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Review

GPR Data Processing and Interpretation Based on Artificial Intelligence Approaches: Future Perspectives for Archaeological Prospection

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Abstract: Ground penetrating radar (GPR) is a well-established technique used in archaeological prospection and it requires a number of specialized routines for signal and image processing to enhance the data acquired and lead towards a better interpretation of them. Computer-aided techniques have advanced the interpretation of GPR data, dealing with a wide range of operations aiming towards locating, imaging, and diagnosis/interpretation. This article will discuss the novel and recent applications of machine learning (ML) and deep learning (DL) techniques, under the artificial intelligence umbrella, for processing GPR measurements within archaeological contexts, and their potential, limitations, and possible future prospects.

Keywords: ground penetrating radar; automated analysis; artificial intelligence; machine learning; archaeological prospection

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1. Introduction

Despite their limited application, compared to other disciplines, the application of machine learning (ML) and deep learning (DL)-based analysis on addressing various archaeological questions is growing rapidly. The archaeological and cultural heritage community has realized the importance of artificial intelligence (AI)-powered tools for predictive modelling, site analysis, data analysis such as classification, clustering, and text mining, and many other digital humanities/computational archaeology research topics. It has experimented with geospatial data/images (satellite, aerial, lidar), texts, categorical tableau data, point clouds, and other datasets. For instance, one can consider some indicative examples such as the work that has been done on bone classification [1], remote sensing archaeology [2–12], geophysical prospection [13–17], detection of objects in paintings [18], classification of pottery [19], and the 3D reconstruction of heritage buildings [20]. The main reason behind this growing trend, which has been noticed in the last five years in all scientific domains, underlies the nuisance generated when dealing with multivariate analysis of high-volume datasets, which are challenging to process and interpret. Furthermore, there is an increasing need to extract preliminary but still reliable and objective results that can guide the subsequent and more challenging stages of processing and, at the same time, cope with the current fast-paced and fast-tracked time- and budget-efficient scientific research. In this sense, AI has risen to enhance processing speed, accuracy, and effectiveness by the mimicking of the human process by computer systems, including learning and reasoning. This review paper aims to explain how AI (ML and DL)-based approaches have contributed to the processing and interpretation of ground penetrating radar (GPR) data, starting from recent applications for various domains but specifically focusing deep analysis on archaeological applications.

2. Artificial Intelligence (Machine Learning and Deep Learning)

Artificial intelligence (AI) is the big umbrella that includes machine learning (ML) and deep learning (DL) techniques. ML can be defined as a corpus of strategies to make a machine learn from a set of existing data. In the concepts of ML, the learning process can be supervised or unsupervised [21,22]. Unsupervised learning is mainly used for clustering, namely, to recognize groups of categories in the data using several algorithms, such as K-means, hierarchical means, density-based algorithms, dimensionality reduction through the principal component analysis (PCA), etc. Additionally, unsupervised learning is generally implemented for regression analysis to find relationships with dependent (targets) and independent variables (predictors) using different regression approaches, such as polynomial regression, decision trees, and random forests. This is similar to the classification methods that rely on the prediction of classes through support vector machines, decision trees, random forests, neural networks, naive Bayesians, etc. [23,24].

DL, as a complex part of ML, describes algorithms that analyze data with a logic structure similar to the human intelligence. This can also be based on both supervised and unsupervised learning approaches. When it comes to computer vision tasks, deep neural networks (DNNs), specifically convolutional neural networks (CNNs or ConvNets) constitute the most commonly used approach for object detection, feature extraction, segmentation, 3D object reconstruction, and image captioning, and provide a dramatic performance improvement compared to traditional image processing algorithms. Basic principles of CNNs can be found in [25–27]. To summarize briefly, CNNs are multi-layer neural networks that typically take pixel intensity values as input, and they learn to process them following a specific pipeline. They mainly consist of convolutional layers, pooling layers, activation layers, batch normalization, and dropout layers [25]. When the networks are trained by an efficient amount of data with the proper hyperparameters, they learn, and then detect, segment, or select the appropriate patterns in an image or video [28]. This is of significant value if we consider that the particular datasets deal with images or point clouds and try to process them in a way to link these with meaningful archaeological information.

