Urban Tree Detection in Historical Aerial Imagery of Sweden

A Test of Automated Detection With Open-Source Deep Learning Models

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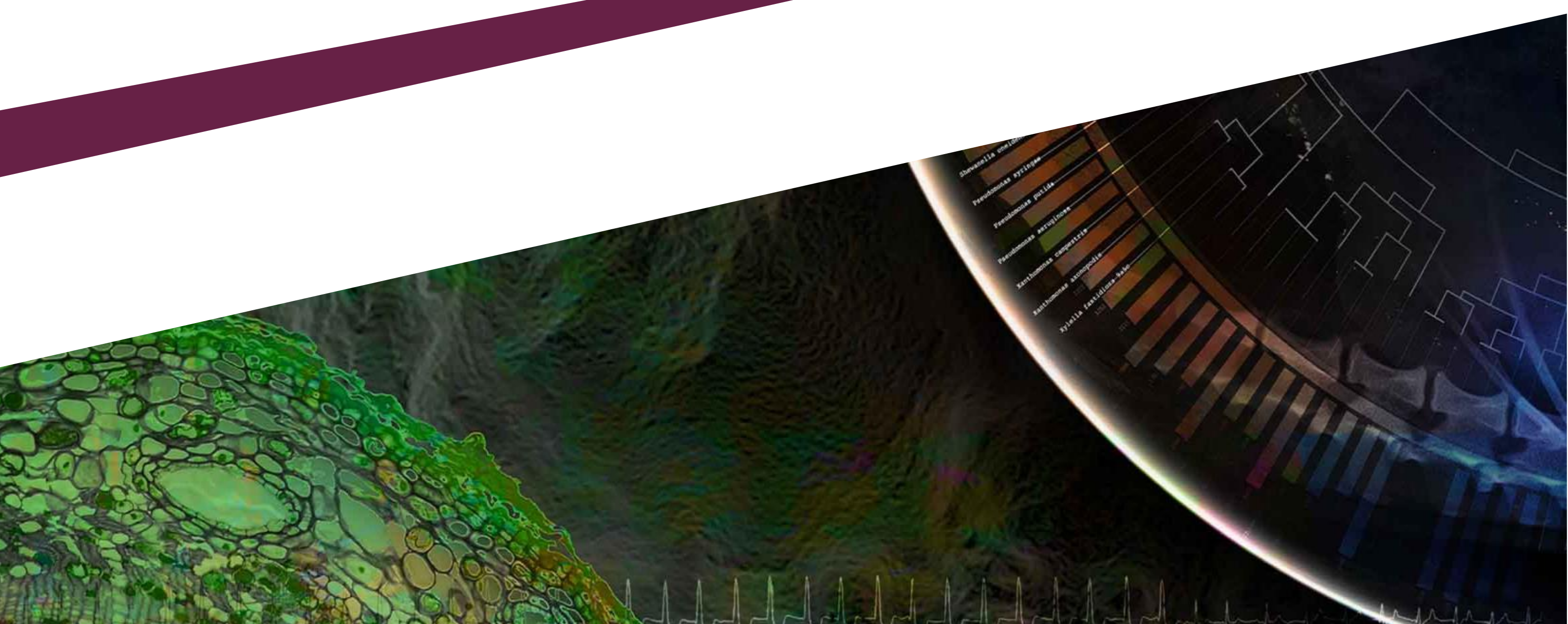

Urban tree detection on historical aerial imagery in Sweden. A test in automated detection with open source Deep Learning models

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Abstract

Urban trees are a key component of the urban environment. In Sweden, ambitious goals have been expressed by authorities regarding the retention and increase of urban tree cover, aiming to mitigate climate change and provide a healthy, livable urban environment in a highly contested space. Tracking urban tree cover through remote sensing serves as an indicator of how past urban planning has succeeded in retaining trees as part of the urban fabric, and historical imagery spanning back decades for such analysis is widely available. This short study examines the viability of automated detection using open-source Deep Learning methods for long-term change detection in urban tree cover, aiming to evaluate past practices in urban planning. Results indicate that preprocessing of old imagery is necessary to enhance the detection and segmentation of urban tree cover, as the currently available training models were found to be severely lacking upon visual inspection.

