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Automated methods for image detection of cultural heritage: Overviews and perspectives

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Abstract

Remote sensing data covering large geographical areas can be easily accessed and are being acquired with greater frequency. The massive volume of data requires an automated image analysis system. By taking advantage of the increasing availability of data using computer vision, we can design specific systems to automate data analysis and detection of archaeological objects. In the past decade, there has been a rise in the use of automated methods to assist in the identification of archaeological sites in remote sensing imagery. These applications offer an important contribution to non-intrusive archaeological exploration, helping to reduce the traditional human workload and time by signalling areas with a higher probability of presenting archaeological sites for exploration. This survey describes the state of the art of existing automated image analysis methods in archaeology and highlights the improvements thus achieved in the detection of archaeological monuments and areas of interest in landscape-scale satellite and aerial imagery. It also presents a discussion of the benefits and limitations of automatic detection of archaeological structures, proposing new approaches and possibilities.

KEYWORDS
archaeological monuments, automated detection, computer vision, image analysis, remote sensing

1 | INTRODUCTION

The many satellites orbiting Earth obtain huge volumes of images from its surface. As a result, a massive amount of data is available for analysis, making it necessary to optimize the manual methods generally used by archaeologists (Câmara & Batista, 2017; Parcak, 2009; Somrak et al., 2020). Moreover, the increase in intensive soil usage results in constant changes to the landscape due to modern land-use requirements, placing greater pressure on cultural heritage. In order to resolve this problem, automated approaches have been applied to detect monuments on a regional/local scale within the field of archaeology (Cerrillo-Cuenca, 2017; Davis & Douglas, 2021; Soroush et al., 2020; Trier et al., 2009). Even though many monuments have been identified, many may still remain undiscovered. The latter are liable to disappear or be destroyed, either by time or directly by human action. To speed up archaeological discovery and benefit from the existing imagery, automatic classification systems are being developed as tools to discover new archaeological monuments and protect them from the risk of being destroyed (Cheng & Han, 2016; Kvamme, 2016; Luo et al., 2014; Opitz & Herrmann, 2018).

Automatic feature extraction (FE) for the detection of archaeological monuments from remote sensing images (RSI) started over 30 years ago (Lemmens et al., 1993). After this period, work in this area appears to have been suspended. However, with the increase in computational capabilities over the past decade, together with improvements to the quality of aerial and satellite images, the automation of feature detection in remote sensing images has become more accurate and different methods have been proposed for the detection of archaeological objects (Davis, 2021; Menze et al., 2006).

Our main goal is to present the current state of the art for applications that use automatic image detection, focusing on approaches for landscape-scale aerial/space-borne remote sensing exploration of archaeological sites, while also highlighting the need to develop specific methods for the identification of archaeological structures, given the particular features of the imagery or the specific nature of the monuments to be identified.

The remainder of this text is organized as follows. Section 2 provides the necessary background to automatic methods for detecting monuments and areas of interest from landscape-scale satellite and aerial imagery, while Section 3 describes the most common automatic detection data-based approaches used to identify monuments and areas of interest in images. The knowledge-based approach is presented in Section 4, followed by a discussion of the current challenges in Section 5, proposing promising line of research for advancing the field. Finally, the conclusions are presented in Section 6.

2 | AUTOMATIC RECOGNITION OF ARCHAEOLOGICAL SITES IN IMAGERY

Automatic methods applied to architectural and microtopographic alterations covering large areas of land are an effective method for visualizing known sites and surveying landscapes for previously unrecorded sites (Freeland et al., 2016). The main goals for this automation are (i) to reduce manual work; (ii) to standardize the methods of analysis by creating replicable workflows and (iii) to increase the probability of successful detection of archaeological remains (Davis, Andriankaja, et al., 2020). Computer vision approaches and algorithms for pattern recognition in this area have been used to convert the image data into tangible information, extract knowledge from it, and make digital prospecting as effective as possible.

Computer vision is concerned with developing techniques that enable the computer to analyse and evaluate visual data (e.g., image and video) using different techniques such as image pattern recognition, which deals with the identification and classification of objects in images. Automatic detection is a technique which classifies an object based on initial knowledge or statistical information from its pattern, or both (Bishop, 2006). According to de Boer (2005), pattern recognition is a set of techniques that makes use of 'feature extraction, discriminant analysis, principal component analysis, cluster analysis, neural networks and image processing to search for data with a set of predefined characteristics' (de Boer, 2005. p. 245). These techniques are applied using various approaches and methodologies to classify objects from images, as shown in Figure 1.

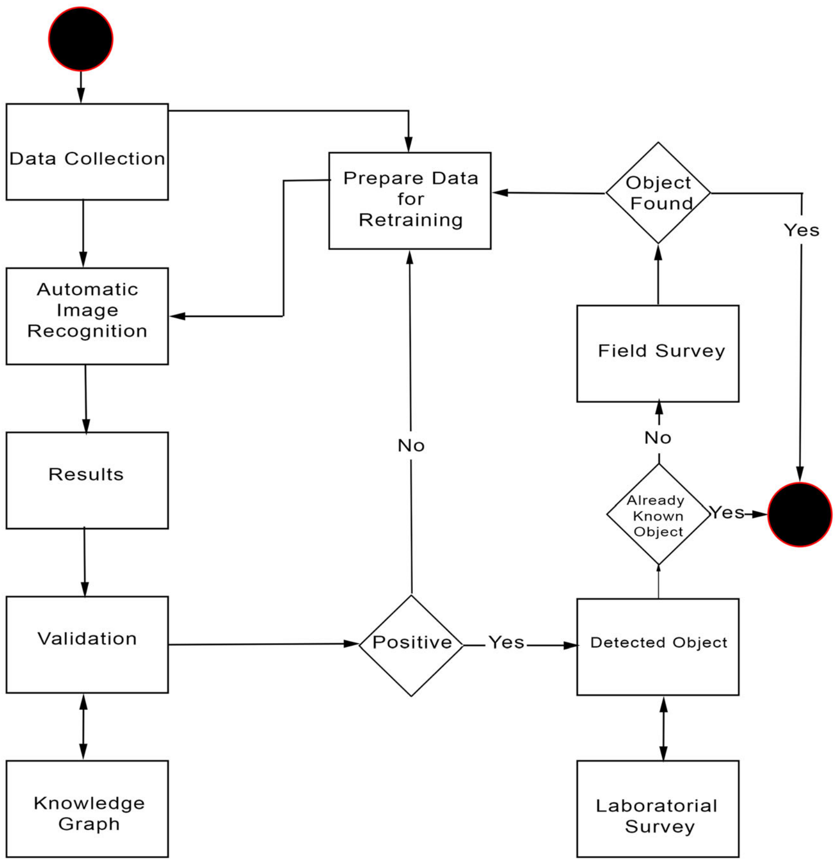

FIGURE 1 Steps often used for supervised automatic analysis of remote sensing data for CH detection [Colour figure can be viewed at wileyonlinelibrary.com]

Automatic imagery detection is a data-based method that is highly dependent on data, and the trend towards automation results from the availability of more complex and high-quality data (Freeland et al., 2016). Data collection involves the extraction and storage of data from various data catalogues held by agencies and different regional initiatives involved in Earth observation (such as the European Space Agency [ESA],[1] Committee on Earth Observation Satellites [CEOS],[2] National Aeronautics and Space Administration [NASA][3] and United States Geological Survey [USGS][4]). These organizations provide Earth observation imagery obtained from different sources and sensors (Arvor et al., 2013).

When using Earth observation imagery, the first goal is to extract relevant information from the image and thus gain knowledge of its geographical area (Lang et al., 2019). Recognizing and classifying familiar or unfamiliar patterns quickly and accurately is one of the goals in pattern recognition. Different algorithms can be used to achieve these goals, taking segmentation, feature detection and classification as the main keywords. Surveys using aerial and spatial data provide more extensive ground coverage than pedestrian survey methods can provide. Automatic classification combined with visual/manual inspection allows for the use of domain knowledge, provided by a specialist, and the detection of additional information, thus providing a sound basis for subsequent laboratory and field surveys (Trier et al., 2015; Trier & Pilø, 2012). These inspections consist of different intrusive (e.g., ground survey) and non-intrusive (e.g., remote sensing techniques such as image analysis) prospection approaches to the detection and study of archaeological monuments on the ground (Drewett, 2011).

The presence of already known archaeological objects is confirmed using prior field surveys. However, in order to validate an unknown object recognized by an automatized approach, a posterior confirmation by a domain specialist is necessary (Câmara & Batista, 2017; Davis, 2019; Rowlands & Sarris, 2007). Thus, subsequent validation by means of an expert laboratory analysis significantly reduces the number of false positives, that is, images that the automated system incorrectly classifies as containing relevant objects. This can either be validated by a test stage (see Figure 3) or later contradicted by fieldwork—since field surveys reveal and validate the detection made by automated procedures. When the characteristics that describe the objects are known, they can be used to label the data. At this point, two different approaches may be taken: (a) This newly acquired annotation is fed back into the system and the model for incorporating this knowledge is retrained—which is the most common machine learning (ML) approach (Figure 1)—or (b) the model is kept to be used without changes.

This description helps to demonstrate that automatic classification methods are a good tool for detecting archaeological monuments. Automation assists in filtering out the massive amount of data, limiting the images to those that will later require human analysis, and provides a good alternative to traditional fieldwork prospection by supporting the detection of environments with a higher chance of providing archaeological sites and facilitating the identification and management of the architectural heritage (Bowen et al., 2017; Câmara & Batista, 2017; Cheng & Han, 2016). We believe it is important to emphasize that automation should be regarded as an aid rather than a substitute for traditional visual inspection, serving as a part of the research process that is integrated into a broader methodology. The following section highlights the most common approaches used for the automatic detection of monuments and areas of interest in landscape-scale satellite and aerial imagery.

3 | AUTOMATIC CLASSIFICATION FOR MONUMENT DETECTION

In image classification, the input data are either an image interpreted as a numerical grid of pixel values or a set of features derived from the image, which aim to predict the correct class of the input image. In the case of archaeological applications, according to Sevara et al. (2016), two methodologies are traditionally used for image analysis: pixel-based image classification and object-based analysis. However, the latter uses the image data set and integrates the image content into the classification procedure (Sevara et al., 2016). Neither method takes precedence over the other, and both have produced successful results. More recently, there has been growing interest in the use of Convolutional Neural Networks (CNN) for object detection (Maggiori et al., 2016; Verschoof-van der Vaart & Landauer, 2021). This approach is known to learn contextual features on different scales. The different approaches make use of image segmentation, feature extraction and subsequent image classification, which is achieved by using different variables such as shape, the texture of existing vegetation, the information contained within the pixels' attributes, and region, among many others (Bowen et al., 2017; Cerrillo-Cuenca, 2017; Davis & Douglas, 2021; De Laet et al., 2007; Guyot et al., 2018; Kalayci et al., 2019; Luo et al., 2014; Trier et al., 2009).

