AI-based approaches in Cultural Heritage

Investigating archaeological landscapes in Scandinavian forestland

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1. Computational methods in archaeology

There is a long tradition of using computers and computational methods in archaeology. In 2023, the Computer and Quantitative methods in Archaeology Conference (CAA) turned 50, with the first meeting originally hosted in Birmingham back in 1973 (Djindjian et al. 2015). As a spatial discipline, archaeology relies on quantitative and statistical methods to investigate and detect patterns connectable to the presence of past humans in a given landscape. There is a constant need of measuring spatial distributions of artifacts, monuments and settlements in a multi-scalar and multi-temporal perspective. Quantification has rapidly become a standard procedure for generating deeper insights into the human past and for this scope the introduction of computational methods marked a tremendous advance in archaeological practice. Geographical Information Systems (GIS) are considered one of the first products to be introduced in archaeology for the purpose of managing spatial datasets related to archaeological excavations, field surveys or landscape investigations. Most of GIS-based analysis was aimed at the detection of new archaeological material in areas not previously investigated, but soon, the importance of these computational methods for generating more complex, explanatory models capable of providing archaeologists with interpretative tools for generating a better understanding of past human activities, became clear. In this context, predictive modelling was introduced as a methodological framework for forecasting archaeological presence in specific portions of landscapes (Kohler/Parker 1986; Wescott/Brandon 2000; Verhagen 2007). It comes as no surprise that the use of GIS among different institutions both in the public and private sector became increasingly popular with many projects starting with the purpose of managing cultural heritage in a more effective way. The very idea of developing a statistical/inferential method to detect, in a semi-automatic way, significant numbers of archaeological material did represent an important game changer in the discipline, enabling archaeologists to re-interpret past landscapes in a totally different manner. Beside predictive modelling, among the most popular GIS applications in landscape archaeology it is worth to mention the use of Least-Cost-Path (LCP) analysis for examining best-suited routes in a landscape that is likely to have been crossed by people in the past based on the analysis of factors that could have either facilitated or prevented human movement, such as slope, natural barriers and distance to be crossed (Herzog 2014). Another very widespread application is viewshed analysis, enabling archaeologists to determine locations in the landscape that were more visually exposed or secluded while considering a number of observation points used to perform the calculation (Wheatley 1995). More recently, thanks to the dramatic advances in hardware and software performance, more sophisticated and efficient tools have been introduced in support of archaeological research. 3D-based technology has marked a significant advance in the area of site documentation and museum communication and dissemination (Barcelo et al. 2000). Apart from traditional laser-scanning techniques, there are now image-based modelling techniques, enabling specialists to rely on relatively low-cost solutions to acquire and document archaeological features and monuments in 3D (Dell'Unto 2014). On a similar way, the advances in Unmanned Aircraft System (UAS) technology led to the definition of innovative pipelines for the data capture and the documentation of large portions of an archaeological landscape, making it possible to investigate archaeological features in a multi-scalar way, increasing the level of spatial definition to a detail that is unparalleled by any of the existing satellite sensors commonly used in landscape archaeology (Adamopoulos/Rinaudo 2020). Among the most notable innovations that impacted the discipline in the last ten years, it is important to mention Artificial Intelligence (AI) and its contributions to the analysis of 'big data' that is now produced on a daily basis as a result of the introduction of more advanced sensing technology and sophisticated methods of data collection. Before examining in detail the impact AI had and is having on archaeological data analysis, the next sections will briefly introduce two technologies that are particularly relevant for the setup of the described work pipeline, namely Remote Sensing and LiDAR, which are related to the techniques and the sensors specifically employed for data acquisition.

