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SURVEY

Findings on Machine Learning for Identification of Archaeological Ceramics: A Systematic Literature Review

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ABSTRACT The identification of archaeological ceramics is a relevant topic in the field of cultural heritage, and the history of archaeological ceramics can be traced back to prehistoric times. At present, there are two main methods for identifying archaeological ceramics, the empirical method and the technical one. In practice, these methods are costly or time-consuming. A systematic literature review of thirty-three studies on the identification of archaeological ceramics using machine learning is presented in this paper, including the collection process to build the dataset, the image processing of archaeological ceramic images, and the machine learning algorithms used for the classification. The main findings show the efficacy of deep learning for the automatic classification of archaeological ceramics compared to other approaches and highlight the need for more comprehensive and standardised datasets to further improve the automatic classification process.

INDEX TERMS Archaeological ceramic identification, archaeological ceramic classification, machine learning, deep learning, archaeological ceramics dataset.

I. INTRODUCTION

Ceramics refer to a broad category of materials, typically inorganic and non-metallic, employed by humans for over 10,000 years [1]. It includes pottery, majolica, faience, terracotta, stone mass, and porcelain [2]. Their remarkable durability has allowed them to withstand the test of centuries, preserving a window into the past and safeguarding the stories of our ancestors [3]. Consequently, ceramics serve as chronological markers that are indispensable for reconstructing the past and comprehending the temporal progression of cultures, from their emergence to their decline, thereby enriching our understanding of the human journey through time [4]. Moreover, since they were among the earliest commodities traded between different regions and cultures, they serve as invaluable artefacts that unveil intricate trade networks and interactions between ancient societies [5]. They trace the paths of cultural exchange, uncover the complexities of ancient trade routes, and highlight the interconnections of diverse civilizations across time and space [3]. For these reasons, it becomes of fundamental importance to accurately date and classify ancient ceramics.

Currently, the methods for the identification of archaeological ceramics, mainly focused on pottery and porcelain, can be grouped into two main families [6]. On the one hand, there is empirical identification [7]. It is a skilled process relying on the expertise of human analysts, that identify archaeological ceramics manually. Hence, it is a time-consuming activity, that often lacks objective constraints leading to inconsistent classifications. On the other hand, there are scientific identification methods that encompass techniques such as X-ray fluorescence analysis, thermoluminescence dating, and spectral analysis [8]. Thermoluminescence dating may cause damage to the porcelains themselves, resulting in irreversible damage [9]. While X-ray fluorescence analysis is a non-destructive technique [10], it does have some drawbacks for definitive identification: i) it primarily detects elements present in the porcelain and it misses subtle details, including

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firing temperature, specific minerals used, or manufacturing techniques; ii) it hinges on the quality and completeness of the reference database used about the elemental makeup of known porcelains; iii) it typically analyzes the surface composition that can be altered because of weathering, restoration, or glazing with a different composition. Moreover, it requires expensive equipment, involves complex identification processes, and is time-consuming.

Hence, the identification of archaeological ceramics, including pottery and porcelain, faces two key challenges: it can be time-consuming and it heavily relies on expert knowledge and experience. This has led researchers to explore Computer Vision (CV) and Artificial Intelligence (AI) as potential tools to aid in the identification process. Thanks to the advancements in these fields [11], [12], [13], more studies investigated their use for the identification of archaeological ceramic images in recent years [14], [15], [16]. Just to cite a few, Wang et al. [17] applied the Support Vector Machine (SVM) algorithm to design a prototype for feature extraction and classification of porcelain images. Instead, Zheng et al. [18] employed a Gaussian colour model and multi-scale filter bank to extract colour texture features.

This paper presents a systematic literature review on ML algorithms for archaeological ceramics identification. The review is based on scientific papers available in the most prominent digital libraries in the computer science field. Papers published between 2013 and 2023 were considered. Following the PRISMA methodology guidelines, 33 papers were finally analysed in terms of data sets, image processing methods, and ML algorithms used.

The rest of the paper has the following structure. Section II presents some literature reviews in the context of archaeological ceramics. Section III describes the research questions that motivated this study and the followed methodology. Section IV then analyses the results of the study and discusses the main findings. Finally, Section V summarises the study and presents some future works.

II. BACKGROUND AND RELATED WORK

The application of ML and DL techniques in the field of archaeological ceramics identification is an interesting area of research. While our review seeks to provide a comprehensive overview, it is important to acknowledge previous works that have explored similar themes. Notably, several surveys and studies have been conducted to examine the intersection of archaeological analysis and computational techniques. These existing reviews serve as foundational references, offering valuable insights and highlighting the progress made in the application of ML and DL methodologies to archaeological ceramics identification.

Cumbajin et al. [19] presented a systematic literature review on deep learning for industrial surface defect detection of several materials, including ceramics. Such a review considered only the use of convolutional neural networks. Our paper differentiates itself by focusing exclusively on the identification and classification of archaeological ceramics, employing a variety of ML and DL algorithms tailored to the unique characteristics of archaeological data. While the industrial review proposes a new taxonomy for surface defect detection, our work seeks to develop and refine methodologies specifically for archaeological ceramics.

Zhang et al. [20] proposed a review on the use of ML the discovery of high-entropy ceramics. High-entropy materials, known for their versatile platform and superior structural and functional properties, present a vast phase space that complicates efficient design through traditional methods. The review highlights how ML accelerates the discovery and optimization of high-entropy ceramics. The paper discusses the entire ML pipeline from data collection and feature engineering to model refinement and performance prediction improvement. In contrast, our review delves into the application of ML algorithms for archaeological ceramics, which, unlike high-entropy ceramics, involves the analysis of artifacts with historical and cultural significance.

Di Angelo et al. in [21] conducted a comprehensive review of automatic methods for analyzing archaeological pottery sherds, encompassing the state-of-the-art up to the end of 2021. They provided a critical analysis of the most significant advancements in pottery analysis, classification, and reconstruction from a 3D discrete manifold model. In contrast to this review, our paper do not focus on 3D models but mainly on images.

Ming et al. [22] provided a review of the application of virtual reality (VR) technology in the conservation and restoration of archaeological ceramics. However, this review does not cover the application of ML algorithms for the identification of archaeological ceramics, although the existing review on VR technology is not directly related to ML, it still can provide future research directions in the field of archaeological ceramics, such as integration of ML algorithms with VR for the identification of archaeological ceramics.

III. METHODS

This section presents the research questions that motivated this research, describes the PRISMA methodology and how the data were collected and processed.

A. RESEARCH QUESTIONS

The main research question that drove this study is:

RQ: What are the main findings derived from the application of machine learning for the identification of archaeological ceramics?

In particular, this work aims to answer the following questions to shed light on three main aspects:

- **RQ1**: Which are the main datasets employed in the identification of archaeological ceramics?
- **RQ2**: What are the findings about the image processing of archaeological ceramics for its identification?
- **RQ3**: What are the main ML algorithms used in the identification of archaeological ceramics?

RQ1 will mainly be centred around ceramic type (pottery and porcelain), country, period, pattern or type, sample count, and data source. RQ2 will focus on different image processing methods and their frequency and tendency. Finally, RQ3 will mainly analyze ML or Deep Learning (DL) algorithms, including their distribution and tendency. Specific analyses and discussions of these three research questions will be presented in Section IV.

B. PRISMA METHODOLOGY

Systematic reviews aim to identify all research addressing a specific and well-defined question to provide a balanced and unbiased literature summary [23]. A systematic review takes advantage of a rigorous and transparent methodology, often outlined in a protocol, to identify, evaluate, and synthesize relevant research studies. The search for relevant studies is often carried out across various databases and sources. Finally, the studies are evaluated and the main findings are synthesized to provide a comprehensive overview.

In this work, we took advantage PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) methodology [24], [25]. PRISMA provides a framework for the conduct of systematic reviews and future analyses in the field of research. It ensures transparency, reproducibility and decrease of bias in the review process and including an organized and complete approach to the organisation and presenting of systematic reviews.

C. DATA COLLECTION AND PROCESSING

We checked published English-language articles or materials that are available on the web through noticeable digital libraries and databases in the field of computer science. They include ACM Digital Library, IEEE Xplore, Scopus, ScienceDirect, SpringerLink, and CNKI. In addition to them, Google Scholar was used to supplement the search to minimise the risk of exclusion.

The following search keywords (Boolean logic) were entered into the six databases: (''computer vision'' OR ''artificial intelligence'' OR ''machine learning'' OR ''deep learning'') AND (''archaeological ceramic'' OR ''ancient ceramic'' OR ''porcelain'') AND (''identification'' OR ''classification'' OR ''recognition''). The search options were title, abstract and keywords for the Scopus database.

We included any conference or journal paper concerning computer vision and machine learning for the identification of archaeological ceramics that have been published during the last ten years (i.e., between 2013 and 2023). To ensure both quality and accuracy, only peer-reviewed journal articles for which the full text is available have been included. The other inclusion and exclusion criteria are listed in Table 1. It is important to notice that ML algorithms and general computer vision approaches must be employed to identify or classify archaeological ceramics and not for other tasks such as reconstruction or restoration. Moreover, we are interested in finding research articles and not other literature reviews.

TABLE 1. Inclusion and exclusion criteria.

Inclusion Criteria	Exclusion Criteria
Focus on image processing techniques and feature extraction approaches for archaeological ceramics images	Focus on chemical elements or spectra of archaeological ceramics
Use computer vision and machine learning approaches for identification or classification of archaeological ceramics	Use computer vision and machine learning approaches for reconstruction or restoration of archaeological ceramics
Empirical studies	Literature reviews, commentaries or meta-analysis
Written in English	Written in other languages
Peer-review	Pre-print

The papers were searched by following four steps: i) collection, ii) screening, iii) eligibility, and iv) information extraction. A summary of the papers selected and excluded at each step of the PRISMA review process is reported in Figure 1. Firstly, we collected all the papers that corresponded to the search criteria. Secondly, the dataset with the most results was Google Scholar with 997 papers. The duplicated records removed (i.e., 56 papers) were found in Scopus, ACM Digital Library, IEEE Explore, Science Direct, Springer Link, and CNKI, and were also found on Google Scholar. From the remaining 1814 papers, we excluded the following ones:

- 1032 papers because: i) the language of the paper is not English, and ii) the title indicates that the paper is not focused on the identification of archaeological ceramics using computer vision techniques.
- 721 papers because at the abstract level, they were not focused on archaeological ceramics but modern ceramics.
- 18 papers because they were not focused on identification and classification but on other different tasks.
- 10 papers because they were not focused on images of archaeological ceramics.