Pixel-based classification techniques rely on establishing a relationship between each pixel, or group of pixels, and a specific target class and on the separability of the classes. To establish this relationship, pixels with similar attribute values form an arrangement describing a relevant feature for classification (Maggiori et al., 2016; Sevara et al., 2016). Pixel features may be derived from different original input data, such as aerial/space-born imagery, or geospatial features generated as digital terrain models (Doneus, 2013; Hesse, 2010; Menze et al., 2006). On the other hand, object-based classification starts with image segmentation - a process that aggregates the pixels into images of objects, whereas traditional image classification methods classify individual pixels. Unlike pixel-based methods, object-based image analysis (OBIA) methods have at least four new components for image analysis in comparison to pixel-based classification - the segmentation procedure, nearest neighbour classifier, incorporation of expert knowledge, and feature space optimization (Platt & Rapoza, 2008). In this method the first OBIA take other components into account for the image analysis, such as shape, texture and morphology (Davis, Andriankaja, et al., 2020), functioning as a '… link between the pixel world and the vector world …' (Arvor et al., 2013).

Object-based approaches are a valuable method for detecting cultural heritage in remote sensing imagery. Since the beginning of the 21st century, new methods for extracting information from images have been implemented (Davis, 2019; De Laet et al., 2007; Guyot et al., 2018; Lambers et al., 2019). In this context, new developments in computer vision help tackle issues arising with object-based image analyses and improve imagery recognition methods. Object-based analysis approaches work by starting with the analysis of the image in terms of the object(s) to be found for subsequent image classification. OBIA techniques are applied to split an image into basic objects that describe the features of the target, beginning with image segmentation techniques, followed by the object classification step that runs the segmented objects through a series of decision rules based on the characteristics of the target (Freeland et al., 2016; Sevara et al., 2016).

Finally, CNN approaches are artificial neural network architectures capable of modelling complex and highly nonlinear functions and extracting the relevant features of the image. These networks use multiple specialized layers between the input (data) and output (results) layers (Maggiori et al., 2016) that collectively encompass (i) feature extraction and (ii) classification (Lambers et al., 2019). In fact, in addition to the input and output layers, a CNN is comprised of at least three sequential components: a convolutional layer, responsible for analysing the inputs and extracting (learning) features from images, thus eliminating the need for manual feature extraction and turning images into feature maps; a pooling layer, capable of summarizing the information obtained from the convolutional layer and reducing the dimensions of the feature maps, thus enabling the objects to be detected independently of their location within the image; a fully connected layer that makes use of the latter summarizations as inputs to classify the image, based on the correlation between the resulting feature maps and the class labels (Caspari & Crespo, 2019; Lambers et al., 2019).

The ongoing technological advances both in remote sensors, allowing for the capture of very-high-resolution data, and in computer vision, make automatic monument detection and classification a promising area of research. In order to automate detection of archaeological objects (such as barrows, burial mounds, enclosures, settlements, tells and qanats, among others) using RSI, researchers have developed and applied methods using different approaches (de Laet et al., 2007; Lasaponara et al., 2016; Lasaponara & Masini, 2011; Trier & Pilø, 2012; Zingman et al., 2016). According to Cheng and Han (2016), approaches for object detection in optical remote sensing images can be classified into five main categories:

1. template matching-based object detection,
2. knowledge-based object detection,
3. OBIA-based object detection,
4. ML-based object detection,
5. Deep Learning (DL)-based object detection.

Detection based on template matching, a high-level computer vision technology, is flexible, relatively straightforward to use, and was one of the most popular object detection methods. Its success in archaeology stems from the fact that it is common for archaeological monuments to display geometric shapes (such as circles and rectangles), while these shapes are rare in natural landscapes (Cheng & Han, 2016; Lambers et al., 2019). This technique essentially generates an 'ideal' template representing the object in question (either handcrafted or learned from the available data), which is then searched for throughout the image, using rotations or translations of the generated templates (Cheng & Han, 2016; De Boer, 2005; Trier et al., 2009).

Due to the use of spatial data presenting geographical components, applications for the detection of objects based on Geographic Object-Based Image Analysis (GEOBIA) have also been widely used by archaeologists in the last 15 years and are an integral part of object-based classification approaches. Used to describe data that represents features or objects on the Earth's surface (whether human-made or natural), this approach has been used, with different objectives, to classify land-use and land cover or to detect archaeological features, and therefore represents the majority of applications found in the field of archaeology (Davis, 2019; Sevara et al., 2016). GEOBIA encompasses techniques that enable an image to be split into meaningful and discrete segments of non-overlapping units based on a set of specific criteria (e.g., shape and scale), providing representations in which, ideally, each split segment would correspond to real-world objects. The segmentation parameters are obtained either through a time-consuming trial-and-error process (Freeland et al., 2016) or by using point-based, edge-based, region-based or combined segmentation techniques (Sevara et al., 2016).

On the other hand, some studies have come to formally regard object detection as a classification problem, opting to use machine learning techniques for object detection, since these methods can be used to aid analysis and data management (Cheng & Han, 2016). Recently, with the advent of deep learning (a branch of machine learning), more accurate results are being obtained. However, the focus of the analysis remains the recognition of simple types of structures that are normally large and distinctive on the ground (Davis, 2021).

Table 1 presents an overview of the different methodologies and types of image data used in the detection of archaeological monuments in landscape-scale satellite and aerial imagery.

3.1 | Feature extraction

The different approaches to object detection share general similarities in their respective processes, given that they must first perform diverse feature extraction and feature fusion techniques at various levels, followed by the creation and training of classification models to detect objects of interest. Depending on which type of process the object detection is based on, the degree of complexity varies. This section will expand on each of the five, previously described, main classes of object detection methods for RSI.

In the first phase, as shown on the left of Figure 2, original input data is typically preprocessed and prepared so that the relevant features are extracted and later used for training/teaching a model that is able to recognize objects of interest (Bishop, 2006). Preprocessing

TABLE 1 RSI data in conjunction with ML methods for identification of archaeological monuments

Reference	Country	Data	Methodology	Goal
de Boer (2005)	Netherlands	ALS	Template matching	Identify burial mounds
Menze et al. (2006)	Syria, Turkey and Iraq	SRTM	Morphometrical variables and RF algorithms (ML)	Identify tells
de Laet et al. (2007)	Turkey	VHR fused MS and PAN	ED + KNN	Identify archaeological features
Trier et al. (2009)	Norway	PAN	Template matching	Identify burial mounds
Trier and Pilø (2012)	Norway	ALS	Template matching	Identify pit structures
Chen et al. (2013)	USA	MA	Statistical classifiers PCA/LDA	Identify archaeological sites
Luo et al. (2014)	China	Google earth	Edge detection	Identify tops of qanat shafts
Lasaponara et al. (2014)	Peru	VHR satellite images	Autocorrelation statistics and K means (ML)	Extract looting patterns
Trier et al. (2015)	Norway	ALS	Template matching	Identify mound structures
Zingman et al. (2016)	Switzerland	PAN	CNN classifier (DL + ontologies) and rectangle detector	Identify rectangular enclosures
Lasaponara et al. (2016)	Turkey	PAN and MS	Unsupervised classification ISODATA (GEOBIA and ML)	Identify and map features linked to buried archaeological remains
Freeland et al. (2016)	Tonga	ALS	Inverted mound algorithm (GEOBIA)	Identify and map settlement patterns
Sevara et al. (2016)	Sweden and Austria	ALS	Minimum distance classification and homogeneity classification	Burial mounds
Cerrillo-Cuenca (2017)	Spain	ALS	(Morphometrical) topographic position index and Hough circle function (GEOBIA)	Identify prehistoric barrows
Trier et al. (2016)	Norway	ALS	CNN (DL) and SVM classifier	Identify charcoal burning platforms
Guyot et al. (2018)	France	ALS	RF classifier (ML)	Identify burial mounds
Lambers et al. (2019)	Netherlands	ALS	Citizen science and R-CNN classifier (DL)	Identify multi-class archaeological objects
Trier et al. (2019)	Scotland	ALS	Pre-trained (DL)	Identify different archaeological objects
Davis, Sanger, and Lipo (2019)	USA	ALS	GEOBIA + template matching	Identify mounds and shell-rings
Abate et al. (2020)	Italy	MS	TCT + PCA matching	Neolithic settlements
Davis, Andriankaja, et al. (2020)	Madagascar	MS	SVM + OBIA	Predict cultural deposit location
Davis, Buffa, and Wrobleski (2020)	USA	ALS	Inverted mound algorithm (GEOBIA)	Predict cultural deposit location
Soroush et al. (2020)	Iraq	Historic satellite imagery	CNN	Identify qanats
Verschoof-van der Vaart and Landauer (2021)	Netherlands	ALS	R-CNN	Detect archaeological object classes

Abbreviations: ALS, airborne laser scanner; ED, edge detection; HCAL, hierarchical categorization and localization; KNN, k-nearest neighbours; LIDAR, Light Detection And Ranging; LDA, linear discriminant analysis; MS, multispectral; ML, machine learning; PAN, panchromatic; PCA, principal components analysis; RF, random forest; TCT, tasselled cap transformation; VHR, very-high-resolution.

means performing tasks such as cleaning the original image or summarizing the original data through dimensional reduction. Following this, feature extraction is usually used to transform the original input, i.e. the raw image pixels, into a new and more representative dimensional data space for features (Cheng & Han, 2016; Opitz & Herrmann, 2018). For images, feature extraction is used to obtain a representation of an object in a lower-dimensional space (Chen et al., 2013), and thus, high-dimensional features are transformed into more compact and distinctive ones, reducing the dimensions of the feature space but still allowing for the detection of objects (Cheng & Han, 2016). Next, an additional step known as feature fusion can also be applied. Feature fusion is part of a group of data fusion techniques responsible for enhancing image analysis results by incorporating data from various sources to help extract information. In remote sensing, these techniques could be applied on three different processing levels: at the pixel level, where raw data from multiple sensors is merged into common resolution data (e.g., pan-sharpening) in an effort to improve spatial and spectral resolution alongside structural and textural details; at the feature level, where similar segmented objects in different data sources are aligned and have their spectral, spatial and textural features extracted then fused to aid in statistical or neural network assessments; at the decision level, which merges extracted information, such as the selection of a relevant feature from a group of extracted features (Rajbhandari et al., 2019).

