chemical analyses (e.g., NAA, XRD, and XRF) within the discipline, petrography has remained a traditional method used to characterize and quantify minerals naturally included and those added by people, as the matrix, inclusions, and voids can be considered individually [2]. Despite the numerous benefits of petrographic analysis, the task remains labor-intensive and time-consuming which makes it difficult to meet the increasing demand for large comparative datasets.

What is Deep Learning?

Deep learning is a subset of artificial intelligence (AI) that uses an algorithm called a "neural network" to recognize patterns in data with limited human interaction. Computer vision, a subset of deep learning, uses "convolutional neural networks" (CNN) to process various aspects of an image (e.g., textures, colors, shapes, etc.) to detect and classify objects [3].

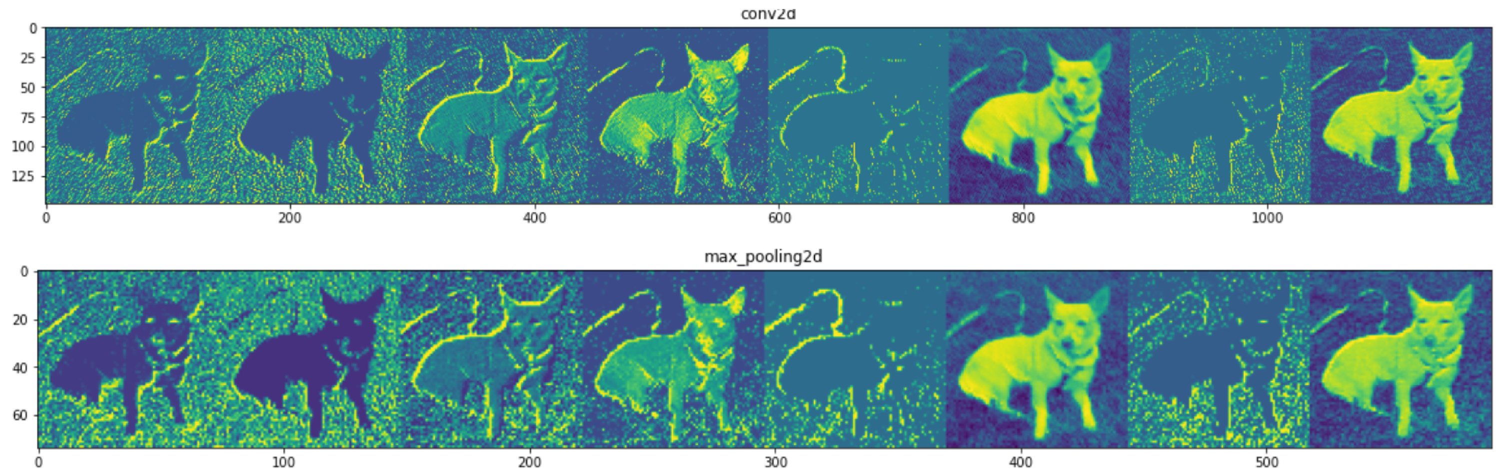


Figure 1. Visual depiction of what each CNN layer is focusing on to classify an image.

Deep Learning for Petrography

As CNN models pre-trained on millions of images have become more accessible, archaeologists have begun to use this technology to increase and standardize data collection. Within petrography, CNNs can be used to classify paste recipes, quantify the densities and sizes of inclusions, and emphasize within-type variability by discerning the optical properties (e.g., relief, birefringence, color, cleavage) of inclusions and voids [4].

