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MULTISPECTRAL IMAGING AND ARTIFICIAL INTELLIGENCE FOR ARCHAEOLOGY: FIRST RESULTS AND FIRST PROJECTS

Cyrille Chaidron, Sébastien Lermenier***

*Université de Picardie Jules Vernes (UPJV) – Amiens, France; ArScAn-GAMA -CNRS, Paris; CEO of ARTEKA

**CTO of Arteka

Abstract

Archaeology is a human science that is very attentive to technological evolution. For decades, it has relied on technologies from the hard sciences (medicine, chemistry, geology, etc.). The emergence of satellite images with increasingly fine resolutions and the massive arrival of the drone in the field of archaeology have created new uses for the detection of archaeological sites. Multispectral imagery now supports other technologies (geophysics, Lidar). But it is above all the arrival of artificial intelligence and the development of Deep-Learning that is taking archaeology into a new era. The large amount of documentation generated by archaeology is conducive to the development of projects that will use artificial intelligence to help archaeologists in their research and enable them to obtain new results, both in the detection of archaeological sites and in the analysis of artefacts such as ceramics.

Keywords

Archaeology, multispectral imaging, satellite images, artificial intelligence, ceramology, roman pottery

1. *Introduction*

Archaeology is a discipline of the human sciences which very early on had to rely on technological developments in order to be more efficient as soon as the pressure of real estate development became apparent.

Archaeologists, in the context of preventive archaeology (i.e. archaeology that takes place before development work is carried out), have had to reinvent themselves in order to meet legislative requirements and economic pressures. This was achieved firstly through technical improvements in the "field" phase (the archaeological excavation as it is understood, i.e. when archaeologists are on the dig). Mechanisation has become more and more important.

Excavation techniques and recording methods have also been developed and improved, but it is during the study phase, i.e. after the excavation (the so-called 'post-excavation' phase) that archaeologists have to 'dip into' the hard sciences to acquire innovative methods of analysis. Archaeologists have drawn on technologies from the space field (Lidar, for example), from the field of medical imaging (X-rays for corroded objects) and from the field of geology (petrography for pottery fragments). Archaeology has also seized upon recent technologies for the general public such as VR and AR in the context of the enhancement of archaeological excavations and exhibitions.

The multidisciplinary nature of archaeology is a breeding ground for innovative experiments, which explains why it is certainly the most "technology enthusiast" discipline in the humanities and social sciences.

It is therefore not surprising that the innovative technologies of multispectral imaging or that of artificial intelligence (or augmented intelligence, dear to the great specialist Luc Julia) find a favourable ground for their development, even if it is still timid.

This is what we are talking about here through some projects carried out within the Trame laboratory of the University of Picardy and within the start-up Arteka.

2. The development of aerial and spatial imaging for archaeology

The traces left in the ground by ancient remains have, for many centuries, questioned scholars and researchers. It is easy to imagine that the grandfather of the famous Giorgio Vasari (1511-1574), Lazzaro, a 15th century painter who discovered pottery workshops from the period of the Roman Emperor Augustus, may have benefited from clues that were visible on the surface, or even from remains that were still in the air.

Technology has then come to aid the eyes of researchers in their quest to discover what is invisible and hidden beneath the ground. The use of advanced technologies in archaeology has been an established fact since the early days of scholarly archaeology. Let us take the example of aerial archaeology.

The history of aerial archaeology is almost as old as that of photography. The information obtained from aerial photography during the First World War was the beginning of the critical analysis of the traces left by human activity in the ground with the aim of locating trenches.

The pioneers of archaeology were the Frenchman Antoine Poidebard and the Englishman Owen Crawford, who were soon able to observe alterations to the ground by aerial photography, particularly in the Syrian desert, where the low-angled light could reveal the infrastructure of the Roman limes (from 1925 to 1932 in particular).