AI-based models can learn from a large number of datasets without setting specific rules or algorithms. It has to be mentioned though that there are no specific rules related to the amount of the datasets to be used, as it all depends on the AI architecture and the evaluation of the metrics results. In contrast, traditional methods are based on the formalization of the relationships between variables based on mathematical equations/statistical analysis and deal with a small amount of data with fewer attributes (Figure 1). Comparing these two different approaches, both of them have cons and pros and are still challenging since all of it depends on the application purpose and specific task. For instance, traditional models can be successful in demonstrating the relationship between variables and in making inferences from data. Still, when the aim is obtaining a model that can make repeatable predictions for a new dataset without any effort, AI-based models are outstanding.

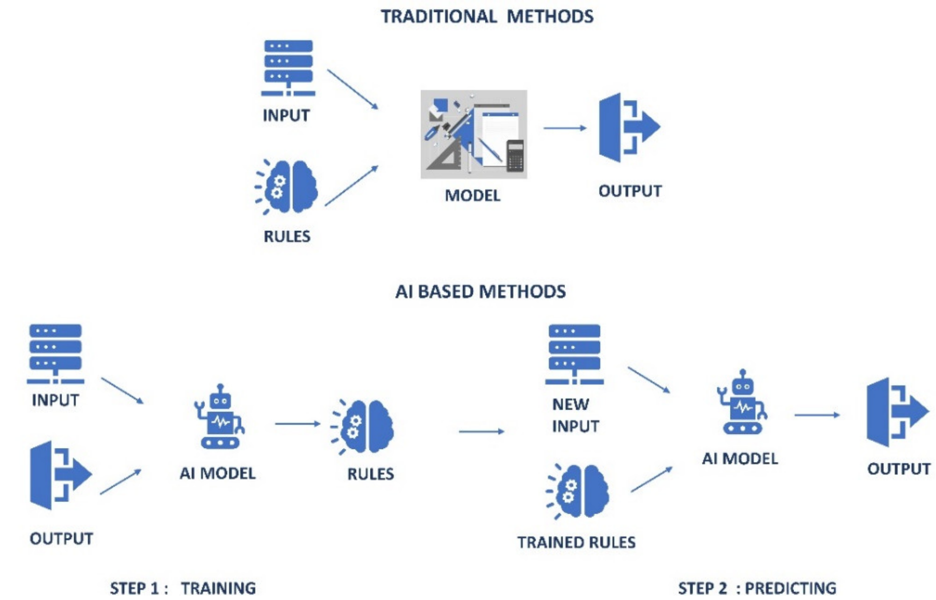

Figure 1. Basic principles of traditional model vs. AI-based model. On the one hand, traditional models use mathematical equations and statistical (usually multivariate) analysis to infer the relationships between the different variables. On the other hand, AI-based models avoid such algorithms, and they are based on the learning capabilities from a sufficient number of datasets.

3. AI Applications on GPR

In this chapter, we aimed to examine the recent AI-based approaches applied on different display formats of GPR data from various disciplines such as civil engineering applications, transportation, and hydrological and environmental applications, which can be an inspiration to solve similar problems in archeological data processing.

As is well-known, the GPR data are processed, analyzed, and interpreted in four display formats: (i) individual signals (A-scans) consist of a repetitive series of short pulses, generated by the transmitter and radiated into the subsurface; (ii) B-scans represent two-dimensional (2D) matrices, so called *radargrams*, which are the (stratigraphic) images formed by combined adjacent A-scans; (iii) C-scans, so called *time slices*, depict the images defined over the x $\times$ y $\times$ t coordinate space (where t is the time of return of the EM waves which can be also interpreted to depth (d) if their velocity of propagation can be estimated) and depict the horizontal spatial distribution of reflectors for different depth levels; and (iv) 3D volumes (3D GPR data), which are created by considering the overlay of all the B-scans together and are usually processed through volume renders with different transparencies or iso-surfaces that isolate specific amplitudes. Independently of the visualization mode, the data must be processed and interpreted in a reliable manner and the primary aim is extracting a meaning related to the target object (modern infrastructures, archaeological remains, stratigraphy, etc.). The need to deal with time-consuming post-processing steps, noise removal, enhancement of weak reflections, and the processing of large scales and amounts of data (especially those produced either by motorized systems or from subsequent field surveys) has required the development of alternative techniques. Thus, the research community has experimented with various AI approaches focusing on specific problems (with limited application in the archaeological domain as we shall see in this chapter) and for dealing with different types of GPR data representations, some of which will be summarized below.

