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Decoding Nature's Patterns: An Innovative Approach to Tree Detection Using Deep Learning and High-Resolution Aerial Imagery

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ABSTRACT

This study investigates the application of deep learning algorithms and high-resolution aerial imagery for individual tree detection in urban areas, using a neighborhood in Mersin, Turkey, as a case study. Employing the DeepForest Python package, we utilize high-resolution (7cm) aerial imagery to detect and map the city's tree population accurately. The results showcase an impressive accuracy rate of 80.87%, demonstrating the potential of deep learning in urban forestry applications and contributing to effective urban planning. The information generated from this study is crucial for conserving urban green spaces, enhancing resilience to climate change, and supporting urban biodiversity. While this research is focused on Mersin, the methods employed are globally adaptable, laying a foundation for further refinement and potential identification of different tree species in future work. This investigation highlights the transformative role of advanced technology in fostering sustainable urban environments.

1. INTRODUCTION

The identification of land characteristics and assets is essential for planning purposes. Land's natural and cultural resources are a compass for decision-making during the planning process (Selim et al., 2019). The most crucial data source for land management is determining ecological infrastructure, such as forests, streams, lakes, meadows and pastures, agricultural texture, etc. The management of lands will be facilitated by the rapid and precise detection of ecosystem assets and the ability to make future planning decisions (Peña-Barragán et al., 2011). In addition, exposing agricultural components such as crop pattern determination, present and potential product quantity, tree numbers, and crown diameters is beneficial because they are the essential data sources for directing the food policies of nations and regions. Consequently, studies on identifying flora have always been a top priority for nations. With the development of remote sensing and geographic information systems, these auto-detection and automatic extraction studies are expanding significantly (Lin et al., 2015).

Satellites are the most significant and frequently used data source in remote sensing. However, unmanned aerial vehicles (UAVs), or drones, are rapidly increasing with technological advances. Utilizing UAVs in remote sensing research is primarily motivated by their low cost and practicality (Díaz-Varela et al., 2015). In addition, this system's advantages include the availability of up-to-date, high-resolution data in a reduced amount of time and its high manoeuvrability. UAV images can be obtained at a lower cost than airborne LiDAR images. A low-cost camera can acquire color images when integrated into controllable UAV imaging systems. (Lim et al., 2015) These images are evaluated using a classification process based on their intended use. Unmanned aerial vehicles (UAVs) are a form of near-surface remote sensing that could significantly advance forest and tree monitoring. Images captured by unmanned aerial vehicles (UAVs) can cover areas ranging from hectares to square kilometers, thus encompassing enough trees to provide large sample sizes for numerous species. Since UAV images view crowns directly from above and can be georeferenced, data on species identity, stem diameter, growth rate,

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physiological measurements, and micro environmental conditions can be associated with each crown in the image.

As with detecting individual trees, this method is insufficient for data processing and information extraction. To cover this vacuum, the Deep Learning (DL) algorithm is used to detect trees in UAV-captured images. The advent of deep learning techniques, coupled with the growing accessibility of high-resolution aerial imagery, has profoundly revolutionized the methodology of individual tree detection (LeCun et al., 2015; Orhan et al., 2021). This convergence of cutting-edge technology with ecological research promises unprecedented precision and efficiency, laying the groundwork for a new era in understanding and managing forest ecosystems (Popkin, 2019). Traditional methods of tree detection, often reliant on manual field surveys or interpretation of satellite images, have been constrained by significant time and resource demands (Wulder et al., 2012). In addition, these methods tend to yield a somewhat rough overview of the forest landscape (Franklin, 2001). They can indicate the presence of trees but often fail to provide detailed information on the tree species, health status, or precise count, especially in denser or more diverse forest landscapes.

