Proceedings of the 3rd International Conference on Machine Learning and Automation
DOI: 10.54254/2755-2721/2025.LD36130

A Survey on Automated Palm Tree Identification from Traditional Machine Learning and Deep Learning Perspectives

Yaxuan Li

Software Academy, Handan University, Handan, China
lic474413@gmail.com

Abstract. This paper reviews automated palm tree identification methods based on traditional machine learning and deep learning, exploring various data sources (e.g., UAV, satellite, and aerial imagery) and imaging modalities (RGB, thermal, multispectral, and LiDAR). It systematically analyzes the strengths and limitations of segmentation, classification, and object detection algorithms, highlighting their practical applications in agriculture, ecological conservation, and urban planning. The study demonstrates that deep learning approaches (e.g., CNNs and Vision Transformers) excel in complex environments and large-scale datasets but face challenges such as species similarity, environmental variability, and computational constraints. Future research should focus on multimodal data fusion, lightweight model development, and dataset expansion.

Keywords: palm tree identification, machine learning, deep learning, remote sensing, multimodal data, object detection

1. Introduction

Palm tree species are fundamental features of ecosystems and agricultural systems worldwide, significantly adding to biodiversity, economic production, and cultural settings [1, 2]. While demand for palm products, particularly palm oil, rises with the need for environmental conservation, accurate identification of palm tree species becomes a very significant activity. Manual identification methods are both time-consuming as well as labor-intensive, often making them impractical for widespread surveillance applications. Consequently, new advances in computer vision and remote sensing technologies have revolutionized this field, enabling computerized identification of palm tree species using high-resolution images as well as sophisticated algorithms [3].

The progress in this area can be considerably accounted for by machine learning, especially deep learning techniques, which have shown generalizability over various sources of images, from unmanned aerial vehicles (UAVs) to aerial imagery and satellites. Compared with traditional machine learning methods relying on hand-designed features, deep learning models, especially convolutional neural networks (CNNs), allow for self-learning of features with improved accuracy [3] and can thus well accommodate diverse resolutions as well as imagery settings.

DOI: 10.54254/2755-2721/2025.LD36130

The paper explores traditional machine learning techniques as well as deep learning approaches for palm tree identification (refer to section 3), with a focus on their tractability for a wide range of sources of data as well as imaging modalities (refer to section 2). We discuss various techniques' pros and cons, which include segmentation, classification, and detection of objects, alongside highlighting their real-world applications in agriculture [4], environmental conservation, as well as landscaping in cities [5] (refer to section 4). Through fusing recent research with accessible technology, this paper hopes to provide an extensive summary of what currently exists for automated palm tree identification as well as its potential future.

2. Data sources for palm tree detection

With advances in imaging technology, palm trees can be sensed across a range of sources, each with varying but sufficient spatial and spectral resolutions. Images from various platforms, manned aircraft, satellites, and UAVs, each with distinct attributes and limitations, are available. UAVs can capture high-resolution images by combining diverse sensors, like RGB, thermal, and multispectral cameras. UAVs provide exceptional detail, making them well suited for high-resolution analyses of palm trees [3, 6, 7]. However, their coverage is limited due to constraints from battery requirements, aviation policies, as well as limited operating distances. Manned aircraft can offer more extensive UAV coverage with a relatively high spatial resolution. Compared to UAVs, they can monitor broad areas within a single sortie, although they are more costly to operate and have lower deployment frequency versatility. Satellites provide the greatest spatial extent of coverage, enabling wide-scale palm tree monitoring [8]. For example, multispectral satellites provide extensive spectral datasets that can enrich deep learning techniques. Their resolution is, however, often lower compared to UAV or aerial imagery, limiting their usefulness in high-detail analyses.

The combination of different classes of visual information, such as RGB, thermal, multispectral, hyperspectral, and LiDAR images, supports different monitoring functions dedicated to palm plants. Each type of image presents different advantages related to inherent qualities of the image. Selection of appropriate imaging technology depends on defined monitoring objectives since every technology measures different aspects of palm tree plantations and related environments in a different manner.