In the case of RSI, learning is achieved by using a set of data containing examples of known (labelled) data; that is, images are labelled as containing the objects of interest (positive matches) or as not containing these objects (negative matches), in order to train a classifying model to detect the object in question (see Figure 2, on the left). After the results are validated via a controlled test using already known examples whose labels have been hidden in order determine the validity of the model's classifications, and if the performance is satisfactory, the trained model is used to predict the existence of new relevant areas of interest that should contain unknown monuments (Cheng & Han, 2016; Guyot et al., 2018). This last phase is depicted in Figure 2, on the right. Whenever images are identified that relate to a new discovery or confirm that it does not exist or, in other words, whenever new images are labelled, they can be added to the training set used to teach a new model and update the previous one.

Figure 3 expands the left side of Figure 2, highlighting the main stages in the creation of a recognition system based on ML methods: feature extraction, feature fusion, dimensionality reduction, classifier training and evaluation via a testing phase, in which the model is evaluated using data that has not been fed into the training.

Deep learning-based object detection is a particular area within ML that refers to special classes of artificial neural network architectures employing multiple specialized layers, which explain the deepness (Maggiori et al., 2016). According to Lambers et al. (2019), the most widely used architecture is the aforementioned CNN, consisting of multiple layers that encompass feature extraction, in which features are learned using several sequencing layers of increasing complexity to model the image's features into a feature map that preserves the spatial relationship between pixels, a pooling stage to enhance generalization and avoid overfitting, and a final classification. This approach has the advantage of learning to generalize and draw features automatically from the data without having to rely on a previously defined hand-crafted set of rules for feature extraction. These architectures tend to present excellent levels of accuracy for image classification, consistently outperforming humans. However, a huge (massive) number of labelled examples are needed as input for the training phase.

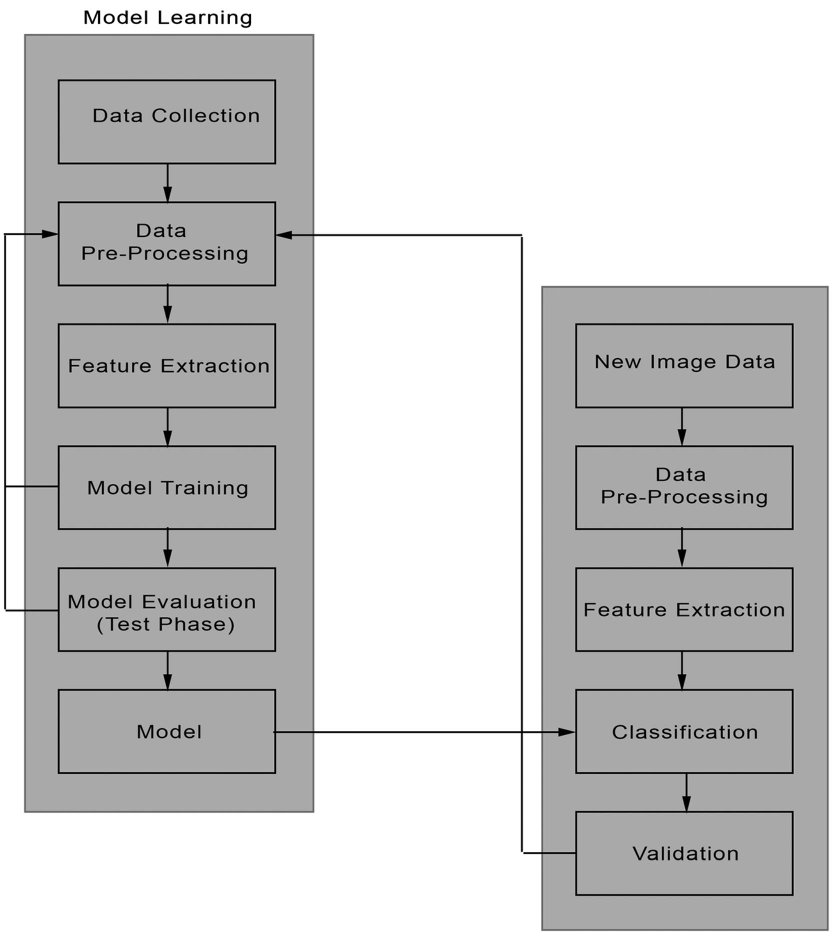

FIGURE 2 Workflow for supervised model learning for specific image data (on the left) and its interactive usage: After validation/field exploration, the result may be used to retrain the model (on the right), thus incorporating new knowledge.

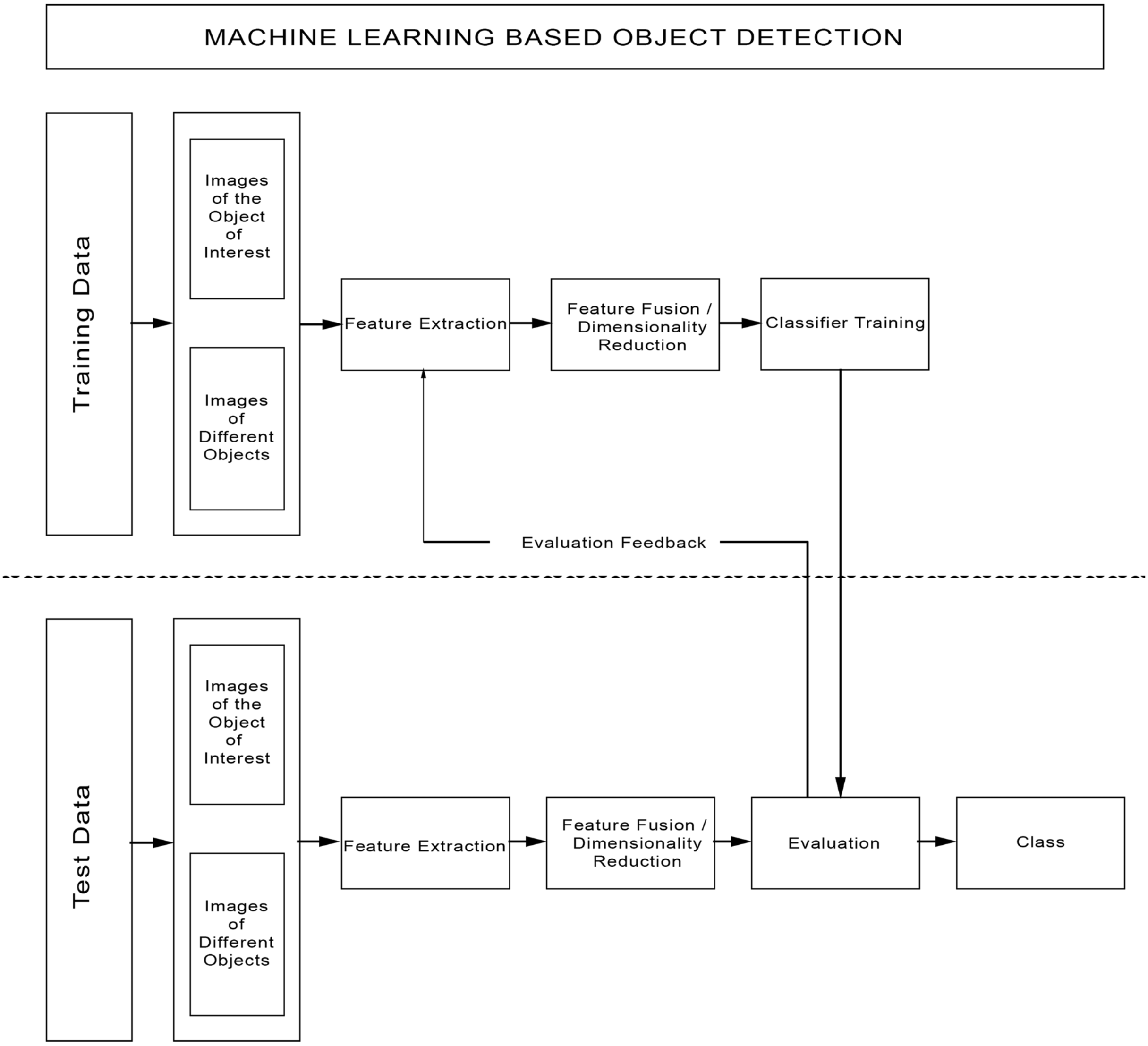

FIGURE 3 Training and test data are two sets of examples required to build an automatic classification method to detect objects in images. They are used in the two steps that must apply the same techniques for feature extraction: feature fusion and data classification. The training phase develops the learning or building of the model, and the test phase, which should use 'new observations', evaluates the model's capacity for generalization (Bishop, 2006).

The challenge for using deep learning-based resources involves the use of very large datasets (labelled archaeological objects) to achieve human-like performance in detecting all variables present in archaeological structures and landscapes. In order to benefit from these approaches, strategies such as transfer learning and data augmentation are mainly used, which reduce the required number of confirmed instances, thereby extending their use to many fields that had previously been restricted due to their smaller datasets, as it is the case with archaeology (Lambers et al., 2019; Soroush et al., 2020).

3.2 | Automatic classifiers

As previously stated, the feature extraction phase is commonly followed by the creation and training of an automatic classifier capable of identifying objects of interest. These classifiers are usually variations on classic machine learning model classifiers. This section examines how each of the five object detection approaches achieve automatic classification. Overall, it can be considered that object detection based on template matching, GEOBIA, and ML create their classifiers through variations on the so-called supervised/unsupervised ML models or DL detectors created from existing CNN architectures.

In general, following the extraction and creation of an 'ideal' template, object detection based on template matching searches through an image using rotations or translations of the generated templates and computes a similarity or correlation measurement that indicates the probable presence of the template (Cheng & Han, 2016; de Boer, 2005; Trier et al., 2009). However, this method has limited application, since the detection of complex data can be time-consuming and tends to generate a high rate of false classifications, both false positives—classifying an image in which the object is not present as a positive match—and false negatives—classifying an image in which the object is present as not matching. In the case of GEOBIA-based detection, following the segmentation process responsible for feature extraction, multi-class labelling is applied by proceeding with a series of decision rules based on the target object's characteristics (such as geometry, spectral values, neighbourhood relationships or semantic groupings) to assign classes to each of the segments (Freeland et al., 2016; Sevara et al., 2016).

Automatic classifiers generated through classic ML can be divided into two main categories, namely those using supervised or unsupervised methods. Regardless of the approach employed, the general process for producing the best possible supervised classifier is split between a training and a subsequent testing phase, as shown in Figure 3. The training phase attempts to build (train) the classifier that best identifies the object of interest in annotated images. This is achieved by applying algorithms that recognize relationships between features observed in the image and its predefined class. In order to determine whether the developed model is the best possible one for detecting the object of interest, a test must be performed by feeding the model annotated images that have never been used in the training phase, whose class is withheld. These images must be preprocessed in the same way, so that the features used in the training phase are available for the images in the test set. Since the images are now used without any information on their predefined class, the prediction results are compared with the corresponding annotated class, resulting in a quantification of the correct matches and incorrect predictions (Bishop, 2006), thus evaluating how the model would perform in a real case scenario. The classic methodological approach is to experiment with different processing, feature extraction and machine learning algorithms to determine the best possible model for the data. Once the best model is established, the classifier is tuned and is ready for application with real new data.