In contrast, combining deep learning algorithms with high-resolution aerial imagery heralds a transformation (Ma et al., 2019). Deep learning, a subfield of artificial intelligence, excels in identifying intricate patterns in large, complex datasets (Goodfellow et al., 2016). When trained on high-resolution aerial images, these algorithms can learn to distinguish between different tree species, discern their health status, estimate their age, and even predict their growth. This capability is particularly crucial in areas with high biodiversity, where manual identification can be challenging and prone to errors (Weinstein, 2018). The adoption of this method extends beyond just the speed and accuracy of tree detection. It also holds the potential to revolutionize how forest inventories are conducted (Duncanson et al., 2015). In traditional forestry, managing resources has often been arduous, involving lengthy field surveys to estimate the number and species of trees. However, With this innovative approach, forest managers can gain a precise and detailed overview of the forest resources, making management decisions far more efficient and informed.

From a conservation perspective, this methodology offers significant advantages as well. Conserving biodiversity and maintaining healthy ecosystems require accurate data on the distribution and status of different tree species. Applying deep learning techniques to high-resolution aerial imagery can provide conservationists with this essential information, facilitating the development of targeted and effective conservation strategies.

Urban planners also stand to gain from this advanced tree detection technique (McHale et al., 2009). As urban areas continue to expand, striking a balance between infrastructure development and the preservation of green spaces becomes increasingly challenging. Detailed information on tree distribution and health can guide urban planners in designing cities that are not only functional but also environmentally sustainable.

The implications for climate science are equally profound. Forests are critical in sequestering carbon, helping mitigate climate change's impacts (Pan et al., 2011). With the ability to detect individual trees and assess their health status, scientists can more accurately model the carbon sequestration potential of different forests, contributing to our understanding of global carbon dynamics.

In comparison to other methods of tree detection, the synergy of deep learning and high-resolution aerial imagery stands as a formidable contender. Conventional remote sensing techniques often struggle to accurately identify individual trees, particularly in dense or diverse forests. Traditional machine learning algorithms, while a step up, are dependent on manually engineered features and might not generalize well across varied landscapes. On the other hand, deep learning methods automatically recognize complex patterns and features, demonstrating superior adaptability and accuracy across a wide range of ecosystems.

In summary, integrating deep learning with high-resolution aerial imagery in tree detection represents a considerable leap forward in forest ecology and management. By improving the speed, accuracy, and level of detail in tree detection, this approach presents exciting opportunities across multiple domains - from forestry and conservation to urban planning and climate science. This advancement underscores the transformative potential of technology in addressing complex environmental challenges and shaping a more sustainable future.

2. METHOD

2.1. Study Area

Our study area encompasses a neighborhood in Mersin, Turkey's rapidly urbanized city (Figure 1). As a prominent port city on the Mediterranean coast, Mersin has experienced rapid urban expansion in recent years. While urbanization provides economic and social benefits, it can also strain local ecosystems and alter natural landscapes. Among these alterations, tree loss is particularly concerning due to trees' critical role in urban environments (Escobedo et al., 2011).

Figure 1. Study Area

Trees provide numerous ecosystem services vital for maintaining the quality of life in urban areas. They act as natural air purifiers, absorbing harmful pollutants and releasing oxygen. They provide shade, thereby reducing the heat island effect often associated with urban areas, and help conserve energy by reducing the demand for air conditioning. Trees also contribute to stormwater management by reducing runoff and erosion (Xiao & McPherson, 2011). Moreover, they enhance the aesthetic appeal of urban areas and provide habitats for various birds and insects, thereby supporting urban biodiversity (Shanahan et al., 2015).

As a coastal city, Mersin is vulnerable to the effects of climate change, such as rising temperatures and changing precipitation patterns. A healthy urban tree population can help mitigate these effects, making the city more resilient to climate change (Livesley et al., 2016). This approach can inform tree planting, maintenance, and protection policies by accurately mapping and monitoring the city's tree population. It can guide urban planners in creating a cityscape that balances development with green spaces, enhancing the livability and sustainability of Mersin.