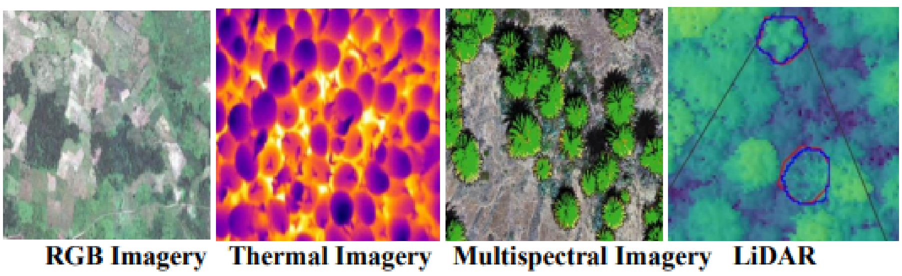

Figure 1. A comparison of different image modalities [9, 10, 11, 12]

2.1. RGB imagery

RGB imagery also plays a significant role in palm tree monitoring due to its high spatial resolution and ease of visual interpretation. Since the three bands of visible spectra—red, green, and blue—most closely resemble human visual perception, RGB is especially well suited for applications of canopy structure mapping, for example, assessing palm spacing, denseness, and crown morphology [7]. Because of its high spatial resolution, it can distinguish between single palm crowns as well as distinguish their spatial distribution features. For land use classification applications, texture features

DOI: 10.54254/2755-2721/2025.LD36130

of RGB images can effectively distinguish palm plantations from other vegetation species [9, 13]. The widespread availability and relatively low cost of RGB sensors further contribute to their popularity in basic palm inventory and monitoring applications.

2.2. Thermal imagery

Thermal imaging provides unique capabilities for palm health assessment by detecting subtle temperature variations in canopies. This modality is particularly valuable for pest infestation detection, as the RPW is a palm borer insect that develops within the soft tissues of the trunk and crown, eventually leading to tree death [14]. Thermal cameras can identify these temperature anomalies before visible symptoms appear, enabling early intervention. For fruit monitoring, thermal imagery exploits the temperature differences between mature and immature fruit clusters, as water content and metabolic activity vary with ripening stages [10]. The passive nature of thermal sensing (detecting emitted rather than reflected radiation) allows day-and-night operation, providing additional monitoring flexibility.

2.3. Multispectral imagery

Multispectral data enhances monitoring capabilities beyond the visible spectrum through strategically placed spectral bands. The inclusion of near-infrared and red-edge bands enables precise vegetation health assessment. Nutrient estimation in oil palm leaves using sensing in the visible and near-infrared ranges with a spectroradiometer and camera was reported in earlier studies, as cited in [15]. Multispectral sensors capture stress-induced spectral variations linked to disease presence. Subtle pigment loss and changes in leaf structure allow early detection before visible symptoms appear. High-resolution and machine learning compatibility support effective and repeatable phytosanitary monitoring [11]. Vegetation and moisture indices correlate with canopy vigor, age, and photosynthetic activity. Multispectral data combined with machine learning enables scalable and cost-efficient yield forecasting under varying climatic conditions [16]. The balance between spectral detail and manageable data volume makes multispectral systems practical for operational palm plantation monitoring.

2.4. LiDAR (light detection and ranging)

LiDAR systems provide unparalleled three-dimensional structural information through precise distance measurements using laser pulses, enabling effective mapping of Amazonian canopy palms by capturing their distinctive star-shaped crown architecture [12]. For 3D canopy modeling, LiDAR's ability to penetrate vegetation and capture multiple returns enables reconstruction of detailed height profiles, supporting growth monitoring and biomass estimation [4]. The direct measurement of vertical structure is particularly valuable for tracking palm growth rates and canopy development over time, overcoming optical sensor limitations through superior canopy penetration and shadow reduction. The trunk diameter measurement is aided by LiDAR technology's high ranging accuracy, making non-invasive inventorying of plantations possible. Unlike optical sensors, LiDAR is not susceptible to lighting variations and can operate effectively within a complex canopy environment where optical methods can be compromised due to occlusion/shadowing effects. This makes wide validation of palm cover possible with a diverse range of forest structures [12, 4].

DOI: 10.54254/2755-2721/2025.LD36130

3. Approaches and algorithms for palm identification

Advanced computer vision and remote-sensing technologies have promoted an assorted set of algorithmic methods for palm tree detection with distinctive features tailored to specific requirements of applications as well as intrinsic qualities of datasets. Such methods are broadly grouped into three main classes: segmentation, classification, as well as object detection. Segmentation methods focus mainly on pixel-level discrimination of palm crowns from external objects with accurate canopy separation, but they entail high demands for extensive labeling efforts as well as high computational requirements. Classification methods evaluate image segments for palm presence with high speed over extensive ground but with a loss of spatial precision. Object detection methods provide an optimal compromise between accurate localization with efficient rapidity using bounding boxes, making them very suitable for applications with a broad scale of operations. Changing from traditional machine learning methods to deep learning methods significantly improves operating efficiency of all types of methods with accurate detection of palm tree presence even in more diverse settings. This section undertakes a comprehensive assessment of each approach with a particular focus on advances of methods, relative merits, as well as applications in palm tree monitoring.