Keywords: urban forestry, urban trees, historical imagery, automated detection, GIS, deep learning

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1. Introduction

Urban tree detection using remote sensing technologies has emerged as a critical tool in urban planning and environmental management (Rashed & Jürgens 2010; Roloff & Auch 2016). As urban areas continue to expand, the management of urban forests becomes increasingly important, not only for enhancing the aesthetic value of cities but also for mitigating environmental issues such as air pollution, heat islands, and loss of biodiversity. Remote sensing, which includes the use of aerial images, satellite data, and LiDAR (Light Detection and Ranging) technology, provides a comprehensive and efficient method for mapping and monitoring urban trees.

The significance of urban trees extends beyond beautification. Trees play a pivotal role in improving urban air quality by filtering pollutants, providing oxygen, and reducing noise levels (Konijnendijk et al. 2005). They also contribute to energy savings in residential areas by providing shade, which lowers temperatures and reduces the need for air conditioning. On top of that, urban green spaces, including trees, have been linked to numerous health benefits, ranging from reduced stress levels to increased physical activity among city dwellers.

Remote sensing technology offers several advantages for urban tree detection. Traditional methods of tree surveying can be labor-intensive, time-consuming, and often limited in scope due to accessibility issues. In contrast, remote sensing allows for the analysis of large and inaccessible areas with high accuracy. Satellites and aerial sensors can capture data over vast urban landscapes, making it possible to conduct comprehensive surveys of urban tree cover without the physical limitations of ground-based observations.

Urban tree cover (or urban canopy cover), is a measure of tree and shrub abundance over a city and is usually derived from aerial or satellite images. As such, it is an important indicator of the health and sustainability of urban environments, as it refers to the combined amount of tree and vegetation cover within urban areas that plays a critical role in providing numerous benefits (or ecosystem services) to communities everywhere. These ecosystem services include, but are not limited to, improved air quality and stormwater mitigation (Nowak et al. 2006; Berland et al. 2017) reduced urban heat island effects that are a major cause of premature deaths (Schwaab et al. 2021) and enhanced aesthetic and recreational value (Price 2003). However, urban tree cover is not static, and it can change over time due to a variety of factors, including urban development, land-use changes, and natural disturbances. Unfortunately, trends show that due to the vulnerability of urban trees, the urban tree cover is declining in many cities across the globe (Nowak & Greenfield 2012). It is, however, unclear if Swedish cities are following the same trend/trajectory as long-term monitoring studies are uncommon, and we lack the necessary empirical evidence for claims about clear trajectories or trends.

In this report, we test the available open-source algorithms to assess their applicability using modern and historical aerial imagery within the scope of long-term monitoring of urban tree canopy change.

2. Methods

For this project, we utilized two open-source Deep Learning algorithms with distinct methodologies to detect urban tree canopies in aerial imagery. Firstly, we employed a tree detection algorithm developed by ESRI, which is based on DeepForest—a Python software package designed for airborne object detection and classification. This algorithm has been trained using data sourced from the National Ecological Observatory Network. Secondly, we employed the Segment Anything Model (SAM), an image segmentation AI developed by Meta. Both of these pre-trained models were accessible through ESRI's Living Atlas and are available through ArcGIS Pro (*ESRI Software,* 2014) data portal.

Both models necessitate Very High Resolution (VHR) imagery formatted in three spectral bands as input. The segmentation models conduct pixel-wise classification, assigning pixels to various classes corresponding to different objects or regions within the image. On the other hand, object-based identification utilizes the random forest classification where multiple decision trees are created using different random subsets of the data and features to delineate objects of interest, rather than relying on hand-crafted pixel features. Subsequently, it draws a square bounding box with a unique identifier around each detected object.

To visually evaluate the performance of these two models, we initially executed them on modern multi-band imagery with a resolution of 15cm. In order to replicate this analysis for the historical aerial imagery from 1962 with a resolution of 50cm, we had to preprocess the raster files. As the necessary input is a three-band raster layer, yet the historical imagery is captured in a single grayscale band, we stacked three identical instances of the raster as a three-band raster to be able to run the model.