2.2. Data

The foundation of this study lies in the utilization of very high-resolution aerial imagery with a precision of up to 7cm. Such high-resolution imagery is a rich source of detailed and accurate spatial information, which is instrumental in detecting individual trees in the study area. The importance of using high-resolution data in this context cannot be overstated.

The high degree of detail captured in these images allows for precise delineation of tree crowns, differentiation between tree species based on their unique spectral signatures, and identification of tree health indicators such as color, texture, and shape. This granularity of data significantly enhances the accuracy of the tree detection process, enabling the deep learning model to make nuanced distinctions between different trees and other vegetation or structures in the urban landscape.

The use of very high-resolution aerial imagery in this study is pivotal. It enables the collection of detailed and accurate spatial information, enhancing the precision of the tree detection process and, consequently, the overall quality of the research outcomes. The contribution of such data to the study is instrumental in advancing our understanding of urban tree populations and informing sustainable urban planning practices (Díaz et al., 2018).

2.3. Method

The general workflow for the tree extraction implemented in this study is given in Figure 2.

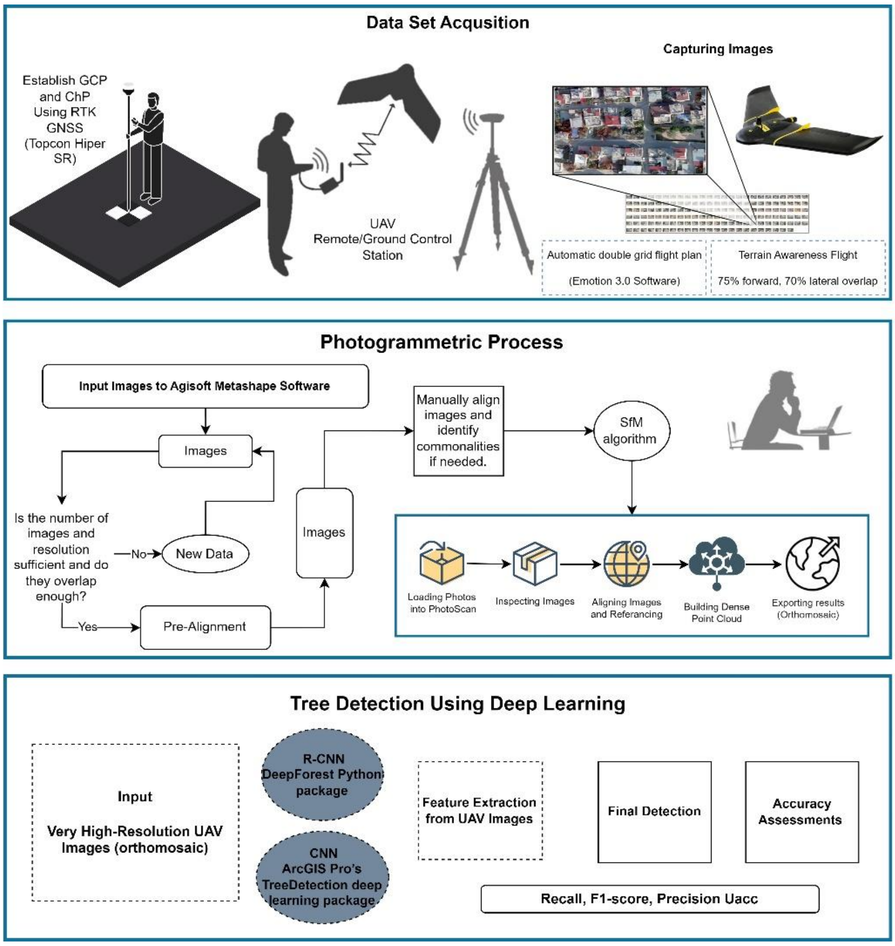

Figure 2. The general workflow for the tree extraction from UAV photogrammetry orthomosaic data using the DL algorithm.

