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Mapping Olive and Palm Trees in Libya Using Computer Vision: A Baseline Study for Food Security and Economic Diversification

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ABSTRACT

The cultivation of olive and date palms is an integral part of the Libyan agricultural sector and contributes significantly to food security and economic diversification. However, the absence of accurate and up-to-date national data on tree populations limits strategic planning and investment. This study introduces an integrated approach using high-resolution satellite imagery, UAV surveys, and AI-based tree detection models to map olive and palm trees in Libya. The project aims to establish the first national baseline for tree populations, providing insight into spatial patterns, productivity potential, and vulnerability hot spots. The study offers actionable recommendations to strengthen sustainable agriculture and economic diversification efforts by linking tree distribution data to food security and economic indicators. The methodology also highlights the transformative potential of information and communication technologies (ICT) and remote sensing in shaping agricultural strategies within fragile contexts like Libya.

Keywords: Computer Vision, Tree Detection, Food Security, Olive and Palm Mapping.

تحديد أشجار الزيتون والنخيل في ليبيا باستخدام الرؤية الحاسوبية: دراسة أساسية للأمن الغذائي والتنويع الاقتصادي

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ملخص البحث

تُعدّ زراعة الزيتون والنخيل جزءًا محوريًا من القطاع الزراعي في ليبيا، وتُسهم بشكل كبير في تحقيق الأمن الغذائي والتنويع الاقتصادي. غير أن غياب البيانات الوطنية الدقيقة والمحدّثة حول أعداد الأشجار وتوزيعها يحدّ من فعالية التخطيط والاستثمار الاستراتيجي. تقدم هذه الدراسة نهجًا متكاملاً يجمع بين صور الأقمار الصناعية عالية الدقة، والمسوح الجوية باستخدام الطائرات بدون طيار **(UAV)** ، ونماذج الكشف الآلي عن الأشجار بالاعتماد على تقنيات الذكاء الاصطناعي لتحديد مواقع وأعداد أشجار الزيتون والنخيل في ليبيا. يهدف المشروع إلى إنشاء خط أساس وطني لأعداد الأشجار وتوزيعها، بما يتيح فهماً أدق للأنماط المكانية والإمكانات الإنتاجية ومناطق الهشاشة. كما تقدم الدراسة توصيات عملية لتعزيز الزراعة المستدامة والتنويع الاقتصادي من خلال ربط بيانات توزيع الأشجار بمؤشرات الأمن الغذائي والاقتصادي. وتُبرز المنهجية كذلك الإمكانات التحويلية لتقنيات المعلومات والاتصال **(ICT)** والاستشعار عن بُعد في تطوير السياسات الزراعية في الدول ذات الأوضاع غير المستقرة مثل ليبيا.

الكلمات الدالة: الرؤية الحاسوبية، الكشف عن الأشجار، الأمن الغذائي، تحديد وتوزيع الأشجار المثمرة، ليبيا

INTRODUCTION

Libya, characterized by vast arid and semi-arid landscapes, has long depended on agriculture as a cornerstone of rural livelihoods and economic stability [1]. Among its most significant crops are olive and date palm trees, which play a critical role in domestic food production and export revenue [2]. However, traditional monitoring methods, such as manual counting and field surveys, are time-consuming, labour-intensive, and prone to inaccuracies [3]. These challenges are exacerbated in Libya by large, often inaccessible agricultural areas, limiting effective data collection and strategic planning. Recent advances in artificial intelligence (AI), combined with high-resolution remote sensing technologies including unmanned aerial vehicles (UAVs) and satellite imagery, offer promising new avenues for agricultural monitoring [4]. AI-powered systems can automatically detect, count, and map individual trees with high precision, even across vast and challenging terrains [5]. Deep learning algorithms—such as convolutional neural networks (CNNs) and transformer-based architectures—have been increasingly applied to analyze aerial imagery for tree crown identification, spatial distribution, and crop health assessment [6].

Despite these technological advances, there remains a critical gap in Libya: the absence of an integrated, large-scale baseline mapping of olive and date palm trees that supports national agricultural monitoring and food security strategies. Applying AI-driven tree mapping in the Libyan context could significantly enhance inventory accuracy, resource management, yield prediction, and disease control, thereby informing policy and revitalization efforts amid climate change and post-conflict recovery [7, 8]. This study aims to harness these technological advancements to map the distribution of olive and date palm trees across Libya. It explores the application of AI methodologies for simultaneous counting of olive and palm trees and assesses their integration potential into national agricultural monitoring systems. By establishing the first national baseline, this research seeks to support food security and economic diversification initiatives, aligning with national programs such as the Green Libya Initiative.