Finally, thirty-three papers meeting the standard were eventually retained (listed in Table 11 in Appendix), labelled ID1-ID33 sequentially.

D. CRITICAL ASSESSMENT

Besides the selection process described in the Subsection III-C, an assessment of the quality criteria was also performed. The results are presented in Table 2, which has one column for each research question (RQ1, RQ2, and RQ3) and as many rows as articles. For each article resulting from the selection process, we assessed whether they included an answer to the different research questions (number 1 in the table), or not (number 0 in the table).

Regarding the RQ1, which focuses on the dataset, most of the papers well described the data details of the study, while three studies, namely ID5 [26], ID10 [27], and ID17 [28] did not provide adequate information. With regard to the RQ2, out of thirty-three papers, only ID13 [29] did not evidently describe the image processing methods used. Regarding the

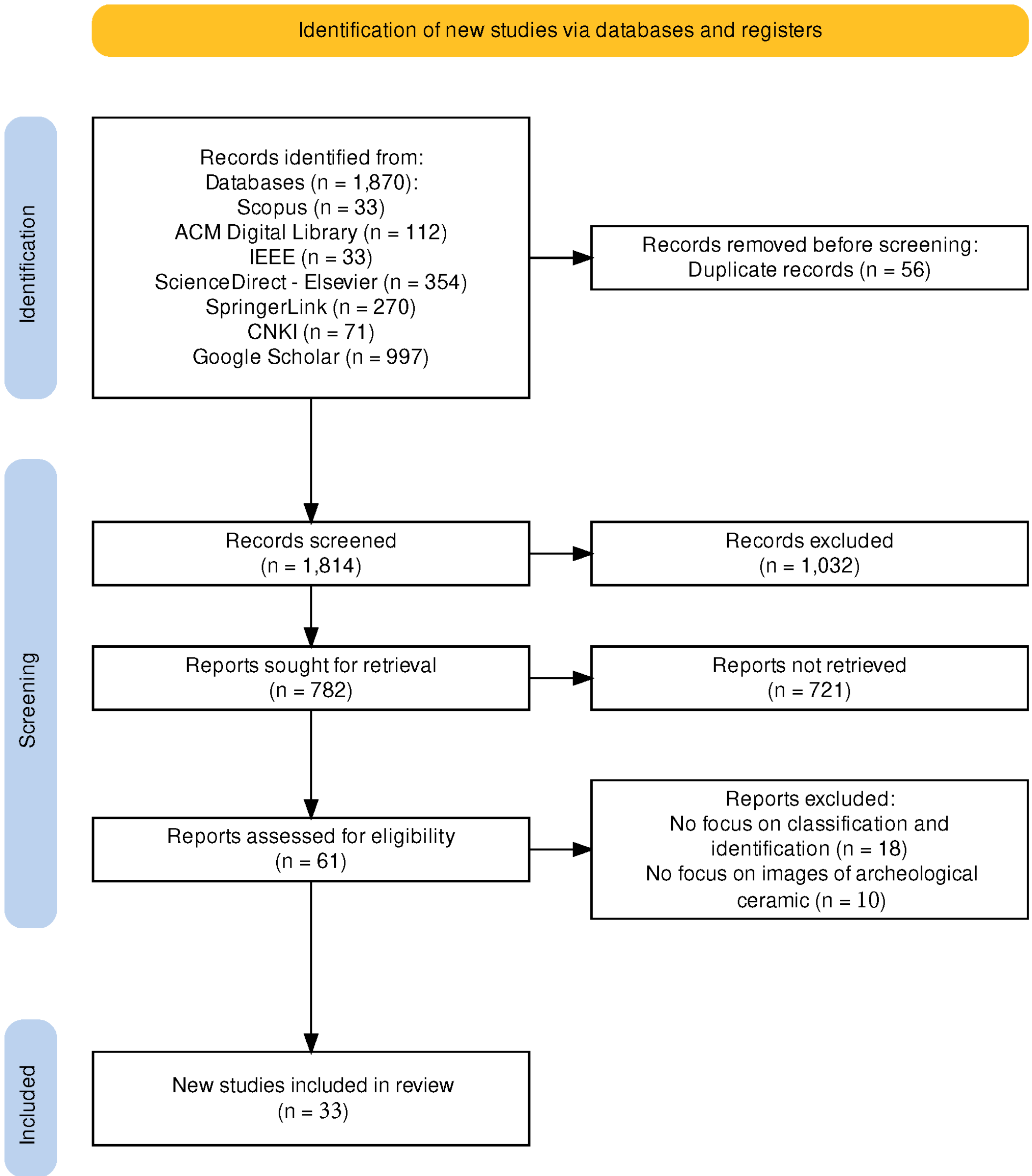

FIGURE 1. Literature selection process following the PRISMA methodology.

RQ3, five studies lacked a clear description of the ML algorithm for the identification of ceramics. In conclusion, twenty-six studies provide enough information to answer all the research questions while the minority of studies (i.e., five ones) obtain a score of two out of three, and two studies ID10 [27] and ID17 [28] obtain a score of one out of three.

E. EXTRACTION OF RELEVANT FIELDS

Finally, the last step of our methodology is to elicit and summarize relevant information from the selected articles. This was done manually by reading the full texts of the selected articles. The elicited information includes the answers to the research questions of the article. The complete list of fields elicited from the articles is provided in Table 3. Three fields that were manually compiled in response to the different research questions.

IV. FINDINGS AND DISCUSSION

This Section presents an initial quantitative analysis regarding the retrieved papers and then the answers to the three research questions are discussed in isolation, in the following subsections.

A. QUANTITATIVE ANALYSIS

In this Section, we provide a quantitative analysis of various attributes of the retrieved papers, including the countries of origin of the datasets used in these studies.

TABLE 2. Critical assessment results of the reviewed studies.

ID	RQ1	RQ2	RQ3	Total
ID1 [30]	1	1	1	3
ID2 [31]	1	1	1	3
ID3 [32]	1	1	1	3
ID4 [33]	1	1	1	3
ID5 [26]	0	1	1	2
ID6 [34]	1	1	1	3
ID7 [35]	1	1	0	2
ID8 [36]	1	1	1	3
ID9 [37]	1	1	1	3
ID10 [27]	0	1	0	1
ID11 [38]	1	1	1	3
ID12 [39]	1	1	1	3
ID13 [29]	1	0	1	2
ID14 [40]	1	1	1	3
ID15 [41]	1	1	1	3
ID16 [42]	1	1	1	3
ID17 [28]	0	1	0	1
ID18 [7]	1	1	1	3
ID19 [43]	1	1	1	3
ID20 [44]	1	1	1	3
ID21 [45]	1	1	0	2
ID22 [46]	1	1	1	3
ID23 [47]	1	1	1	3
ID24 [48]	1	1	1	3
ID25 [49]	1	1	1	3
ID26 [50]	1	1	1	3
ID27 [51]	1	1	1	3
ID28 [52]	1	1	0	2
ID29 [53]	1	1	1	3
ID30 [14]	1	1	1	3
ID31 [54]	1	1	1	3
ID32 [55]	1	1	1	3
ID33 [56]	1	1	1	3

TABLE 3. Information extracted from the papers included in the systematic literature review.

	Field	Description
1	ID	Unique identifier for the study
2	Title	Title of the paper
3	Authors	Authors of the paper
4	Year	Year of publication
5	Country	Country of the first author of the paper
6	Keywords	The keywords listed by the authors in the paper
7	Main results	Main results presented in the paper
8	Information about the quality analysis	Criteria presented in Section III-D
9	RQ1	Datasets employed in the archaeological ceramics identification for computer vision
10	RQ2	Findings related to the image processing of archaeological ceramics for identification
11	RQ3	ML algorithms used in the identification of archaeological ceramics

As mentioned before, the research process retrieved thirty-three relevant studies. These studies employed datasets from twelve different countries across five continents. Table 4 shows the distribution of datasets used in these studies, classified by the country in which the datasets were collected. The country presenting the most datasets was China (n = 16), followed by the United States of America (USA) (n = 5), and two datasets from France and Greece respectively.

TABLE 4. Number of datasets from each article per country.

Country	Number of Datasets
China	16
United States of America	5
France	2
Greece	2
Egypt, Honduras, Italy, Japan, Korea, New Zealand, South Africa, Thailand	1
Total	**33**

TABLE 5. Information about the Journals.

Journal	Publisher
Across Space and Time	Amsterdam University Press
Advances in Mathematical Physics	Hindawi Limited
Applied Artificial Intelligence	Taylor & Francis
Archaeology in New Zealand	New Zealand Archaeology Association
Ceramics International	Elsevier
Current Applied Science and Technology	King Mongkut's Institute of Technology Ladkrabang
IEEE Access	IEEE
International Journal of Heritage in the Digital Era	SAGE Publications
Journal of Archaeological Science	Elsevier
Journal of Archaeological Science: Reports	Elsevier
Journal of Ceramics	CNKI
Journal on Computing and Cultural Heritage	ACM
Journal of Computer Applications in Archaeology	Ubiquity Press
Journal of the Chinese Ceramic Society	CNKI
Research Journal of Applied Sciences, Engineering and Technology	Maxwell Scientific Organization
Revista Argentina de Clinica Psicologica	Fundacion Aigle
Soft Computing	Springer

Of the thirty-three papers, ten of them were published in proceedings of computer sciences conferences. The others were all published in journals. Table 5 lists the different journals and their publishers. In contrast to the conference papers, the journals that published such articles are not exclusively computer science journals but range from archaeology to cultural heritage computing.