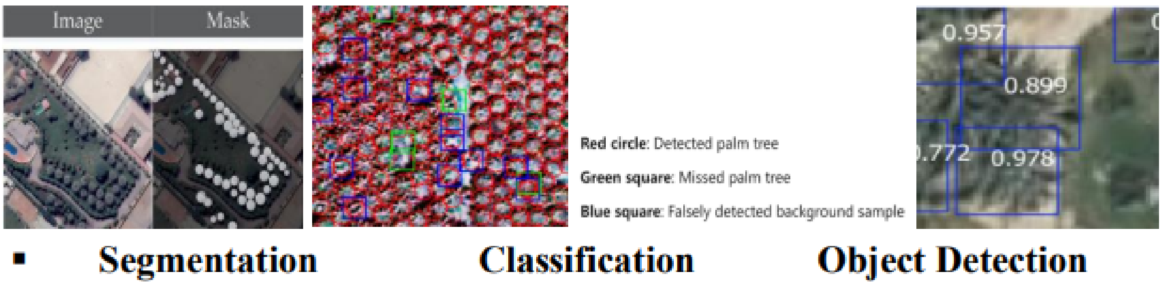

Figure 2. A comparison of different approaches for palm identification [5, 17, 18]

3.1. Segmentation

Segmentation is a common method used for palm tree identification due to its ease of accurate localization from differentiation of palm crowns from their surroundings. Commonly used segmentation techniques include using circular masks with canopies' centroids as centers or using polygonal annotations outlining canopies' borders. While traditional methods provide interpretability and require a lesser quantity of labeled data, deep learning methods offer high accuracy, robustness, and scalability in various settings.

The conventional machine learning techniques have been prominent in earlier efforts of segmentation. For instance, Shafri, Hamdan, and Saripan [19] have presented a semi-automatic approach for oil palm tree detection as well as counting using high-spatial-resolution imagery acquired from airborne platforms. This combines spectral characteristics for extracting oil palm locations for counting thereafter. Texture analysis for improving canopy texture is incorporated into it as well as edge enhancement for details as well as for improving clarity of shapes. Morphological reconstruction separates oil palms from the scene after oil palm elimination from the scene via oil palm-background separation followed by oil palm objects extraction. Blob analysis is finally done for oil palm crowns' identification as a connected region detection for corresponding expected size as well as shape attributes. It realized an average accuracy of about 95% for oil palm tree identification as well as counting, thus presenting a successful approach for extracting palm details

DOI: 10.54254/2755-2721/2025.LD36130

from high-resolution imagery for plantation applications. Fawcett et al. [20] emphasize UAV-derived Structure-from-Motion point clouds integrated with segmentation methods for detecting oil palm tree individuals using canopy height models (CHMs). Local maximum filtering function was used for applying it to a CHM with high accuracy for palm detection. Point cloud segmentation allowed for extracting structural attributes such as stem as well as canopy height. UAV-based SfM concept attained a 98.2% accuracy for a 7-year-old plot for palm identification accompanied with RMSEs for 0.27 m (R^2=0.63) as well as 0.45 m (R^2=0.69) for 7-year-old as well as 10-year-old palms for stem height prediction, respectively. This presents a realistic method for palm tree mapping without LiDAR.

More recently, deep learning approaches have revolutionized segmentation performance by enabling end-to-end learning and stronger feature representation. For example, Gibril et al. [21] developed an end-to-end deep learning approach using various deep vision transformers (particularly Segformer and UperNet-Swin) for accurate and transferable large-scale mapping of date palm trees from multiscale UAV and aerial imagery, achieving superior segmentation performance (mIoU up to 86.3%, mF-score up to 92.44%) and outperforming CNN-based models in both generalization and computational efficiency. Al-Ruzouq et al. [17] leverage high-resolution WorldView-3 multispectral satellite imagery. They also use the strong global feature representation capabilities of state-of-the-art Vision Transformers (ViTs) to achieve precise mapping of date palm trees. By integrating spectral data, the segmentation performance was significantly enhanced. Additionally, a novel postprocessing strategy was developed to accurately delineate and count individual trees from semantic segmentation outputs. The ViT-based approach with WV-3 multispectral data achieved up to 84.36% mIoU and 90.95% mF-score in date palm crown segmentation, significantly improving over RGB-based results.