Since then, aerial archaeology has evolved with the material but not in the methodology. Other pioneers have allowed this discipline to develop to help archaeological researchers, such as Roger Agache (1926-2011) in France, or Edmond Bernus and Yveline Poncet (Bernus, Poncet, 1981, Poncet 1985). Since then, sensors have become more precise and allow a greater accuracy of surface anomalies. Vegetation is a privileged vector and seasonal cycles are landmarks for the aerial archaeologist. The researchers then added the satellite images. Summary books are regularly published (Goguey, Cordier, 2015, Ceraudo, 2010) and publications and specialized journals on the subject of aerial archaeology are numerous (for example the Italian journal Methodology Applied to Archaeological Potential Predictivity).

The early 2000s saw the development of public satellite image platforms. The creation of Google Earth in 2001, followed in 2005 by Bing Maps and then the French service Géoportail in 2006, greatly contributed to the democratisation of the use of mapping tools, rapidly followed by the use of satellite images by the archaeological community.

Several articles on the use of satellite images in archaeology were published following the launch of these programmes (De Laet, Paulissen & Waelkens, 2007; Garrison, Houston, Golden & Inomota, 2008; Goossens, de Wulf, Bourgeois, Gheyle & Willems, 2008; Déodat, Lecoq, 2009).

From the 2010s onwards, space archaeology has experienced a turning point with high-profile projects, in particular the one led by Sarah Parcak, a professor at the University of Birmingham, in the state of Alabama, in the USA. The GlobalXplorer project is a collaborative online platform where anyone can search for archaeological sites around the world using satellite images and feed a very rich database. It is at this time that the CNN revolution really took off, notably thanks to the Imagenet competitions and especially in 2012 with the performances of the AlexNet neural network. This is what archaeology has been missing and these numerous exploitable data. The projects and publications are taking on a real magnitude since the emergence of these CNN and the associated Deep Learning. Since then, research teams have coupled satellite images, sometimes with different spectral bands, with artificial intelligence. This is the case, for example, of the remarkable work of detection of archaeological sites in the steppes of Central Asia (Caspari, Crespo, 2019) or that on the detection of sites of the Indus civilization in Pakistan (Orenga et al., 2020) or in Peru (Karamitrou et al., 2022) or in Iraq (Soroush et al., 2020). The power of Deep Learning (with some CNN) also allows the fusion of geophysical data or Lidar data for the detection of archaeological sites (Küçükdemirci, Sarris, 2020, Bonhage et al., 2021).

Deep-Learning is also used in the detection of archaeological sites not only by the traces left in the ground but by the presence of ceramic fragments (potsherds) identified by artificial intelligence and by drone. It is a new approach to archaeological prospecting (Agapiou et al., 2021).

In France, a few projects are being structured, notably in the North of France with Tahar Ben Redjeb, a specialist in archaeological site prospecting within the Regional Archaeology Department (DRAC Hauts-de-France), which we are joining.

As early as 2013, we had established a search for archaeological sites in a geographical sector located in the east of the Somme department. The results were then integrated into T. Ben Redjeb's programme. From 2013 to 2015, this project made it possible to integrate and geo-reference more than 1,500 archaeological sites on the QGIS. The methodology was presented at the Regional Archaeology Days in 2013 and 2016, and then in an article by R. Parpworth-Reynolds of Microsoft Bing Maps on the Grey Matter blog (Parpworth-Reynolds, 2019).

The first results were able to highlight particular occupation dynamics. The Somme valley develops from east to west. Some of its confluences are oriented from south to north and in this case the archaeological sites are mainly located on the western side (Selle valley).

In parallel, technological development has led to the development of publications oriented towards aerial archaeology but increasingly presenting results by mixing technologies such as RGB ortho-photography and Lidar (e.g. in Northern France and Belgium. Henton, Hannois, 2014 ; Henton, Fourny, Van Assche & Clarys, 2016) or the use of thermography (Beaufrère, Dabas, Décriaud & Tabbagh, 1999; Calastrenc, Baleux, Poirier & Rendu, 2020).

Faced with the large amount of data to be processed, archaeology is increasingly turning to artificial intelligence.