In supervised ML, relevant features are selected from the data before model training, using a set of labelled or annotated data. Supervised methods allow an expert to use his/her domain knowledge to fine-tune a learning algorithm over a predetermined feature space to train it how to recognize objects (Sevara et al., 2016). It should be noted that architectural heritage typically presents a high number of variables (e.g., shape, colour, texture, building materials and depth of archaeological remains) linked to soil surface characteristics (e.g., desert, forest, mountain and rural areas). This usually makes it difficult to extract features and select the image parameters (spectral channels, band combination, etc.) used to process and detect the subtle signals which typically characterize archaeological remains (Câmara, 2017; Lasaponara et al., 2016). On the other hand, unsupervised ML is applied to problems where there is a need to understand which patterns may automatically be discovered in a set of unlabelled input data. These methods can be applied to discover groups of similar objects within the data (Bishop, 2006), which is known as clustering. Unlike supervised classification approaches, unsupervised approaches do not require the a priori definition of classes, thus allowing for the discovery of unknown relations shared among groups of input data, and may require only a minimal amount of training data (Lasaponara et al., 2014).

Finally, on the subject of automatic classifiers developed using DL techniques, as previously stated, this approach avoids the manual extraction of features. The state-of-the-art CNN architectures can be separated into two groups, depending on the number of detections they execute: the single-stage detectors (e.g., You Look Only Once or Single Shot Multibox Detector) or the two-stage detectors (e.g., Faster Region-based CNN or Mask Region-based CNN) (Verschoof-van der Vaart & Landauer, 2021; Soviany & Lonescu, 2018). According to Soviany and Lonescu (2018), single-stage detectors detect objects in a single stage by learning the class probabilities and bounding-box coordinates of the object in question from the input image (Soviany & Lonescu, 2018). This allows models that make use of this type of CNN architecture to perform much faster than the two-stage detectors, at the cost of lower accuracy rates. In contrast, two-stage detector architectures perform two rounds of detections: the first to generate regions of interest in the input image through the application of Region Proposal Network and the second to learn the class probabilities and bounding-box coordinates of the regions of interest. Models implementing this type of architecture have the highest accuracy rates, at the cost of being slower than single-stage detectors. In aerial/satellite archaeological research, two-stage detectors are the primary choice, due to their capacity to detect multiple objects (regions) of interest within a larger image when compared to obtaining a single object from the input image. Moreover, their higher accuracy rates not only produce higher true positives, or correct identification matches but, even more importantly, a reasonably low number of false positives (Lambers et al., 2019; Soroush et al., 2020).

3.3 | Approaches and methodologies

This section will expand on the various types of approaches to object detection described above by outlining successfully implemented processes for object detection based on template matching, GEOBIA, ML, DL and knowledge-based methods, respectively.

Approaches using template matching for the automatic detection of archaeological features have been well-demonstrated in de Boer (2005); Davis, Lipo, and Sanger (2019); Trier et al. (2009); Trier and Pilø (2012); and Trier et al. (2015). Among these, de Boer (2005) succeeded in constructing a template resembling burial mounds using LIDAR images in the form of a sinusoidal template in cross-section, but circular if seen from above (de Boer, 2005). In addition, the Trier et al. (2009) use of MS and PAN images proved successful in creating a ring-shaped template, with various radii and different thicknesses, for the detection of ring marks (Trier et al., 2009). The same general approach can be found in Trier and Pilø (2012), where the authors succeeded in detecting pits in LIDAR images by creating ring-shaped templates with various radii (Trier & Pilø, 2012). Finally, Trier et al. (2015), using ALS images, managed to successfully develop a mound-shaped template for different radii (Trier et al., 2015). Currently, template matching is being used in object-based approaches, as we will describe, allowing for the use of statistical probabilities generated from features extracted from an image, such as shape, texture and pattern.

GEOBIA approaches have become increasingly popular since the beginning of the 21st century, with many applications and methods developed in this area (Lang et al., 2019; Magnini & Bettineschi, 2019). Emerging trends use object-based methods in multiple subfields (e.g. object-based feature extraction) in conjunction with statistical algorithms, and these are being applied with great success, achieving satisfactory detection results (de Laet et al., 2007; Guyot et al., 2018). These categories are not necessarily independent, since different methods can be used within the same project to obtain better results or to identify which method is better in each case (Cheng & Han, 2016; Davis, Andriankaja, et al., 2020; De Laet et al., 2007; Guyot et al., 2018; Lambers et al., 2019). An example can be seen in Cerrillo-Cuenca (2017), who used LIDAR data, GEOBIA methodology, morphometric and morphological classification methods to identify and extract, with a 46% success rate, terrain shapes to locate tomb structures dispersed throughout the Extremadura region in Spain (Cerrillo-Cuenca, 2017). LIDAR data has been gaining attention and producing increasingly accurate results when stochastic classifiers are used with different datasets (Lasaponara & Masini, 2011). Guyot et al. (2018) used LiDAR-derived digital terrain model data, ML, and a GEOBIA method for the identification of megalithic funerary structures in the Carnac, Quiberon and Gulf regions of Morbihan (France). This work combined multi-scalar terrain analysis methods with Random Forest algorithms for classification. The authors report having obtained 1% false positives, 98% true positives, plus the identification of a Neolithic tomb previously unknown in the Carnac region, thus validating the use of ML to identify and classify monument typologies (Guyot et al., 2018). Davis, Andriankaja, et al. (2020) used satellite imagery from Sentinel-2, SVM, and OBIA to predict the location of previously unrecorded cultural deposits and analyse previously recorded archaeological sites in Madagascar, obtaining a classification accuracy of 93.6% with SVM and 97.7% with OBIA in the chosen environmental land-type (Davis, Andriankaja, et al., 2020).

Regarding ML approaches within the field of remote sensing archaeology, visual features extracted from two-dimensional (2D) data are obtained by analysing spatial relationships such as shape, texture, composition patterns and electromagnetic behaviour. It is possible to analyse other variables such as topographic information in different ways when structures are present that alter the terrain by using three-dimensional (3D) data (Barceló & Barceló, 2009; Davis, 2019). Regardless of the data used, sophisticated mechanisms are required to analyse all of the complex archaeological features. In the light of this, researchers have been using different data (individually or combined), such as 2D and 3D imagery, to map and identify archaeological structures, as seen in Menze et al. (2006) in which the authors developed a semi-automated method to detect cells in the Near East/Mesopotamian region. This study used digital terrain model elevation SRTM, Landsat ETM imagery to assess the sites detected in the SRTM, morphometric variables (e.g. shape), and a Random Forest algorithm for classification. This was one of the first studies to use 3D topographic datasets to automatically detect archaeological features (Davis, 2019; Menze et al., 2006). Another example can be seen in Orengo et al. (2020), who performed a multitemporal analysis on synthetic-aperture radar data alongside multispectral images obtained from Sentinel-1 and Sentinel-2 satellites, respectively, to show the potential of machine learning-based classification that makes use of cloud-based computational processing for the remote detection and mapping of archaeological mounded settlements in arid environments (Orengo et al., 2020).

Other studies have instead used unsupervised ML capacity to group similar pixels in order to automatically create meaningful clusters from the input data and have proved their relationship to actual features in known monument locations, in addition to applying pattern recognition techniques to identify circular archaeological tops of qanats (Luo et al., 2014) and circular traces of illegal excavations in Peru (Lasaponara et al., 2014). This has also proved capable of detecting buried archaeological remains, even when the features are partially or completely unknown and characterized by a very small spectral separability from the background, by grouping more similar pixels, followed by the application of segmentation to the resultant groups to obtain those which are geometrically shaped (Lasaponara et al., 2016). By proving existing correlations between created clusters and anthropological and ecological features present in known sites, other studies have been able to detect new sites, as in Klehm et al. (2019), in which evidence was detected for previously unidentified Iron Age sites in Botswana (Klehm et al., 2019).

In the past decade, ML has been used to support archaeologists in the assessment and classification of areas of interest that may contain archaeological monuments, thus speeding up the classification process and increasing the success rate. This new approach differs from other methods as it does not require pre-acknowledgment of the target object under analysis and can learn which class is to be identified from the data input. In Chen et al. (2013), principal components analysis and the linear discriminant analysis algorithm were used to detect, in 8-band multispectral Worldview-2 data, areas likely to contain archaeological sites in Irwin, CA, USA (Chen et al., 2013). Machine Learning-based image recognition has been used to automatically detect archaeological monuments (Cerrillo-Cuenca, 2017; Trier et al., 2009; Trier et al., 2015), identify potential damage in archaeological sites (Bowen et al., 2017; Lasaponara et al., 2014), map archaeological features (Lasaponara et al., 2016), establish social analyses (organizations and settlements) (Cerrillo-Cuenca, 2017) and for predictive modelling of archaeological sites based on ecological proxies and anthropological knowledge (Klehm et al., 2019; Thabeng et al., 2019; Yaworsky et al., 2020).

ML methods can improve feature selection, generate implicit knowledge, extract rules faster than humans and improve the detection of features. Recently, DL has shown a greater potential to reduce false positive results, which have so far remained high in the automatic detection of archaeological monuments.

Conversely, DL approaches used to detect archaeological sites have been applied since 2016. In Zingman et al. (2016), different methodologies are used to detect ruins of livestock enclosures in alpine areas, using high-resolution RSI. Several feature vectors were generated for the study from pre-trained deep convolutional networks (e.g., GoogleNet, AlexNet and OverFeat) to compare and evaluate developed rectangularity-size features. Although linear classifiers trained from rectangularity-size features outperformed any other method in these images, the evaluation showed that using features obtained from pre-trained deep CNN architectures produces a detector that performs well. In the latter case, the generic features (obtained at some intermediate layer of the network) proved beneficial in detecting low contrasts and enabled the linear classifier to be retrained with examples of non-rectangular enclosure shapes to extend the detection of objects (Zingman et al., 2016).

Another good example can be found in Trier et al. (2016), using DL for semi-automatic mapping of charcoal kilns from ALS. A CNN was used to extract features from a DTM derived from the ALS in Norway. Ignoring its last layer, where features are mapped to classes, and instead directly using the features as input to train a linear SVM classifier, this model was able to detect 84.5% of the known kilns (Trier et al., 2016). Thus, the authors achieved better results in comparison to previous attempts that relied on the semi-automatic detection of ring-shaped remains of burial mounds based on the template matching approach. The latter only achieved a 64% success rate for detecting the known rings (Trier et al., 2009). Significantly, the former reduced the false classification results by almost half (Trier et al., 2016). Recently, Trier et al. (2021) used LIDAR and R-CNN to map cultural heritage (grave mounds, pitfall traps in deer hunting systems, and charcoal kilns) from Norway, detecting 75% of the predicted cultural heritage objects with only 24% false positives. However, when this same methodology was applied to a large landscape, the accuracy was drastically reduced (Trier et al., 2021).