B. DATASETS FOR ARCHAEOLOGICAL CERAMICS IDENTIFICATION

This Section answers the first research question **RQ1**, "Which are the main datasets employed in the identification of archaeological ceramics?". The answer includes six main aspects of the selected dataset: ceramic type (porcelain and pottery), country, period, pattern or type, sample count, and data source. Table 6 presents the dataset employed in each paper. As expected, the mass of them (30 out of 33 ones, that is 90.9%) clearly designated the dataset used. For the other three papers (9.0%), ID5, ID10, and ID17, the label "N/A" is used, since they were mainly focused on the image processing methods [26], [27].

As already anticipated, in the field of archaeology, ceramics include pottery, majolica, faience, terracotta, stone mass, and porcelain [2]. In the selected studies, the datasets mainly contain two categories, pottery and porcelain, which are distinguished in Table 6 by the labels "Pottery" and "Porcelain". If the type of ceramic is not specified, we used the label "Ceramic". For the other characteristics (Period, Pattern Types, Sample Count, Data Source), they are set to N/A if in the original paper such information is not specified. More detailed information about the dataset is listed in Table 12 in the Appendix V.

1) TYPE, COUNTRY, AND PERIOD OF CERAMICS

These datasets mainly contain two different categories of ceramics, porcelain and pottery. They cover a wide range of periods (from the Neolithic period to the early 19th century). The datasets belong to 12 countries, including the United States of America, China, France, Greece, Egypt, Honduras, Italy, Japan, Korea, New Zealand, South Africa, and Thailand.

Porcelain is a special type of ceramic, that originated in China during the Tang dynasty (ca.1332 to 1043 aBP) [2]. Among thirty papers, sixteen papers selected Chinese porcelains as the dataset, ranging from Tang to Song (ca.990 to 671 aBP), Yuan (ca.679 to 582 aBP), Ming (ca.582 to 306 aBP), and Qing (ca.306 to 38 aBP) dynasty. Figure 4 shows the distribution of dynasties in the porcelain datasets. Two papers focused on only one dynasty for the identification of porcelains. ID1 [30] classified the porcelains from the Yaozhou kiln of the Song dynasty while ID21 [45] identified the washer-type porcelains from the Ming dynasty. Meanwhile, seven papers discussed two or more dynasties for the identification of porcelains. ID3 [32] discussed the porcelain ewers from the Tang, Song, and Yuan dynasties, Figure 2 shows the samples of dataset in ID3. ID4 [33] classified porcelains with four different patterns from Ming and Qing dynasties, ID8 [36] identified porcelain shards from Yuan, Ming, and Qing dynasties, Figure 3 shows the samples of dataset of ID8, and ID11 [38] classified two types of porcelain vases from Ming and Qing dynasties. Moreover, ID13 [29] identified different types of porcelain from Song, Yuan, Ming, and Qing dynasties, ID20 [44] classified porcelains with Banana leaf patterns from Yuan, Ming, and Qing dynasties, and ID28 discussed porcelain jars from Tang, Song, Yuan, and Ming dynasties.

Different dynasties have different styles, and of course, the style of the porcelain depends on the kiln, so the shape of the porcelain, the colour, and its pattern will have different characteristics depending on the style. The Ming dynasty is the most studied dynasty with seven papers focused on it. The reasons are two-fold. Firstly, such a dynasty has the largest number of preserved porcelain samples, and, secondly, it is the second flourishing period in the development of Chinese

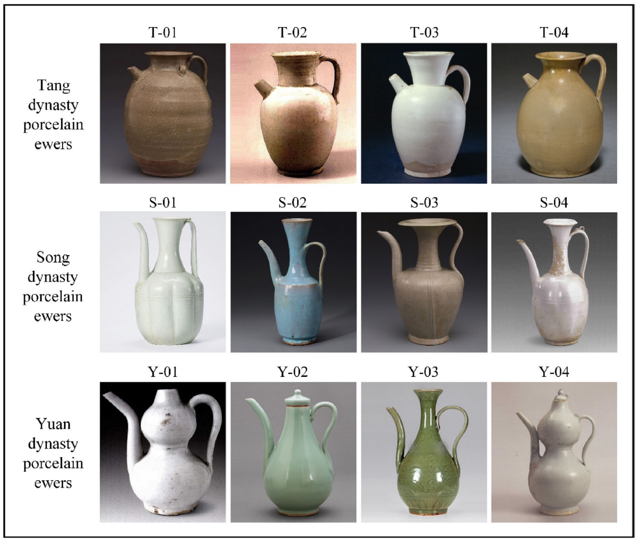

FIGURE 2. Samples of typical chinese porcelain ewers in ID3 [32].

FIGURE 3. Samples of archaeological porcelain pieces in ID8 [36].

porcelain, which is valuable for research. Meanwhile, the Tang, Song, and Yuan dynasties had not been studied as much in comparison, which also provides a direction for future research, it can be expanded by focusing on the three less studied dynasties to broaden the scope of research. In addition, almost all of the selected papers focus on only one feature of porcelain, such as different types of porcelain from the same dynasty [38], or different patterns of porcelain from the same dynasty [34], or the study of the same type of porcelain from different dynasties [32]. No research integrates these features, such as different types of porcelain from different dynasties with different patterns, to expand the depth of the study of porcelain, which is also one of the directions that can be researched in the future.

Pottery is another type of ceramics, eleven papers indicate that their chosen datasets were potteries, from Japan, Italy, the United States of America, Honduras, France, Egypt, South Africa, and Greece, ranging from the Early Neolithic period (ca. 7850 to 7450 aBP) to the early 19th century (ca. 175 to 125 aBP). Although from different countries, each paper selected only pottery samples from a single period to be studied and classified. One case is under the same period

TABLE 6. Dataset of the reviewed studies.

ID	Type	Country	Period	Pattern Types	Sample Count	Data Source
ID1 [30]	Porcelain	China	Song dynasty	N/A	N/A	Museum collection
ID2 [31]	Pottery	Japan	Late jomon period	N/A	1036 X-ray images	Not provided
ID3 [32]	Porcelain	China	Tang, Song, and Yean dynasties	Ewers	232 images	Museum collection
ID4 [33]	Porcelain	China	N/A	19 types of vases	N/A	Baidu PaddlePaddle
ID5 [26]	Porcelain	China	N/A	N/A	N/A	N/A
ID6 [34]	Porcelain	China	Ming and Qing dynasties	Dragon, Fish, Peony, Lotus patterns	N/A	Museum Website
ID7 [35]	Porcelain	China	N/A	Various	5834 images	Online Repository
ID8 [36]	Porcelain	China	Yuan, Ming, and Qing dynasties	Shards by incomplete patterns	373 images	Scholarly book Jingdezhen relics
ID9 [37]	Pottery	Italy	Between the Late bronze age and the Orientalizing period	Vessel profiles	4992 images	Latium Vetus and Etruria archaeological sites
ID10 [27]	Porcelain	China	N/A	N/A	N/A	N/A
ID11 [38]	Porcelain	China	Ming and Qing dynasties	Mei vase, Yuhuchun vase	248 images	Beijing Museum and Taipei Museum website
ID12 [39]	Ceramic	Thailand	N/A	7 types of patterns	557 images	Museum collection
ID13 [29]	Porcelain	China	Song, Yuan, Ming, and Qing dynasties	Blue and white porcelain, Purple sand, Doucai	2750 images	Palace Museum website
ID14 [40]	Pottery	USA	ca.1125 to 650 aBP	Tusayan White Ware sherds	3064 images	Museum collection
ID15 [41]	Ceramic	Korea	N/A	Various	19610 images	Museum collection
ID16 [42]	Porcelain	China	N/A	7 types of bottles	5624 images	Baidu crawled data
ID17 [28]	Porcelain	China	N/A	N/A	N/A	N/A
ID18 [7]	Pottery	Honduras	Cocal period	Various	1069 images from 66 pottery sherds	Guadalupe archaeological site
ID19 [43]	Pottery	France	Early Neolithic period	Coiling and Spiral Patchwork	16 sherds	Pendimoun rock shelter
ID20 [44]	Porcelain	China	Yuan, Ming, and Qing dynasties	Banana leaf patterns	230 pieces	Museum collection
ID21 [45]	Porcelain	China	Ming dynasty	Washer	N/A	Academic research
ID22 [46]	Pottery	USA	Pre-Colonial	Paddle impressions on pottery sherds	N/A	North America archaeological sites
ID23 [47]	Pottery	Egypt	Nile clay and Marl clay	Nile clay and Marl clay	69 samples	Museum Collection
ID24 [48]	Ceramic	New Zealand	N/A	Various	N/A	New Zealand sites
ID25 [49]	Pottery	South Africa	N/A	Zulu pottery fabrics	50 per class	Field collection.
ID26 [50]	Ceramic	USA	ca.175 to 125 aBP	N/A	8 classes of fragments	Independence National Historical Park
ID27 [51]	Porcelain	China	N/A	N/A	288 pieces	Academic research
ID28 [52]	Porcelain	China	Tang, Song dynasty, Yuan, and Ming dynasties	Jars	50 images	Forbidden City Museum
ID29 [53]	Ceramic	USA	ca.175 to 125 aBP	N/A	6 pieces of fragments	Independence National Historical Park
ID30 [14]	Pottery	France	ca.1524 to 924 aBP	Wheel-carved	957 patterns	Saran archaeological site
ID31 [54]	Pottery	Greece	N/A	N/A	203 pottery sherds	Koroneia archaeological site
ID32 [55]	Ceramic	USA	ca.175 to 125 aBP	N/A	N/A	Independence National Historical Park
ID33 [56]	Pottery	Greece	Byzantine era	N/A	110 pottery sherd images	Byzantine antiquities

for pottery with different patterns, such as ID19 [43], which investigated potteries with coiling and spiral patchwork, ID14 [40] that focused on TWW pottery sherds with decorative patterns, Figure 5 shows the samples of dataset in ID14. The other case regards the same period but focuses on different types of pottery, such as ID9 [37] where the authors classified potteries of different vessel profiles. At the same time, most of the datasets are focused on pottery sherds, which is one

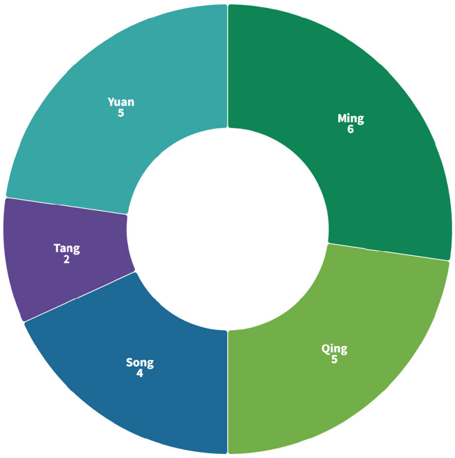

FIGURE 4. Distribution of the dynasties in the porcelain datasets.