3. *Multispectral imaging for archaeology*

Aerial image capture has always been carried out with RGB sensors and the first 'adventurers' who embarked on experiments chose to test infrared sensors and essentially thermal cameras. The principle is based on the existence of a temperature differential between the buried remains and the surface environment (Eppelbaum, 2009). In this way, it is possible to see the shapes of substructions or anthropogenic excavations. However, the quality of resolution of the cameras used by these pioneers was not equivalent to what we have today

After two years of R&D, the start-up Arteka has developed a multispectral imaging protocol based on proven technologies such as satellite multispectral imaging. Several wavelengths were tested, some were abandoned, others were retained, between the 360 and 16,000 nm bands (see Figure 1). Bands in the visible spectrum are also widely used as they are very effective on certain anomalies.

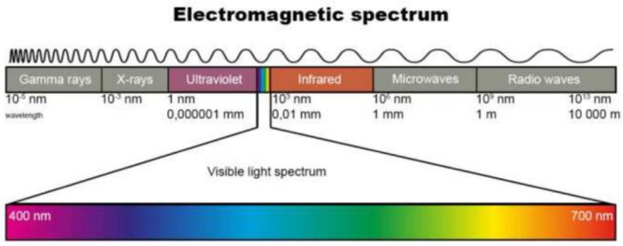

Fig. 1: The electromagnetic spectrum (Rahrig, Drewello & Lazzeri, 2018)

The choice of wavelengths is essential. It has been necessary to modify some cameras to try out different wavelengths. Some of them have not been satisfactory so far, while others, especially in the infrared, have proved to be more relevant.

For more than two years, different sensors on board drones were used on different terrains in the North of France during the four seasons. The terrain presented the essential characteristics: plateau, upper slope, lower slope, cultivated, ploughed or fallow land.

All these parameters allowed us to calibrate the protocol and to identify the types of land and the period of the year most likely to produce positive multi-spectral responses. If the protocol is operational, other wavelengths should be tested as the potential of multispectral imaging is significant.

The images are captured at 50m altitude with 12MP cameras giving a GSD of about 2cm (2cm per pixel). The photos are geo-referenced which allows the creation of precise ortho-photographs in geo-tiff format. Several calculations are then carried out by combining different ortho-photographs. Each ortho-photograph corresponds to a precise spectral band. The calculations then carried out make it possible, in the manner of NDVI, to show anomalies specific to archaeological excavations.

The results vary from one type of land to another.

When the ground is freshly ploughed, the results are almost nil (with the exception of imposing buried structures such as Roman roads).

In Figure 2, this is a major site in northern France, a former military camp that would have hosted Julius Caesar's armies in 57 BC. The image shows traces of ploughing but the vegetation had already grown slightly. Anomalies in the form of zigzag tracks appear (see Figure 3). They may correspond to trenches from the First World War. Other trenches are indicated on military maps of the time, a few hundred metres to the north, but those discovered here have not been referenced. This is therefore new information for the knowledge of WW1 trenches or gutters behind the front line.

Fig. 2: Aerial image of the site (in black the trench area). Geoportail (IGN 2021 ©)

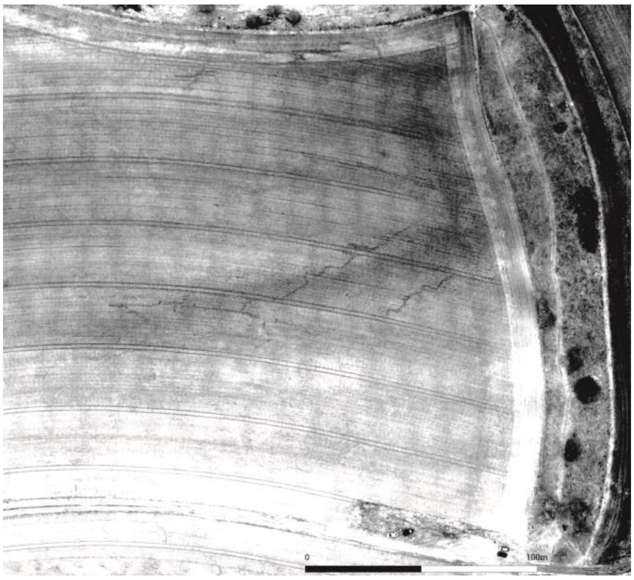

Fig. 3: Result with a specific spectral band. The zigzag trenches can be seen on the left of the image (ARTEKA ©)

Another example, near Amiens, in the North of France, with this uncultivated land, as it is a model airfield. The land is not altered by recent agricultural activity. However, it has been used as a dumping ground, a motorbike cross-country track and a football field (see Figure 4).