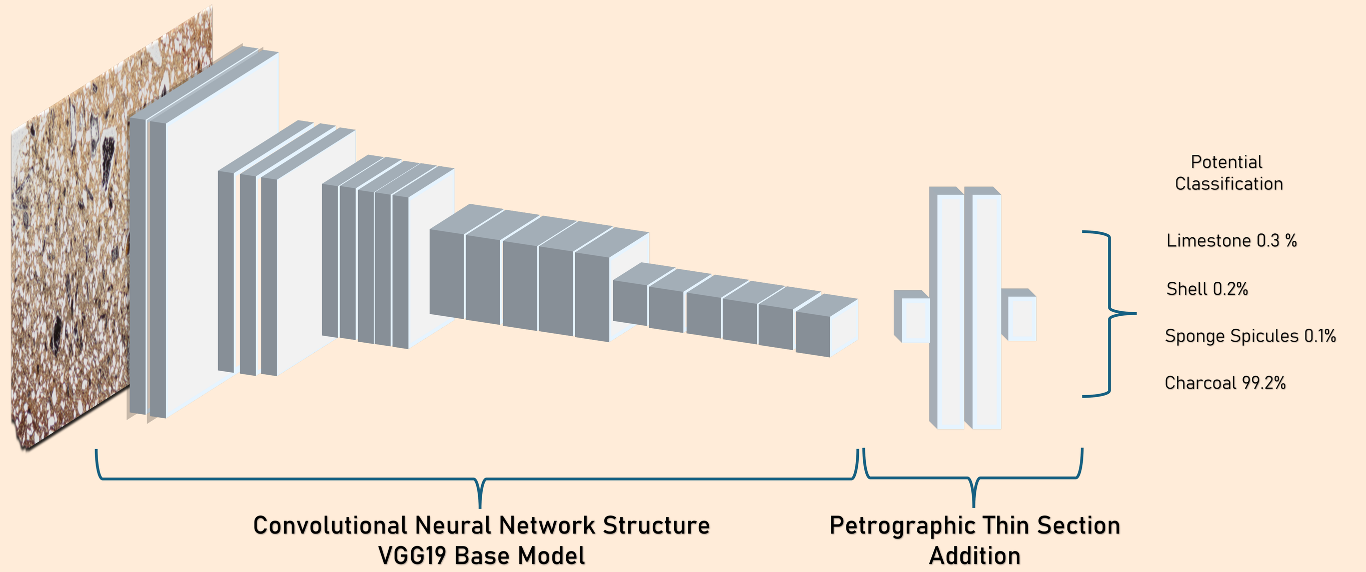


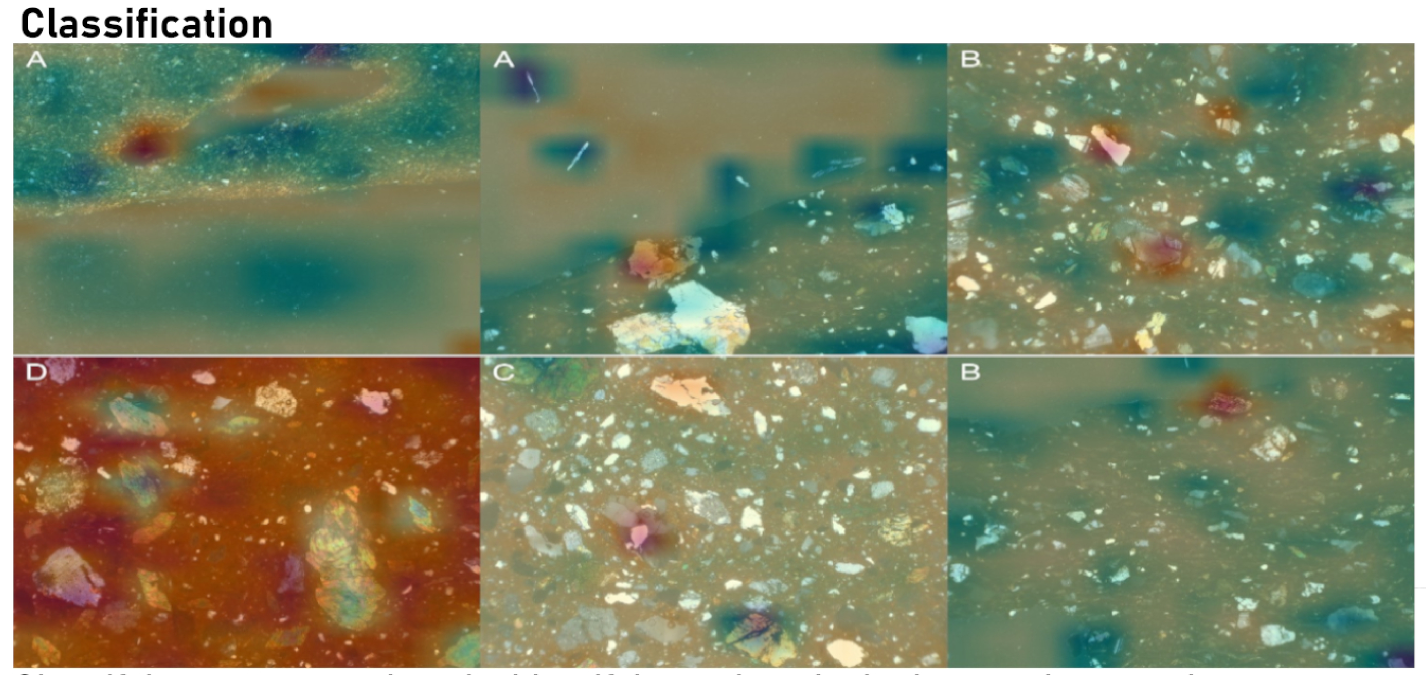
Figure 2. Diagram of a CNN used for petrographic analysis. The convolutional layers act as an "information distiller" that extracts meaningful features from the pixels in an image to be used for classification.