In recent studies, AI applications on the GPR dataset have mainly focused on signal processing and image processing. For instance, inversion modeling in geophysics, basically dealing with the approximate estimation of the subsurface distribution of a physical property of the ground from observed raw data, needs automated analysis because of the long processing times through classical modeling approaches. Travassos et al. used artificial neural networks to solve an inversion problem related to the detection and characterization of inclusions in concrete structures [29]. Liu et al. proposed a neural network to invert the targets' location and backscattering intensity from GPR data [30]. Recently, Leong and Zhu proposed a neural network model for similar inversion purposes that shows promising potential to use deep learning-based 1D zero-offset inversion to predict velocity models from GPR data [31]. Liu et al. applied a DNN-based inversion process to invert the dielectric properties of tunnel linings and reconstruct complex defects with irregular geometries in their studies [32]. In contrast, for forward modeling, which predicts the response (data) from a given model, AI-based approaches to simulate the GPR for high-frequency applications have been suggested by Giannakis et al. [33,34].

Apart from modeling purposes, AI-based experimental studies on radargrams (B-scans) were mainly based on hyperbolic pattern recognition. Ali et al. used a support vector machines (SVMs) classifier to recognize geometrical shape cubes, cylinders, discs, and spheres which were tested on synthetic models [35]. Chen et al. proposed a specific region-based network, called the cascade regional convolutional neural network, for object detection tasks [36]. In a similar case, Gong et al. used faster R-CNN to classify and recognize GPR images automatically [37]. Elsaadany et al. extracted the buried features using LeNet CNN [38], and Pham et al. detected buried objects from B-Scan using fasterRCNN [39]. These studies were held on data collected within laboratory-controlled experiments to understand the characteristics of the anomalies derived from buried objects. Additionally, in most of these studies, because of the limited number of the training dataset, a synthetic dataset was generated using gprMax opensource software (gprmax.com) [40] to be used during the training of the neural network.

Many of the above studies have started to be applied to actual case studies in civil and transport engineering topics, hydrology and geological studies, or small-size target detection such as rebars and pipes. For instance, detection of the defects inside tree trunks [41], inspection of railways [42], automated landmine and UXO detection [43], pavement distress detection [44,45], evaluation of pavement thickness [46], and determination of rock depth [47]. Although most of these case studies do not fall directly within the archaeological context, they are all applicable to address archaeological research questions regarding parameter estimation, modelling, and feature extraction problems.

4. AI Approaches Applied in GPR within Archaeological Research

With recent advances in ground penetrating radar technology, as the sensors and mass storage devices became more efficient, it is possible to survey large scales of archeological sites in a short time. It has been this critical step that shifted emphasis of archaeological prospection to archaeological landscape mapping. The extensive site surveys require more intensive data processing and, additionally, a more comprehensive interpretation, which can also be challenging since the human eye may miss the small-scale features when dealing with large-scale datasets and areas of coverage. Automated or semi-automated analysis of GPR data using traditional statistical and mathematical approaches recently showed its potential in such archaeological surveys [48–55]. These attempts are quite promising but mainly data-specific, which means that rules should be set each time for the new case dataset.