Fig. 4: Photo-editing with satellite image of the terrain (Google Earth ©) at the top and the terrain at the bottom revealing excavations by multispectral imaging (ARTEKA ©)

After multispectral processing, we can clearly see many dark traces that correspond to hidden diggings in the ground. The difference in soil density between an excavated pit and the natural terrain can be seen in the vegetation, which will react differently. This is a principle that has been known for a very long time in aerial archaeology. Here, the precision of the sensors can reveal diggings (such as the ancient post holes of Gallic houses for example) of a few tens of centimetres in diameter (see Figure 4).

While multispectral imagery provides more accurate information than satellite images on land before the start of an archaeological dig to locate remains in the excavation area but also on its periphery, we were also able to test it on a site during excavation. Equipped with precise wavelengths, we worked on the excavation of the Evéha company in Ilies-Salomé, in the Pas-de-Calais (Northern France) in August 2020. The ground was particularly dry due to a major drought episode. Stripping had made it possible to distinguish the remains, but variations that were not very visible to the naked eye had made it difficult for the archaeologists to form certain impressions. The presence of a talweg was suspected but it was not possible to locate it on the site. The multispectral was able to highlight geological anomalies.

The light pink area corresponds to a thalweg that was not visible during the stripping, even though the archaeologists had spotted a variation in the soil, without being able to identify the precise limits of this thalweg. Another contribution was the use of multispectral imagery to confirm relative chronology data by showing overlapping archaeological structures, thus confirming their chronology. The drains that were uncovered intersect with the principle of stratigraphy: what is below is older (see Figure 5).

Fig. 5: Multispectral orthophotography of an archaeological excavation with stripping. The soil shows visible geological anomalies. Overlapping drains can also be seen, allowing a relative chronology

4. Computer vision for archaeology

4.1 Satellite imagery

The mass of data has motivated the setting up of a research project within the Trame laboratory of the University of Picardy which consists of using an artificial intelligence algorithm to automatically locate archaeological sites on satellite images, without image processing.

We were able to integrate the data collected and integrated into a GIS (QGIS) before testing the recognition of archaeological remains visible to the naked eye, with a computer vision algorithm. The choice fell on an artificial intelligence algorithm based on supervised learning. An initial, very limited dataset was established to test the methodology and the algorithm. The dataset consists of satellite images as well as aerial photographs of about 400 entries, some of which include several archaeological sites. More than 950 images were selected to be included in the new database.

The first step was to define the elements that would be taken into account in the computer analysis ("Tags". See Figure 6). Five types of archaeological occupation (remains observable on the satellite photos) were chosen for the first iterations: Simple ditches, Bronze Age burial rings (ca. 2300 BC-800 BC), Roman roads, ditched enclosures (protohistoric or ancient settlements), Roman roads, and finally the remains of buildings/villas (traces of foundations : residential buildings, agricultural buildings, temple/religious buildings).

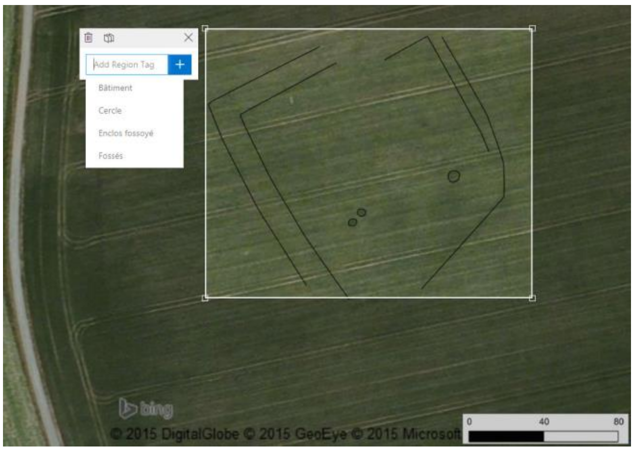

Fig. 6: Constitution of the dataset. The remains have been traced. Satellite image (Bing Maps/Microsoft)