2. Remote sensing

Numerous studies have extensively documented the use of satellite remote sensing in archaeology (Campana/Forte 2006; Parcak 2009; Lasaponara/Masini 2012). These studies have specifically examined a wide range of geographical regions and time periods, providing valuable insights into the application of this technology in diverse contexts. Satellite remote sensing relies on sensors that can capture and analyze radiating energy across various wavelengths in the electromagnetic spectrum. These sensors can convert this energy into new information regarding the physical and chemical attributes of the specific area on the Earth's surface that is being examined. Archaeological use of satellite multispectral images can be traced back to the 1970s when the initial satellite missions were launched by NASA and the Landsat program was initiated (Giardino 2012). These early endeavours marked the beginning of employing satellite multispectral images for archaeological purposes. Right from the start, it became evident that this form of remote sensing would have a profound impact on archaeology. It provided specialists with the ability to survey expansive areas of land, enabling them to identify numerous ground anomalies. During the initial stages of using multispectral images, the spatial resolution was relatively low. As a result, the primary focus at that time was on identifying paleo-environmental elements and small-scale field systems (Rainey et al. 1976). This emphasis allowed archaeologists to develop a more comprehensive understanding of how landscapes were utilized and exploited during prehistoric and historical periods. By studying these features, researchers could gain valuable insights into the human interactions and activities that shaped the landscape in the past. Satellite remote sensing also plays a crucial role when examining landscapes that can be described as challenging from a logistical standpoint. Within the field of archaeology, there exist numerous geographical regions that have restricted accessibility due to environmental obstacles or administrative/political circumstances. An illustrative example of this is the exploration and identification of Mayan cities in Central America, where the dense and expansive rainforest poses a significant challenge to traditional on-site research methods (Saturno et al. 2007). An additional issue arises in conflict and war zones, where conducting archaeological investigations on the ground becomes either impossible or, if attempted, can only take place after heritage sites have suffered damage and looting. In this respect, Campana et al. (2022) showcased how remote sensing played a vital role in assessing the extent of war damages inflicted on the ancient city of Niniveh following the occupation and destructive actions carried out by ISIS. On a similar note, in the context of the EAMENA project, which focuses on safeguarding endangered heritage sites, a new open-access database was established. The main objective of this initiative was to provide archaeologists and cultural heritage experts with access to satellite imagery from regions in the Middle East and North Africa that have been impacted by war and looting (Bewley et al. 2016). This database allows users to visualize and analyze the imagery for research and preservation purposes. In summary, over the past two decades, satellite multispectral images have had a significant influence on landscape archaeology. There is now a widespread agreement on the importance of utilizing such datasets for investigating archaeological sites from various scales and temporal perspectives. The introduction of high-resolution sensors capable of producing satellite images with a spatial resolution of up to 30 cm has been a true game changer in this field. This significant advancement in landscape archaeology has permitted archaeologists to utilize multispectral information when investigating individual monuments or sites in a manner that was unimaginable during the early stages of satellite remote sensing. Similarly to geophysical prospecting techniques, it is crucial to emphasize the importance of conducting ground-truthing when interpreting satellite imagery. This process involves verifying the actual presence of archaeological material on the ground, which serves to validate the performance and accuracy of the sensor used in the investigation.