As a novel way of understanding (and interpreting) these extensive images, artificial intelligence-assisted image analyses, especially those based on CNNs, are well-adapted for various datasets aiming towards automated interpretation, feature extraction, and object detection. In archaeological prospection, although the initial processing of radargrams (B-scans) is important for the interpretation of GPR anomalies, we rather tend to visualize the data as 2D time/depth slices (C-scans), since it is more efficient to map the whole landscape and depict the spatial distribution of the buried features (reflectors), trying to define at the same time their geometric properties and dimensions. Here, we analyzed the AI-based models which were recently applied for archeological context on these two different visualization modes of GPR data. Verdonck presented the automated analysis of diffraction hyperbolas in the B-scans [56]. He proposed a region-based object detector of R-CNN that briefly extracts the regions from the image, called region proposals. These sections of interest are represented by rectangle boundaries that define areas of object detection and can be helpful in understanding the characteristics of archaeological features in B-scans. Another study from Green and Cheetham [15] and Green [16] used a machine learning algorithm as a classification task to detect buried graves from radargrams (B-scan). The training dataset was annotated as classes of graves and non-grave/background. They created a training dataset of around 1000 images, which was enriched with simulated data using GprSIM [57] and gprMax software [40]. Data augmentation was applied to increase the number of images for the training process. Training was held by a transfer learning approach using the Inception V3 architecture pre-trained on ImageNet data, VGG, and Resnet models, and the results were compared. Based on the results from initial tests of the CNNs, ResNet152 was chosen as the base model for the image classification and object detection tasks and achieved a 94% accuracy. The model was also tested on various actual case data, which is essential for reliable decision-making.

The first attempt for an automated interpretation of anomalies in GPR time slices as a segmentation task was performed by Küçükdemirci and Sarris [13,14]. This work developed an algorithm using a specific U-shaped convolutional neural network architecture to segment the 2D time slices to subsequently extract the possible archaeological features from the image. Since it is crucial to train the network with a large number of datasets, almost 2000 data annotated by expert human knowledge were prepared from different GPR case studies; that dataset was obtained from various soil and environmental conditions. As is very well-known, hyperparameter choices, depth of the networks, kernel sizes, and network architecture are also essential factors in obtaining reliable predictions. In this sense, several experiments have been performed to tune the parameters mentioned above. The number of datasets was increased by the data augmentation strategy and reached up to 4000 annotated images to enhance accuracy. The model was trained from scratch, which means no pre-trained model weights were used, solely annotated GPR data, and still the dice coefficients evaluation metrics reached up to 92%. As aforementioned, this AI-based approach can be transferred and deal with different cases of archaeological architectural remains since the training dataset covers various kinds of anomaly traces (and geometry) related to archaeological features (see case study from Lechaion, Peloponnese in Figure 2). Here in Figure 2a, the output of GPR survey for the depth slice of 100–110 cm and in Figure 2b, the output of automated interpretation of anomalies based on the convolutional neural network, are presented. Comparing the manual interpretation of original output, the outcome of the automated interpretation seems quite promising to be used as a guidance for further detailed archeological interpretation. There is no doubt that the model has to be further tested for various real case GPR time slices and compared with manual interpretation. Although there are still obstacles and limitations that will be discussed further, this attempt seems to help the preliminary visualization of the GPR results (in minutes) and generalize to other tasks and datasets for which the network has not seen before.

Additionally, via transfer learning approach, Manataki et.al. demonstrated the use of deep learning (DL) algorithms through the AlexNet architecture for the automatic interpretation of C-scans [17]. They applied CNN for classification purposes divided into three categories, namely unidentified geophysical anomalies/geological features, potential archaeological features, and noise, mainly in stripe form. After several experimental tests, metrics reached an accuracy of 92%. The classification of noise is essential to get reliable results, and in the next step it may help a lot when generating an annotated dataset for training.