A different case is presented by Verschoof-van der Vaart et al. (2020) in describing WODAN 2.0, a workflow using DL for the automatic detection of multiple archaeological objects such as barrows, Celtic fields and charcoal kilns. In order to reduce the false positive results caused by specific regions, a new approach was developed using Location-Based Ranking and Bagging, which led to an improved performance (varying between 17% and 35%). However, general automatic approaches still cannot match or exceed human performance (Verschoof-van der Vaart et al., 2020).

Recent studies using a pre-trained and adapted ResNet18 CNN architecture on an ImageNet database and ALS data to assess existing developments were developed on the island of Arran, Scotland (Trier et al., 2019). Different results were obtained for each class of monument analysed: 73% of the roundhouses were detected with just four false positives, whereas predictions of small cairns and shieling hut monuments presented a higher number of false positives. The known huts in this area are small, with a diameter of less than 3×5 m, while the data used for training the model involved sizes of 16×16m. Nevertheless, this study showed the potential for these methodologies in archaeology and highlighted that it is possible, albeit difficult, to detect small monuments (Trier et al., 2019).

The most recent uses of DL to detect archaeological sites in RSI involve applying CNN algorithms in combination with other methods, yielding highly accurate results (Lambers et al., 2019; Trier et al., 2016; Zingman et al., 2016). In particular, Lambers et al. (2019) demonstrated a method that combines a Faster R-CNN architecture and a two-tier citizen science project to survey archaeological objects in the Netherlands. This project detected new potential barrows and charcoal kilns in a largely forested area of circa 1,100 km^2, located in Veluwe in the Netherlands (Lambers et al., 2019).

To sum up, researchers use different data and different approaches to extract information from images, coupled with other methods such as citizen science, knowledge-based methods, and GEOBIA. Although RF and CNN algorithms have presented interesting results in recent years, these types of archaeological site classification approaches are still recent and only a few applications exist in large-scale fieldwork.

4 | KNOWLEDGE-BASED METHODS

While new technologies and methodologies have been developed and assist in understanding data, new information on different archaeological sites is still being discovered every day, and vast amounts of remote sensing images are being acquired and require proper classification, processing and interpretation. We are living in the so-called information age, in which knowledge about monuments, acquired over the centuries, but especially in the last two decades, is being accumulated and registered in different ways, resulting in a need for standardization and digitalization.

Humans cannot search massive databases and manipulate huge sets of rules, and the help provided by ontological data representation models in this process has therefore been gaining attention. In this sense, the format of the contextual data has become a major area of interest in aerial and satellite archaeology, since the information on monuments and their surrounding environment provides context for the images and can also enable both humans and machines to improve their understanding of each available image. Thus, one focus of the current research trend has been developing methods and routines to automatically extract relevant information from images, as discussed at the annual Conference on Computer Applications and Quantitative Methods in Archaeology (CAA) in 2016.

When working with spatial data, prior knowledge is needed in order to understand and extract the correct information from images, as well as to set the classification rules for this extraction. Experts need to convert their visual perception into a classification rule set. These definitions are symbolic and expressed on the basis of human perceptual knowledge. For data to be understood by a machine, symbolic knowledge must be converted into a numerical representation that maintains relations, which can be achieved through the use of ontologies (Arvor et al., 2019). Simultaneously, these standard features can be used to infer implicit knowledge through deductive and inductive inference, thus helping users to deal with complexity and uncertainty, two fundamental problems that make visual detection difficult.

Biological cognitive systems can easily exploit all scenarios and learn through experiences and examples, using this as a hybrid form of inference that allows them to discover different parameters. In contrast, computer vision solutions applied to data-based methods such as CNN use inductive inference, in which a priori knowledge is encoded by a static design (Lang et al., 2019). Knowledge-based techniques, on the other hand, provide the domain knowledge representation of the object and its surroundings given by a domain expert (Lambers et al., 2019; Trier et al., 2019) and the knowledge-based system makes use of all available knowledge to emulate the reasoning of an expert. Classification based on ontology is a knowledge-based approach and the innovation in using an ontology concerns how knowledge is represented and formalized (Arvor et al., 2019).

Knowledge-based detection of objects has featured in attempts to resolve the high number of false positives found in previous classification techniques due to problem complexity, that is, the large volume of knowledge relevant to the problem (e.g., previous experience with similar cases, precise knowledge of certain specific aspects of the objects to be detected). The detection of archaeological sites in one image requires domain knowledge of the object in question (key features) and its surroundings and requires the analysis of different parameters (Câmara, 2017; Câmara & Batista, 2017). For example, an expert interested in identifying vegetation and soil use in Portugal can gather information on this from different data sources, such as the Corine Land Cover (CLC), a contribution to the Land Cover Use System (COS) proposed by the Direção Geral do Território (DGT). The CLC consists of an inventory of land cover, presenting 44 classes that describe which areas are occupied by artificial surfaces, agricultural areas, forest and semi-natural areas, wetlands or water bodies. This data can be inserted into a knowledge-graph which contextualizes what is shown in the image and helps identify what exists in the region (e.g., in agricultural areas, it is possible to determine past and current soil use, permanent crops, types of crops, pastureland and different agricultural areas). In Câmara and Batista (2017), the CLC was used to identify patterns in the ground where dolmens can be found and determine whether the soil use interferes with their conservation (Câmara & Batista, 2017).

Symbolic knowledge of objects is often implicit in traditional remote sensing, as users generally implement the rules directly, based on trial-and-error tests and prior domain information, without formalizing them. Humans can describe the objects and their context verbally/semantically (Nuninger et al., 2020), although for the knowledge to be interoperable between humans and machines, it is necessary to formalize and develop explicit rules for it and convert perceptual/symbolic knowledge into numerical knowledge. The use of knowledge-based methods makes it possible to represent symbolic and numerical knowledge both from the real world and from the point of view of the image, so that it can be used to represent and develop the sharing of understandable information, while facilitating the analysis of the massive volume of RSI (Davis, Andriankaja, et al., 2020; Lang et al., 2019). Moreover, through the knowledge represented in an ontology, it is possible to infer facts that contextualize the information that is to be classified.

Ontologies are 'a means to formally model the structure of a system, i.e., the relevant entities and relations that emerge from its observation, which are useful to our purposes'. (p. 2) (Guarino et al., 2009). They are defined as 'explicit specifications of conceptualizations'. (p. 8) (Guarino et al., 2009) and are a commonly used and powerful way to represent knowledge. Ontologies are created to facilitate the sharing and reuse of information while increasing the shared understanding of knowledge of a domain between machine and man, enabling machines to process and collect resources intelligently, while simultaneously facilitating communication between the various devices in the network (Morais & Ambrósio, 2007). The World Wide Web Consortium has adopted several languages to represent ontologies, such as the Resource Description Framework, which provides a basic structure to describe any concept and its associations/attributes in triples (subject-predicate-object). The Web Ontology Language, OWL, defines how to model the knowledge semantically in Resource Description Framework (Liebig, n.d.; Harvey & Raskin, 2011; Stock et al., 2011). These are the international languages used to represent the most widely used ontologies in information systems, and there is now a series of software packages to support the development of different studies that use semantic models to work with spatial data (Garozzo et al., 2017; Nys et al., 2018; Rajbhandari et al., 2017).

The development of ontologies that support working with Earth observation data may require a collection of different upper and local ontologies for different purposes. Upper ontologies consist of general terms common to all domains and should be used to achieve greater semantic interoperability between different systems, providing a common starting point for formulating definitions. Several upper ontologies have been proposed, such as the General Multilingual Environmental Thesaurus and the Web for Earth and Environmental Terminology (Harvey & Raskin, 2011). In this context, researchers from different areas, such as archaeology, geology, geography and hydrology, who need access to various data sets that are common to their respective areas of specialization can use these ontologies in combination with their domain specificities.

Few academic and commercial projects for modelling and managing spatial–temporal data specifically target the field of archaeology, with certain exceptions, such as the Archaeological Prospection Information System (Doneus et al., 2019). However, there is no consistency in data modelling and, of course, no physical database model that is uniformly accepted or contains all the data in one place. Despite this, various national archives (e.g., the Portuguese DGPC-Portal do Arqueólogo and SIPA) and international archives (such as UNESCO and ICOMOS) present information on archaeological monuments that have already been mapped. Many of the knowledge-based systems for archaeology are compatible with CIDOC-CRM (Bekiari et al., 2021; Garozzo et al., 2017; Hyvönen et al., 2011; Koch et al., 2019; Nys et al., 2018; Ronzino, 2015), a formal ontology that defines the semantics and structures of documents used in different sources of cultural heritage data, which became an ISO Standard in 2006 (ISO 21127) (Bekiari et al., 2021).

5 | DISCUSSION

Automatic detection methods using RSI have been applied over the last five years with success (Bowen et al., 2017; Davis, 2019; Guyot et al., 2018; Sevara et al., 2016; Trier et al., 2016; Trier et al., 2019). However, this methodology has met with scepticism, occasionally justified by the fact that 'structures and landscapes present a significant number of variables' and 'the computer is incapable of perceiving subtleties related to cultural heritage' (Hanson, 2010; Parcak, 2009). This is due to the desire of some experts not to lose control over any part of the interpretation process (Traviglia et al., 2016), therefore expressing concerns over social and technological factors associated with the development of automated approaches in the image analysis process for detection of cultural heritage (Opitz & Herrmann, 2018).

Nevertheless, there are currently algorithms (mainly used for segmentation and classification) that are able to identify relevant variables in the images and accurately detect objects in the soil using various types of Earth observation data. Furthermore, different approaches, such as the combination of spectral indexes commonly used in satellite-based archaeology to capture the spectral signatures of soil and crop marks for the identification of buried structures (Abate et al., 2020), can contribute towards improving the classification results. These authors took advantage of the fact that some anthropogenic or natural buried structures such as ditches and walls create spatial and spectral anomalies which can be perceived from the way in which the objects and their background appear in the image. Among the different approaches for automated classification, ML-based experiments are increasingly on the rise and there is clearly a great emphasis on methodologies applying ML that have appeared in the last 15 years (Lasaponara et al., 2014; Lasaponara et al., 2016; Menze et al., 2006), and more recently on using deep learning architectures (Verschoof-van der Vaart & Landauer, 2021; Guyot et al., 2018; Kazimi et al., 2018; Lambers et al., 2019; Trier et al., 2016; Zingman et al., 2016). In fact, for certain objects, and given sufficient data, DL approaches can achieve or exceed 80% accuracy (Lambers et al., 2019; Trier et al., 2016). Davis (2020b) has quantified this rise in the explosion of worldwide research using machine learning with archaeological remote sensing data. While the use of machine intelligence in archaeology is widespread, there is a geographic imbalance in use between Northern and Southern studies since this technology mostly features in the literature for countries such as the United States or in Western Europe (Davis, 2020b).