Table 1. Summary of machine learning and deep learning algorithms

No.	Method Type	Key Techniques/Models	Data Source	Main Advantages	Performance Metrics & Results
[19]	ML	(1) Spectral discrimination, (2) texture analysis, (3) edge enhancement, (4) segmentation, (5) morphological reconstruction, (6) blob analysis	High-resolution airborne imagery	Interpretable; less reliance on labeled data	95% accuracy
[20]	ML	UAV-based SfM point clouds, canopy height model segmentation, local maximum filtering	UAV Structure-from-Motion (SfM) point clouds	No LiDAR required; uses height data for improved segmentation	98.2% accuracy; stem height RMSE 0.27–0.45 m
[21]	Deep Learning	Deep Vision Transformers (particularly Segformer, UperNet-Swin)	Multiscale UAV and aerial imagery	End-to-end training; strong generalization; efficient computation	mIoU: 86.3%, mF-score: 92.44%
[17]	Deep Learning	Vision Transformer (ViT), multispectral data fusion, novel postprocessing	WorldView-3 high-res multispectral satellite imagery	Spectral fusion improves precision; accurate crown boundary mapping	84.36% mIoU; 90.95% mF-score

3.2. Classification

Classification involves dividing the image into small patches and determining whether each patch contains palm trees. By aggregating classification results and overlaying them on the original image, approximate palm locations can be inferred. while traditional machine learning methods have

DOI: 10.54254/2755-2721/2025.LD36130

provided effective solutions for palm tree classification, deep learning approaches, particularly convolutional neural networks (CNNs) and transfer learning frameworks, have shown superior performance in large-scale, complex environments.

Traditional machine learning classifiers remain widely used for palm tree classification. For example, Luo et al. [22] systematically evaluated five feature selection methods and four classifiers for object-oriented classification of betel palm and mango plantations using Gaofen-2 imagery in complex tropical agricultural regions. The results showed that applying feature selection methods improved classification accuracy by 1–4%, with the random forest–logistic regression and support vector machine–logistic regression combinations achieving the highest overall accuracies (89%+).Hidayat et al. [9] developed a semi-automated classification approach within an object-based image analysis (OBIA) framework that combines support vector machine (SVM) classification with recursive feature elimination (RFE) to accurately identify sago palms. The use of RFE alongside the SVM classifier effectively revealed the optimal combination of features from spectral, arithmetic, geometric and texture domains, significantly improving classification accuracy to 85%. The current research emphasizes the significance of feature selection in enabling both redundancy reduction as well as model generalization enhancement, thus presenting a feasible approach to assessing sago palms with remote sensing in a multidimensional environment. Malek et al. [13] proposed an autonomous system intended for palm tree detection using high-resolution images derived from unmanned aerial vehicles (UAVs), with a series of advanced methods related to computer vision. Firstly, a Scale-Invariant Feature Transform (SIFT) algorithm is used to extract keypoints from UAV images, which are further examined with an Extreme Learning Machine (ELM) classifier intended for the discrimination of palm and non-palm features—assigning a number of keypoints to each discovered palm tree. Such keypoints are further integrated using an active contour model related to level sets (LS) to determine tree shape. Finally, Local Binary Patterns (LBP) are used for estimating region texture derived from a level set, thus enabling a differentiation of palm trees from nearby vegetation. UAV-based SIFT-ELM-LS-LBP approach provided promising outcomes for an autonomous palm tree detection using UAV images of a resolution of 3.5 cm derived from two agricultural fields.