A Digital Petrography Workflow

A full petrographic imaging workflow can be developed with easily-accessible hardware and software [5].

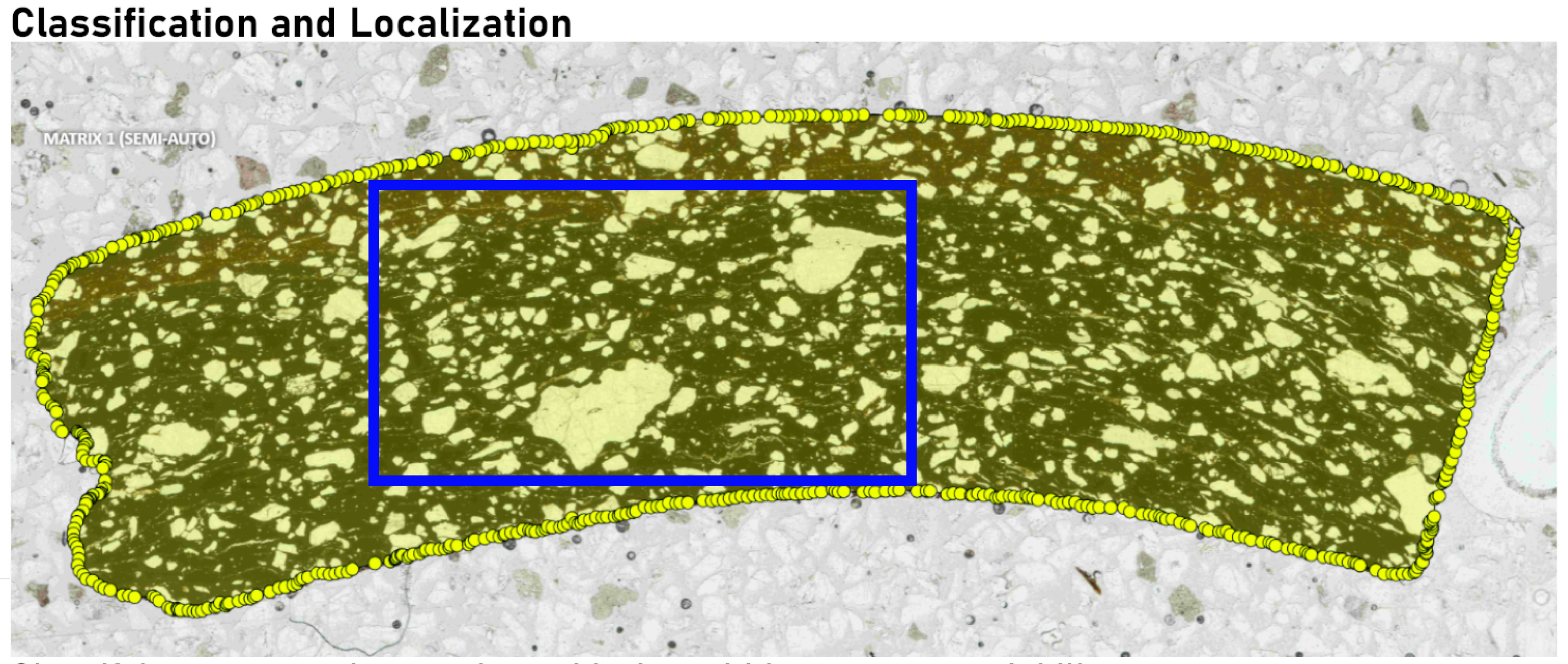
Figure 3. Using a low cost film scanner (**Plustek 8100 OpticFilm scanner**), 3D-printed slide holders, and polarizing filters, thin sections can be scanned in plane and circularly polarized light. **VueScan** is then used to process and edit these scans, and inclusions and voids of interest can be annotated in **CVAT**. These annotations can then be used to train a CNN model in **R** or **Python** [4].