2.3.1. Image Processing

The UAV images were captured in March 2022 using a fixed-wing Sensefly Ebee Plus UAV equipped with a 20-megapixel RGB camera and a 10.5-millimetre autofocus lens (See Table 1 for detailed information.) The axis is parallel to the terrain and vertical for a nadir view of the images. With a cruising pace of 43ms, the UAV flew 305 m above the study area. A total of 523 images with a front of 85% and a side of 70% overlap were captured for two flights separated by approximately sixty-five minutes and conducted between 10:00 and 12:00 am. Before the missions, eight triangular ground control points (GCPs) were established along the study area's perimeter. A dual-frequency GNSS receiver was installed at each GCP to acquire GPS and GLONASS data for two minutes. Following post-processing, the average horizontal and vertical precision of the GCPs were 1.4 cm and 3 cm, respectively. Finally, the Agisoft Metashape software's Structure from Motion (SfM) algorithm was used to generate an orthomosaic of the study area with a ground sampling distance (GSD) of 7 cm.

Table 1. Sensefly Ebee Plus UAV and S.O.D.A Camera's basic technical features

Specialty	Value
Weight/ Size	1100 g /1100 mm
Cruising speed	40-110 m/s
Max of flight time	About 50 minutes
PPK/RTK	+
Radiolink distance	3 km
Sensor type/ Sensor size	R-G-B (20 mp)/ 1-inch
Image Width/Height	5280 X 3956 px
Sensor Width/Height	12.75 X 8.5 mm
Focal Length	10.5 mm

A dense point cloud is a collection of millions of points positioned in three dimensions (x,y,z) by GNSS (Global Navigation and Satellite System). It is utilized to produce the DSM and ortho mosaics (Şasi & Yakar, 2017). A DSM contains the altitude of each pixel relative to the earth datum and serves as a validation tool for nDSM in our investigation. Orthomosaic images comprise all unprocessed images from each flight and are geographically corrected to their true position, thereby reducing camera, lens, and topographic distortion (Mesas-Carrascosa et al., 2016; Kabadayı, 2022). An orthomosaic facilitates the labelling of trees to develop DL's training and assessment patches. After aligning the raw RGB images of each flight using Agisoft Metashape, dense point clouds and orthomosaics were produced for this study. The dense point cloud and orthomosaics for each flight's entire dataset were generated in Metashape using the bulk procedure (Lucieer et al., 2013; Hamal & Ulvi, 2022). First, each set of RGB images were aligned without using ground control points (GCP) with an accuracy limit of 40,000 key points and zero bind points. The "optimize alignment" phase was then reset to its default value. Next, the "dense point cloud" (high quality, aggressive filtration), "mesh", and "texture" were constructed. DSM (interpolation enable) and orthomosaics (surface = DSM, blending mode = mosaic, hole infill = yes) were used to complete the procedure. All dense point clouds, digital surface models, and orthomosaics were exported to the International Terrestrial Reference Frame96 3 degrees 33N Zone. The exact pixel size and extent were specified for each flight's orthomosaic to overlay and process in Python. This is the initial step, followed by the detection of treetops, classification of treetops, and, ultimately result in validation.

The SfM procedure begins by acquiring photographs of the object of interest from multiple positions and angles with sufficient overlap (e.g., 85% front and 70% side in this study). Based on advancements in image feature recognition, such as the scale-invariant feature transform (SIFT) (Lowe, 2004; Hamal, 2022), it is possible to autonomously detect, describe, and match characteristic image objects between photographs (Yakar & Doğan, 2019). Then, a bundle block adjustment is performed on the matched features to determine the 3D position and orientation of the cameras, as well as the XYZ location of each feature in the photographs, resulting in a sparse 3D point cloud (Snavely et al., 2008; Yüksel et al., 2022). Using multi-view stereopsis (MVS) or depth mapping techniques (Campbell et al., 2008; Kabadayı & Uysal, 2020; Tükenmez & Yakar, 2023), a subsequent densification technique can be used to derive highly dense 3D models. Georeferencing of the 3D model in a real-world coordinate system is possible through GCPs and the incorporation of camera GPS locations. Last, the model can be exported to a grid-based DEM, and orthophoto mosaics (orthomosaics) can be derived from projected and blended photographs. The SfM workflow was utilized in this investigation, as implemented by the commercial software Agisoft Metashape.