However, despite the previous examples, most cases of object-based monumental architecture archaeological use study simple archaeological objects such as mounds, qanats and shell craters (Davis, 2021; Freeland et al., 2016). Since these types of object are generally more uniform in nature and contain elements that present similar behaviours, they can be defined with a limited set of descriptors and parameters (Magnini & Bettineschi, 2019). Moreover, different methods can be applied for the recognition of different objects. Considering the examples previously mentioned, bounding-box methods can be used for the detection of simple types of objects (e.g., those presenting a circular, standardized pattern). For adjacent, small, multiple and overlapping objects, methods such as Mask R-CNN may be more suitable for localization and classification (Soroush et al., 2020; Soviany & Lonescu, 2018; Trier et al., 2021; Verschoof-van der Vaart et al., 2020).

Given the current capabilities of the different automation methods that can be applied to improve recognition, one interesting application that merits consideration in future studies is the detection of small-scale monuments from larger scale cultural heritage proxies. The smaller size of some structures, such as circular tombs in rugged terrain, makes it difficult to map them in the field. Due to their size, spectral similarity in imagery (e.g., neighbouring pixels) and the tendency of these structures to erode and collapse over time, new methods are needed to detect such small objects that blend in with the surrounding environment (Schuetter et al., 2013). However, the use of ML for automatic detection in RSI has great potential to speed up the examination of large amounts of data and replicability of the image analysis.

Machine learning makes it possible to train a machine to extract features and detect different patterns, even with an enormous volume of high dimensional data, and these techniques can be combined with different approaches to build the best methodology for each project. Recent studies are achieving greater success by using different combined methods. GEOBIA, for example, which is designed to take local variations into consideration (complex topological and non-topological spatial relationships), has been used together with ML (Lasaponara et al., 2016) or template matching methods (Davis, 2019), with promising results. Furthermore, by employing multiple morphological parameters to detect archaeological sites, GEOBIA methods are also adequate for the detection of smaller monuments and for structures which present similarities, as in Cerrillo-Cuenca (2017) and Sevara et al. (2016).

Each RSI task using RSI employs a different methodology depending on the data type, the object, and the landscape (Lambers et al., 2019; Lang et al., 2019). An example can be found in the identification of archaeological sites that evade detection due to dense vegetation, agricultural soil, pasture and other natural elements. LIDAR data provides high levels of 3D spatial resolution to overcome this challenge, detecting both small and large topographic features, as in Cerrillo-Cuenca (2017) and Davis, Sanger, and Lipo (2019). It is also possible to identify subtle relief features which are difficult to detect from field surveys (Doneus, 2013; Hesse, 2010; Opitz & Herrmann, 2018). Multispectral data enables the creation of multispectral images by building up image layers, each representing a single spectral band response to the same scene, thus providing the ability to differentiate objects that cannot otherwise be resolved by differences in texture or shape.

In order to significantly reduce the manual workload involved in finding helpful information in the 'oceans of data', recent automatic/semi-automated algorithms for image detection have shown that they can effectively find patterns in the training data. However, in focusing on the traces of extant or subsurface structural remains present in the training images, such as different marks on the ground, automated approaches fail to leverage the vast amount of background knowledge (Fang et al., 2017). In this process, the machine can learn from previously specified features or train an algorithm to find a specific pattern with particular variables, such as settlements, tracks or burial mounds. Nevertheless, in using artificial intelligence to automate the data analysis process, the machine can encounter difficulties in terms of the precision of detection of non-geometric archaeological features with a more amorphous shape and structure, usually identified through subtleties related to or generated by the presence of the object. The incorporation of previous/semantic knowledge would naturally reinforce automatic object detection, providing an informed decision that would otherwise lack sufficient information to understand all the rules linking observed properties, in order to co-occur the instances and be capable of generalizing (Fang et al., 2017; Sonnemann et al., 2017).

Deductive (cognitive) tools such as knowledge bases can be used as an enhancement for automatic systems to generalize information. Cognitive systems seem to be inspired by how humans learn to generalize and fill in the gaps based on available information (Nys et al., 2018). Hence, hybrid approaches that combine inductive and deductive processes are recommended for exploring RSI data. The development of knowledge-based approaches is considered one of the most important directions in RS research (Arvor et al., 2019; Davis, 2021). Knowledge-based approaches in this context enable the correct concepts to be associated with the entities and facilitate information sharing by defining and standardizing vocabulary and semantics, thus allowing for greater interoperability between systems and enhancing the reasoning. Unlike the data-based methods that have been used for a long time, knowledge-based approaches have recently been gaining attention as a means of reducing existing data gaps and addressing the needs of the end-user who deals with the automatic detection of geospatial features complexes (Arvor et al., 2019; Davis, 2020a).

Knowledge-based methods for RS data still need standards for storing information to deal with the data flow that is constantly generated (Arvor et al., 2019). The lack of standardization in terms of collection, storage and interpretation, and the data dispersion, inconsistency and inaccuracy are reasons cited as restricting the use of automated approaches in this field (Casana, 2020; Orengo et al., 2020). This lack of standardization stems from the fact that, for a long time, databases have been created or maintained by different individuals and institutions with different objectives, within a framework of varied knowledge and understanding (Cooper & Green, 2016). The Portuguese database Endovélico, for example, started as a manual inventory that began to be digitized at the end of the twentieth century and now has more than 35,000 archaeological records registered by different experts over the past 40 years (Bugalhão et al., 2002).

Different organizations have been concerned with data storage methods and management and have joined forces at national and local level to develop a database for the collection and storage of spatial data. For example, the Archaeology Data Service provides information on past research and the location of monuments from different countries, thus helping to organize and prevent future conflicts in existing data by means of a protected repository for archaeological knowledge, while also promoting non-destructive analysis. However, in most databases, access to images is restricted or is not openly available for analysis, and in archaeology it has been common not to share data (Gunnarsson, 2018).

Regardless of the archaeological reach of automatic approaches, the subject has been attracting greater interest in recent years. It is fair to say that computer vision systems are being driven by enhanced computer processing power at hardware and software levels. Together with the increasing image resolution levels (either spatial, spectral, radiometric, or temporal) and faster availability of data, technological advancements are ensuring greater use and acceptance of automation in image analysis (Opitz & Herrmann, 2018; Traviglia et al., 2016).

Despite its advances, archaeology still has a long way to go in terms of cyberinfrastructure. At the same time, the standardization and accessibility of the data itself must be revised and even enforced. Hybrid approaches that use data-driven and knowledge-driven approaches for RSI are an exciting development for the future of automatic detection in archaeology. Another future direction is related to the development of collaborative domain ontologies, mainly dedicated to remote sensing science. With the increased availability of data, the manual annotation of semantic content is becoming unfeasible. Thus, new methods for capturing knowledge from machine learning applications and automatically deriving new ontologies that can represent this knowledge have emerged as a new research trend (Arvor et al., 2019).

New advances in computer vision and artificial intelligence will undoubtedly continue to exist alongside traditional investigation methods, in an interactive and complementary relationship in which the expertise of archaeologists plays an essential role in interpretation. Regardless of the approach used to work with the data, the interpretation and validation of objects extracted from images is the archaeologist's prerogative (Quintus et al., 2017; Traviglia et al., 2016; Verdonck et al., 2017). In any case, in order to set up automated earth image analysis/detection, it is necessary to start by feeding the automated systems with a large amount of data, which would be difficult to visualize manually in the first place (Kazimi et al., 2018), given that over the last century a gigantic 'black box' of data has been collected and stored but is yet to be visualized.

6 | CONCLUSION

Nowadays, many satellites orbiting Earth generate remote images which, together with the large amount of aerial images and airborne laser scanning data, have produced vast quantities of surface images.

Remote sensing data covering large geographical areas can be easily accessed and is being acquired with increased frequency. On the other hand, intensive soil usage and modern infrastructure requirements result in constant changes to the landscape, placing cultural heritage under greater pressure. Hence, we are faced with the need to speed up and enhance the accuracy of archaeological prospection. By isolating areas with a higher probability of containing heritage, automated approaches to archaeological object identification provide faster monumental typology detection. These tools facilitate access in hard-to-reach areas, provide protection for the existing cultural heritage and help develop innovative technologies in the field of archaeology.

With very high-resolution data and improvements to modern machine learning, automatic methods in archaeology show promise for the future. In recent years, researchers have been using different approaches, including those based on templates, GEOBIA, ML, DL and knowledge-based methods to automatically detect archaeological objects in RSI. In fact, automated image recognition techniques working with very large existing data sets have by now proved their worth in the detection of archaeological monuments. Nevertheless, an analysis of the literature highlights the need to develop new optimized process methodologies to work with even more and even better data that has become available over the years from new sensing devices.

Hence, it is imperative to design more precise automatic and faster classification systems, especially to identify smaller monuments, since these are most at risk. To this end, analysis of the complex patterns of human activity and landscape modification could enhance the performance and thus the utility of these methods. Such a system would not only contribute to the detection but also the preservation of heritage monuments. In addition, it would enable researchers to survey geographic areas that are physically difficult to access and to limit development in regions that are more likely to contain monuments. The results can be used both for planning fieldwork and for preventing or redirecting construction in areas that are highly likely to provide cultural monuments. Finally, it is important to note that such a tool needs to incorporate multidisciplinary methodologies and technological innovations as the drivers for new archaeological research.

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CONFLICT OF INTEREST

The authors have no conflicts of interest to declare.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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ENDNOTES

[1] ESA (access at earth.esa.int/web/guest/home).

[2] CEOS (accessed at ceos.org/)

[3] NASA (access at disc.gsfc.nasa.gov/).

[4] USGS (access at glovis.usgs.gov/).

REFERENCES

Abate, N., Elfadaly, A., Masini, N., & Lasaponara, R. (2020). Multitemporal 2016-2018 Sentinel-2 data enhancement for landscape archaeology: The case study of the Foggia Province, southern Italy. *Remote Sensing*, *12*(8), 1309.

Arvor, D., Belgiu, M., Falomir, Z., Mougenot, I., & Durieux, L. (2019). Ontologies to interpret remote sensing images: Why do we need them? *GIScience & Remote Sensing*, *56*(6), 911–939. https://doi.org/10.1080/15481603.2019.1587890

Arvor, D., Durieux, L., Andrés, S., & Laporte, M.-A. (2013). Advances in geographic object-based image analysis with ontologies: A review of main contributions and limitations from a remote sensing perspective. *ISPRS Journal of Photogrammetry and Remote Sensing*, *82*, 125–137. https://doi.org/10.1016/j.isprsjprs.2013.05.003

Barceló, J. A., & Barceló, J. A. (2009). *Computational intelligence in archaeology*. Information Science Reference.