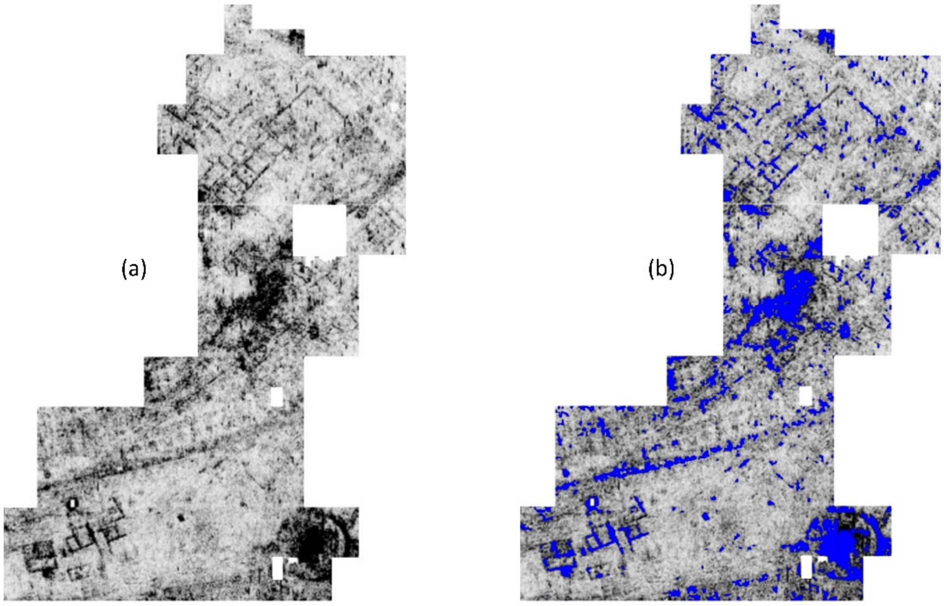

Figure 2. A prediction result by using CNN for extracting the possible archaeological features from the GPR survey (Noggin Plus with 225 MHz antenna) at the coastal settlement of Lechaion, Peloponnese, Greece (the Lechaion Harbor and settlement Land Project): (**a**) processed depth slice (100–110 cm below the current surface) indicating a number of extensive structural remains and (**b**) automated interpretation of possible archaeological features. Despite the fact that an experienced practitioner may be able to recognize many more features and label the archaeological meaning to each one of them, AI results are capable of providing a preliminary visualization in a very short time.

It is obvious from the above that all different types of applications of AI models for object detection, classification, and segmentation tasks seem promising and helpful in understanding and interpreting the GPR data. Once the network is trained with proper hyperparameters and enough annotated datasets, this information can be transferred to be applied in new fieldwork cases without any further effort. Obviously though, the model can be further trained with an increased number of actual data.

5. Discussion

5.1. Limitations and Suggestions

Although we emphasized the advantages of applying AI-based models for GPR data processing and interpretation, there are several limitations to its wider applicability. One of the challenges commonly addressed in the AI community is the scarcity of annotated data in all scientific domains. By far, the most critical part of this approach is training and feeding the network with a sufficient number of reliable data. Enhancing the amount of data through the annotation of original data and training the model from scratch is favored. However, additionally simulated data derived by using GPRSIM and gprMAX can be quite useful to generate more A-scans, B-scans, and based on them, more C-scans. However, simulated datasets can be mainly used to tune the hyperparameters of the network, rather than increasing the number of real case datasets. Considering our experiences with the automated interpretation of C-scans, enhancing the amount of labeled data for training by using data augmentation based on values of shear range, zoom range, flipping, rotation ranges, and cropping is quite effective. However, we should highlight that the quality of the annotated data is as important as its quantity, since as well-known network algorithms learn through these annotated datasets and good representative data, it provides an improved performance. Thus, reliable data annotation carried out by experts in this topic and optimum balanced data augmentation are recommended to reach consistent and accurate results. The proposed annotated data and model for segmentation on time slices [14] and for image classification [17] tasks could be helpful in future studies of AI-based analysis of C-scans. Additionally, the dataset from Verdonck's work [56] and Green's study [16] could be useful for the automated processing of B-scans.

In case of a lack of a sufficient amount of annotated data, alternatively, transfer learning approaches, employing pre-trained models, and using model's weights directly to train solely the last layer with own data, can be helpful depending on the task. A similar alternative way is fine tuning, which lets us retrain the whole stage of the network. This requires a relatively large amount of annotated data compared to the transfer learning approach.

Even though the proper amount of the training set is critical, decisions of network architecture and tuning the hyperparameters, such as kernels, learning rate, epochs, and activation function, are also quite important. To choose the best parameters, several experiments and real case validations have to be done until reaching the acceptable level of accuracy. The practitioners should be careful about reliable generalizations which means how well the concepts learned by a machine learning model apply to specific examples not seen by the model when it was learning. For instance, an underfitting issue, oversimplifying the case and not performing good learning with a given training set, can be encountered if the model is too simple. This can be overcome by increasing the complexity of the model and training the model for a longer epoch to reduce the error. Overcoming the overfitting issue, (the model memorizes all specific details of the training data but fails to generalize), is also compelling. These issues should be controlled in all training steps since the network may produce fake positive values of evaluation metrics, but in actual cases, it does not provide good reliable results.