The second step was to feed the software with satellite photos of which the remains have been redrawn. Computer analysis is thus facilitated by a worked image. The aim of this phase is firstly to make the protocol valid with easier indications. The purpose of submitting images with traced sites to the NCC is to provide them with images in which the tracks are very visible, as may be the case in some terrain after periods of drought. It is a way to simulate a particular climatic condition.

At this stage, it is not a question of performing the algorithm but of establishing the methodology for labelling the elements to be located on the image. The results were convincing for iterations 1 and 2. Images not used in the training phase of the machine were then proposed to the machine (80/20 ration). The results were positive in many cases. For iteration 1, the number of training images is 171, and the percentage accuracy is 80% (8.9% Recall, 16.2% mAP). The enclosures are the most numerous artefacts with 72 images giving 100% accuracy (15.8% Recall, 39.9% mAP). This information is only intended to show the methodological direction.

For iteration 2, the number of images increased to 260. The accuracy rate increased to 84.6%, 15.9% Recall and 33.4% mAP. Enclosures and Bronze Age circles are the two categories where the number of images is sufficient for the machine. With 110 images for the enclosures, the accuracy rate is still 100% (Recall: 20.8%; mAP: 45.0%). The circles have an accuracy rate of 66.7% (R.: 25%; A.P.: 49.2%). Although the number of images is insufficient for 'buildings' and 'ditches', the accuracy rate is 100%. Only the 'tracks' have a 0% accuracy rate with 27 images.

Once the training phase was completed, it was possible to carry out image analysis tests using the "Quick test" function and the results confirmed the methodology. The algorithm easily detects the remains and identifies them according to the groups defined, sometimes with very high precision.

As the protocol was validated for images in which the archaeological sites had been traced on the image, the next stage of the tests was to determine whether the machine could identify archaeological sites on untouched satellite images.

Two iterations were carried out with a number of images comprising those from iterations 1 and 2 to which we added 'raw' images.

Iteration 3 was used as a quick test, which was not very convincing (9 additional images, i.e. 269 images in total). The accuracy rate fell to 70% (Recall: 10.8%; mAP: 24.7%).

The last iteration (iteration 7) added more "raw" images. Iteration 7 covers a total of 525 images distributed as follows: 120 images for building foundations, 233 images for ditched enclosures, 72 images for Bronze Age circular enclosures (very simple shape) and 100 images for ditches (mainly Celtic and Roman).

The accuracy rate is now 82.9% with 38% Recall and 47.8% mAP. The results are still weak but the evolution of the statistical data allows first encouraging and very relevant tests. The results were obtained after a short 2-hour training of the CNN.

The machine training therefore generated different percentages with the addition of these "raw" images. Tests were then performed with images that were specially kept and not used to feed the CNN. In some cases, when the tracks are very discrete, the machine cannot detect them. However, in many cases, the results are positive. This shows the limits of the exercise when the database is still weak.

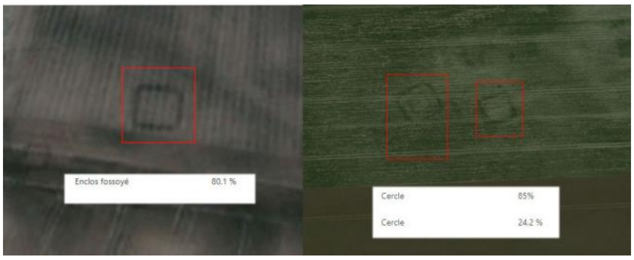

Fig. 7: Location of archaeological excavations [7] On the left, a quadrangular fossilized enclosure perfectly identified (80.1% accuracy). On the right, two quadrangular ditched enclosures confused by the AI into a circular enclosure (85% and 24% accuracy).