3. LiDAR

LiDAR, one of the latest technologies introduced in landscape archaeology, has undeniably had a significant impact on site detection, particularly in areas characterized by dense forest coverage. The acronym LiDAR stands for Light Detection and Ranging, which involves the use of a sensor that emits a laser beam towards a target surface. The receiver measures the time it takes for the laser beam to return, enabling the calculation of the distance between the sensor and the target. This data allows for the derivation of precise 3D coordinate values for each measured point. Through the application of specific filtering algorithms, the resulting point cloud from LiDAR data can be classified based on their positions on the land surface. This classification enables the differentiation of points belonging to the ground surface from those associated with vegetation elements. The ability of LiDAR to penetrate dense vegetation and detect ground anomalies makes it an ideal solution for investigating areas with extensive vegetation cover. This capability surpasses the limitations of other sources, such as satellite multispectral images, which may not be able to detect such ground-level details. Indeed, LiDAR has marked a significant transformation in various research scenarios, ranging from the tropical landscapes of Central America to the forests of Northern Europe. A notable example is the systematic investigation of the Mayan site of Caracol in Belize, where the utilization of airborne LiDAR enabled archaeologists to detect and map extensive sections of an ancient city, including structures, causeways, and agricultural terraces, unveiling the complex nature of the site (Chase et al. 2011). Similarly, in a completely different context, this technology has enabled archaeologists to reexamine the archaeological landscape surrounding Stonehenge in Southern England. Through LiDAR, they were able to map a substantial number of features, such as field systems, burial mounds, and ancient river courses, in a manner that surpassed the limitations of solely analyzing aerial photographs (Bewley/Crutchley/Shell 2005). While the conventional method for data acquisition involves the use of aircrafts, such as small planes or helicopters, in the last few years a new generation of drones equipped with LiDAR sensors has emerged. This development has resulted in a significant enhancement in the point density of the acquired surface data and has made lower-cost solutions available for individual data acquisitions. Traditionally, data collection was limited to professional commissioned flights conducted with aircrafts, but the advent of LiDAR-equipped drones has revolutionized this process (Casana et al. 2021). Regarding data output, the point cloud obtained from LiDAR acquisition is commonly filtered to extract points classified as 'terrain'. These filtered points are then utilized to generate a Digital Terrain Model (DTM). The DTM is typically represented as a raster grid, where each grid cell corresponds to an elevation value, providing a detailed representation of the terrain. DTMs can be further processed and converted into thematic maps, where ground anomalies can be emphasized using specialized algorithms. One notable application, as further described in the next sessions, is the integration of LiDAR-derived raster images with Artificial Intelligence (AI) techniques. By training AI models on known features within a dataset, this approach enables the semi-automatic extraction of similar features from the larger landscape. Archaeologists can benefit from this method as it facilitates the faster and more efficient detection of numerous archaeological features, aiding in their research efforts (Küçükdemirci et al. 2022).

4. Artificial Intelligence and archaeology

Artificial Intelligence (AI) has emerged as a powerful tool in archaeology, revolutionizing various aspects of research and analysis. AI techniques, such as machine and deep learning for computer vision tasks, are being applied to archaeological data to assist in tasks such as feature detection, classification, data interpretation, and predictive modelling. One of the significant contributions of AI in archaeology is in the field of image analysis. AI algorithms can be trained to recognize and identify archaeological features, artifacts and patterns in large datasets of images, including satellite imagery, aerial photographs and ground-based photographs. This enables archaeologists to automate the process of feature identification, saving time and effort in data analysis. AI also plays a crucial role in data processing and analysis. By utilizing machine and deep learning algorithms, large archaeological datasets can be analyzed to identify patterns, correlations and trends that may not be easily discernible by human researchers. This allows for more comprehensive and efficient data analysis, leading to new insights and interpretations.

Artificial Intelligence (AI) has been introduced in the archaeological discourse as early as the 1980s, with the purpose of supporting expert systems for the definition of heuristic frameworks in the analysis of the archaeological record based on a joint effort involving domain specialists (archaeologists), software engineers and computer scientists (Wilcock 1985).

Baker (1987) instead seems to use the definition of 'expert systems' synonymously with 'AI', pointing out the problematic nature of these computational tools and its applicability in the archaeological domain. Patel and Stutt (1989) identify different application areas for AI/expert system technology, highlighting the urgency for archaeologists to get confronted with significant amounts of data. Archaeological reasoning being an important field in the application of AI, the authors introduce KIVA, a programming language capable of simulating reasoning in connection with archaeological data, providing different interpretations based on the combination of data and context conditions where artifacts and single findings have been collected.