1. MATERIALS AND METHODS

2.1 Related Work

Numerous research efforts demonstrate the transformative potential of remote sensing and computer vision in agricultural tree mapping. Foundational reviews have outlined the evolution of deep learning and remote sensing in agriculture [3, 4, 7]. Various studies have explored CNN-based classifiers for tree detection, with [9] developing a MobileNet-v1 application to detect oil palm trees in very high-resolution satellite imagery. Mask Region-based Convolutional Neural Network (R-CNN) has also been employed for date palm detection and counting in Bahrain [10]. Real-time olive tree enumeration using Unmanned Aerial Systems (UAS) and cloud processing has been demonstrated in [11]. These advances build on pixel-level classifiers achieving high accuracy in generic tree segmentation [13], and are complemented by the use of multi-temporal satellite data for improved tree species classification [15]. More recently, You Only Look Once Version 8 (YOLOv8) models have shown superior accuracy and speed for palm detection [12-16].

Regional implementations have adapted these frameworks to Mediterranean agroecosystems. In Libya and Tunisia, remote sensing and UAV-based systems have been used to monitor olive and date palm orchards, with studies reporting high accuracy in canopy quantification [17-19]. However, persistent challenges remain, including the lack of integrated monitoring systems and ground-truth validation, particularly under drought conditions [19]. Socioeconomic and traditional importance of date palms in the region has been well documented [2], and climate change impacts have been mapped for the Arab region [8]. The operationalization of these technologies has direct socioeconomic implications. Tunisian studies quantify centennial olive systems' contributions to erosion prevention and carbon sequestration [17]. In Libya, a significant dependency on imported olive oil underscores the urgent need for precise tree mapping to support domestic production chains [20]. National and regional frameworks emphasize the strategic importance of agricultural monitoring for food security [1]. Despite these advances, three persistent limitations emerge. First, most YOLO implementations focus on single-tree detection, with little work on simultaneous detection of olive and palm trees [12, 11]. Second, multi-class detection systems are underdeveloped for mixed agroforestry systems typical of Libyan oases. Third, regional studies often prioritize either computational precision or operational speed, rarely achieving synergistic integration. Our study addresses these gaps through: 1) hybrid YOLOv8 architectures for simultaneous olive-palm detection; 2) cross-validation using multi-platform satellite/UAV data; and 3) spatial integration of detection outputs with Libyan food security indices, advancing both methodological rigor and practical relevance in fragile agroeconomic contexts.

2.2 Methodology

To develop a computer vision model based on the YOLOv8 model capable of efficiently detecting and counting olive and palm trees simultaneously, a three-phase approach was followed, each comprising several steps as shown in Figure 1. These phases are: Data Acquisition & Preprocessing, Model Preparation & Training, and Deployment & Testing.

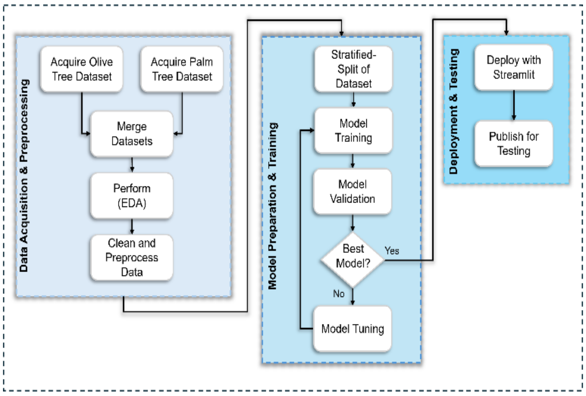

Fig 1. Overall workflow of the study, illustrating the main phases including data acquisition, preprocessing, training of the YOLOv8 model, evaluation, and deployment.

Firstly, the Data Acquisition & Preprocessing phase began by collecting data for both tree types. After conducting an extensive literature review, two datasets were identified [21, 22] from previous studies, each focused on one tree type individually. Since our objective was to detect and count both olive and palm trees, these datasets were merged into a single, unified dataset. Next, an exploratory data analysis (EDA) was conducted to gain a deeper understanding of the combined dataset's characteristics. This included examination of class distribution, image resolution, and annotation quality. The findings of the EDA are summarized in Table 1. The table shows the number of images and the corresponding number of labelled trees for each class (Olive and Palm), as well as the total across both classes. The image resolution used for each set is also specified. Following the EDA, the data was cleaned by removing duplicate and/or corrupted images. In addition, image size standardization was applied. The initial olive tree images were sized at 960x640, while the palm tree images were 640x640, so they were unified at a size of 640x640 for consistency. The labels were also adjusted to reflect the binary nature of our problem. Since the original datasets were obtained from studies designed to detect just one tree type, the data was relabelled to ensure both olive and palm trees are correctly represented in a binary format.