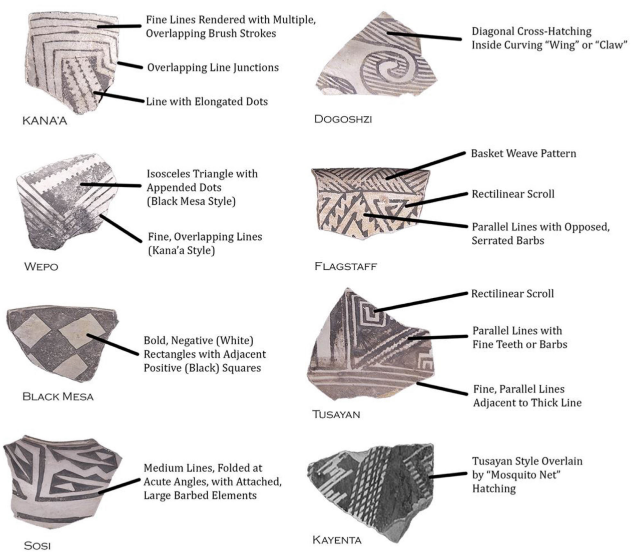

FIGURE 5. Samples of TWW sherds in ID14 [40].

of the dilemmas faced by archaeological pottery. The manual classification of a large number of sherds is a time-consuming activity [7]. Hence, the main objective of the researchers is to reduce the time of pottery classification and improve the consistency of results.

The remaining six papers, which do not specify the type of ceramics, from Thailand, Korea, New Zealand, and the United States of America and do not specify the period of the dataset, but focus mainly on ceramic patterns, such as ID12 [39], that classified ceramics with seven types of patterns from Sukhothai kiln, Figure 6 shows the samples of dataset in ID12.

2) DATA SOURCE AND SAMPLE COUNT OF CERAMIC

The size of the dataset ranges from tens of samples to thousands of samples, depending on the preservation of the ceramics. For example, in ID2 [31], the number of samples preserved from this period was insufficient and therefore

FIGURE 6. Samples of CMC sukhothai ceramics dataset in ID12 [39].

the labelled data was insufficient, and self-built experimental data had to be used for the study. ID20 [44] has a similar situation with a limited number of available porcelain with banana leaf patterns. Therefore, the dataset size was only 230 samples. Having larger datasets enables the use of powerful algorithms, such as deep learning models, which typically yield superior results. The richness and volume of data allow these algorithms to learn more complex patterns and representations, thereby improving their accuracy and generalization capabilities.

As shown in Table 6 (column Data Source), the majority of the data were collected from the museum collection, which includes both images photographed in the museum and images downloaded from the museum's website, as well as datasets obtained from archaeological excavation sites. Additionally, a small number of datasets were obtained through web crawling (ID4, ID7 and ID16). The diverse methods of data collection ensure a broad and varied dataset, enriching the training material for the models. However, the quality of these datasets, as well as the trustworthiness of the labels of the images, is crucial. For instance, images obtained from official museum sources are likely to have accurate and reliable labels due to the expertise and meticulous documentation practices of museum professionals. Conversely, images from non-official museum websites or those collected via web crawling might have less reliable labels. This variability in label accuracy can significantly impact the training of machine learning models. Accurate labels are essential for the models to learn correctly, as they guide the algorithms in understanding and categorizing the images. Inaccurate labels can lead to incorrect learning, reducing the effectiveness and accuracy of the trained models. Therefore, ensuring the reliability of the labels, especially in self-built datasets, is vital for developing robust and effective machine learning models.

3) DATA SCARCITY AND FUTURE DIRECTIONS

While ML algorithms have emerged as a promising tool for archaeologists, offering the potential to streamline the identification of archaeological ceramics, they still have to face a significant hurdle, data scarcity. In fact, to be truly effective, machine learning algorithms require a robust dataset of well-documented ceramic artefacts. This data should include detailed information on the origin, type, composition, and visual characteristics of each ceramic piece. Unfortunately, such comprehensive datasets are often scarce in archaeology.

Several factors contribute to data scarcity. On the one hand, archaeological excavations are often resource-intensive, and not all recovered ceramics receive in-depth analysis due to time and budget constraints. However, even if museums possess this data, several challenges remain. In fact, this information often exists in data silos, not readily transformed into usable datasets for training ML algorithms. Cataloguing and documenting ceramics can be a time-consuming and resource-intensive process. Many museums lack the staff or funding to create comprehensive, digital datasets for their entire collections. Finally, even if museums have digitized data, they might not readily share it for free due to concerns about ownership and potential commercial use.

To partially address this challenge, there are several initiatives to establish standardized recording practices for archaeological ceramics, with the aim of building and sharing open-access databases of ceramic data. Finally, the recent advancements in multimodal Large Language Models able to generate images from text inputs could be exploited to generate synthetic data to augment the size of the datasets [57].

C. IMAGE PROCESSING FOR ARCHAEOLOGICAL CERAMICS IDENTIFICATION

This Section aims to answer the second research question **RQ2**, "What are the findings about the image processing of archaeological ceramics for its identification?". Image processing is the process of transforming an image into a digital form and performing certain operations to get some useful information from it [58]. It encompasses a variety of techniques applied to digital images, typically in a sequential order, such as image enhancement, image segmentation, and feature extraction. Table 7 reports on image processing methods of the reviewed studies. Among all the thirty-three papers reviewed, thirty-two (97%) of them employed image processing methods for tasks such as feature extraction [30] and image segmentation [34] of archaeological ceramics. The remaining paper, ID33 [55], did not provide specific information on any image processing method.

1) OVERVIEW OF IMAGE PROCESSING METHODS

Image processing is crucial in the classification of ancient ceramic images and in the reviewed studies, including three main image processing approaches: feature extraction, image segmentation, and image enhancement.

Regarding feature extraction, an image feature is a primitive attribute of an image. Some features are natural and they are defined by the visual appearance of an image, while others are artificial features that result from specific manipulations of an image. Natural features include the luminance of a region of pixels and gray-scale textural regions [59]. Image amplitude histograms and spatial frequency spectra are examples of artificial features. Image features are important in the isolation of regions of common property within an image (image segmentation) and the subsequent identification or labelling of such regions (image classification).

Segmentation of an image involves dividing or separating the image into regions with similar attributes. The most basic attribute for segmentation is image luminance amplitude for a monochrome image and colour components for a colour image. Image edges and texture are also useful attributes for segmentation [60].

Image enhancement is a collection of techniques designed to improve the visual appearance of an image. For example, an image enhancement system might use high-frequency filtering to emphasize the edges of objects in an image [59]. In this application, the image enhancement processor would emphasize salient features of the original image and simplify the processing task of data extraction.

2) FOCUS ON FEATURE EXTRACTION, IMAGE SEGMENTATION, AND IMAGE ENHANCEMENT

Depending on the objectives of the papers, different image processing methods are used. Primarily, they regard feature extraction, image segmentation, image pre-processing, image enhancement, colour space transformation, and image registration. Figure 7 shows the frequency of image processing tasks in the reviewed literature. In some studies, there is not a single task, but a combination of them.

Thirty papers (93.7%) employed a feature extraction method, highlighting the central role of feature extraction in machine learning applications [30]. Different studies took advantage of several feature extraction methods according to different ceramic types (pottery and porcelain). Figure 8 shows the distribution of feature extraction methods in reviewed papers. These methods include traditional approaches, such as GVF and LBP to measure the counter of porcelains (ID3 [32]), GLCM to extract texture features, and HSV to extract color features (ID7 [35]), Tamura texture feature (ID21 [45]). In addition to traditional feature extraction methods, there are shallow ML-based methods. ID27 [51] applied Kernel mean shift clustering to extract features (color, texture, and shape) of porcelain images. Both ID30 [14] and ID31 [54] used BoVW to extract features

TABLE 7. Image processing of the reviewed studies.