In some cases, the AI is able to locate a more or less square ditched enclosure with an accuracy of 80.1% while for other similar enclosures, the AI sees circular enclosures. However, in both cases, the archaeological remains were detected (Figure 7).

The rest of the protocol will have to feed the machine with other "raw" photos and test the machine's reactivity with raw images that have not been used for training (test images).

Eventually, algorithms developed on open source platforms will be preferred (here we used the Custom Vision CNN from Microsoft's Azur suite) in order to facilitate bridges with open source GIS software and to allow the integration of geo-referenced data in order to automate the integration on a map. For other projects, the AWS CNN has also shown its effectiveness.

Finally, with the development of multispectral imagery, it is not impossible to imagine being able to couple this technology with artificial intelligence and allow the multi-computer detection of terrain anomalies such as archaeological sites. Currently, this type of analysis cannot be performed live because it requires processing time.

4.2. An assistant for the study of ancient ceramics

As the study of ancient ceramics is at the heart of our research activity, we used the same algorithm to test the recognition of ceramic fragments, which are particularly numerous on archaeological sites. To understand how artificial intelligence will be able to revolutionise a speciality of archaeology such as ceramology, it is necessary to understand what it brings to archaeological reflection today.

Ceramology as it is currently understood in archaeology was established progressively from the end of the 1960s (Goudineau, 1968; De Laet, Thoen, 1969 for example). The first boom came in the 1970s when, under the impetus of a few Anglo-Saxon (Peacock, 1977) and French (Picon, 1973) researchers, the study of ceramics no longer focused on a catalogue of reasons but on a detailed analysis of the clays, or fabrics, as the English term is used. The ceramologist thus left the role of an expert in dating, in typology (catalogue) with a macro-economic vision (diffusion of amphorae for example) to one that is also nourished by the Earth sciences with micro-economic visions of the productions.

Since then, studies have, depending on the financial means allocated, opted for the use of archaeometry to characterise petrographically and chemically the clays used.

To identify the origin of an ancient vase, ceramologists proceed by visual comparisons between reference sherds from attested workshops and sherds from excavations.

Since the 1990s, particularly in northern France, correlations have been systematised. Groups of production have been defined by grouping sherds with the same characteristics.

A synthesis article was published in the proceedings of the French Society for the Study of Ancient Ceramics in Gaul held in Chelles (France) in 2010. It presents the main productions as well as the associated typological repertoire. Diffusion maps indicate the limits of the marketing areas for each group of workshops, defining each time a specific cultural entity (Clotuche, Chaidron, Comont, Dubois & Willems, 2010).

This is a synthesis of a group of researchers over a period of twenty years, covering hundreds of thousands of shards. Today, this work can be done more quickly and take into account the large amount of data collected in the several hundred excavation reports or archaeological diagnoses produced in France in particular.

Ceramics remain the most numerous manufactured element (artefact) (volumes can sometimes be counted in several hundred kilos per archaeological excavation) but also the one that allows a multiple approach, providing major information for the understanding of an archaeological site over time. Ceramology also allows a change of scale because, if it can reveal the place of imports, of influences, on a settlement site, it can also model trade flows of different calibres: long-distance land trade, but also supplies that we would now call "short circuit" of small local workshops belonging to landowners, who come to distribute the fruit of their labour in cities of different sizes. By following the evolution of production over time, the ceramist can also understand how a form spreads from its centre of production to the various centres of consumption.

The ceramologist will also be able to observe the impact of the "Romanisation" of food customs and habits (for the Roman period, of course) with the arrival of certain forms intended for uses hitherto unknown in northern Gaul (for example, mortars). It can also understand the cultural influences, particularly in the "buffer" zones located on the borders of the cities, which sometimes allow one influence to be felt more than another.

Another problem addressed by the study of ceramics is the identification of the civilian or military character of the furniture. Since the excavation of major military sites closely or distantly associated with Julius Caesar's "Gallic War" (Actiparc-Saint-Laurent-Blangy, La Chaussée-Tirancourt, Amiens "Square Jules Bocquet", Arras "Baudrimont", Rouvignies "ZAC du plateau d'Hérin"), it was possible to identify a specific military pack that had shapes that were not to be found in the catalogue of civilian tableware (this is not a general rule, as many imported shapes used by the military would remain). It is therefore possible, by reading the discarded tableware, to prove the military character, total or partial, of an archaeological site (Chaidron, Clotuche & Willems, 2017).