Bekiari, C. Bruseker, G., Doerr, M., Ore, C.-E., Stead, S., & Velios, A. (2021). Volume a: Definition of the CIDOC conceptual reference model. Vol. 7.2. Copyright.

Bishop, C. M. (2006). *Pattern recognition and machine learning*. Springer.

Bowen, E., Tofel, B. B., Parcak, S., & Granger, R. (2017). Algorithmic identification of looted archaeological sites from space. *Frontiers in ICT*, *4*, 4.

Bugalhão, J., Lucena, A., Bragança, F., Neto, F., Sousa, M. J., Gomes, S., Pinto da Costa, J., Caldeira, N., Viralhadas, P., & Fraga, T. (2002). Endovélico. Sistema de Gestão e Informação Arqueológica. *Revista Portuguesa de Arqueologia*, *5*(1), 277–283.

Câmara, A. (2017). A fotointerpretação como recurso de prospeção arqueológica. Chaves para a identificação e interpretação de monumentos megalıticos no Alentejo: aplicação nos concelhos de Mora e Arraiolos. MA thesis. Universidade de Évora.

Câmara, A., & Batista, T. (2017). Photo interpretation and geographic information systems for dolmen identification in Portugal: The case study of Mora and Arraiolos. In: *2017 12th Iberian conference on information systems and technologies (CISTI)*. IEEE, 1–6.

Casana, J. (2020). Global-scale archaeological prospection using CORONA satellite imagery: Automated, crowd-sourced, and expert-led approaches. *Journal of Field Archaeology*, *45*(sup1), S89–S100. https://doi.org/10.1080/00934690.2020.1713285

Caspari, G., & Crespo, P. (2019). Convolutional neural networks for archaeological site detection–finding "princely" tombs. *Journal of Archaeological Science*, *110*, 104998.

Cerrillo-Cuenca, E. (2017). An approach to the automatic surveying of prehistoric barrows through LiDAR. *Quaternary International*, *435*, 135–145. https://doi.org/10.1016/j.quaint.2015.12.099

Chen, L., Comer, D. C., Priebe, C. E., Sussman, D., & Tilton, J. C. (2013). Refinement of a method for identifying probable archaeological sites from remotely sensed data. In *Mapping archaeological landscapes from space* (pp. 251–258). Springer. 10.1007/978-1-4614-6074-9_21

Cheng, G., & Han, J. (2016). A survey on object detection in optical remote sensing images. *ISPRS Journal of Photogrammetry and Remote Sensing*, *117*, 11–28. https://doi.org/10.1016/j.isprsjprs.2016.03.014

Cooper, A., & Green, C. (2016). Embracing the complexities of 'big data' in archaeology: The case of the English landscape and identities project. *Journal of Archaeological Method and Theory*, *23*(1), 271–304. https://doi.org/10.1007/s10816-015-9240-4

Davis, D. S. (2019). Object-based image analysis: A review of developments and future directions of automated feature detection in landscape archaeology. *Archaeological Prospection*, *26*(2), 155–163. https://doi.org/10.1002/arp.1730

Davis, D. S. (2020a). Defining what we study: The contribution of machine automation in archaeological research. *Digital Applications in Archaeology and Cultural Heritage*, *18*, e00152.

Davis, D. S. (2020b). Geographic disparity in machine intelligence approaches for archaeological remote sensing research. *Remote Sensing*, *12*(6), 921. https://doi.org/10.3390/rs12060921

Davis, D. S. (2021). Theoretical repositioning of automated remote sensing archaeology: Shifting from features to ephemeral landscapes. *Journal of Computer Applications in Archaeology*, *4*(1), 94. https://doi.org/10.5334/jcaa.72

Davis, D. S., Andriankaja, V., Carnat, T. L., Chrisostome, Z. M., Colombe, C., Fenomanana, F., Hubertine, L., Justome, R., Lahiniriko, F., Léonce, H., Manahira, G., Pierre, B. V., Roi, R., Soafiavy, P., Victorian, F., Voahirana, V., Manjakahery, B., & Douglass, K. (2020). Satellite-based remote sensing rapidly reveals extensive record of Holocene coastal settlement on Madagascar. *Journal of Archaeological Science*, *115*, 105097. https://doi.org/10.1016/j.jas.2020.105097

Davis, D. S., Buffa, D. C., & Wrobleski, A. C. (2020). Assessing the utility of open-access bathymetric data for shipwreck detection in the United States. *Heritage*, *3*(2), 364–383. https://doi.org/10.3390/heritage3020022

Davis, D. S., & Douglas, K. (2021). Remote sensing reveals lasting legacies of land-use by small-scale communities in the southwestern Indian Ocean. *Frontiers in Ecology and Evolution*, *9*, *689399*. https://doi.org/10.3389/fevo.2021.689399

Davis, D. S., Lipo, C. P., & Sanger, M. C. (2019). A comparison of automated object extraction methods for mound and shell-ring identification in coastal South Carolina. *Journal of Archaeological Science: Reports*, *23*, 166–177. https://doi.org/10.1016/j.jasrep.2018.10.035

Davis, D. S., Sanger, M. C., & Lipo, C. P. (2019). Automated mound detection using lidar and object-based image analysis in Beaufort County, South Carolina. *Southeastern Archaeology*, *38*(1), 23–37. https://doi.org/10.1080/0734578X.2018.1482186

de Boer, A. (2005). Using pattern recognition to search LIDAR data for archeological sites. In: The World Is in Your Eyes: Proceedings of the XXXIII Computer Applications and Quantitative Methods in Archaeology Conference (March 2005—Tomar, Portugal), 245–254.

de Laet, V., Paulissen, E., & Waelkens, M. (2007). Methods for the extraction of archaeological features from very high-resolution Ikonos-2 remote sensing imagery, Hisar (Southwest Turkey). *Journal of Archaeological Science*, *34*(5), 830–841. https://doi.org/10.1016/j.jas.2006.09.013

Doneus, M. (2013). Openness as visualization technique for interpretative mapping of airborne lidar derived digital terrain models. *Remote Sensing*, *5*(12), 6427–6442. https://doi.org/10.3390/rs5126427

Doneus, M., Forwagner, U., & Kiedl, C. (2019). *APIS-archaeological prospection-information-system*. Archaeological Prospection.

Drewett, P. (2011). *Field archaeology: An introduction*. Routledge.

Fang, Y., Kuan K, Lin J, Tan C, & Chandrasekhar V. (2017). Object detection meets knowledge graphs.

Freeland, T., Heung, B., Burley, D. V., Clark, G., & Knudby, A. (2016). Automated feature extraction for prospection and analysis of monumental earthworks from aerial LiDAR in the Kingdom of Tonga. *Journal of Archaeological Science*, *69*, 64–74. https://doi.org/10.1016/j.jas.2016.04.011

Garozzo, R., Murabito, F., Santagati, C., Pino, C., & Spampinato, C. (2017). CulTO: An ontology-based annotation tool for data curation in cultural heritage. *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, *42*, 267–274.

Guarino, N., Oberle, D., & Staab, S. (2009). What is an ontology? In *Handbook on ontologies* (pp. 1–17). Springer. https://doi.org/10.1007/978-3-540-92673-3_0

Gunnarsson, F. (2018). Archaeological challenges, digital possibilities: Digital knowledge development and communication in contract archaeology. PhD thesis. Linnaeus University Press.

Guyot, A., Hubert-Moy, L., & Lorho, T. (2018). Detecting Neolithic burial mounds from LiDAR-derived elevation data using a multi-scale approach and machine learning techniques. *Remote Sensing*, *10*(2), 225.

Hanson, W. S. (2010). The future of aerial archaeology in Europe. *Photo Interprétation European Journal of Applied Remote Sensing*, *46*(1), 3.

Harvey, F., & Raskin, R. G. (2011). Spatial cyberinfrastructure: building new pathways for geospatial semantics on existing infrastructures. In *Geospatial semantics and the semantic web* (pp. 87–96). Springer. https://doi.org/10.1007/978-1-4419-9446-2_4

Hesse, R. (2010). Lidar-derived local relief models—A new tool for archaeological prospection. *Archaeological Prospection*, *17*(2), 67–72. https://doi.org/10.1002/arp.374

Hyvönen, E., Tuominen, J., Kauppinen, T., & Väätäinen, J. (2011). Representing and utilizing changing historical places as an ontology time series. In *Geospatial semantics and the semantic web* (pp. 1–25). Springer. https://doi.org/10.1007/978-1-4419-9446-2_1

Kalayci, T., Lasaponara, R., Wainwright, J., & Masini, N. (2019). Multispectral contrast of archaeological features: A quantitative evaluation. *Remote Sensing*, *11*(8), 913.

Kazimi, B., Thiemann, F., Malek, K., Sester, M., & Khoshelham, K. (2018). Deep learning for archaeological object detection in airborne laser scanning data. In: *2nd Workshop on Computing Techniques for Spatio-Temporal Data in Archaeology and Cultural Heritage (COARCH 2018)*. 2230, 21–35.

Klehm, C., Barnes, A., Follett, F., Simon, K., Kiahtipes, C., & Mothulatshipi, S. (2019). Toward archaeological predictive modeling in the Bosutswe region of Botswana: Utilizing multispectral satellite imagery to conceptualize ancient landscapes. *Journal of Anthropological Archaeology*, *54*, 68–83. https://doi.org/10.1016/j.jaa.2019.02.002

Koch, I., Freitas, N., Ribeiro, C., Lopes, C. T., & da Silva, J. R. (2019). Knowledge graph implementation of archival descriptions through CIDOC-CRM. In *International conference on theory and practice of digital libraries* (pp. 99–106). Springer. 10.1007/978-3-030-30760-8_8

Kvamme, K. (2016). An examination of automated archaeological feature recognition in remotely sensed imagery. *Computational Approaches to Archaeological Spaces*, *1*, 53–68.

Lambers, K., Verschoof-van der Vaart, W. B., & Bourgeois, Q. P. (2019). Integrating remote sensing, machine learning, and citizen science in Dutch archaeological prospection. *Remote Sensing*, *11*(7), 794.

Lang, S., Hay, G. J., Baraldi, A., Tiede, D., & Blaschke, T. (2019). GEOBIA achievements and spatial opportunities in the era of big earth observation data. *ISPRS International Journal of Geo-Information*, *8*(11), 474.