More recently, the use of AI-based applications had a dramatic increase in archaeological practice, becoming a de-facto standard in many sub-fields of the discipline. As Mantovan and Nanni (2020) show, the research areas include (but are not limited to) musealization, artifact and ecofact analysis, landscape interpretation, ancient building monitoring and underwater archaeology. Image recognition has been employed for automatic detection and comparison of categories of pictures belonging to different museum collections from all over the world with the aim to describe objects from the same cultural/historical context in order to facilitate findability and accessibility of material that would be otherwise difficult to retrieve (Wilbrink et al. 2023). Similarly, AI-based approaches including machine learning and deep learning have been used to develop supportive tools for archaeologists in the field to allow a quick and efficient recognition of ancient pottery classes based on the examination of images taken from sherds and other fragmentary material that is typically found in the archaeological stratigraphy (Gualandi/Gattiglia/Anichini 2021; Anichini et al. 2021). Concerning the study and the analysis of ancient buildings, significant results have been obtained in the analysis of the Forbidden City in China by introducing advanced point cloud classification tools thanks to the introduction of more refined algorithms such as PointNet++ which enabled users to improve the accuracy of the 3D point segmentation, reducing the number of data sample to be collected (Hu et al. 2022). Still, it is in archaeological remote sensing that most of current AI-based approaches are employed with image classification and object detection being the main functionalities applicable to investigate an archaeological landscape by examining the presence of ancient features and any transformation occurring in the natural environment. Karamitrou et al. (2022) recently explored the possibility of using Google Earth's freely available satellite high-resolution images to test deep learning networks for the automatic detection of archaeological features in very diverse geographical areas distributed worldwide. The application of AI in the analysis of satellite multispectral images has proven significant results also on relatively low spatial resolution datasets such as Corona, enabling specialists to refine the quality of data interpretation due to an improved performance of the classification tools, with a lower number of false positives obtained (Soroush et al. 2020). Orengo and Garcia-Molsosa (2019) further improved the capabilities of small finds detection in UAS-derived images by introducing a machine learning approach that allows archaeologists to easily spot small pottery shards scattered over a field surface and to obtain a better performance than the one obtained by on-site visual inspection. In underwater archaeology, machine learning approaches have been recently explored for detecting shipwrecks and other categories of submerged sites based on the processing of datasets of images derived from Autonomous Underwater Vehicles (AUVs) acquisition, in which data augmentation was applied in order to increase the number of samples for the training dataset, due to the relative scarcity of submerged sites available (Nayak et al. 2021).

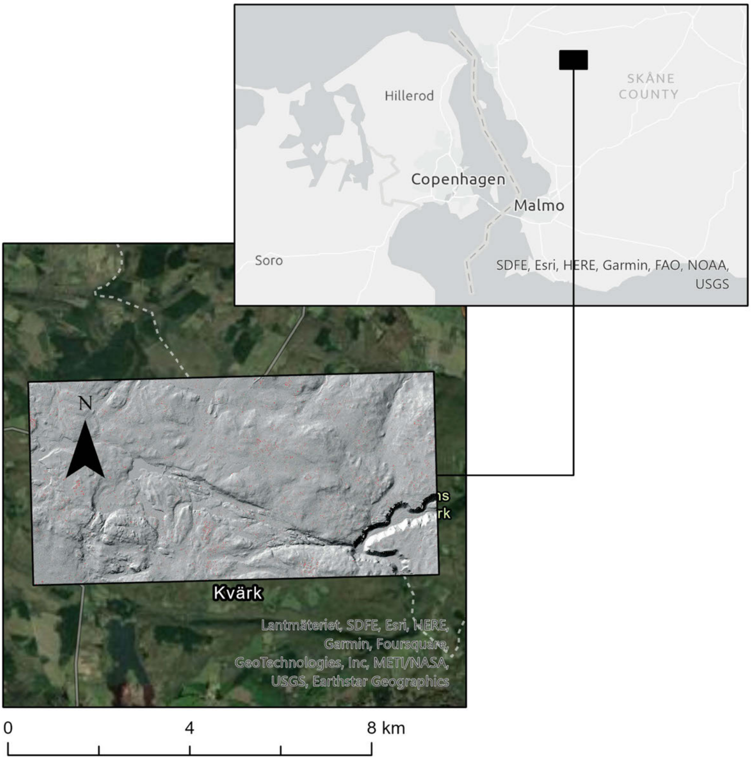
Another important field of application for AI is geophysical prospections, a very effective tool for the detection of buried structures and to collect subsoil information. A typical dataset produced during a Ground Penetrating Radar (GPR) survey consists of a very large number of images where it is possible to extract in an automatic way information that is useful for the archaeological interpretation. In this sense, CNN-based approaches have proven to be very effective for the automated interpretation of these datasets (Küçükdemirci/Sarris 2020; Küçükdemirci/Sarris 2022).