Recent advances have moved towards deep learning methods, which are specifically well-suited for learning intricate features end-to-end from image data, providing superior performance across a range of settings. Cui et al. [3] developed PalmProbNet, a probabilistic transfer learning approach that couples ResNet with a multilayer perceptron (MLP). Through utilization of dual-scale image patches for extracting both localized details as well as entire scene context, as well as a multi-scale sliding window approach, the model produces probability heatmaps that successfully identify palms in compact rainforest settings with an accuracy of 97.32% (κ = 94.59%). Li, et al. [8] created a two-stage convolutional neural network for detecting oil palm trees at a very large scale using high-resolution QuickBird satellite images. The resulting approach involves an overlapping partitioning technique for partitioning large images, a multi-scale sliding window mechanism for estimating oil palm coordinations, as well as a minimum distance filter for post-processing. Together, these parts allow for efficient as well as accurate detection across a 55 km^2 region with an average F1-score of 94.99% as well as significantly lower confusion with additional vegetation as well as buildings when compared to available techniques. Li, et al. [18] offers a deep learning approach reliant upon CNNs for accurate oil palm tree detection as well as counting in high-resolution Malaysian remote-sensing images. Through utilization of manually interpreted sample sets for CNN learning as well as tuning, a sliding window approach for estimating labels throughout an image collection, as well as overlap merging of multiple predictions for estimating specific palms, the approach addresses

DOI: 10.54254/2755-2721/2025.LD36130

challenges like overlapping crowns as well as high-density tree distribution progressively with detection accuracies of >96% as well as superior capability compared to conventional techniques.

Table 2. Summary of machine learning and deep learning algorithms

No.	Method Type	Key Techniques/Models	Data Source	Main Advantages	Performance Metrics & Results
[22]	ML	Feature selection (5 methods), classifiers (RF–LR, SVM–LR), object-oriented classification	Gaofen-2 imagery (Betel palm & mango)	Feature selection improves accuracy and generalization	Accuracy >89%, with 1–4% gain from feature selection
[9]	ML	Object-Based Image Analysis (OBIA), SVM with Recursive Feature Elimination (RFE)	Remote sensing of sago palms	RFE reduces redundancy; improves classifier generalization	Classification accuracy up to 85%
[13]	ML	SIFT for keypoints, Extreme Learning Machine (ELM), active contour (level set), LBP for texture analysis	High-resolution UAV imagery	Combines shape and texture for refined palm detection	Promising detection; 3.5 cm UAV imagery
[3]	Deep Learning	PalmProbNet (ResNet + MLP), dual-scale image patches, multi-scale sliding window, probabilistic heatmaps	Dense rainforest UAV imagery	Learns complex features; robust in occluded and dense environments	Accuracy: 97.32%, κ = 94.59%
[8]	Deep Learning	Two-stage CNN, overlapping partitioning, multi-scale sliding windows, minimum distance filter	QuickBird satellite (55 km² area)	Handles large-scale mapping; reduces confusion with vegetation/buildings	F1-score: 94.99%
[18]	Deep Learning	CNN trained with manual samples, sliding window, overlapping prediction merging	High-res remote sensing imagery (Malaysia)	Handles dense distribution and overlapping crowns	Detection accuracy >96%, superior to traditional methods

3.3. Object detection

Object detection directly identifies and localizes palm trees by drawing bounding boxes around them, providing both high precision and computational efficiency. This method has become the dominant approach in recent palm tree identification studies due to its ability to handle large-scale data and provide more accurate localization compared to earlier techniques like classification and segmentation.

For instance, Culman, et al. [5] presents the first region-wide spatial inventory of Phoenix palm trees in Spain's Alicante province, using a CNN-based object detection model (RetinaNet) applied to high-resolution RGB aerial imagery. To overcome the limited training data in Alicante, the authors adopted transfer learning from manually labeled remote sensing imagery of the Canary Islands. They argue that this approach improves results because it helps the model better adapt to the characteristics of remote sensing images—rather than relying solely on models pre-trained on natural images. As a result, their best model achieved a high mAP of 0.861, successfully detecting over 511,000 Phoenix palms, demonstrating the effectiveness of deep learning for large-scale, accurate vegetation mapping. Cui et al. [6, 7] proposed PRISM and a bimodal reproduction model that advance palm tree localization and spatial modeling using high-resolution UAV imagery. PRISM integrates YOLO and RT-DETR detectors with SAM-based segmentation, and a bimodal spatial reproduction algorithm models the spatial patterns, both to address challenges such as dense canopy occlusion, uneven lighting, and background heterogeneity. It achieves real-time detection speed and demonstrates strong ecological relevance by combining Poisson processes (to model random palm distributions) with Gaussian models (to capture local clustering patterns). PRISM also

DOI: 10.54254/2755-2721/2025.LD36130

incorporates calibrated object detection and saliency mapping in its pipeline, therefore enhances model interpretability and generalization across different forest environments, enabling accurate and adaptable palm identification across diverse tree species while maintaining ecological insight.