Classification



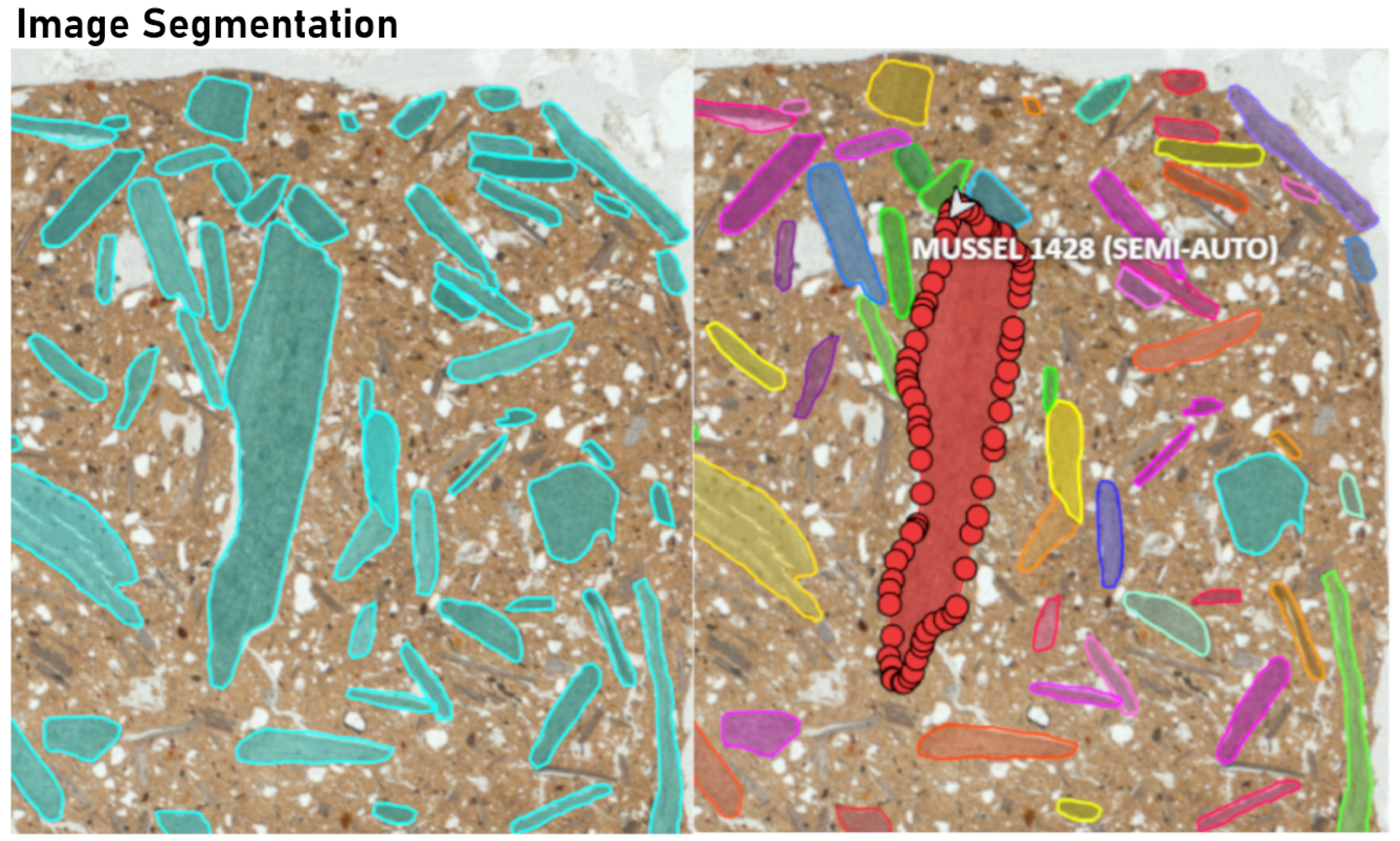
Classifying pottery recipes by identifying unique inclusions and properties