5. Investigating archaeological features in a forestland

The combination of non-destructive methods presents a vast range of case studies that can be explored and examined. In the context of Scandinavia and specifically Sweden, the utilization of AI-based techniques plays a crucial role in identifying and studying archaeological features within the landscape. Particularly in Sweden, the use of image recognition methods holds great potential in the analysis of LiDAR datasets. This is because LiDAR enables the observation of archaeological features on the ground surface, even in areas covered by vegetation where traditional satellite or aerial multispectral imagery fails to provide adequate information. By employing AI-driven approaches, the analysis of LiDAR data can yield highly effective results in the detection and analysis of archaeological traces in these challenging environments. So far, only a few studies have tried to investigate archaeological traces hidden in the woodland, consisting of several categories of sites including burial areas, settlements and productive areas such as kilns or mints. Recently, Lindholm et al. (2021) demonstrated the pivotal role of boreal forest land by providing its ancient inhabitants with important sources of the economy of Scandinavian regions from the Roman Iron Age (1st to 4th century CE) to the later Middle Ages (1050 to 1520 CE). Such research now allows archaeologists to challenge the current view of Scandinavian forest land as a marginal space and to investigate more thoroughly vast portions of landscape where traditional forms of survey have long been discarded due to a significant imbalance between benefits and costs. To fill this gap, researchers at Lund University have recently tried to introduce innovative approaches to the study of forestland regions by relying on integrated methods including AI, ML, LiDAR and GIS. The main purpose for this project is to understand diachronic transformations that occurred in the landscape of the Scania region (Southern Sweden), witnessing the change in destination from agricultural fields into woodland areas. In this context, there is a significant variety of archaeological features that lie beneath the dense canopy coverage and that consists of artifacts connected to the ancient agricultural exploitation of the landscape. These consist of stone walls, boundaries, clearance cairns, terraces and Celtic fields and all of these features that can only be detected by examining the LiDAR-derived imagery where the ground-related information is visualized in the form of a Digital Terrain Model (DTM). Indeed, differences in the elevation values observed in DTMs are important markers of the presence of buried structures or features whose appearance is marked by patterns of discontinuity in the topography of the area under scrutiny. As for this project, the main focus was the analysis of the so-called clearance cairns, human-made piles of stones that were created in ancient times as a result of clearing space for agriculture in selected portions of land. This category of finds is very widespread all over Scandinavia and represents one of the most common archaeological features identifiable in Swedish forests. Their shape is quite regular (2–6 meters in diameter and 0,2–0,5 meters high) and is characterised by a moss or grass turf coverage (Lagerås/Bartholin 2003).

Figure 1: Clearance cairn located in the study area of Söderhånsen National Park. Typically, prehistoric or medieval ones can be recognized either by its diameter (between 2 and 6 meters), or the reduced size of the stones and the presence of moss partially covering it. Image courtesy of the author.

Figure 2: Case study area in the national park of Söderhånsen, central Scania (Southern Sweden). Red-marked features indicate areas of possible clearance cairns as a result of CNN data processing. Image courtesy of the author.