Table 3. Summary of deep learning algorithms

No.	Method Type	Key Techniques/Models	Data Source	Main Advantages	Performance Metrics & Results
[5]	Deep Learning	CNN-based RetinaNet; transfer learning from Canary Islands remote sensing images	High-resolution RGB aerial imagery (Spain)	Effective transfer learning for limited labeled data; large-scale detection	mAP: 0.861; detected >511,000 Phoenix palms
[6,7]	Deep Learning	PRISM: YOLO /RT-DETR detectors + SAM segmentation; bimodal spatial reproduction model combining Poisson & Gaussian models	High-resolution UAV imagery	Real-time detection; handles occlusion, lighting; ecological relevance; interpretable	Real-time speed; strong spatial pattern modeling

4. Applications

Palm tree monitoring serves diverse purposes across agricultural, ecological, and urban contexts. The choice of monitoring techniques and algorithms depends heavily on the specific application, as different objectives require distinct approaches to data collection, analysis, and interpretation.

4.1. Agricultural and forestry applications

Palm trees hold significant economic value as key producers of palm fruit and oil, making their monitoring crucial for yield optimization and disease management. The nutritional richness of palm-derived products (particularly palm oil's unique composition of palmitic and oleic acids) makes them indispensable in food manufacturing (e.g., margarine, shortening, and frying fats) while offering substantial health benefits [23]. Beyond food, palm-derived products have demonstrated therapeutic potential, with applications spanning nutraceuticals and pharmaceuticals. Recent advances have also enabled the extraction of phenolic- and flavonoid-rich antioxidants from palm oil milling waste, further expanding the value chain and driving global demand for sustainable palm cultivation [3].

To support sustainable production, the palm industry increasingly integrates advanced technological tools for pest and disease monitoring. Remote sensing techniques, including ground-based LiDAR and thermal imaging systems, are applied to detect early symptoms of basal stem rot (BSR) and pest infestations. These technologies empower plantation managers to implement timely interventions, reduce yield losses, and promote effective integrated pest management strategies, thereby enhancing both productivity and plantation health [14, 4].

4.2. Ecological protection

Palm trees play crucial ecological roles, particularly in biodiversity hotspots and protected reserves. In these sensitive areas, remote sensing technologies—including UAVs, satellite imagery, and LiDAR—are essential for conservation efforts, enabling the monitoring of species distribution, habitat quality, and ecological changes over time.

The application of palm detection using high-resolution imagery allows population dynamics to be monitored as well as logging violations to be determined. For instance, deep learning methods have been used to identify palm species in rainforest communities [3] using algorithms which can support deforestation reduction efforts.

DOI: 10.54254/2755-2721/2025.LD36130

On a wider scale, palm oil expansion has been recognized as one of the major drivers of tropical deforestation and loss of biodiversity, especially in countries with tropical rainforests like South America and Southeast Asia. For curbing such issues, sustainable land use planning must be exercised with certification initiatives guaranteeing deforestation-free operations—like the Roundtable on Sustainable Palm Oil (RSPO)—to secure vulnerable forests as well as endangered species' habitats [1].

Palm-dominated systems provide ideal sites for studying species interactions with biodiversity patterns. Addition of natural tree islands in these systems creates very organized habitats that boost conservation of diverse biological communities. Studies have shown that biodiversity as well as ecosystem function is improved with increased diversity of tree assemblages as well as wider island sizes, all of this with agricultural production levels not substantially compromised [24].

Apart from the economic value of palm fruit as well as oil, incorporation of UAV imagery with deep learning technologies makes it possible for palm trees to be identified, segmented, as well as enumerated in real time, thus presenting key tools for ecological monitoring [6]. Such techniques strengthen conservation efforts as well as promote sustainable tropical forest resource utilization.

4.3. Landscape

The detection of palm trees for diverse land uses is of paramount significance for land planning, biodiversity tracking, as well as assessing green infrastructure. Mapping of palm tree distribution helps in vegetation denseness estimates, species diversity tracking, and creation of sustainable cities with an ecological approach [5].

Ornamental palm trees in an urban environment not only strengthen green infrastructure but also increase aesthetic value as well as cultural value. An exemplary case is the various roles as well as historical significance of palm trees in Greece's urban environment—primarily in Athens. Brought in as tropical plants, palms have become an integral component of Greek society, emulating symbols of strength, victory, justice, as well as good governance. Through the time from the Byzantine Empire to the Ottoman Empire and up to the establishment of the Greek state as it exists today, palm trees were broadly planted in town squares, hotel lawns, residential plots, as well as beach promenades. Consequently, they have developed into an integral component of attractions for tourists as well as an embodiment of historical continuity for Greece, cultural core, as well as societal values [2]. Similarly, in south China, palm trees are widely planted next to city streets for beautification of greenery as well as cityscape aesthetics.