The list of problems is long and can be further extended by taking into account funerary furniture or, for example, workshop crockery (comparing the crockery produced and that used).

If the list of problems is long, the list of pasta groups is even longer. The methodology of the reasoned study of ceramic pastes, which began after the Second World War in Great Britain (Hawkes, Hull, 1947) and again in the 1980s in Great Britain (Rigby, Freestone, 1986), was then widely disseminated in France, particularly in the 1990s in the North of France (even though the first elements had been put in place in the 1980s). The detailed analysis of pottery "pastes", which are commonly referred to under the British term "fabric" (fabric covers the type of clay used, the degreasing agent, the elements present naturally, the firing method and surface treatment/decoration), has made it possible to establish coherent zones of diffusion and to define production areas even if the workshops have not been discovered (which resulted in a summary publication. Clotuche, Chaidron, Comont, Dubois & Willems, 2010).

To do this, chemical and petrographic analyses had to be carried out to define groups as observed by macroscopic analysis. Shards from workshops were thus analysed and compared with shards found in consumption centres.

The macroscopic analysis protocol of the fabrics was thus validated and allowed the ceramologists to find in the studied sets, the fragments corresponding to the workshops thus defined.

This work is fastidious and has been based on published quality references, and we would like to mention in particular the work of our colleagues from the Museum of London Archaeology Service (Tomber, Dore, 1998). Tedious because it is necessary to use the microscope (or stereomicroscope) to identify certain productions whereas others, on the other hand, are easily identifiable by the ceramologist as soon as he has the necessary experience. Experience is a major factor in the identification of provenance, and this is one of the major points of the AI contribution.

Moreover, it is very regular for the ceramologist to come across fragments that cannot be attributed to workshops characterised by chemical analysis. This results in an army of undetermined fragments. It is not feasible to send all the undetermined sherds from all the excavations for chemical analysis, which, moreover, will give nothing as long as the clays that were used are not in the chemical or petrographic reference base.

To try to answer this problem, in 2021, the company Arteka, in collaboration with the company Arkéocéra (a ceramics research company), launched an image recognition analysis programme with a machine learning algorithm (Deep Learning). The first step was to create an initial database of certain fabrics from the North of France that were defined by chemical analyses (workshops in Arras and Beuvraignes, for example).

The first results are very encouraging and have confirmed that the use of an artificial intelligence algorithm would make it possible to identify more precisely unidentified productions by attributing them (by probability) to the main groups of workshops (See Figure 8).

Without being able to give a workshop name to the hitherto unknown pastes, the algorithm set up by Arteka, will make it possible to propose identification leads, to place the shards in a production zone by probability with the reference zones, to classify them.

A study phase use is currently under consideration after initial tests have proven positive. Tests are scheduled for live analysis on a microscope with Arteka's AI analysis technology (patent pending).

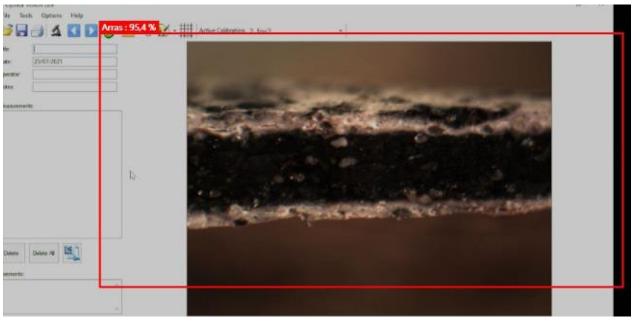

Fig. 8: AI identification of a ceramic sherd (cross-sectional view) from the Gallo-Roman potters' workshops of Arras (France) (ARTEKA ©)

This type of scientific approach is gaining momentum and it is worth mentioning the European Archaïde project, which is a leading project in the use of AI and archaeology.