Secondly, in the Model Preparation & Training phase, the data was split into two subsets, one for training and the other for validation and tuning. The training process was done using the training subset with specific hyperparameters, including the Stochastic Gradient Descent (SGD) optimizer. Which is a simplified version of the gradient descent algorithm, where model parameters are updated based on gradients calculated from a small batch or a single data point rather than the entire dataset [23]. Also, the batch size was set to 16, meaning 16 training examples were processed per iteration, and the number of epochs is 10.

The training process followed an iterative cycle, where the model's performance was continuously evaluated using a validation subset. If the results were unsatisfactory, the parameters are tuned, and the model is retrained and re-evaluated. This cycle is repeated until an optimal performance is achieved. In our case, the training ended after 10 epochs, as specified in the initial training configuration. Finally, in the Deployment & Testing phase, the best-performing model gets deployed as a web application using the Streamlit library and published for testing. The app aims to provide a simple, user-friendly interface that allows users to easily upload images to detect and count olive and/or palm trees present in the scene.

2. RESULTS AND DISCUSSION

Over the course of 10 training epochs, the model exhibited a consistent and stable learning trend, with clear improvements in both loss functions and evaluation metrics. All training losses showed a downward trend, indicating effective learning. Specifically, the box regression loss (train/box_loss) decreased from 1.30 in epoch 1 to 0.95 by epoch 10. Similarly, the classification loss (train/cls_loss) saw a significant drop from 1.55 to 0.52, and the distribution focal loss (train/dfl_loss) was reduced from 1.25 to 1.03, as shown in Figure 2.

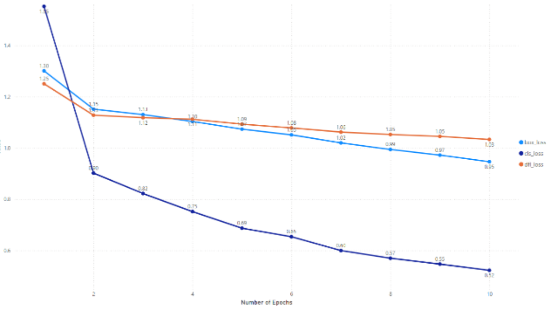

Fig 2. Training performance over epochs

These trends were mirrored in the validation metrics as well. The validation box loss fell from 1.08 to 0.87, and the classification loss presented a notable decline from 0.99 to 0.50. The validation DFL loss also followed this trend, decreasing from 1.04 to 0.97. Together, these results suggest that the model was not only learning effectively from the training data but also generalizing well to unseen samples. As illustrated in Figure 3, the evaluation metrics also indicate that the model is improving over the epochs. Precision improved from 0.84 to 0.91, and recall increased from 0.86 to 0.93. And the mean Average Precision at IoU 0.50 (mAP50) increased from 0.89 to 0.94, while the stricter mAP50-95 rose from 0.60 to 0.70. As a result, these improvements were also reflected in the F1-score, which climbed steadily from 0.85 in the first epoch to 0.92 by the end of training.

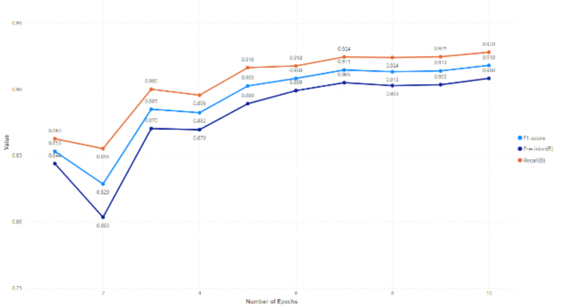

Fig 3. Evaluation metrics showing the progression of recall, precision, and F1-score over training epochs.