5. Challenges and discussions

The third section tests a set of four decision templates developed for palm species detection using their corresponding palm images as test datasets.

Data Sources: Satellite imagery covers a wide geographical area; however, its low resolution restricts analysis at an individual tree level. UAVs can obtain high-resolution imagery, but they are limited because of short endurance flights, regulations, and obstruction from crowded canopies. Airborne imagery finds a balance between resolution and coverage; however, often its acquisition entails more costs, with difficulties concerning temporal availability.

Modalities: RGB imagery is widely used; however, it is subject to spectral ambiguity for visually similar species. While deep learning architectures, namely CNNs and Transformers, are effective in improving detection, they are not sufficiently robust when subjecting images to variable lighting or occluding objects.

DOI: 10.54254/2755-2721/2025.LD36130

Thermal imaging can be applied in tree health diagnosis but is still environmentally sensitive, i.e., to air temperature, and cannot be feasible to deploy to identify early progression of disease. HSI can provide spectral resolution to enable species differentiation; however, poor spatial resolution restricts fine-scale analysis, and so it is effective in broad-scale surveys. LiDAR is effective in capturing higher-order structural information; however, it is expensive and computationally extensive to deploy in real-time applications.

Applications: Ecological monitoring is still dataset-starved for low-abundance species and therefore still needs transfer learning or semi-supervised approaches. Precision agriculture requires real-time processing for UAVs but effective models (e.g., MobileNet, YOLO etc.) occasionally make concessions in accuracy to ensure efficiency. Hybrid approaches (UAV-satellite data fusion) and multimodality fusion (RGB+LiDAR/HSI) are promising but restricted due to algorithmic complications and computation-requirement-heavy necessities. These are where scalable annotation strategies and adaptive models are required.

6. Conclusion

Automated recognition of palm tree species has been significantly transformed by synergies among high-resolution images acquired using UAVs, satellites, and aircraft and improvements in deep and machine learning. Convolutional Neural Networks (CNNs) and Vision Transformers have been observed to attain superior competence in segmentation, classification, and object detection and facilitate scalable applications in crop monitoring in agriculture, ecological monitoring, and urban planning. They have been observed to perform extremely well with adverse environments and big data, and have a significant contribution to improving automated systems to be more accurate and useful.

Even with suchnovelties, there are significant issues like species similarity, environmental patchiness, and computational limitations. Future research to be conducted needs to embrace multimodal data fusion (e.g., RGB, LiDAR, HSI), design lightweight descriptors that may be utilized in UAVs' real-time use, and supplement rare species' data with synthetic data and domain adaptation. Integrations of autonomous recognition systems with ecological models will also enable shared uses, e.g., climate projections and species conservation. Future research in this ongoing interdisciplinary work will be priceless to make palm tree tracking systems more stable, scalable, and generalizable in the future.

References

[1] Vijay, V., Pimm, S. L., Jenkins, C. N., & Smith, S. J. (2016). The impacts of oil palm on recent deforestation and biodiversity loss. *PloS One, 11*(7), e0159668.

[2] Makedonopoulou, C. H. (2023). Palmscaping Athens: Towards a new reading of the Greek landscape. *Edinburgh Architecture Research, 38*(1), 6–20.

[3] Cui, K., et al. (2024). PalmProbNet: A probabilistic approach to understanding palm distributions in Ecuadorian tropical forest via transfer learning. In *Proceedings of the 2024 ACM Southeast Conference* (pp. 272–277).

[4] Husin, N. A., Khairunniza-Bejo, S., Abdullah, A. F., Kassim, M. S., Ahmad, D., & Azmi, A. N. (2020). Application of ground-based LiDAR for analysing oil palm canopy properties on the occurrence of basal stem rot (BSR) disease. *Scientific Reports, 10*(1), 6464.

[5] Culman, M., Delalieux, S., & Van Tricht, K. (2020). Individual palm tree detection using deep learning on RGB imagery to support tree inventory. *Remote Sensing, 12*(21), 3476.