Following on from the Archaïde project, the University of Leicester has launched a programme comparable to Archaïde and just as fundamental. It aims at "automatic recording and machine learning for the collection of Roman ceramics and investigating food and consumption practices".

Finally, the University of Louvain (S. Willems, Centre de Recherches en Archéologie Nationale (CRAN), Université Catholique de Louvain-La-Neuve), the University of Vienna (B. Borgers, Department of Classical Archaeology, University of Vienna) and the company Arteka (C. Chaidron - Laboratoire Trame-Université de Picardie Jules Verne) are building on the initial work of Arteka to also launch a European research project (presentation at the 28th International Congress European Association of Archaeologists (EAA) with a paper entitled : "The use of Deep Learning algorithms for the study of Roman pottery fabrics (FabricAI)"). The aim is to establish a database of the main ceramic productions supported by chemical or petrographic analyses and then use artificial intelligence. The algorithm will aim to identify fragments from multiple excavations in order to characterise production areas, draw up precise distribution maps and refine the chronologies in use in the Roman province of "Belgium" (Northern France, Belgium and the Netherlands). The project is based on Arteka's autonomous live AI analysis solution (patent pending).

Ceramologists identify fragments by precise criteria: firing modes (e.g. reducing or B-mode ceramics/Grey Wares, oxidising or A-mode ceramics/White Wares, Terra Sigillata, stoneware), surface treatment (slip, glaze), paste or clay (Northern Gaul, Central Gaul, Italic, Eastern Gaul, Britain or even by workshops) as well as shape or also called "typology". All these criteria are very important pieces of information that the ceramist must learn. Experience will allow to identify a vase with a very small fragment but this experience is long to acquire. Similarly, the bibliography is immense and one cannot imagine an archaeologist being able to compile hundreds or even thousands of articles published since the middle of the 20th century. This is another opportunity for AI to free the researcher from certain tasks so that he can concentrate on the analytical phases. For this reason, initial tests have been carried out to identify ceramic fragments using a supervised learning artificial intelligence algorithm (See Figure 9).

Fig. 9: Detection of several categories (White Wares, Terra Sigillata and Grey Wares. Grey Wares are indicated by CR with 94% relevance)

Archaeology is a data and image science. AI, which is still in its infancy in this field, will allow important advances that were not possible before, or that would have required too much time for archaeologists.

5. Conclusions

Archaeology is a science that generates data, data collected before the excavation (satellite image research, archaeological diagnosis), during the excavation itself and also during the study phases, once the excavation is complete. These quantities of data are significant. Just look at the number of excavation reports submitted to the authorities each year in France (more than 200) and the number of scientific articles published each year (almost 200 French publications per year between 2011 and 2016; Rapport de synthèse et prospective de l'archéologie française, 2019).

Scientific publications distort the reading of the masses of information to be processed because their aim is to present the results of a research project and therefore, de facto, a synthesis of the data and the researcher(s)' thoughts.

Excavation reports, considered as 'grey literature', do not make the economy of data since 'raw' information is generally integrated among which the thousands, even hundreds of thousands of artefacts collected during the excavation.

This is where artificial intelligence comes into its own when faced with masses of data that archaeologists do not have the time to process. Artificial intelligence comes as a tool that will accelerate certain tasks and free up the researcher's time to work on the substance, where the added value lies.

AI projects are likely to develop in the archaeological and cultural field and not only for scientific research purposes. At the end of 2020, the German Fraunhofer-Gesellschaft developed a mobile application to identify stolen cultural property.

Finally, cross-spectral imaging comes into play at another stage of scientific thinking. While it can help to locate remains, it will above all enable archaeologists to obtain information on large areas where satellite images will be confronted with their resolution (generally 50cm/pixel). The advantage of the drone is, in addition to better resolution (which will be challenged by the development of aerial photography projects such as the French Géoportail platform with its 5cm resolution photos), the possibility of multiplying spectral bands very easily, which will always be easier than changing a spectral band on a satellite in orbit, but also its ease of deployment to go quickly to an area and acquire data in only a few hours.

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