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What Should We Do With These? Challenges related to (semi-)automatically detected sites and features. A note

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Recent advances in machine learning and computer vision techniques have brought (semi-)automatic feature detection within reach of an increasing number of archaeologists and archaeological institutions, including those in Finland. These techniques improve our ability to detect and gather information on archaeological cultural heritage over vast areas in a highly efficient manner. However, the widespread adoption of such methods can also pose significant challenges for archaeological cultural heritage management, especially in relation to certain types of near-ubiquitous archaeological remains from the 17th-20th centuries.

In general, machine learning based methods are especially well suited for detecting features that have relatively uniform characteristics, are present in sufficiently high numbers, and are easily discernible in remote-sensing datasets. In Finland, most archaeological features that meet these criteria are relatively recent features, such as tar and charcoal kilns from the 17th-20th centuries or remains of World War I and II era defensive structures. Although there are some exceptions to this rule, such as prehistoric pitfall trap systems, the archaeological features selected by the use of (semi-)automatic detections is heavily skewed towards only a handful of relatively recent feature types. While this is not necessarily a problem *per se*, it poses a series of questions for the cultural heritage management sector, such as:

- How to manage extremely large numbers of relatively standardised sites and features? Should everything be protected? If not, which features should be selected for protection?
- How to make most efficient use of the data from automatic feature detection?
- How to verify automatically detected features? Is a GIS-based assessment enough? When is ground truthing required?
- How to ensure that the (semi-)automatically detected sites and features do not drain resources or divert attention from other kinds of archaeological heritage?

In Finland, these questions have sparked active discussion in response to the results from the LIDARK-project (2021-2022) which focused on automatic detection of archaeological features, especially within the context of ongoing efforts to modernise legislation on the management of archaeological cultural heritage. This article seeks to summarise and reflect on some of these perspectives presented in the Finnish discussion.

1. Discussion

Recent advances in deep learning techniques and improved availability of high-resolution aerial laser scanning datasets have brought semi-automatic detection of archaeological features within reach of an increasing number of research groups and institutions (see e.g. Anttiroiko *et al*. 2023; Bonhage *et al*. 2021; Davis and Lundin 2021; Suh *et al*. 2021; Snitker *et al.* 2022; Trier *et al.* 2021; Verschoof-van der Vaart and Lambers 2019). Such techniques make it possible to detect and extract information about very large numbers of archaeologically relevant features over potentially vast areas in a highly efficient manner and, hence, are likely to have a significant positive impact on the amount and quality of data available to heritage management institutions. However, these techniques also have some limitations and making use of such data in a heritage management context may prove complicated and challenging owing to a lack of guidelines and potential impacts on heritage management workloads and processes.

This article seeks to discuss such challenges based on Finnish responses to preliminary feature detection results of the LIDARK-project (see Anttiroiko *et al*. 2023). The workflow developed in the LIDARK-project is based on using a deep learning model to detect archaeologically relevant features from airborne laser scanning (ALS) data. The ALS dataset provided by the National Land Survey of Finland has an average point density of 5 points per square metre and current coverage of approximately 165,000 square kilometres. Most of the work was focused on archaeological features that are very common and relatively easy to identify in ALS data, such as tar kilns, charcoal kilns, and pitfall trap systems. More than 30,000 archaeological features were detected during the project, most of which belong to previously unknown archaeological sites. To put this number in perspective, there are currently about 61,000 archaeological sites in the Finnish Heritage Agency's database.