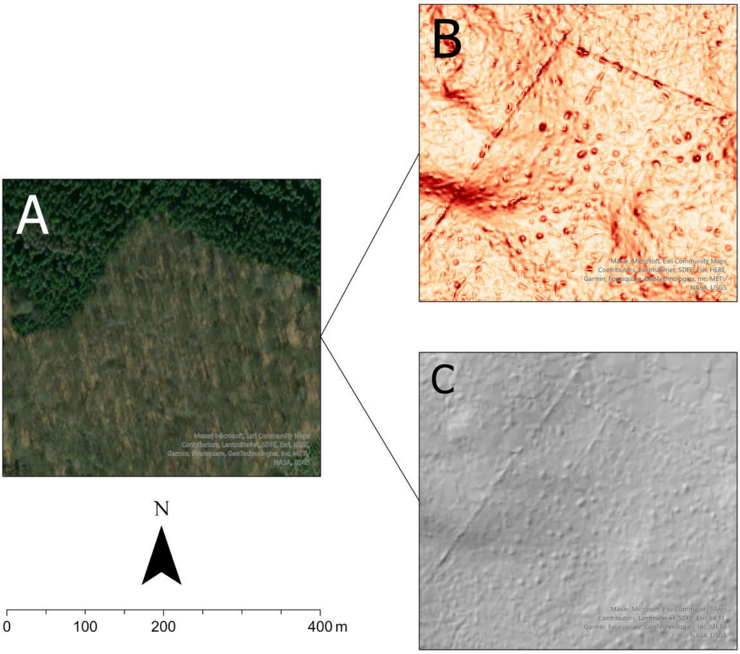
Concerning their chronology, the oldest clearance cairns date back to the Bronze Age (9th to 6th centuries BCE) and their presence indicates an area that used to be agricultural land and whose boundaries were often defined by straight lines made of clearance stones too. Identifying those features can mark an important advance in the study of forestland and provide a significant contribution to the management of cultural heritage and forest resources along with a powerful instrument for planning new development. So far, only a relatively small number of clearance cairns has been identified and reported on the Swedish National Heritage Board (RAÄ, https://app.raa.se/open/fornsok/), with most of them still to be identified.

In this respect, advances in remote sensing techniques, including the use of LiDAR-derived sources combined with AI and GIS can now dramatically contribute to a more effective identification of these archaeological traces. To prove this working hypothesis, a test case area was selected in the Söderånsen National park, located in central Scania, where a very vast portion of land is now covered by protected forest land (fig. 2). In this area, a number of clearance cairns was previously identified and reported in the RAÄ registry. Still, by examining a LiDAR-derived DTM it is possible to observe an even larger number of ground anomalies in areas not previously documented and that can be possibly interpreted as ancient clearance cairns. Having the geometrical reference provided by the known previously identified clearance cairns allowed to obtain a training and a comparison dataset to be used for testing the prediction of the AI network.

6. Methodology

As previously stated, the workflow for the identification, classification and interpretation of clearance cairns in the study areas is based on the integration of different acquiring techniques and data processing methods. At the core of the system, a spatial geodatabase was set up to collect, store and process all the datasets related to the landscape of Söderåsen National Park. LiDAR-derived raster DTMs were chosen as a primary source for performing the AI-based spatial analysis. This source is freely made available for researchers through the Swedish Cadastral Agency web portal (Lantmäteriet, https://www.lantmateriet.se) and comes in the form of a vector 3D point cloud with an average spatial density of 0,75 points per square meter. These data are then processed and converted into raster DTMs with a spatial resolution of 0,5. These raster images are the result of GIS-based filtering operations that allow users to remove any vegetation point and to obtain a 'clean' model of the terrain made by ground surface points. These points are eventually used to derive a Triangulated Irregular Network (TIN) model that will be in turn transformed into a raster DTM by applying specific interpolating algorithms. As a final step of this process, a slope and a hillshade map are generated in order to enhance the visibility of the archaeological features that need to be spotted (fig. 3).

Figure 3: Portion of the study area covered by woodland, as appears in a RGB aerial image (A). From the LiDAR-derived DTM, slope (B) and hillshade (C) algorithms were applied to enhance the visibility of clearance cairns (that show up in a pretty circular shape and are evenly distributed throughout the selected areas). Image courtesy of the author.



More GIS-based operations are performed to extract tiles that must have included known clearance cairns in order to create a valid training dataset to feed the network. Typical metadata configuration for each tile was characterized by an uncompressed .tiff file with a depth of 8 bit.