Initially, SfM techniques extract individual features from each image of the photogrammetric block, which is then matched with their corresponding feature in the other images of the photogrammetric block (Guerra-Hernández et al., 2018). These characteristics are used to ascertain the sensor's relative position during flight, allowing the position and orientation of each sensor to be calculated. At this juncture, the results' spatial quality depends on the geolocation sensor, GNSS sensor, and IMU sensor (Cruzan et al., 2016). Generally, the geolocational precision of images captured by commercial UAVs is moderate to low. Therefore, this investigation determined geolocation using aerial triangulation (Ebrahimikia & Hosseininaveh, 2022). A group of GCPs was dispersed throughout the study area to enhance the spatial quality of the results. These GCPs were measured with greater spatial precision than GSD on a field. After aerial triangulation was computed, a DSM was produced in three steps: feature extraction, multi-image matching, and error detection. Using DSM and external orientation, each image was orthorectified. Finally, individual orthorectified images were mosaicked to produce a UAV orthomosaic of the entire study area. Each orthomosaic was created with the same GSD as the corresponding UAV flight.

2.3.2. Deep Learning

The methodology adopted for individual tree detection using deep learning techniques and high-resolution aerial imagery comprises several stages. These include data acquisition and preprocessing, model training and validation, and finally, model testing and evaluation (Wäldchen & Mäder, 2018). The DeepForest Python package, which forms the core of this process, is built upon deep learning libraries like PyTorch and utilizes a pre-trained neural network model for tree crown detection (Weiss et al., 2014).

At the heart of this methodology is the DeepForest Python package, which utilizes a variant of the Region Convolutional Neural Networks (R-CNN), a state-of-the-art object detection algorithm. R-CNNs are adept at identifying and localizing objects within an image, making them suitable for detecting individual tree crowns (Zou et al., 2018).

The DeepForest model is pre-trained on a large dataset of RGB aerial images, where individual trees have been manually annotated. In the training phase, the model learns to recognize patterns and features that distinguish tree crowns from the rest of the forest canopy. The model adjusts its parameters through backpropagation to minimize discrepancies between its predictions and annotations.

The DeepForest package leverages the computational efficiency and flexibility of the PyTorch library, a popular choice for deep learning applications (Paszke et al., 2019). PyTorch provides a dynamic computational graph, which allows for more flexibility in building and modifying models, a feature that is particularly useful when dealing with complex tasks like tree detection. Additionally, PyTorch's compatibility with GPU acceleration enables faster model training, which is essential when working with large image datasets.

Following the training phase, the model undergoes testing to evaluate its performance in detecting trees in new, unseen aerial images (Huang et al., 2017). Metrics such as precision, recall, and F1 score are computed to assess the model's accuracy and reliability. These metrics provide a comprehensive overview of how well the model identifies and localizes individual tree crowns (Gu et al., 2018).

Incorporating deep learning into tree detection methodology via the DeepForest package significantly advances accuracy, efficiency, and scalability. This approach empowers researchers and practitioners alike to glean valuable insights from high-resolution aerial images, advancing our understanding and management of forest ecosystems.

Moreover, we also use ArcGIS Pro's TreeDetection deep learning package. Although specific details about the architecture used in the Tree Detection package are proprietary information and not publicly available, it likely uses a form of Convolutional Neural Network (CNN), commonly used for image classification tasks.