We obtained the imagery from the Swedish Land Authority (Lantmäteriet) via the GET imagery portal (*Geodataportalen*, 2024).

3. Results

3.1 Automated detection on modern imagery

We ran two tests over a smaller area in Lund, Sweden where we adjusted the likelihood/confidence between tests. The Deep Learning algorithm drew square bounding boxes over the features that were identified as trees. The results are visible in different colors, with the red color showing object detection with comparatively higher confidence.

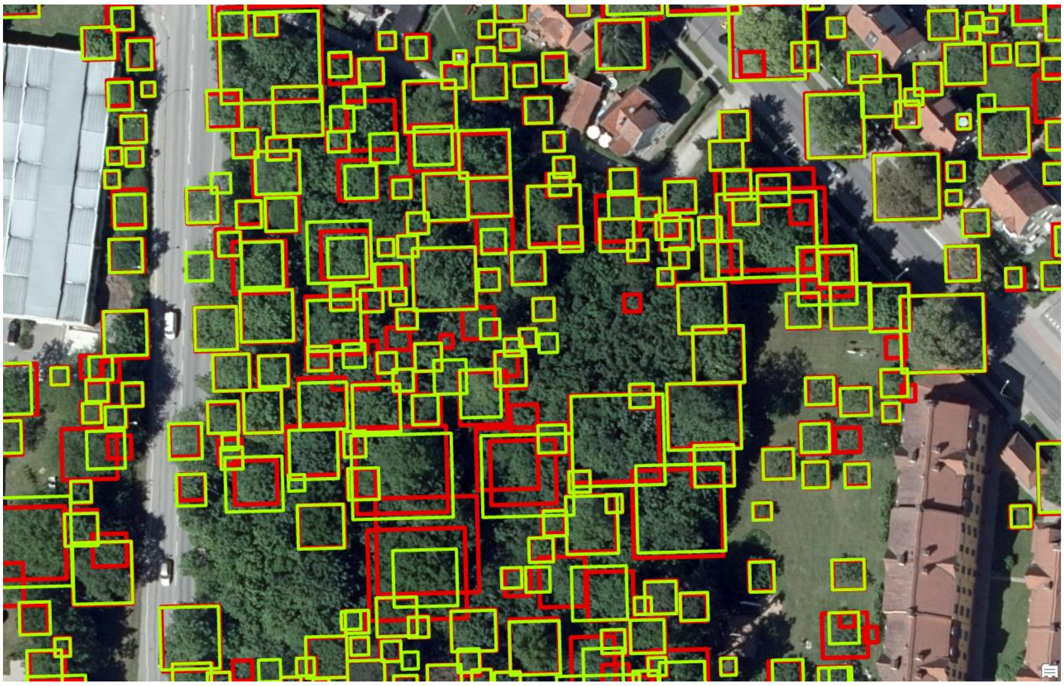

Figure 1: Result of the tree detection algorithm over a smaller area in Lund, Sweden. Several areas that under visual inspection should be detected as tree canopy were not, despite very good image quality.

In the second test we used SAM algorithm for segmentation of images. The algorithm was not calibrated to segment just tree canopy, but rather all types of land cover.

Figure 2: Result of Segment Anything Model segmentation of a small area in Lund, Sweden.

3.2 Automated detection on historical imagery

We ran both algorithms over a park area (Kungsparken) in Malmö, Sweden. The Deep Learning algorithm drew bounding boxes over the features that were identified as trees in teal color (Figure 3) and segments were identified in the next step (Figure 4).

Figure 3: Result of the identical tree detection algorithm as in Figure 1 on historical imagery in a small area in Malmö, Sweden. As expected, the algorithm has performed worse on image resolution that is lower than Figure 1 and in a grayscale form. Several areas with abundance of trees are not identified as such.