ID	Tasks	Image Processing Methods
ID1 [30]	Feature Extraction Image Segmentation	Convolutional neural network (CNN) used for feature extraction of porcelain patterns while Otsu's method is employed for image segmentation.
ID2 [31]	Feature Extraction	This study used the CNN for feature extraction of potteries.
ID3 [32]	Feature Extraction Image Segmentation	This study used the gradient vector flow field (GVF), soft contour information, and LBP operator to measure spatial coherence, contour continuity, and texture similarity of porcelain ewer images. Principal Component Analysis (PCA) was used to reduce the dimensionality. The segmentation was based on the SLIC-Ncut.
ID4 [33]	Feature Extraction	This study used the CNN for feature extraction of porcelain vases.
ID5 [26]	Feature Extraction Image Segmentation	This study used gray level co-occurrence matrix (GLCM) to extract texture features of archaeological ceramic surfaces. Employed the CNN for feature extraction of ceramics. Used the watershed segmentation algorithm to segment the ceramic decoration images.
ID6 [34]	Image Segmentation	Four CNN models pyramid scene parsing network (PSPNet), DeepLabv3+, dual attention network (DANet), high-resolution network (HRNet) to segment porcelain patterns: dragon, fish, lotus, and peony.
ID7 [35]	Feature Extraction	GLCM and average Euclidean distance of Tamura texture features used as texture features of porcelains. Colour histogram and hue, saturation, value (HSV) colour space average similarity rate as colour features.
ID8 [36]	Image Preprocessing Image Enhancement Feature Extraction	A color segmentation algorithm is employed as part of the image preprocessing strategy, converting the color space from red, green, and blue (RGB) to HSV. FCutMix was used as an image enhancement method based on the CutMix method. Features extracted by two CNN models (ResNet) of different depths at different stages.
ID9 [37]	Feature Extraction	Variational autoencoder (VAE) used to compress images into a lower-dimensional space and then reconstruct them, thereby learning to extract the essential features from the pottery profiles.
ID10 [27]	Feature Extraction	Prewitt directional derivative approximation operator used to detect the edges of the copied image, Zernike moment discretization for feature extraction.
ID11 [38]	Image Preprocessing Feature Extraction	Data augmentation was achieved by a series of image preprocessing methods, rotation, translation, adjustment of chromatic aberration, amplification, distortion, and increase of noise. CNN used for feature extraction.
ID12 [39]	Image Enhancement Feature Extraction	Image enhancement included rotation, width shift, and zoom. Employed five CNN models (DenseNet121, InceptionV3, VGG16, GoogLeNet, and AlexNet) for feature extraction of patterns from ceramics.
ID13 [29]	Not provided	Not provided
ID14 [40]	Feature Extraction	Employed two CNN models(VGG16, ResNet50) for feature extraction of patterns from potteries
ID15 [41]	Image Segmentation Feature Extraction	Mask R-CNN used for segmentation to classify the ceramic form and generate the mask of the ceramic colours. Applied CNN model Inception V2 to extract features of ceramics according to their forms, materials, and patterns.
ID16 [42]	Feature Extraction	This study used VGG16 for feature extraction of porcelain bottles
ID17 [28]	Image Preprocessing Image Segmentation	Image quality improved using geometric distortion correction, image enhancement, and smoothing filtering. Edge detection is employed to define the shape and contours of the ceramics; and threshold segmentation for differences in grey characteristics between the ceramics and the background to produce a binary image.
ID18 [7]	Image Enhancement Feature Extraction	Image enhancement including random rotation, horizontal and vertical flipping, and random image brightness adjustments. Employed two CNN models (VGG19, ResNet50) for feature extraction of pottery fabrics.
ID19 [43]	Image Segmentation Feature Extraction	Image Segmentation for segment pore regions. Applied Hough Transform for feature extraction to investigate pores of potteries. Employed CNN model (GoogleNet) for feature extraction of segmented images
ID20 [44]	Image Preprocessing Feature Extraction	Image preprocessing including grayscale processing, ROI region detection, size normalization, filter denoising for improve quality of patterns. Applied LBP and HOG fusion feature extraction of banana leaf patterns.
ID21 [45]	Feature Extraction Image Segmentation	Eight-chain code method combined with a watershed algorithm is used for the shape extraction. The texture feature was extracted by Tamura method. Inscriptions segmented into single handwritten Chinese characters.
ID22 [46]	Image Segmentation Feature Extraction Image Registration	Extract curve patterns from a sherd using an FCN-based image segmentation method. A dual-source CNN was applied for feature extraction. Chamfer matching algorithm to match the pottery sherds to find their underlying designs
ID23 [47]	Feature Extraction	Combination of three texture features extraction methods: i) Gabor filters for local and oriented ones; ii) Laws' texture for levels, edges, spots, waves, and ripples; iii) Haralick's texture features for the distribution of grey levels.
ID24 [48]	Image Registration Feature Extraction	Image registration includes template matching algorithms to search for a specific pattern within a larger set of data according to the variations in scale, rotation, and colour. Employed deep neural network for feature extraction.
ID25 [49]	Feature Extraction	Applied weighted neighbour distance using Compound hierarchy of algorithms representing morphology to extract features from pottery images including statistical, textural, and pattern features.
ID26 [50]	Color Space Transformation Feature Extraction	Ceramic fragments images converted from RGB to HSV colour. The images were then divided into six equal-sized sub-blocks and the features extracted from these sub-blocks were based on the HSV values.
ID27 [51]	Feature Extraction	Applied kernel mean shift clustering to extract features (colour, texture, and shape) of porcelain images.
ID28 [52]	Feature Extraction	Employed LBP to extract texture features; A multi-channel colour histogram in the HSI (Hue, Saturation, Intensity) colour space is utilized to characterize the glaze colours of the porcelains.
ID29 [53]	Color Space Transformation Feature Extraction	The images of ceramic fragments were converted from RGB to HSV colour space. GLCM was applied to extract the texture feature of ceramic images.
ID30 [14]	Feature Extraction	Gabor filters were applied for extraction of descriptors while Bag of Visual Words (BoVW) extracted visual words based on the local image descriptors.
ID31 [54]	Feature Extraction	BoVW extracted features on the local image descriptors; colour and texture features were extracted from pottery images.
ID32 [55]	Feature Extraction	Pyramid histogram of visual words (PHOW), which is an extension of BoVW mode by extracting local features from different levels of a pyramid structure and then quantizing these features into a visual vocabulary.
ID33 [56]	Feature Extraction Image Segmentation	LBP was used to capture the texture information by analyzing the local spatial pattern of the pixels. Kirsch edge detection was used to detect edges in the sherds.

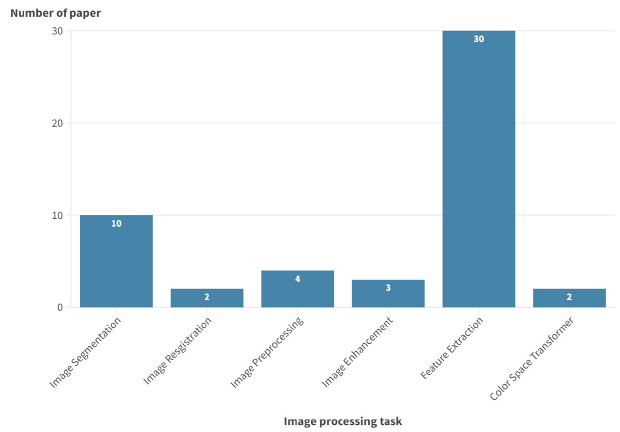

FIGURE 7. Frequency of image processing tasks in reviewed literature.

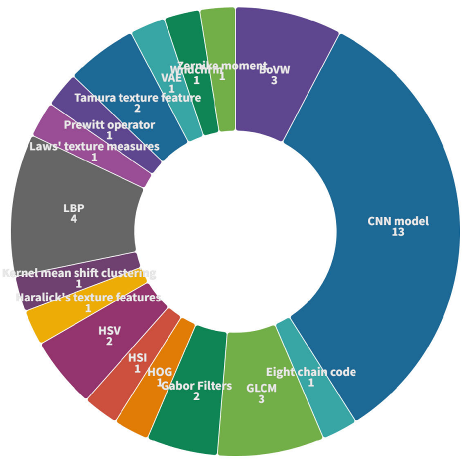

FIGURE 8. Distribution of feature extraction methods in reviewed papers.

from pottery images. Finally, thirteen papers employed deep neural networks for feature extraction including VAE model [37] and CNN model such as ResNet [36], AlexNet [39], VGG16 [42]), etc. From Figure 8, it can be seen that the CNN model for feature extraction is the most used method since DL has proven to be effective in feature extraction [30] and CNN represents the state-of-the-art in many image-related tasks [61].

Ten papers employed image segmentation techniques. Figure 9 shows the distribution of such methods. ID1 [30] used Otsu's method for image segmentation of porcelains, ID3 [32] applied SLIC-Ncut algorithm to segment porcelain ewers. Finally, ID6 [34] used four CNN models to segment porcelain patterns while ID15 [41] employed Mask R-CNN for ceramics segmentation.

Finally, three papers employed image enhancement techniques. ID8 [36] used FCutMix which is an image enhancement method based on DL, ID12 [39] and ID18 [7] used traditional enhancement methods including random rotation, horizontal and vertical flipping. Two papers indicated image registration such as Chamfer matching algorithm [46] and

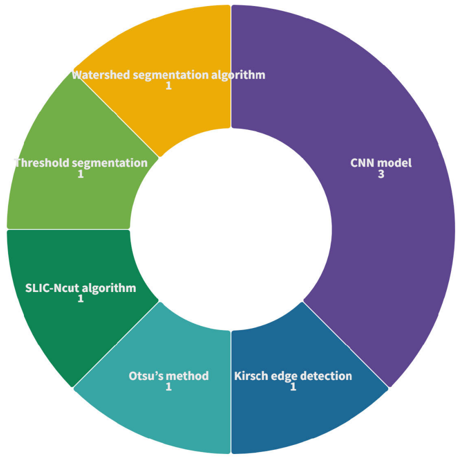

FIGURE 9. Distribution of image segmentation methods in reviewed papers.

template matching algorithm [48] for matching the pottery sherds or patterns. The other two papers (ID26 [50] and ID29 [53]) discussed color space transformation to convert RGB color format to HSV color format.

3) EVOLVING LANDSCAPE OF IMAGE PROCESSING METHODS

The previous Subsection highlighted that CNNs are the most used algorithms for both feature extraction and image segmentation. Figure 10 shows the evolving trend in the use of CNNs for these two tasks. Especcially from 2021, CNNs became the dominant method for image processing in the field of archaeological ceramic images.

Such a shift in terms of popularity from traditional image processing methods (LBP, GLCM, Tamura texture feature, etc.) and traditional ML-based methods (Kernal mean shift clustering) to DL ones, reflects the same behaviour that can be observed in other research areas based on image analysis. In fact, traditional approaches rely on well-defined features of ceramics, and manual feature design is considered time-consuming and inflexible. On the other hand, DL overcome this limitation of handcrafted feature processing [30].

Although CNN's feature extraction method improves the accuracy of extraction, feature extraction of ancient ceramics still faces some challenges, including the inconsistency of surface quality and the complexity and diversity of texture [26]. A promising research direction that could be exploited regards the use of Transformers for feature extraction.