In tree detection, CNNs can be trained to identify features and patterns unique to trees in imagery. The first step in this process is training the model on a large dataset of labelled images, where the presence or absence of trees has been manually annotated. The trained model can then be used to predict the presence of trees in new, unlabeled images. The model scans the new image in the inference phase, applying the learned filters and weights to identify tree-like features. If the aggregate of these features surpasses a certain threshold, the model classifies that section of the image as containing a tree.

3. RESULTS

A tree detection algorithm based on the R-CNN architecture was applied to Very High-Resolution Aerial Imagery and successfully detected trees. The algorithm used a combination of convolutional neural networks and region recommendation networks to identify trees in the images. The identified trees were then extracted and displayed on a map showing their location and distribution. Figure 3 shows the map with the extracted trees using DeepForest. Moreover, Figure 4 shows the map with extracted trees using ArcGIS Pro's TreeDetection deep learning package.

The map shows that the detected trees are distributed in various areas of the image and indicates the presence of trees in these locations. The proposed algorithm was able to detect small trees as well as large trees with high accuracy. The false positive rate is also low, indicating that the algorithm does not misidentify other image features as trees.

The proposed tree detection algorithms (DeepForest and ArcGIS Pro) achieved an overall accuracy of 80.87% and 48.95% on the test dataset of Very High-Resolution Aerial images. The DeepForest algorithm successfully detected trees of different sizes and shapes. The precision and recall values are 82.15% and 94.59%, respectively, indicating a good balance between false positive and false negative errors (Table 2).

Table 2. Accuracy Analysis

	Total	**TP**	**FP**	**FN**	**Recall**	**F1 Score**	**Precision (UAcc)**
Deep Forest	213	175	38	10	0.9459	0.8794	0.8215
ArcGIS Pro	70	32	38	35	0.48	0.47	0.46

Overall, the proposed tree detection algorithm based on R-CNN architecture using Very High-Resolution Aerial images data has shown promising results and proved its effectiveness in Very High-Resolution Aerial images. The proposed algorithm can be applied to real-time tree detection and monitoring systems.

Figure 3. Detected trees in the study area with DeepForest

Figure 4. Detected trees in the study area with ArcGIS Pro

4. CONCLUSION

This study demonstrates the immense potential of employing deep learning techniques in combination with high-resolution aerial imagery to detect individual trees in urban environments. Achieving an impressive accuracy of 80.87% in our case study of Mersin, Turkey, this methodology underscores the feasibility and effectiveness of using advanced machine learning models to analyze and understand urban green spaces.

Detecting and analysing individual trees in urban landscapes is critical, given trees' various ecosystem services. From enhancing air quality and reducing urban heat islands to supporting biodiversity and aesthetic appeal, trees are an indispensable component of sustainable and resilient cities. Accurate tree detection, thus, lays the groundwork for informed urban planning and management strategies, enabling the design of cities that harmoniously blend development with nature.

We use the DeepForest model and high-resolution aerial imagery to create detailed and dynamic maps of urban tree populations. The application of this methodology extends beyond Mersin, as it can be adapted for different urban contexts worldwide, contributing to the global goals of urban sustainability and resilience.

However, despite the promising results, the field of tree detection using deep learning and aerial imagery is still relatively nascent. As we move forward, there are several avenues for further research. One potential direction is to enhance the model's precision and recall, perhaps by refining the training process or integrating other data sources like LiDAR. Another intriguing prospect is to extend the model to identify individual trees and different tree species, which would add another dimension to our understanding of urban green spaces.

In conclusion, this study represents a significant stride in using deep learning for environmental applications. It illuminates the path towards a more nuanced understanding of our urban ecosystems and underlines the pivotal role of technology in fostering sustainable urban futures.

Author Contributions

Halil İbrahim Şenol: Conceptualization, Methodology, Software, Visualization, Writing-Reviewing and Editing **Abdurahman Yasin Yiğit**: Data curation, Writing-Original draft preparation, Writing-Reviewing and Editing

Statement of Conflicts of Interest

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

Research and publication ethics were complied with in the study.

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