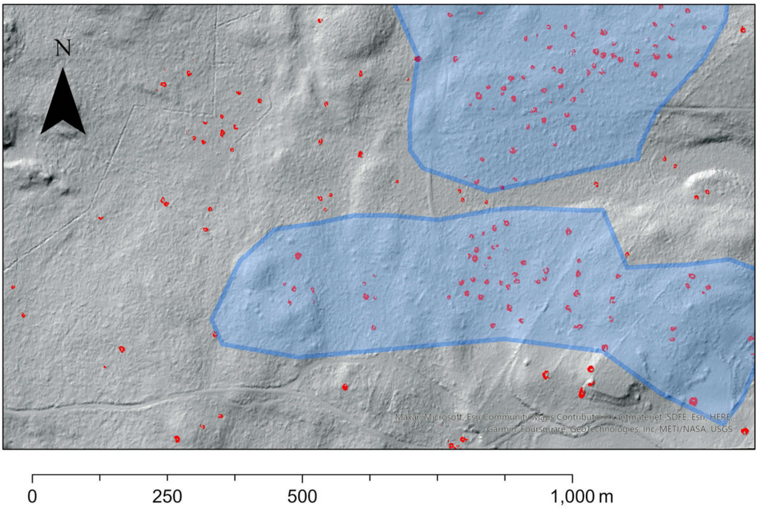
As thoroughly described by Küçükdemirci et al. (2022), the present research utilizes a U-net, a U-shaped convolutional neural network (CNN) in order to identify, detect and segment the data and extract the mentioned archaeological characteristics of clearance cairns from the LiDAR dataset. This modified CNN architecture goes beyond conventional approaches by enabling pixel-level localization, classification as well as learning from limited training samples, which offers significant advantages.

The initial findings of this study are presented based on a limited amount of labeled data. At the beginning, 290 images containing cairns, each measuring 64x64 pixels, were labeled. Subsequently, the training dataset was expanded to include a total of 1054 images through the application of data augmentation techniques such as varying shear range, zoom range, flipping, and rotation ranges. However, the training metrics did not yield satisfactory results, possibly due to the extensive distortion in the training image datasets, causing them to deviate significantly from their original forms. Consequently, a decision was made to enhance the data augmentation solely by incorporating vertical and horizontal flipping. This led to a dataset consisting of 627 images, which were randomly divided into a training set of 501 images and a validation set of 126 images (ibid.).

7. Preliminary results

As a result of a preliminary investigation of the selected area (fig. 1), measuring 9984x4992 meters, the following findings are presented. As figure 4 shows, there is an apparent matching between areas predicted as likely to have clearance cairns with those ones reported in the Swedish national heritage registry where actually these features were located. The red pixels on the image represent ground anomalies, potentially indicating clearance cairns, which were detected using the proposed CNN model. Despite using a limited amount of labeled training data during this phase of the study, the outcomes are promising and showcase the model's effectiveness in identifying previously unknown or undocumented archaeological features, as evidenced in this portion of the sample image.

Figure 4: A portion of Söderhånsen National Park, where the areas previously known and reported on the Swedish National Heritage Board website as 'fossil fields' are marked in blue. As a result of the CNN data processing, several ground anomalies are detected in the hillshade map used to feed the network (red pixels). Image courtesy of the author.