In fact, parallel to what is happening in computer vision [62], Transformers could also be exploited in image analysis of archaeological ceramics. These models excel at capturing long-range dependencies within data [63], a crucial aspect for analyzing complex visual details in ceramics. Unlike traditional methods that focus on local features, transformers can identify subtle relationships between different parts of the image, potentially revealing characteristics like

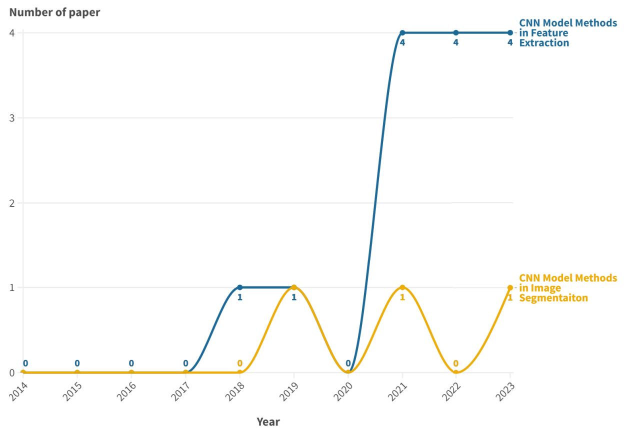

FIGURE 10. Trend of CNN model methods in feature extraction and image segmentation.

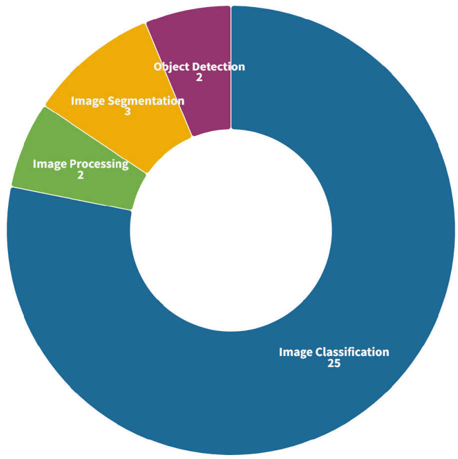

FIGURE 11. Distribution of applications in reviewed papers.

decorative patterns, specific glazing techniques, or even signs of wear and tear. This deeper understanding of the image could lead to a more accurate identification of ceramic origins, types, and potential historical context. Furthermore, transformers can be trained on diverse datasets encompassing a wide range of ceramics, potentially overcoming limitations caused by data scarcity in this field.

D. ML ALGORITHMS FOR THE IDENTIFICATION OF ARCHAEOLOGICAL CERAMICS

This Section answers the third and final research question **RQ3**, "What are the main ML algorithms used in the identification of archaeological ceramics?". The algorithms employed for the identification of archaeological ceramics mainly consist of classification and object detection algorithms [64]. Table 8 reports on the various ML algorithms employed. Among thirty-three papers, twenty-eight (84.8 %) of them use ML algorithms. Among these twenty-eight papers employing ML algorithms, seventeen of them (60.7%) used DL algorithms to identify archaeological ceramics, using various CNN architectures: VGG16, ResNet50, DenseNet121, InceptionV3, GoogLeNet, and AlexNet [38], [40], [42], [43]. The papers employing traditional ML algorithms to classify archaeological ceramics took advantage of SVM, KNN, and SOM [49], [50], [53].

The remaining ones (15.1%), instead, are primarily focused on datasets and image processing methods of the archaeological ceramics and did not conduct experiments for the classification or identification of archaeological ceramics.

1) APPLICATION OF ML ALGORITHMS IN ARCHAEOLOGICAL CERAMIC IMAGES

Figure 11 shows the distribution of applications based on ML/DL algorithms in reviewed papers. Among twenty-eight papers, twenty-five of them applied ML/DL algorithms to image classification, three of them focused solely on image segmentation, and two of them discussed image processing and object detection respectively. It is worth noting that some papers have more than one application, but combine image segmentation with another application. Anyway, these distributions highlight that the problem of archaeological ceramic identification is often modelled and tackled as a classification one.

Fourteen studies employed a DL algorithm, such as VAE [37] and CNN like VGG [31], ResNet [33], EfficientNet [31], MobileNet [33], GoogleNet [39], etc., while thirteen studies took advantage of an ML algorithm, including [53], SVM [49], SOM [50], KNN [53], etc.

Although there is a similar amount of reviewed literature based on ML and DL, they were used in different periods. Figure 12 shows the tendency of ML/DL algorithms for image classification. There's a notable increase in the use of DL algorithms starting around 2022, as indicated by the sharp upward line, while ML algorithms trend line shows fluctuations over the years, with peaks and troughs, indicating variable usage or effectiveness during that period. It is interesting to notice that after 2021, ML algorithms are mainly used as baseline models for comparison. Hence, we can conclude that DL algorithms for the classification of archaeological ceramic images have been the dominant trend in the last three years.

Finally, the only paper about object detection is also based on the DL algorithm. It combines object detection with image segmentation, proposing a new tool to allow users to analyze the visual elements of ceramics using their smartphones and devised a method to extract representative colors of ceramics for object detection.

2) PERFORMANCE EVALUATION

The performance evaluation of algorithms for image classification, image segmentation, and object detection is mainly based on evaluation metrics including accuracy, precision, recall, and F1 score [41].

With regard to image classification, the papers based on CNNs architectures perform differently on various datasets. In the reviewed literature, the performance evaluation of the

TABLE 8. ML algorithms of the reviewed studies.

ID	Application	ML Algorithms
ID1 [30]	Image Classification	This study employed a convolutional neural network (CNN) as a primary tool for porcelain image classification with an accuracy of 94.2%.
ID2 [31]	Image Classification	The study employed CNN for image classification of potteries. Evaluated the performance of three different CNN architectures: Visual geometry group (VGG), Residual neural network (ResNet), and EfficientNet, achieving accuracy of 66%, 77%, and 79%, respectively.
ID3 [32]	Image Classification	This study employed logistic regression cross-validation (CV) for the image classification with an accuracy of 90.7%.
ID4 [33]	Image Classification	The study employed CNN for image classification of porcelain vases. Compared and evaluated the accuracy and loss values under different optimization parameters under three different CNN models: ResNet, Inception, and MobileNet, achieving an accuracy of 93.8%, 91.2%, and 94.2%, respectively.
ID5 [26]	Image Classification	The study employed CNN to extract texture features of ceramics for image classification with an accuracy of 76.3%.
ID6 [34]	Image Segmentation	This paper was based on four CNN models PSPNet, DeepLabv3+, DANet, HRNet to segment porcelain patterns: dragon pattern, fish pattern, lotus pattern and peony pattern. Results show that the image segmentation methods of HRNet and DANet models are better than the other two models.
ID7 [35]	Not provided	Not provided
ID8 [36]	Image Classification	This study employed a Feature Fusion Convolutional Network (FFCNet), this architecture extends the typical capabilities of the standard CNN (ResNet) by incorporating mechanisms specifically designed for effective feature fusion, improving the recognition and classification accuracy from 71.7 to 79.5%.
ID9 [37]	Image Processing	Convolutional VAE was designed to work in an unsupervised learning style, suitable for this study where labeled data was not available. VAE extracted the essential features of archaeological pottery profiles. The model demonstrated its effectiveness and was validated through visual inspection of the reconstructed images against the original profiles.
ID10 [27]	Not provided	Not provided
ID11 [38]	Image Classification	This paper employed CNN for image classification of porcelain vases, accuracy of the network in identifying the types and ages of ancient ceramics was above 96.4%.
ID12 [39]	Image Classification	This study employed and compared the performance of five CNN models(DenseNet121, InceptionV3, VGG16, GoogLeNet, and AlexNet), the comparison of the CNN performance showed that the VGG16 achieved the best results with accuracy of 86.5%.
ID13 [29]	Image Classification	This study compared ML algorithm logistic regression for DL algorithm based on transfer learning, and found that the accuracy of DL algorithm was 70% and the accuracy of logistic regression was 48%, the DL algorithm improved classification results by more than 20% over the logistic regression.
ID14 [40]	Image Classification	This research presented the evaluation for image classification of decorated potteries using two CNN models(VGG16 and ResNet50) with an accuracy of 82.5%.
ID15 [41]	Image Segmentation Object Detection	This article employed Mask R-CNN for segmentation to classify the ceramic form and generate the mask of the ceramic, the average accuracy of Mask R-CNN was 79.5%. For the analysis of material and pattern, the Faster R-CNN was applied by using the region proposal networks (RPN), the average accuracy of Faster R-CNN was 60%.
ID16 [42]	Image Classification	This paper compared two different models for image classification: a DL model (VGG16) with an accuracy of 83.9%, an integration of DL and ML model (VGG16-GSSVM) with an accuracy of 89.3%
ID17 [28]	Not provided	Not provided
ID18 [7]	Image Classification	This research presented the evaluation for image classification of pottery fabrics in thin sections using two CNN models (VGG19 and ResNet50) and the accuracy remained above 93%.
ID19 [43]	Image Classification	This study compared ML method SVM with DL method CNN model (GoogleNet) for image classification. The CNN method(higher than 90%) showed more accurate than the SVM one(less than 80%).
ID20 [44]	Image Classification	This study employed SVM combined with LBP-HOG fusion feature extraction for the porcelain image classification of three dynasties, achieved 75% of Yuan dynasty, 80% of Ming dynasty and 90% of Qing dynasty.
ID21 [45]	Not provided	Not provided
ID22 [46]	Image Segmentation Image Classification	This paper used an FCN-based image segmentation method to extract curve patterns from a sherd A dual-source CNN (AlexNet) was applied for feature extraction, and the segmented curve patterns could be implicitly classified through this method.
ID23 [47]	Image Classification	This paper employed k-Nearest Neighbours (KNN) algorithm for image classification, compared three different methods for texture extraction, Gabor filters with an accuracy of 68.1%, Laws' texture measures with an accuracy of 73.9%, Haralick's texture features with an accuracy of 71.1%.
ID24 [48]	Image Classification	This study employed a deep neural network for image classification of ceramics.
ID25 [49]	Image Classification	The classification in Wndchrm involves different ML algorithms(decision trees, SVM, or simple statistical comparisons), integrated within its framework to classify pottery images. The classification accuracy reached between 90% to 95%.
ID26 [50]	Image Classification	This paper applied a Self-Organizing Map(SOM), a type of unsupervised ML model to group the fragments with an accuracy of 89.6%.
ID27 [51]	Image Classification	This paper employed semi-supervised mean shift clustering, an ML method for image classification with an accuracy of 75.6%
ID28 [52]	Not provided	Not provided
ID29 [53]	Image Classification	This paper employed the KNN algorithm for image classification with an accuracy of 86.5%.
ID30 [14]	Image Classification	SVM was used to classify different patterns of pottery shards using features extracted from Gabor filters and features generated by Bags of visual words. Results of classification were presented by a confusion matrix.
ID31 [54]	Image Classification	Compared five different ML algorithms for classification, SVM, KNN, Naive Bayes, Sequential Minimal Optimization (SMO) and Simple Logic, SVM achieved the accuracy of 93.96%.
ID32 [55]	Image Classification	Employed two ML algorithms, KNN and SVM on image classification of patterns from ceramics.
ID33 [56]	Image Classification	KNN and SVM used for the classification of patterns from pottery sherds.