Classification and Localization



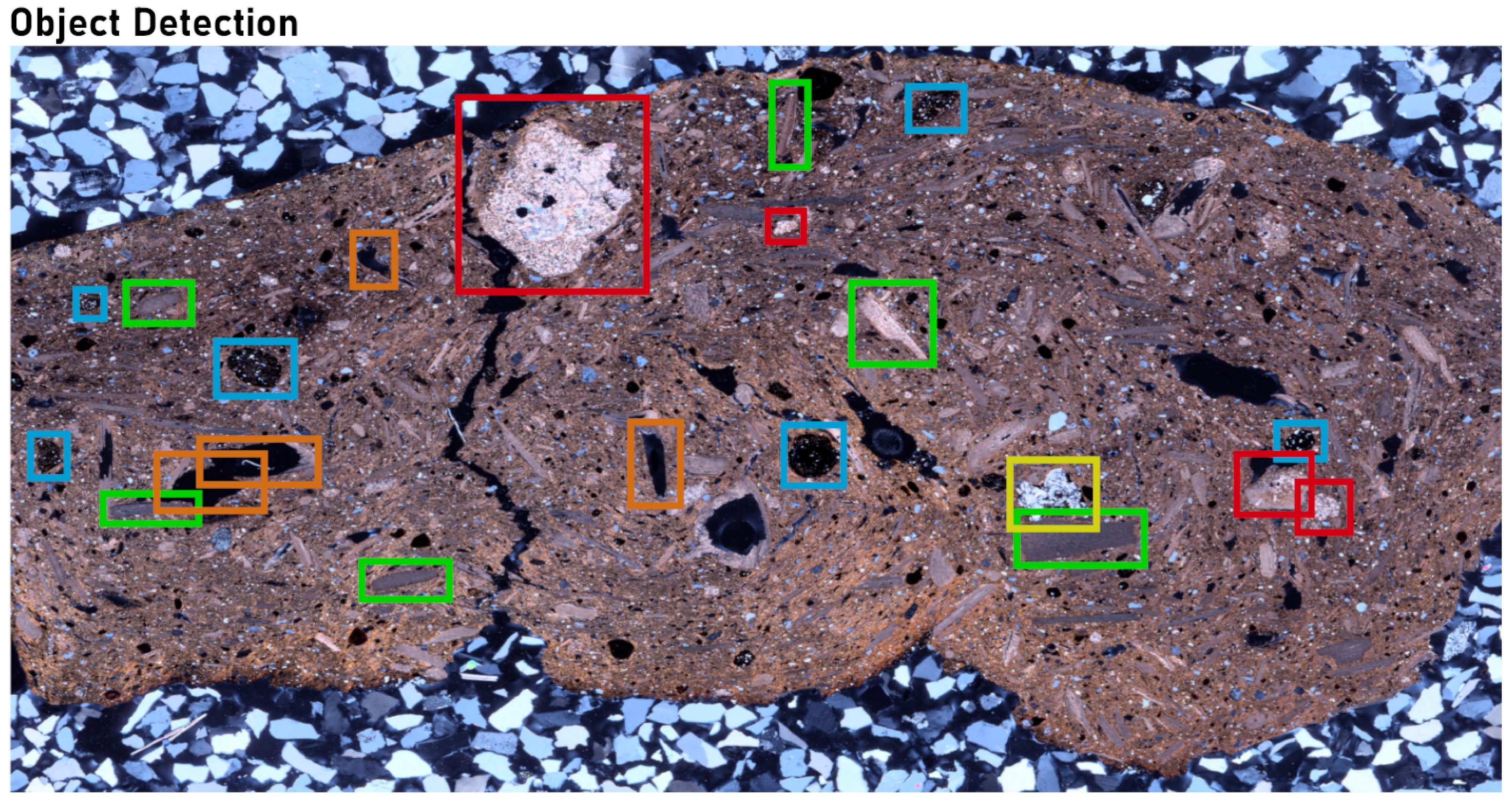
Classifying paste recipes and considering within category variability

Image Segmentation



Identifying all mussel shell collectively (***semantic***) or considering each shell inclusion individually (***instance***)

Object Detection



Identifying iron, shell, shell voids, limestone, and chalcedony in images or video

Case Study: Detecting Bivalve Fracture Patterns

As Pensacola communities adopted Mississippian potting traditions along the Northern Gulf Coast (1250 CE), shell tempering practices expanded to include mussel, clam, and other coastal species [6]. Identifying specific species in cross sections of pottery remains challenging, as fragmentation and firing eradicates morphological and chemical signatures [7, 8]. **Here, we annotated experimental thin sections of mussel and clam shells to train a deep learning model to identify the different species in cross-section.**

Figure 4. Experimental thin section samples with known inclusion types and frequencies. Clam shell in green, Mussel Shell in blue, and Oyster in pink.

The model performs well at detecting shell tempers and classifying their species. The best-performing model has an **average precision of (75-90%)** and an **average recall of (55-94%)** on unseen data, indicating that up to 90% of identified objects are correctly classified and up to 94% of actual shells present are successfully detected and identified. Model performance depends on the size of the inclusions, with the smallest clam fragments being the most difficult to identify.

Takeaways

- Petrographic analysis can be streamlined with accessible deep-learning techniques
- Computer vision can help classify paste recipes, identify inclusions, assess particle-size distributions, and more
- Deep learning will not replace petrographers, as experience is needed to develop and test quality models

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nicolas.gauthier@ufl.edu