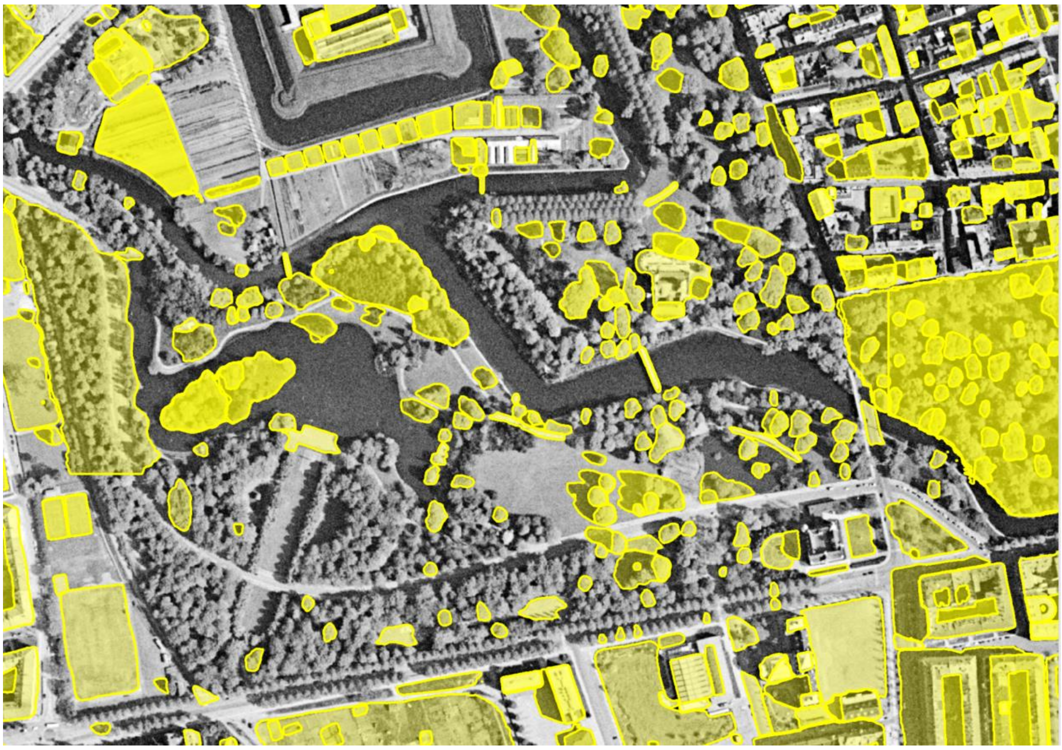

Figure 4: Result of Segment Anything Model of a park in Malmö, Sweden. When comparing to the result in Figure 2 we can see that large cohesive areas of trees and other types of land use are not segemented.

4. Discussion

Both segmentation and object detection deep learning models often struggled when detecting trees on historical aerial imagery due to several inherent challenges. Historical aerial imagery frequently suffers from issues such as low resolution, varying image quality, occlusions, and environmental changes over time. Segmentation models, which aim to delineate individual objects within an image, can falter when faced with the complex and irregular shapes of trees, especially amidst cluttered backgrounds or partial occlusions. Moreover, the lack of consistent labeling standards for historical imagery makes it difficult for segmentation models to accurately learn the intricate features of trees across different time periods and locations.

Similarly, object detection models, which identify and localize specific objects within an image, can struggle to distinguish trees from other visually similar elements like buildings or vegetation, particularly in instances where trees exhibit varying appearances due to seasonal changes or growth patterns. The limited availability of annotated datasets for historical aerial imagery hinders the training of deep learning models, resulting in suboptimal performance and generalization capabilities when using models trained on modern imagery. Overall, the combination of these factors contributes to the poor performance of both segmentation and object detection deep learning models when tasked with detecting trees on historical aerial imagery.

To obtain precise metrics of success, such as accuracy, precision, recall, and F1 score, a larger control dataset is essential for constructing a reliable confusion matrix. A confusion matrix is a fundamental tool in evaluating the performance of classification models, including those used in object detection and segmentation tasks. It tabulates the true positives, true negatives, false positives, and false negatives, allowing for a comprehensive assessment of model performance.