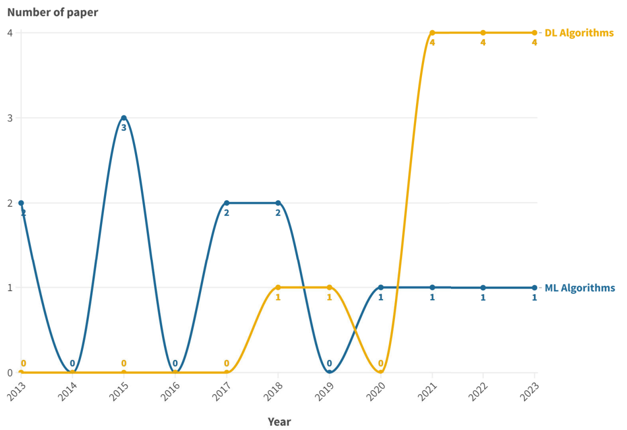

FIGURE 12. Tendency of ML/DL algorithms on image classification.

TABLE 9. Accuracy of DL algorithms on image classification.

ID	Ceramic Type	Number of Classes	DL Algorithms	Accuracy
ID1 [30]	Porcelain (Yaozho kiln)	N/A	CNN model	94.2%
ID2 [31]	Pottery	7 classes	VGG ResNet EfficientNet	66% 77% 79%
ID4 [33]	Porcelain	19 types of vases	MobileNet ResNet Inception	94.2% 93.8% 91.2%
ID5 [26]	Porcelain	N/A	CNN model	76.3%
ID8 [36]	Porcelain	14 types	ResNet FFCNet	71.7% 79.5%
ID11 [38]	Porcelain	2 types of vases	CNN model	96.4%
ID12 [39]	Ceramic (Sukhothai kiln)	7 types of patterns	VGG16	86.5%
ID13 [29]	Porcelain	3 glaze colours	CNN model	70%
ID14 [40]	Pottery	8 design classes	VGG16, ResNet50	82.5%
ID16 [42]	Porcelain	7 types of bottles	VGG16 VGG16-GSSVM	83.9% 89.3%
ID18 [7]	Pottery	5 types	VGG19, ResNet50	93%
ID19 [43]	Pottery	2 types of patch-work	CNN model	90%
ID22 [46]	Pottery	98 non-composite patterns 20 com-posite patterns	AlexNet	N/A
ID24 [48]	Ceramic	7 classes	CNN model	N/A

models is mainly based on accuracy. Table 9 reports the accuracy of DL algorithms in the classification of ancient ceramics. It can be seen that the classification accuracy is more than 70% in both pottery and porcelain, and the accuracy of ID1, ID4, ID11, ID18, and ID19 even exceeds 90%.

TABLE 10. Accuracy of ML algorithms on image classification.

ID	Ceramic Type	Number of Classes	ML Algorithms	Accuracy
ID3 [32]	Porcelain	3 dynas-ties	Logistic regression cross-validation	90.7%
ID13 [29]	Porcelain	3 glaze colours	Logistic regression	48%
ID19 [43]	Pottery	2 types of patch-work	SVM	80%
ID20 [44]	Porcelain	3 dynas-ties	SVM	75%
ID23 [47]	Pottery	2 classes	KNN	68.1%
ID25 [49]	Pottery	2 types of clays	SVM	90%
ID26 [50]	Ceramic	8 classes of frag-ments	SOM	89.6%
ID27 [51]	Porcelain	13 classes	Mean shift clustering	75.6%
ID29 [53]	Porcelain	6 classes of frag-ments	KNN	86.5%
ID30 [14]	Pottery	6 classes	SVM	N/A
ID31 [54]	Pottery	N/A	SVM	93.96%
ID32 [55]	Ceramic	6 classes of frag-ments	KNN, SVM	N/A
ID33 [56]	Pottery	2 classes of sherds	KNN, SVM	N/A

The achieved results are in line with the state-of-the-art image classification using deep learning algorithms.

Table 10 reports the accuracy of ML algorithms in image classification. Seven papers employed SVM and achieved accuracy higher than 70%. In ID13 and ID19, ML and DL algorithms were applied separately to image classification to compare the results. They showed that the accuracy of DL algorithms was higher than the on achieved by ML algorithms. Although SVM has achieved good classification results as an ML algorithm, for example on pottery shards, its performance was still inferior to that of the DL algorithm on the same dataset [43]. Therefore, the choice of the DL algorithm as an image classification of archaeological ceramics appears to be a natural choice.

E. LIMITATIONS OF THIS REVIEW

To address the traditional limitations of systematic reviews, we followed the PRISMA methodology in this work. However, this approach still presents several limitations. Firstly, the review process was highly selective, focusing only on scientific articles published in journals or conference proceedings from reputable databases to ensure high-quality content. Secondly, the study of citations or reference analysis was deliberately excluded in order to keep the paper more concise and focused. However, future research efforts aimed at a more comprehensive overview could expand the range

TABLE 11. Details of the reviewed studies.

ID	Paper Title	Published Year
ID1 [30]	Technological innovation in the recognition process of Yaozhou Kiln ware patterns based on image classification	2023
ID2 [31]	Classification of unexposed potsherd cavities by using deep learning	2023
ID3 [32]	Identification of porcelain ewers in Tang, Song, and Yuan dynasties by digital shape characterization	2023
ID4 [33]	Comparative Study on Image Classification Models of Ancient Ceramic Types	2023
ID5 [26]	Ceramic Texture Extraction Method Based on Convolution Neural Network and Image Processing	2023
ID6 [34]	Typical Ceramic Pattern Extraction Based on Convolutional Neural Network	2023
ID7 [35]	Using Image Feature Extraction to Identification of Ancient Ceramics Based on Partial Differential Equation	2022
ID8 [36]	Automatic Classification of Blue and White Porcelain Sherds Based on Data Augmentation and Feature Fusion	2022
ID9 [37]	A deep variational convolutional Autoencoder for unsupervised features extraction of ceramic profiles. A case study from central Italy	2022
ID10 [27]	Ceramic Decoration Extraction Method Based on Computer Vision and Image Processing	2022
ID11 [38]	Intelligent Dating of Chinese Ancient Ceramics Based on Convolutional Neural Network	2022
ID12 [39]	Using Deep Learning for the Image Recognition of Motifs on the Center of Sukhothai Ceramics	2022
ID13 [29]	Ceramic Type Recognition Algorithm Based on Ontology Modeling and Transfer Learning	2022
ID14 [40]	Applications of deep learning to decorated ceramic typology and classification: A case study using Tusayan White Ware from Northeast Arizona	2021
ID15 [41]	Smart Culture Lens: An Application That Analyzes the Visual Elements of Ceramics	2021
ID16 [42]	Identification Method of Ancient Ceramics Revision	2021
ID17 [28]	The Application of Computer Vision in the Detection of Ancient Ceramic Art	2021
ID18 [7]	Ceramic Fabric Classification of Petrographic Thin Sections with Deep Learning	2021
ID19 [43]	Applications of learning methods to imaging issues in archaeology, regarding ancient ceramics manufacturing	2021
ID20 [44]	Characteristics of Banana Leaf Pattern for Ceramics in Yuan, Ming and Qing Dynasties	2020
ID21 [45]	Research on ancient ceramics identification by artificial intelligence	2019
ID22 [46]	A Framework for Design Identification on Heritage Object	2019
ID23 [47]	Automated classification of archaeological ceramic materials by means of texture measures	2018
ID24 [48]	Machine learning identification and classification of historic ceramics	2018
ID25 [49]	Using supervised machine learning to classify ceramic fabrics	2018
ID26 [50]	Classification Archaeological Fragments into Groups	2017
ID27 [51]	Porcelain image classification based on semi-supervised mean shift clustering	2017
ID28 [52]	Machine Vision Based Classification and Identification for Non-destructive Authentication of Ancient Ceramic	2017
ID29 [53]	Using Both HSV Color and Texture Features to Classify Archaeological Fragments	2015
ID30 [14]	Automatic pattern recognition on archaeological ceramic by 2D and 3D image analysis: A feasibility study	2015
ID31 [54]	Towards the automatic classification of pottery sherds: two complementary approaches	2015
ID32 [55]	A Semantic Analysis Approach to Thin-Shell Ceramic Fragment Classification	2013
ID33 [56]	Automatic classification of archaeological pottery sherds	2013

of review sources and employ knowledge graphs to visually describe developing tendencies and research hot spots in the application of machine learning algorithms to archaeological ceramics identification in a more sophisticated way. Thirdly, this literature also had unaddressed research areas, first was integration with other technologies, the potential integration of DL algorithms with other technologies such as 3D scanning and VR for more comprehensive analysis of archaeological ceramics, second was cross-cultural comparative studies, investigating how DL algorithms can be used to the identification of archaeological ceramics across different cultures and historical periods more effectively. Finally, since this research began at the beginning of 2024, it includes reviewed studies that have been published during the last ten years (i.e., between 2013 and 2023). The limitation of this timeframe indicates that future works could combine studies from 2024 and subsequent years, which will have the potential to provide deeper insights and more varied applications for the review of archaeological ceramics.

V. CONCLUSION

The purpose of this paper is to examine the trends of machine learning in the identification of archaeological ceramics. Specifically, it focuses on the application of ML and DL algorithms between 2013 and 2023, on several types of ceramic (pottery and porcelain). It investigates several aspects such as the available datasets, the image processing methods, and ML or DL algorithms.