Comparing a traditional data processing, ML and DL require vastly more computation and high processing power is needed because of the size of the data, number of hidden layers and nodes of the network, and number of connections between each layer. Computers with powerful GPUs, memory, and storage and, alternatively, cloud-based platforms, play essential roles in the development of AI applications, but are still expensive.

When it comes to application, for a wide range of the community, the operation behind the AI systems seems like a "black box". Training a computer system to understand/classify big data and complex tasks sounds complicated and it requires knowledge on programming languages, especially Python, Java, R, C++, JavaScript, etc. However, there are a number of helpful libraries and frameworks that have been developed with various sets of functions and modules that can overcome the issues of coding. Table 1 provides a catalogue of the most commonly used frameworks and documentations related to the application of AI.

Table 1. Useful Frameworks and Libraries for Machine and Deep Learning applications, (web links accessed on 1 May 2022).

Frameworks	***Web Link***
Tensorflow	https://www.tensorflow.org/
Keras	https://keras.io/
Scikit-learn	https://scikit-learn.org/
PyTorch	https://pytorch.org/
Caffe	https://caffe.berkeleyvision.org/
MXnet	https://mxnet.apache.org/
XGboost	https://xgboost.readthedocs.io/
Fastai	https://www.fast.ai/
Microsoft Cognitive Toolkit	https://docs.microsoft.com/en-us/cognitive-toolkit/

5.2. Future Possibilities

Image analysis and classification were among the first areas that manifested the great potential of DL with the rise of CNNs. Whilst through aerial and ground-based remote sensing data, the AI-based algorithms have been generally applied for 2D images, 3D point cloud segmentation and classification through AI models have not been explored sufficiently yet [58,59]. With advances in data acquisition by multichannel GPR systems, which have three-dimensional (3D) visualization capability, the 3D CNNs could be developed and applied for classification or segmentation tasks in the future since analyzing the full 3D GPR data by the naked eye is a challenging and time-consuming process [60–62]. This approach would be helpful for archaeological prospection studies where 3D visualization can provide 3D reconstructions of archaeological features.

AI models can also contribute to missing data recovery, as seen for geophysical data in the case of seismic measurements, which has been demonstrated by Chai [63]. This could be a practical example of GPR data processing and missing data recovery as well.

As has been demonstrated by Manataki [17], AI-based processing could also contribute to noise removal, contributing to signal noise separation and the improvement of the resolution of images.

From a slightly different perspective, artificial intelligence powered semi-autonomous UAVs for building structural analysis and it was involved in all stages of the study spanning from the data acquisition to image processing and crack analysis [64]. This may enable a new potential application for the AI technology in GPR data acquisition, as has been demonstrated by Vasudev [65], who employed it for the calibration of the GPR for specific site properties.

6. Conclusions

As has been highlighted by Verdonck [66], although the geophysical surveys are in relatively high demand in archaeological research, the interpretation of the data and the linkage of the results with the archaeological context is underutilized, possibly due to the fact that the practitioners are mostly geophysicists rather than archaeologists, or missing collaboration between them during archaeological interpretation. From this aspect, an automated analysis could act as a preliminary guidance for practitioners who may lack sufficient experience on the interpretation of GPR data.

AI-based automated analysis starts from pixel scale and ends with suggestions of the meaningful features of interest. During detection, classification, or segmentation, the model works starting from edges (low-level features) using several hidden nodes and layers and finalizes its recognition of objects (high-level features) through the correlation of the whole anomalies or hyperbolas to their geometry (e.g., circular anomalies, linear anomalies, stratigraphic layers, etc.). Thus, when it comes to reliability, statistical or AI-based interpretation is not so far from human intelligence since as humans we are trying to follow these similar geometries and link them with archaeological features. In the end, however, the powerful prospects of AI technology can be thought of as a supportive tool for both geophysicists and archaeologists, being able to adapt to both the geophysical methods applied and the goals of the archaeological research, but without substituting the human agent, which in the end will be the one to deliver and decide about the final interpretation of the results.

Whether biological or digital, intelligence is a matter of information and computation. Thus, to improve the automated/semi-automated analysis using artificial intelligence, more progress needs to be made by enhancing the annotated dataset, including various data types, with different resolutions and characteristics, and by developing our knowledge in computation.

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