A larger control dataset provides a more representative sample of the population, encompassing a broader range of scenarios and variations that the model might encounter in real-world applications. This expanded dataset helps mitigate biases and ensures that the evaluation results are more statistically robust and generalizable. With a larger dataset, there are more instances available for each class, reducing the impact of random variability and enabling a more accurate estimation of the model's performance metrics. Therefore we would encourage future researchers to build a reference historical imagery dataset for similar studies. Unfortunately, providing a dataset for this control was not feasible within the duration of this research venture, but further attampts to advance this topic should prioritize allocating resources towards it.

The results show that training a specialized automated detection model is crucial for enhancing the success of existing deep learning models in detecting trees on historical aerial imagery for several reasons. Firstly, historical aerial imagery often presents challenges such as varying image quality, resolution, and environmental changes over time, making it difficult for traditional algorithms to accurately identify objects like trees. By training an automated detection model specifically tailored to these nuances, the model can learn to adapt to the unique characteristics of historical imagery, thereby improving its accuracy and robustness in detecting trees. Continuous training and refinement of the detection model allow it to stay updated with evolving datasets and detection requirements, ensuring its effectiveness in detecting trees across different temporal and spatial contexts. By investing in the training of automated detection models, we can significantly enhance the efficiency and reliability of tree detection on historical aerial imagery, facilitating crucial applications in environmental monitoring, urban planning, and land management.

Our analysis results could pe potentially improved by adding fidelity and texture information to raster bands. Fidelity bands represent the original spectral information of the scene, while texture analysis focuses on the spatial patterns and variations within the image. By incorporating both fidelity and texture information into raster data analysis, analysts can extract a more comprehensive set of features that capture both the spectral and spatial characteristics of the underlying objects or phenomena (Awrangjeb et al. 2011). This combined approach enhances the capabilities of automated detection systems by providing richer and more discriminative feature representations. We would suggest that future attempts at using automated detection with sub-par imagery quality utilize this approach.

References

Awrangjeb, M., Zhang, C. & Fraser, C.S. (2011). IMPROVED BUILDING DETECTION USING TEXTURE INFORMATION. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XXXVIII-3/W22, 143–148. https://doi.org/10.5194/isprsarchives-XXXVIII-3-W22-143-2011

Berland, A., SHIFLETT, S.A., SHUSTER, W.D., GARMESTANI, A.S., GODDARD, H.C., HERRMANN, D.L. & HOPTON, M.E. (2017). The role of trees in urban stormwater management. *Landscape and urban planning*, 162, 167–177. https://doi.org/10.1016/j.landurbplan.2017.02.017

ESRI Software (2014). ESRI. https://www.arcgis.com/sharing/rest/content/items/4af356858b1044908d9204f8b79ced99 [2024-04-19]

Geodataportalen (2024). Lantmäteriet. https://www.geodata.se/geodataportalen

Konijnendijk, C.C., Nilsson, K., Randrup, T.B. & Schipperijn, J. (2005). *Urban Forests and Trees: A Reference Book*.

Nowak, D.J., Crane, D.E. & Stevens, J.C. (2006). Air pollution removal by urban trees and shrubs in the United States. *Urban Forestry & Urban Greening*, 4 (3), 115–123. https://doi.org/10.1016/j.ufug.2006.01.007

Nowak, D.J. & Greenfield, E.J. (2012). Tree and impervious cover change in U.S. cities. *Urban Forestry & Urban Greening*, 11 (1), 21–30. https://doi.org/10.1016/j.ufug.2011.11.005

Price, C. (2003). Quantifying the aesthetic benefits of urban forestry. *Urban Forestry & Urban Greening*, 1 (3), 123–133. https://doi.org/10.1078/1618-8667-00013

Rashed, T. & Jürgens, C. (eds) (2010). *Remote sensing of urban and suburban areas*. Springer. (Remote sensing and digital image processing; v. 10)

Roloff, A. & Auch, E.F. (eds) (2016). *Urban tree management: for the sustainable development of green cities*. Wiley Blackwell.

Schwaab, J., Meier, R., Mussetti, G., Seneviratne, S., Bürgi, C. & Davin, E.L. (2021). The role of urban trees in reducing land surface temperatures in European cities. *Nature Communications*, 12 (1), 6763. https://doi.org/10.1038/s41467-021-26768-w

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