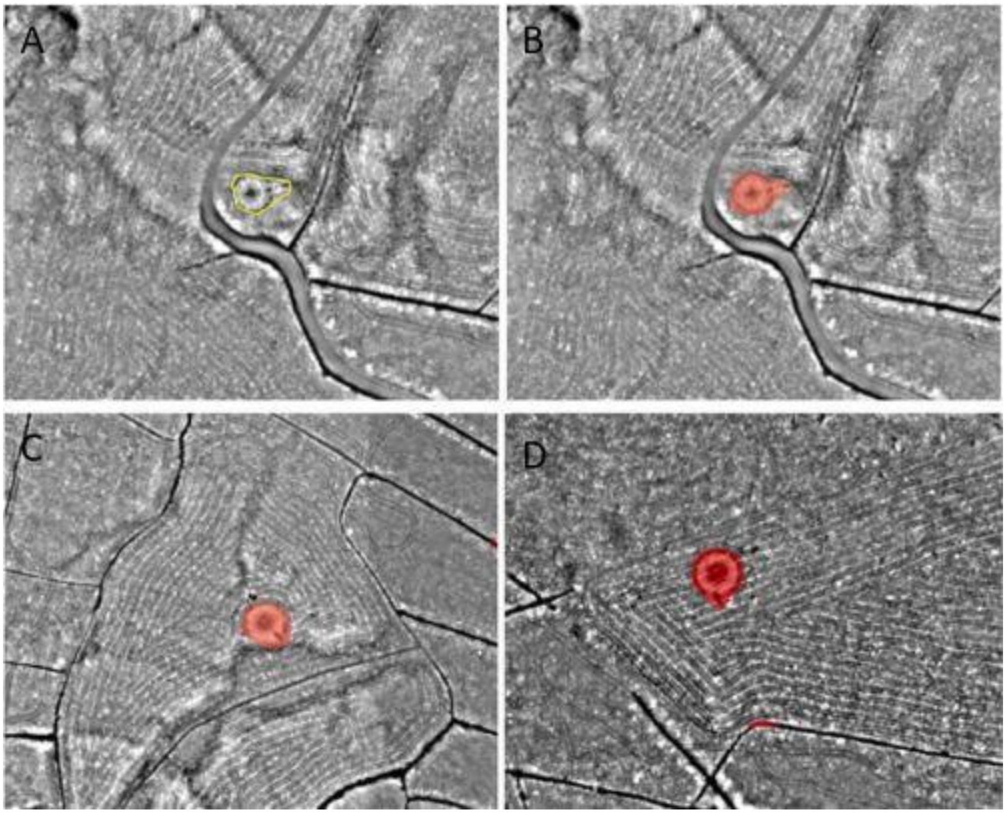

Figure 1: Examples of semi-automatically detected tar kilns and labels used for training the deep learning model. The yellow outline (A) shows a manually created label. Areas highlighted in red (B, C & D) indicate tar kilns predicted by the deep learning model. ALS visualisations are based on ALS 5p data from the National Land Survey of Finland 2020

As semi-automatic feature detection can clearly be highly effective, it is important that heritage management institutions can make use of and effectively act upon such information. In the context of Finnish legislation, archaeological sites and features that meet the criteria are automatically protected by law from the moment they are identified as such. However, under existing guidelines, it is not clear whether automatically detected sites and features could or should be considered protected as a matter of course, unless their existence can be verified through observations made through archaeological fieldwork or other means. Efforts to find a workable solution to this issue are complicated by potential practical and legal ramifications. For example, ground truthing all detectable tar and charcoal kilns in Finland would take at least 50 years for a single archaeologist, which would be impossible to accomplish within a reasonable timeframe. On the other hand, using and evaluating semi-automatic feature detection data in heritage management contexts requires specialist GIS and remote sensing-related skills and knowledge, which may not be currently available to all institutions. Therefore, there is an urgent need for revised guidelines and training materials to help heritage management institutions make efficient use of feature detection data.

Large numbers of semi-automatically detected features may also cause anxiety about increased workloads for heritage management institutions. However, at the moment, these impacts are poorly understood, as experience of actually using feature detection data in routine heritage management tasks is still fairly limited. In Finland, semi-automatic feature detection data would probably have the greatest impact on forestry-related heritage management tasks, as these often focus on areas where archaeological surveys are not available and rarely involve commissioning new surveys. On the other hand, most planning and land-use related processes that typically involve commissioning archaeological surveys would likely remain largely unaffected, because most of such features would be detected regardless. In any case it has been recognised that keeping the heritage management workload at sustainable levels may require making the affected processes more efficient, possibly through increased use of automation, but also prioritisation of different heritage management tasks.

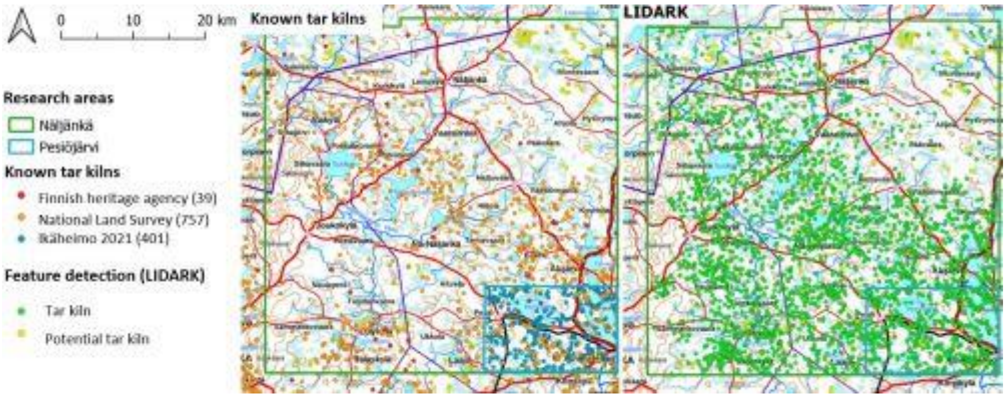

Figure 2: Impact of semi-automated feature detection on the number of known tar kilns in one of the research areas studied in the LIDARK-project. Data on previously known tar kilns was provided by the Finnish Heritage Agency, National Land Survey of Finland, and a desk-based survey by Janne Ikäheimo that focused on a smaller study area (Ikäheimo 2021)

Semi-automatically detected features have also been debated in the context of a new law on archaeological heritage, which is currently being prepared. Most attention has focused on the potentially large number of relatively recent features, such as tar and charcoal kilns, which has been perceived as problematic because of the potential implications for heritage management workload and the position of landowners. It appears likely that the number of tar and charcoal kilns that would be automatically protected will be limited by using an earlier *terminus ante quem* cut-off year of 1721 for automatic protection, compared to 1860 for most other features.

While semi-automatic feature detection may present heritage management institutions with tough decisions, it should be stressed that the overall impact is likely to be overwhelmingly positive. The vast amounts of data produced with the help of deep learning techniques allows heritage management institutions to improve their datasets, develop more efficient processes, and make informed decisions when responding to the eventual challenges. However, reaping those benefits also requires heritage management institutions to not only react but actively engage in using, developing, and creating guidelines for the use of semi-automated feature detection techniques in archaeology.

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