

Research proposal – PhD in Earth Sciences – 39th cycle Curriculum in Environment and Cultural Heritage

Development of a Deep Learning model for the classification of ceramic thin sections

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Introduction and state of the art

Ancient ceramic artifacts represent social and human markers within archaeological contexts, playing a fundamental role for the study of trade relationships and technological development of past societies.

Currently, petrographic analysis of ceramic thin sections through the description of inclusions, matrix, and voids, is one of the most effective and widespread methods for the classification and reconstruction of the technological and material aspects of ceramics. In this context, Whitbread introduced the concept of *fabrics*, groups of thin sections sharing similar characteristics [1], and representative of the *opératoire chaîne*, the actions and technological choices of the production process, essential to rebuild the development of ancient societies. However, this procedure is time-consuming and strongly influenced by the expertise of the individual operator, making it challenging to compare results across different contexts.

In the last decade, researchers have started to use automatic methodologies to group ceramics, by applying classification algorithms, which have significantly contributed to recognize specific compositional, technological or stylistic patterns [2]. There has been a substantial growth in the application of Machine Learning for the classification of ceramic types, through the recognition of decorative shapes and patterns [3] and the processing of geochemical data to support provenance analysis [4,5]. For about 20 years, efforts have been made to apply artificial intelligence techniques for the thin sections analysis in the field of petrography and geoscience. Deep Learning applications have been tested for the automatic classification of thin section rock images, taking into account pore information, mineral identification and rock classification [6]. An example is the concatenated convolutional neural network (Con-CNN), based on the use of multiple images for each petrographic section as input data with the aim of facilitating rock classification [7]. Regarding ceramics, artificial neural networks (ANNs) coupled with image analysis have recently been tested to perform the identification of inclusions and pores in sections. The idea is to improve the visual separation of components in a section, working on various parameters such as colour, shape, size, percentage of inclusions, and porosity [8]. The data extracted from image analysis were used to supervise the training of ANNs [9]. In another application, Convolutional neural networks (CNNs) with bottom layers pre-trained on dataset have been used for classifying samples of ceramic sections into their corresponding *fabrics* [10].

CNNs are designed specifically for image pattern recognition. They learn from the training data the best set of filters to extract diverse features from an image, enabling them to achieve maximum performance in the required task. In this way, classification is performed by identifying as many specific features as possible present in the image of the objects to be recognized. It's not easy to determine which features the algorithm relies on for the classification. The most accurate DL models are difficult to explain and often are defined as 'black boxes'. Explainable Artificial Intelligence (XAI) is an emerging field that aims at studying the interpretability of DL models through explainability techniques with the goal of understanding which variables are considered during the training [11].

Studies conducted up to now have highlighted the necessity of predefining the classes for the model, developing and collecting a labelled dataset for these classes. In the present project, the aim is to create a generalized model able to categorize classes not included or specified *a priori* during the training phase, allowing the classification of independent ceramic groups that were excluded from the initial training of the model (Fig. 1).

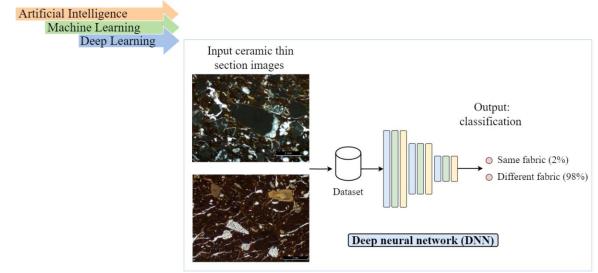


Fig. 1. Schematic example of the CNN model.

General objective/goal

Development of Deep Learning (DL) classification models capable of classifying and grouping ceramic thin sections with the aim of understanding ancient relationships and trade routes.

Specific objectives

- Development of a DL model based on convolutional neural networks (CNNs) for the classification and grouping of ceramic thin sections with similar characteristics.
- Validation of the CNN model using ceramic samples from the archaeological site of the Basilica of the Holy Sepulchre, Jerusalem.
- Definition of the composition and provenance of the Holy Sepulchre ceramics through archaeometric investigations.
- Comparison of archaeometric results with those of the CNN model in order to evaluate its effectiveness.

Future implications

The development of a generalized CNN model will allow the objective classification and grouping of many types of ceramics from different fabrics, cultural groups, and archaeological contexts. This will significantly contribute to clarify the interactions and trade networks of ancient populations.

<u>Work plan</u>

Task 1 - Bibliographic research (Months 1-4)

The first months of the project will be focused on the bibliographical research with the aim of collecting information on the use of CNNs for image-based classification and grouping of ceramics. There will also be a planning phase concerning the study of the geological setting and ancient ceramic production in Jerusalem to gain a comprehensive understanding of their morphology, production technologies, and the raw materials used in their production. The bibliographic research will continue for the duration of the project.

Task 2 - Acquisition of ceramic thin sections (Months 5-20)

The starting point for the development of the CNN model, consists in a phase of selection and acquisition of a large number of ceramic thin sections images, which will be used as training dataset.

- Task 2.1. Images selection (Months 5-12)

Thousands of images need to be selected to optimize the training of the CNN model. The thin sections selected should be representative of the Near and Middle East archaeological contexts since the validation of the model will be performed on ceramics from the Holy Sepulchre in Jerusalem.

- Task 2.2. Images acquisition (Months 10-20)

For each individual ceramic section selected, multiple images will be acquired in PNG and under both cross-polarized light and plane-polarized light.