In terms of the application of ML algorithms to the image classification of ceramic images, papers from 2013 to 2020 tend to use traditional ML algorithms such as SVM and KNN. However, there is a general shift towards the use of DL based on CNN models for classification in papers from 2020 to 2023. In fact, based on the conclusions drawn from these papers, DL algorithms have made significant breakthroughs in many tasks due to their powerful automatic feature extraction capabilities. Among CNN models, VGG16, MobileNet and ResNet have achieved good performance on archaeological ceramic images and higher accuracy compared to traditional ML algorithms such as SVM and KNN. This indicates that DL algorithms such as CNN models will be the main trend in the future for archaeological ceramic classification applications.

Various studies demonstrated the technical potential of DL for the identification of archaeological ceramics. The manual classification of a large number of pottery sherds is a time-consuming activity and empirical identification methods of porcelains often lack objective constraints. The

TABLE 12. Dataset details of the reviewed studies.

ID	Ceramic Type	Dataset
ID1 [30]	Porcelain	This study analyzed Yaozhou kiln ceramic from China. The production period is not provided.
ID2 [31]	Pottery	This study analyzed archaeological pottery fragments from the Late Jomon period (ca.4000 to 3200 aBP) in Japan. The proposed dataset is composed of 1,036 X-ray images from seven classes.
ID3 [32]	Porcelain	This study selected images of porcelain ewers from the Tang (ca.1332 to 1043 aBP), Song (ca.990 to 671 aBP), and Yuan (ca.679 to 582 aBP) dynasties in China. There were 85 images from the Tang Dynasty, 85 from the Song Dynasty, and 62 from the Yuan Dynasty. Images were photographed at museums in China.
ID4 [33]	Porcelain	The study used the porcelain image dataset provided by Baidu PaddlePaddle to collect archaeological porcelain images in the datasets, including 19 different types of vases in China. The production period is not provided.
ID5 [26]	Ceramic	Not provided
ID6 [34]	Porcelain	The datasets are mainly derived from Chinese museums' photo scans and websites. Four typical porcelain pattern datasets of dragon, fish, lotus, and peony are established. The production period is not provided.
ID7 [35]	Porcelain	The study extracted and validated 5,834 images of archaeological ceramics from China, including 272 types of kilns, Yaozhou kiln, and Yue kiln with manual labelling. The production period is not provided.
ID8 [36]	Porcelain	This paper employed blue and white porcelain shards by incomplete patterns, a total of 373 ceramic image samples of 14 types in the Yuan (ca.679 to 582 aBP), Ming (ca.582 to 306 aBP) and Qing (ca.306 to 38 aBP) dynasties from China.
ID9 [37]	Pottery	This study focused on Lazio and Etruria pottery, a dataset of 4992 complete vessel profiles from 117 sampled contexts between the Late Bronze Age and the Orientalizing period (ca.3100 to 2530 aBP) in Italy.
ID10 [27]	Ceramic	Not provided
ID11 [38]	Porcelain	This paper takes Mei vase and Yuhuchun vase in Ming (ca.582 to 306 aBP) and Qing (ca.306 to 38 aBP) dynasties as the research object, all samples are from the Beijing Museum and Taipei Museum website. A total of 248 available samples were obtained.
ID12 [39]	Ceramic	The images in the dataset were obtained by photographing the ceramics of Sukhothai kilns in many private museums. A total of 557 images that featured seven types of patterns were collected from Thailand. Not provided the production period of the ceramics.
ID13 [29]	Porcelain	The dataset of the paper was collected from the official website of the Palace Museum in China. A total of 2750 pictures of the most representative ceramics, color glaze, under-glaze color, blue and white porcelain, purple sand, and doucai from Song (ca.990 to 671 aBP), Yuan (ca.679 to 582 aBP), Ming (ca.582 to 306 aBP) and Qing (ca.306 to 38 aBP) dynasties.
ID14 [40]	Pottery	A set of 3064 Tusayan White Ware(TWW) sherd photographs for the dataset from regional museum collections in the United States of America (ca.1125 to 650 aBP), providing a rich source of imagery due to the contrast between the paint and background of the sherds.
ID15 [41]	Ceramic	The dataset required for this study was created using two approaches. First, A total of 5,684 images of 5,211 ceramics were collected by the National Museum. Second, 13,926 Pictures of 2,135 ceramics were selected at 19 institutions in the Republic of Korea. Not provided the production period of the ceramics.
ID16 [42]	Porcelain	The self-built porcelain set includes seven types, 5624 pieces of porcelain bottles which had been crawled through Baidu in China. Not provided the production period of the porcelains.
ID17 [28]	Ceramic	Not provided
ID18 [7]	Pottery	The selected dataset used was primarily composed of 66 pottery sherds images of petrographic thin sections under cross-polarized light from the Cocal-period archaeological site of Guadalupe from Honduras (ca.950 to 425 aBP). In total, 1069 images were used to train each model.
ID19 [43]	Pottery	The dataset selected in this study was composed of sixteen sherds: four coiling technology (CoT) sherds and twelve spiralled patchwork technology (SPT) sherds. The dataset originates from the early Neolithic period (ca.7850 to 7450 aBP) in southeastern France.
ID20 [44]	Porcelain	A total of 230 pieces of ancient porcelains containing banana leaf patterns from Yuan (ca.679 to 582 aBP), Ming (ca.582 to 306 aBP) and Qing (ca.306 to 38 aBP) dynasties, collected from museums in China.
ID21 [45]	Porcelain	Analyzed the porcelain washer from Ming dynasty (ca.582 to 306 aBP) in China.
ID22 [46]	Pottery	The dataset consists of curvilinear paddle impressions on pottery sherds and comes from North America, specifically during the period (ca.1600 to 1300 aBP)
ID23 [47]	Pottery	The dataset discussed in the paper involves archaeological pottery materials specifically sourced from two different types of Egyptian clays: Nile clay(ca.2250 to 2450 aBP) and Marl clay (ca.3250 to 3450 aBP). A total of the 69 samples were imaged under the optical microscope as thin sections using cross-polarized light.
ID24 [48]	Ceramic	The dataset includes historic ceramics recovered from archaeological sites in New Zealand. Not provided the production period of the ceramics.
ID25 [49]	Pottery	The dataset used in the study consists of pottery samples from Zulu communities in South Africa. The potteries are contemporary, made by modern potters who employ traditional methods that are reflective of historical practices.
ID26 [50]	Ceramic	This study selected eight classes of the Independence National Historical Park dataset(ca.175 to 125 aBP), a collection of ceramic fragments in the United States of America.
ID27 [51]	Porcelain	Dataset images consist of 288 porcelain pieces, including 13 different porcelains from China. Not provided the production period of the porcelains.
ID28 [52]	Porcelain	A total of 50 porcelain jar images were selected from Forbidden City Museum of China, including five ages of Neolithic (ca.12000 to 4000 aBP), Tang (ca.1332 to 1043 aBP), Song (ca.990 to 671 aBP), Yuan (ca.679 to 582 aBP) and Ming (ca.582 to 306 aBP).
ID29 [53]	Ceramic	This study selected six images of the Independence National Historical Park dataset (ca.175 to 125 aBP), a collection of ceramic fragments in the United States of America.
ID30 [14]	Pottery	The dataset used includes 935 shard imprints manually obtained by archaeologists (ca.1524 to 924 aBP) from France.
ID31 [54]	Pottery	A set of 203 pottery sherds collected from Greece. Not provided the production period of the potteries.
ID32 [55]	Ceramic	This paper selected ceramic images of the Independence National Historical Park dataset (ca.175 to 125 aBP), a collection of thin shell ceramic fragments in the United States of America.
ID33 [56]	Pottery	A set of 110 pottery sherd images including six different classes. The sherds were selected and photographed from Byzantine Antiquities in Greece (ca.1330 to 330 aBP).

image classification based on DL provides support for the classification of archaeological ceramics. This review and its conclusions should be seen as a first step in the analysis of machine learning for ceramic identification in the sector.

Overall, the use of machine learning algorithms in archaeological ceramics classification complements traditional methods by offering efficiency, accuracy, and new avenues for data analysis and interpretation. By combining the strengths of both approaches, researchers can gain deeper insights into past civilizations and cultural practices. The efficiency of these algorithms can speed up the classification process allowing archaeologists to analyze larger datasets and automate repetitive tasks, such as sorting and categorizing artifacts based on specific attributes. This automation frees up archaeologists' time to focus on higher-level analysis and interpretation. Moreover, machine learning algorithms can uncover hidden relationships or correlations within ceramic datasets that may not be apparent through traditional methods. By analyzing these insights, archaeologists can gain a deeper understanding of cultural practices, trade networks, and historical contexts.

ABBREVIATIONS

AI:	Artificial Intelligence.
BoVW:	Bag of Visual Words.
CNN:	Convolutional Neural Network.
DANet:	Dual Attention Network.
DL:	Deep Learning.
FCN:	Fully Convolutional Network.
FFCNet:	Feature Fusion Convolutional Network.
GLCM:	Gray Level Co-occurrence Matrix.
GVF:	Gradient Vector Flow Field.
HOG:	Histogram of Oriented Gradient.
HRNet:	High-Resolution Network.
HSI:	Hue, Saturation, Intensity.
HSV:	Hue, Saturation, Value.
KNN:	K Nearest Neighbor.
LBP:	Local Binary Patterns.
ML:	Machine Learning.
PCA:	Principal Component Analysis.
PSPNet:	Pyramid Scene Parsing Network.
PRISMA:	Preferred Reporting Items for Systematic Reviews and Meta-Analyse.
ResNet:	Residual Neural Network.
RGB:	Red, Green, and Blue.
RPN:	Region Proposal Networks.
SOM:	Self-Organizing Map.
SSD:	Single Shot Detection.
SVM:	Support Vector Machine.
TWW:	Tusayan White Ware.
VAE:	Variational Autoencoder.
VGG:	Visual Geometry Group.
VR:	Virtual Reality.
Wndchrm:	Compound hierarchy of algorithms representing morphology.
YOLO:	You Only Look Once.

APPENDIX

See Tables 11 and 12.

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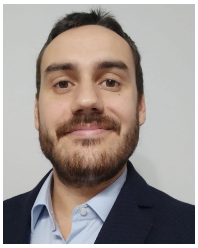

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