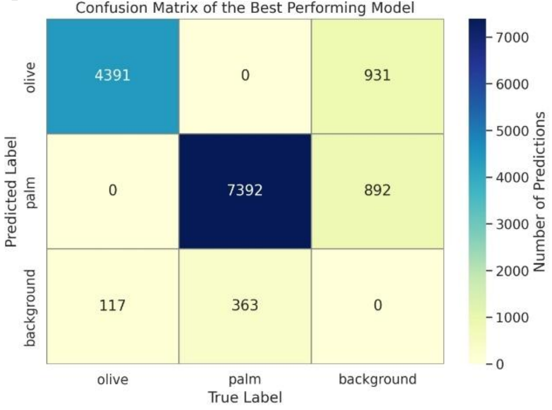

Fig 4. Confusion matrix of the best-performing model, illustrating classification performance across the three classes: olive, palm, and background

The learning rate was gradually reduced throughout training for all parameter groups (pg0, pg1, and pg2), beginning at 0.00055 and decreasing to 0.00018. This decay likely contributed to stabilizing the training process and mitigating overfitting, especially in the later epochs.

The training results confirm the model's ability to extract meaningful patterns from the data while maintaining strong generalization. The consistent improvement across all key metrics highlights the robustness of the training process and indicates that the model is well-prepared for deployment in downstream applications. To evaluate the overall classification of the model, a confusion matrix was generated for the best-performing model. The matrix reveals a strong ability to distinguish between olive and palm trees on one hand, and reasonably differentiate them from the background on the other hand. Out of all true palm tree instances, 7,392 were correctly predicted, and only 363 cases were misclassified as background. In addition, the olive tree class was identified with reasonable accuracy, with 4,391 correct predictions and 117 misclassifications, which were confused with the background. Notably, the dataset doesn't include a dedicated class for the background. However, anything that doesn't belong to the two target classes is considered background. From the confusion matrix, it can be noticed that the model misclassified 931 background objects as olive trees and 892 as palm trees. It's worth highlighting that the model never confused olives with palms or vice versa, which indicates how well it was able to learn and distinguish between the two types of trees. The misclassifications occurred only between the tree classes and the background, suggesting that while the model is generally robust, it occasionally struggles when the features of the objects are less distinguishable, possibly due to low resolution or visual similarity between trees and their surroundings. Still, the strong diagonal trend in the confusion matrix confirms the model's effectiveness in learning and generalizing class-specific features.

Table 1. Summary of the dataset used for training and validation.

Class	Total	Train Set	Val Set	Resolution
Both Classes	2681 (38330 trees)	1876 (26067 trees)	805 (12263 trees)	640x640
Olive (0)	1334 (14391 trees)	934 (9883 trees)	400 (4508 trees)	960x640
Palm (1)	1347 (23939 trees)	942 (16184 trees)	405 (7755 trees)	640x640

3. CONCLUSIONS

This study demonstrates the feasibility and effectiveness of applying deep learning, specifically YOLOv8, for the simultaneous detection and enumeration of olive and palm trees in Libya. Through a carefully structured three-phase workflow, data acquisition and preprocessing, model training, and deployment, the project successfully developed a performant model capable of supporting agricultural monitoring efforts at scale. The consistent improvements in loss metrics and evaluation scores, including precision, recall, and mAP, confirm the model's robustness and its ability to generalize to unseen data. The deployment of the model as a user-friendly web application further showcases its potential for practical use in real-world agricultural settings, offering a scalable solution to bridge critical data gaps in Libyan agroforestry. A web-based interface was developed using the Streamlit Python library, as illustrated in Figure 5. This foundational work lays the groundwork for establishing a national baseline of tree populations, with direct implications for food security, economic diversification, and environmental resilience. Future work will focus on expanding the dataset to include more diverse geographic regions known for olive and palm cultivation, such as Aljufra and Tarhuna. Addressing current limitations, such as the use of single-species datasets and potential annotation inconsistencies, will require the integration of expert-labelled, multi-species imagery and ground-truth validation. Seasonal changes, varying resolutions, and visual background similarities also call for techniques like data augmentation, domain adaptation, and multi-temporal analysis. Moreover, incorporating other crop types and land cover classes would expand the platform's utility for broader agroforestry monitoring. Near-real-time tracking via UAVs or satellite streams could support dynamic assessments of tree health and vulnerability to climate stressors. Linking spatial tree data with food security metrics, yield statistics, and market accessibility will further enable informed decision-making. Finally, pilot deployments with agricultural cooperatives and relevant agencies will ensure practical adoption and long-term impact. These steps will enhance both the technical resilience and real-world relevance of the system, advancing climate-resilient agricultural development in Libya.

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