Task 3 - CNN development (Months 13-24)

After acquiring the images of ceramic thin sections, the development of the CNN model will begin in this third phase in collaboration with the Department of Information, Electronics, and Telecommunications Engineering at La Sapienza.

Task 4 - Archaeometric characterization (Months 9-24)

This phase will focus on the archaeometric investigation of ceramic samples collected from the Holy Sepulchre. The city is located in the central area of the Judean Mountains, characterized by the presence of limestone and various clay deposits, making the ceramic analysis complex. Mineropetrographic and chemical characterization aims, therefore, at defining and clarifying the profile of ceramic production in Jerusalem. The analysis will be carried out through a multi-analytical approach that includes optical microscopy (OM), X-ray diffraction (XRD), scanning electron microscopy with energy-dispersive spectroscopy (SEM-EDS), Fourier-transform infrared spectroscopy (FTIR), and inductively coupled plasma mass spectrometry (ICP-MS).

Task 5 - Validation of the CNN model (Months 25-30)

- Task 5.1 CNN validation test (Months 25-28)

During this phase, the CNN model developed will be tested. The validation test will be carried out on the ceramic samples from the Holy Sepulchre. These fragments were found in the filling layers of the foundations, an area where stratigraphic reconstruction is complex. Consequently, classifying and grouping ceramics is challenging. In this scenario, the application of the CNN model plays a crucial role in clarifying the archaeological context and the ceramic production of Jerusalem.

- *Task 5.2 Results comparison (Months 29-30)* The results obtained through the CNN classification model will be compared with those from archaeometric investigations to evaluate its effectiveness.

Milestones

M1 - month 24 – Development of the CNN model for the ceramic classification

M2 - month 30 – Validation of the CNN model on the ceramic samples from the Holy Sepulchre

Dissemination

At the end of the first year of work, I planned to present the results of my research at the main conferences in the fields of cultural heritage such as SIMP-SGI-SOGEI-AIV, BeGeo, and AIAr (Italian Association of Archaeometry) congresses. During the second year, I planned to attend international conferences such as EMAC (European Meeting on Ancient Ceramics) and TECHNART (the list will be increased). Starting from this second year I will proceed with the writing and

submitting of articles, which will continue throughout the third year. Specifically, the last months of work (31-36) will be dedicated to the writing of the final thesis and scientific manuscripts.

Training Activities

- Institutional courses of the PhD school: Intro to MatLab; Creazione e uso dei database nelle Scienze della Terra; Diagnostica applicata: progetto di valutazione e tutela di un bene culturale; Suggerimenti su come scrivere un lavoro scientifico, preparare una presentazione e scrivere un progetto di ricerca; Tecniche analitiche per lo studio di rocce e materiali cristallini; Postdoctoral Fellowships - Marie Skłodowska-Curie Actions. Starting Grant | ERC - European Union.
- *Scuola di Spettroscopia Infrarossa e Raman*, organized each year by Centro di Conservazione e Restauro La Venaria Reale, Turin.
- "Fundamentals of Machine Learning" from Communications Engineering, Sapienza University of Rome. Third year, second semester.
- "Neural Networks for Data Science Applications" from Data Science, Sapienza University of Rome. Second year, second semester.

Mobility Abroad

At the end of the first year, there is a scheduled one-month period at Ben Gurion University of the Negev (Israel). During this time, representative and useful ceramic thin sections for the creation of the model, will be available (in case of any difficulties in travelling to Israel, the material will be sent). During the second year, another mobility period of 3 months is scheduled for the ICP-MS analyses at the University of Évora (Portugal).

References

1 Hunt (2017). The Oxford handbook of archaeological ceramic analysis. Oxford University.

2 Bickler (2021). Machine learning arrives in archaeology. Adv Arch 9, 186.

3 Hörr et al. (2014). Machine learning based typology development in archaeology. J Comp Cult Heritage 7,1.

4 Ruschioni et al. (2023). Supervised learning algorithms as a tool for archaeology: Classification of ceramic samples described by chemical element concentrations. J Arch Sci 49, 103995.

5 Anglisano et al. (2022). Supervised Machine Learning Algorithms to Predict Provenance of Archaeological Pottery Fragments. Sustainability 14, 11214.

6 Zhang et al. (2019). Intelligent identification for rock-mineral microscopic images using ensemble machine learning algorithms. Sensors 19, 3914.

7 Su et al. (2020). Rock classification in petrographic thin section images based on concatenated convolutional neural networks. Earth Sci Inform 13, 1477.

8 Lopez et al. (2015). Discrimination of ceramic types using digital image processing by means of morphological filters. Archaeometry 57, 146.

9 Aprile et al. (2014). Combining image analysis and modular neural networks for classification of mineral inclusions and pores in archaeological potsherds. J Arch Sci 50, 272.

10 Lyons (2021). Ceramic Fabric Classification of Petrographic Thin Sections with Deep Learning. J Comput Appl Arch 4, 1.

11 Zhong et al. (2022). Explainable machine learning in materials science. Computational Materials, 8, 204.

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Activities		First year										Second year										Third year															
		Nov.	Dec.	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sept.	Oct.	Nov.	Dec.	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sept.	Oct.	Nov.	Dec.	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sept.	Oct.
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Task 4	Archaeometric characterization																																				
Task 5	CNN validation test																																				
	Results comparison																														M2						
Dissemination																																					
Training activities																																					
Mobility abroad																																					
Thesis writing																																					