Lasaponara, R., Leucci, G., Masini, N., & Persico, R. (2014). Investigating archaeological looting using satellite images and GEORADAR: The experience in Lambayeque in North Peru. *Journal of Archaeological Science*, *42*, 216–230. https://doi.org/10.1016/j.jas.2013.10.032

Lasaponara, R., Leucci, G., Masini, N., Persico, R., & Scardozzi, G. (2016). Towards an operative use of remote sensing for exploring the past using satellite data: The case study of Hierapolis (Turkey). *Remote Sensing of Environment*, *174*, 148–164. https://doi.org/10.1016/j.rse.2015.12.016

Lasaponara, R., & Masini, N. (2011). Satellite remote sensing in archaeology: Past, present and future perspectives. *Journal of Archaeological Science*, *9*(38), 1995–2002. https://doi.org/10.1016/j.jas.2011.02.002

Lemmens, J. P. M., Stancic, Z., & Verwaal, R. G. (1993). Automated archaeological feature extraction from digital aerial photographs. In: *CAA92-Computing the Past: Computer Applications and Quantitative Methods in Archaeology*, 45–51.

Liebig, T. (n.d.). Neo4j: A reasonable RDF graph database reasoning engine. Retrieved from neoj.com/blog/neoj-rdfgraph-database-reasoning-engine/. Accessed: 01.09.2020.

Luo, L., Wang, X., Guo, H., Liu, C., Liu, J., Li, L., Du, X., & Qian, G. (2014). Automated extraction of the archaeological tops of qanat shafts from VHR imagery in google earth. *Remote Sensing*, *6*(12), 11956–11976. https://doi.org/10.3390/rs61211956

Maggiori, E., Tarabalka, Y., Charpiat, G., & Alliez, P. (2016). Fully convolutional neural networks for remote sensing image classification. In: 2016 IEEE international geoscience and remote sensing symposium (IGARSS). IEEE, 5071–5074.

Magnini, L., & Bettineschi, C. (2019). Theory and practice for an object-based approach in archaeological remote sensing. *Journal of Archaeological Science*, *107*, 10–22. https://doi.org/10.1016/j.jas.2019.04.005

Menze, B. H., Ur, J. A., & Sherratt, A. G. (2006). Detection of ancient settlement mounds. *Photogrammetric Engineering & Remote Sensing*, *72*(3), 321–327. https://doi.org/10.14358/PERS.72.3.321

Morais, E. A. M., & Ambrósio, A. P. L. (2007). Ontologias: conceitos, usos, tipos, metodologias, ferramentas e linguagens. In: Relatório Técnico–RT-INF-001/07, dez.

Nuninger, L., Opitz, R., Verhagen, P., Libourel, T., Laplaige, C., Leturcq, S., le Voguer, N., Fruchart, C., Kokalj, Ž., & Rodier, X. (2020). Developing FAIR ontological pathways: Linking evidence of movement in lidar to models of human behaviour. *Journal of Computer Applications in Archaeology*, *3*(1), 63–75. https://doi.org/10.5334/jcaa.46

Nys, G.-A., Kasprzyk, J.-P., Hallot, P., & Billen, R. (2018). Towards an ontology for the structuring of remote sensing operations shared by different processing chains. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *42*(4), 483–490. https://doi.org/10.5194/isprs-archives-XLII-4-483-2018

Opitz, R., & Herrmann, J. (2018). Recent trends and long-standing problems in archaeological remote sensing. *Journal of Computer Applications in Archaeology*, *1*(1), 19–41. https://doi.org/10.5334/jcaa.11

Orengo, H. A., Conesa, F. C., Garcia-Molsosa, A., Lobo, A., Green, A. S., Madella, M., & Petrie, C. A. (2020). Automated detection of archaeological mounds using machine-learning classification of Mul-tisensor and multitemporal satellite data. *Proceedings of the National Academy of Sciences*, *117*(31), 18240–18250. https://doi.org/10.1073/pnas.2005583117

Parcak, S. H. (2009). *Satellite remote sensing for archaeology*. Routledge. https://doi.org/10.4324/9780203881460

Platt, R. V., & Rapoza, L. (2008). An evaluation of an object-oriented paradigm for land use/land cover classification∗. *The Professional Geographer*, *60*(1), 87–100. https://doi.org/10.1080/00330120701724152

Quintus, S., Day, S. S., & Smith, N. J. (2017). The efficacy and analytical importance of manual feature extraction using lidar datasets. *Advances in Archaeological Practice*, *5*(4), 351–364. https://doi.org/10.1017/aap.2017.13

Rajbhandari, S., Aryal, J., Osborn, J., Lucieer, A., & Musk, R. (2019). Leveraging machine learning to extend ontology-driven geographic object-based image analysis (O-GEOBIA): A case study in forest-type mapping. *Remote Sensing*, *11*(5), 503.

Rajbhandari, S., Aryal, J., Osborn, J., Musk, R., & Lucieer, A. (2017). Benchmarking the applicability of ontology in geographic object-based image analysis. *ISPRS International Journal of Geo-Information*, *6*(12), 386.

Ronzino, P. (2015). CIDOC CRMba a CRM extension for buildings archaeology information modelling. In: *Unpublished doctoral thesis*. The Cyprus Institute, Nicosia, Cyprus.

Rowlands, A., & Sarris, A. (2007). Detection of exposed and subsurface archaeological remains using multi-sensor remote sensing. *Journal of Archaeological Science*, *34*(5), 795–803. https://doi.org/10.1016/j.jas.2006.06.018

Schuetter, J., Goel, P., McCorriston, J., Park, J., Senn, M., & Harrower, M. (2013). Autodetection of ancient Arabian tombs in high-resolution satellite imagery. *International Journal of Remote Sensing*, *34*(19), 6611–6635. https://doi.org/10.1080/01431161.2013.802054

Sevara, C., Pregesbauer, M., Doneus, M., Verhoeven, G., & Trinks, I. (2016). Pixel versus object—A comparison of strategies for the semi-automated mapping of archaeological features using airborne laser scanning data. *Journal of Archaeological Science: Reports*, *5*, 485–498. https://doi.org/10.1016/j.jasrep.2015.12.023

Somrak, M., Džeroski, S., & Kokalj, Ž. (2020). Learning to classify structures in ALS-derived visualizations of ancient Maya settlements with CNN. *Remote Sensing*, *12*(14), 2215.

Sonnemann, T. F., Comer, D. C., Patsolic, J. L., Megarry, W. P., Herrera Malatesta, E., & Hofman, C. L. (2017). Semi-automatic detection of indigenous settlement features on Hispaniola through remote sensing data. *Geosciences*, *7*(4), 127. https://doi.org/10.3390/geosciences7040127

Soroush, M., Mehrtash, A., Khazraee, E., & Ur, J. A. (2020). Deep learning in archaeological remote sensing: Automated qanat detection in the Kurdistan region of Iraq. *Remote Sensing*, *12*(3), 500.

Soviany, P., & Lonescu, R. T. (2018). Optimizing the trade-off between single-stage and two-stage deep object detectors using image difficulty prediction. In: *In 2018 20th International Symposium on Symbolic and Numeric Algorithms for Scientific Computing* (SYNASC).

Stock, K., Hobona, G., Granell, C., & Jackson, M. (2011). Ontology-based geospatial approaches for semantic awareness in earth observation systems. In *Geospatial semantics and the semantic web* (pp. 97–118). Springer. https://doi.org/10.1007/978-1-4419-9446-2_5

Thabeng, O. L., Merlo, S., & Adam, E. (2019). High-resolution remote sensing and advanced classification techniques for the prospection of archaeological sites' markers: The case of dung deposits in the ShasheLimpopo confluence area (southern Africa). *Journal of Archaeological Science*, *102*, 48–60. https://doi.org/10.1016/j.jas.2018.12.003

Traviglia, A., Cowley, D., & Lambers, K. (2016). Finding common ground: Human and computer vision in archaeological prospection. *AARGnews*, *53*, 11–24.

Trier, Ø. D., Salberg, A. B., & Pilø, L. H. (2016). Semi-automatic mapping of charcoal kilns from airborne laser scanning data using deep learning. In: *CAA2016: Oceans of Data. Proceedings of the* 44th conference on computer applications and quantitative methods in archaeology, 219–231.

Trier, Ø. D., Cowley, D. C., & Waldeland, A. U. (2019). Using deep neural networks on airborne laser scanning data: Results from a case study of semi-automatic mapping of archaeological topography on Arran, Scotland. *Archaeological Prospection*, *26*(2), 165–175. https://doi.org/10.1002/arp.1731

Trier, Ø. D., Larsen, S. Ø., & Solberg, R. (2009). Automatic detection of circular structures in high-resolution satellite images of agricultural land. *Archaeological Prospection*, *16*(1), 1–15. https://doi.org/10.1002/arp.339

Trier, Ø. D., & Pilø, L. H. (2012). Automatic detection of pit structures in airborne laser scanning data. *Archaeological Prospection*, *19*(2), 103–121. https://doi.org/10.1002/arp.1421

Trier, Ø. D., Reksten, J. H., & Løseth, K. (2021). Automated mapping of cultural heritage in Norway from airborne lidar data using faster R-CNN. *International Journal of Applied Earth Observation and Geoinformation*, *95*, 102241. https://doi.org/10.1016/j.jag.2020.102241

Trier, Ø. D., Zortea, M., & Tonning, C. (2015). Automatic detection of mound structures in airborne laser scanning data. *Journal of Archaeological Science: Reports*, *2*, 69–79. https://doi.org/10.1016/j.jasrep.2015.01.005

Verdonck, L., Launaro, A., Millett, M., Vermeulen, F., & Bellini, G. (2017). Semi-automated object detection in GPR data using morphological filtering. In: *AP 2017:12th International Conference of Archaeological Prospection*. Archaeopress Publishing Ltd, 261–263.

Verschoof-van der Vaart, W. B., Lambers, K., Kowalczyk, W., & Bourgeois, Q. P. (2020). Combining deep learning and location-based ranking for large-scale archaeological prospection of LiDAR data from the Netherlands. *ISPRS International Journal of Geo-Information*, *9*(5), 293.

Verschoof-van der Vaart, W. B., & Landauer, J. (2021). Using Carcasson-Net to automatically detect and trace hollow roads in LiDAR data from the Netherlands. *Journal of Cultural Heritage*, *47*, 143–154. https://doi.org/10.1016/j.culher.2020.10.009

Yaworsky, P. M., Vernon, K. B., Spangler, J. D., Brewer, S. C., & Codding, B. F. (2020). Advancing predictive modeling in archaeology: An evaluation of regression and machine learning methods on the grand staircase-Escalante National Monument. *PLoS ONE*, *15*(10), e0239424. https://doi.org/10.1371/journal.pone.0239424

Zingman, I., Saupe, D., Penatti, O. A. B., & Lambers, K. (2016). Detection of fragmented rectangular enclosures in very high resolution remote sensing images. *IEEE Transactions on Geoscience and Remote Sensing*, *54*(8), 4580–4593. https://doi.org/10.1109/TGRS.2016.2545919

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