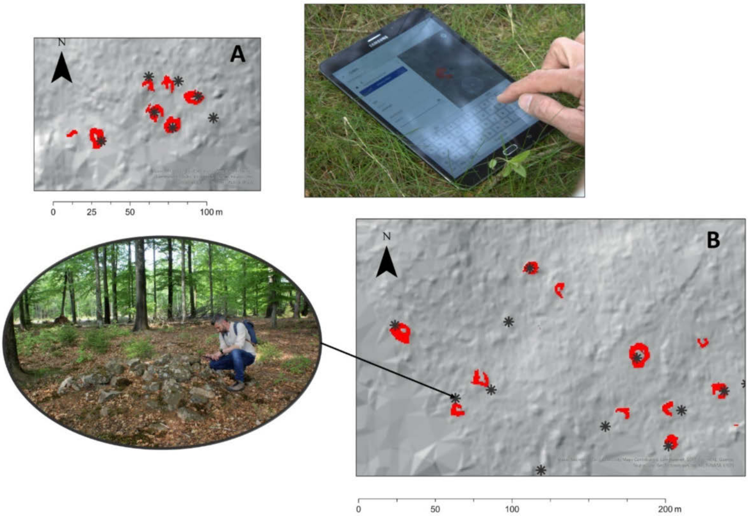


8. Ground truthing

The external validation survey was conducted in a specific area within the network's predicted region, within the Söderånsen National Park, which revealed the presence of numerous anomalies both inside and outside the boundaries defined by the RAÄ surveyed areas. Through field surveying and by comparing the GPS position of the observed clearance cairns with the location of the red-marked ground anomalies detected by the network, the results indicate an approximate average 74 percent success rate in accurately predicting clearance cairns (fig. 5). This percentage derives from the examination of 3 separate cluster areas with a concentration of ground anomalies with a matching ratio of 7/9, 8/13, and 10/12 good predictions corresponding to 77, 61, and 83 percent of relative success rate.

However, it has become evident that the terrain morphology and vegetation type introduced background noise into the quality of the LiDAR data. The presence of bedrock outcrops in the landscape created uneven areas, which can negatively impact the visual interpretation of the data and the model's effectiveness in detecting cairns, potentially resulting in false positive identifications. From a methodological perspective, another limitation in the field of data collection is the weakness of the GPS signal, due to the tree canopy coverage, which makes it difficult to properly use any differential or single-antenna GPS, thereby reducing the instrument accuracy to a few meters.

Figure 5: Ground truthing was performed to validate the model prediction on new external, independent data collected in the field (asterisk points). The selected areas were not previously reported as fossil fields, probably due to a lack of surveying coverage. Interestingly, as figures A and B show, there is a good matching (around 74 percent) between clearance cairns observations and the model prediction characterized by red pixels. Image courtesy of the author.



9. Conclusion

Despite being at a very preliminary stage, the project conducted so far provided very encouraging results in terms of prediction accuracy. Based on the field surveying assessment, most of the predicted ground anomalies have been identified on the ground and interpreted as actual clearance cairns. This pilot project marks a significant advance in the use of AI-based approaches for the study of archaeological landscapes and the identification of spatial patterns related to past land exploitation and human activity. Nevertheless, from an interpretative perspective, it is important to outline the need for more solid and accurate information to be used as a training dataset. Taking clearance cairns for instance, the features, as they appear in DTM-derived slope or hillshade maps, can be easily misinterpreted, if not misexamined, in relation to the surrounding context.

While our primary focus was on clearance cairns, it is apparent that this approach holds promise for providing fresh insights into the examination of complex agricultural systems from the past. It also offers a means to gain a deeper understanding of various types of farming landscapes in Scandinavia. In this sense, this contribution has sought to demonstrate the feasibility of utilizing a tool to semi-automatically detect archaeological features in challenging and peripheral areas where traditional survey methods are impractical.

As for the future, we are developing an alternative network for multiclass segmentation. This network will employ annotated data associated with different ground anomalies linked to agricultural activities, such as linear boundary walls and Celtic fields. Due to the combination of more features with different geometries, we believe this new approach can provide more accurate information about the presence of areas of past agricultural activity, reducing the risk of misinterpretation. Nonetheless, to construct an effective model that can assist archaeologists, heritage specialists and developers in addressing the challenge of archaeological predictability and expanding our knowledge of landscape transformations, we need to incorporate even more parameters. These parameters include geology, geomorphology, hydrological conditions and historical maps. Adopting a multi-scalar and multi-temporal perspective will enable us to comprehend human interactions with the environment and landscape.

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