[6] Cui, K., et al. (2025). Efficient localization and spatial distribution modeling of canopy palms using UAV imagery. *IEEE Transactions on Geoscience and Remote Sensing.*

[7] Cui, K., et al. (2025). Detection and geographic localization of natural objects in the wild: A case study on palms. *arXiv preprint, arXiv*:2502.13023.
[8] Li, W., Dong, R., Fu, H., & Yu, L. (2018). Large-scale oil palm tree detection from high-resolution satellite images using two-stage convolutional neural networks. *Remote Sensing, 11*(1), 11.
[9] Hidayat, S., Matsuoka, M., Baja, S., & Rampisela, D. A. (2018). Object-based image analysis for sago palm classification: The most important features from high-resolution satellite imagery. *Remote Sensing, 10*(8), 1319.
[10] Zolfagharnassab, S., Shariff, A. R. B. M., Ehsani, R., Jaafar, H. Z., & Aris, I. B. (2022). Classification of oil palm fresh fruit bunches based on their maturity using thermal imaging technique. *Agriculture, 12*(11), 1779.
[11] Casas, E., Arbelo, M., Moreno-Ruiz, J. A., Hernández-Leal, P. A., & Reyes-Carlos, J. A. (2023). UAV-based disease detection in palm groves of Phoenix canariensis using machine learning and multispectral imagery. *Remote Sensing, 15*(14), 3584.
[12] Dalagnol, R., et al. (2022). Canopy palm cover across the Brazilian Amazon forests mapped with airborne LiDAR data and deep learning. *Remote Sensing in Ecology and Conservation, 8*(5), 601–614.
[13] Malek, S., Bazi, Y., Alajlan, N., AlHichri, H., & Melgani, F. (2014). Efficient framework for palm tree detection in UAV images. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 7*(12), 4692–4703.
[14] Ahmed, A., Ibrahim, A., & Hussein, S. (2018). Detection of palm tree pests using thermal imaging: A review. In *Machine Learning Paradigms: Theory and Application* (pp. 253–270).
[15] Chungcharoen, T., Donis-Gonzalez, I., Phetpan, K., Udompetaikul, V., Sirisomboon, P., & Suwalak, R. (2022). Machine learning-based prediction of nutritional status in oil palm leaves using proximal multispectral images. *Computers and Electronics in Agriculture, 198*, 107019.
[16] Watson-Hernández, F., Gómez-Calderón, N., & da Silva, R. P. (2022). Oil palm yield estimation based on vegetation and humidity indices generated from satellite images and machine learning techniques. *AgriEngineering, 4*(1), 279–291.
[17] Al-Ruzouq, R., et al. (2024). Spectral–spatial transformer-based semantic segmentation for large-scale mapping of individual date palm trees using very high-resolution satellite data. *Ecological Indicators, 163*, 112110.
[18] Li, W., Fu, H., Yu, L., & Cracknell, A. (2016). Deep learning based oil palm tree detection and counting for high-resolution remote sensing images. *Remote Sensing, 9*(1), 22.
[19] Shafri, H. Z., Hamdan, N., & Saripan, M. I. (2011). Semi-automatic detection and counting of oil palm trees from high spatial resolution airborne imagery. *International Journal of Remote Sensing, 32*(8), 2095–2115.
[20] Fawcett, D., Azlan, B., Hill, T. C., Kho, L. K., Bennie, J., & Anderson, K. (2019). Unmanned aerial vehicle (UAV) derived structure-from-motion photogrammetry point clouds for oil palm (Elaeis guineensis) canopy segmentation and height estimation. *International Journal of Remote Sensing, 40*(19), 7538–7560.
[21] Gibril, M. B. A., Shafri, H. Z. M., Al-Ruzouq, R., Shanableh, A., Nahas, F., & Al Mansoori, S. (2023). Large-scale date palm tree segmentation from multiscale UAV-based and aerial images using deep vision transformers. *Drones, 7*(2), 93.
[22] Luo, H., et al. (2022). Combinations of feature selection and machine learning algorithms for object-oriented betel palms and mango plantations classification based on Gaofen-2 imagery. *Remote Sensing, 14*(7), 1757.
[23] Sundram, K., Sambanthamurthi, R., & Tan, Y. A. (2003). Palm fruit chemistry and nutrition. *Asia Pacific Journal of Clinical Nutrition, 12*(3).
[24] Zemp, D. C., et al. (2023). Tree islands enhance biodiversity and functioning in oil palm landscapes. *Nature, 618*(7964), 316–321.