Evaluating AI for Palm Tree Disease Detection: A Comparative Study of YOLOv8 Object Detection and U-Net Segmentation Using UAV Imagery

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Abstract

Agriculture is a cornerstone of economic stability and food security, particularly in regions like Morocco, where palm trees are vital to the environment and local livelihoods. The Figuig oasis, known for its extensive palm plantations, faces significant threats from the spread of palm tree diseases, which can lead to substantial agricultural losses. Early and accurate disease detection is critical to mitigating these impacts. This study evaluates the effectiveness of deep learning models YOLOv8 for object detection and U-Net for segmentation in detecting and segmenting healthy and diseased palm trees using Unmanned Aerial Vehicle (UAV) imagery. A dataset of 400 UAV images was annotated and divided into training (70%), validation (20%), and test (10%) sets. YOLOv8 achieved an accuracy of 78.48%, with a precision of 58.38% and a recall of 47.70%, demonstrating robust object detection capabilities but highlighting the need for improved recall to reduce false negatives. On the other hand, U-Net excelled in segmentation, achieving an overall precision of 0.8746, recall of 0.8713, and F1-score of 0.8727, with powerful performance in delineating diseased regions. The results underscore the complementary strengths of YOLOv8 and U-Net, with YOLOv8 offering efficient detection and U-Net providing detailed segmentation for precise health assessment. This study highlights the potential of integrating UAV imagery and deep learning for automated palm tree health monitoring, paving the way for early disease detection and sustainable agricultural practices. Future work will focus on optimizing model performance, expanding the dataset, and exploring advanced architectures to further enhance accuracy and recall.

1. Introduction

Palm trees play a crucial role in global agriculture (Amuda & Alabdulrahman, 2024), particularly in arid and semi-arid regions, where they serve as essential sources of food, income, and ecological balance (Hadji & Petrişor, n.d.). However, recent years have seen increased threats to palm cultivation due to the spread of diseases and pests (Murphy et al., 2021). These health issues pose significant challenges to global food security, local economies, and environmental stability (Oosterveer et al., 2014). Diseases such as Bayoud, caused by the fungus Fusarium oxysporum f. sp. Albedinis (Freeman & Maymon, 2000), and infestations like the Red Palm Weevil (Rhynchophorus ferrugineus) have notably reduced date palm productivity across North Africa and the Middle East (Al-Dosary et al., 2016). These impacts are further exacerbated by climate change, which accelerates disease spread and weakens plant resilience through rising temperatures, prolonged droughts, and water scarcity (Abubakar et al., 2023).

In Morocco, agriculture is vital to the national economy (Abdelmajid et al., 2021), and palm trees are economically important and culturally significant, contributing to environmental sustainability (Hamriri et al., 2024). Palm groves provide livelihood for thousands of rural households and serve as barriers against desertification (Kabiri & Remini, n.d.). The Figuig oasis, situated in eastern Morocco near the Algerian border (Salgot et al., 2014), exemplifies a traditional oasis system characterized by extensive date palm plantations (Houssni et al., 2023). This region, known for its biodiversity and unique agro-ecological practices, relies heavily on palm cultivation for survival (Mercha et al., n.d.). Nevertheless, Figuig has not been immune to palm diseases, posing serious threats to both local livelihoods and ecological balance(Kassem et al., 2017).

Traditional palm disease detection methods involve manual inspection, a process that is time-consuming, labor-intensive, and susceptible to human error (Ruslan et al., 2019). Advances in remote sensing and artificial intelligence (AI) present significant opportunities to revolutionize agricultural monitoring through automation (Fuentes-Peñailillo et al., 2024). Unmanned Aerial Vehicles (UAVs), equipped with high-resolution cameras, efficiently capture large-scale imagery, while deep learning models can accurately analyze these images to detect and segment diseased regions (Wu et al., 2019).

Among the promising deep learning methods, YOLOv8 excels in object detection due to its real-time capabilities, making it ideal for identifying healthy and diseased palm trees from UAV imagery (D. Ahmed et al., n.d.). Conversely, U-Net, a convolutional neural network (CNN) originally developed for biomedical image segmentation (Ronneberger et al., 2015), demonstrates outstanding performance in delineating precise regions of interest, critical for accurately assessing disease severity (Park et al., 2019).

Previous research by Bouthina et al. (2024) highlighted the effectiveness of CNNs in palm disease classification, achieving accuracy rates of up to 98%. However, these studies primarily focused on classification without precise disease localization, leading to limited detection of early-stage infections (Bouthaina et al., 2024). Similarly, Yarak et al. (2021) successfully employed deep learning for oil palm health monitoring using high-resolution UAV imagery, utilizing Faster R-CNN with ResNet-50 and VGG-16 backbones (Yarak et al., 2021). Their study achieved F1-scores up to 95.09% for detection and 92.07% for classifying healthy trees. Nonetheless, they encountered challenges detecting early-stage diseases (57.14% F1-score for unhealthy trees) and young palms due to limited crown visibility. These limitations underscore the necessity of integrated detection and segmentation approaches, as addressed in this study.

Our research directly addresses these gaps by combining YOLOv8's object detection capabilities with U-Net's segmentation precision (Elsharkawy et al., 2025). This integrated methodology enables effective disease identification and precise mapping of affected areas in UAV imagery, enhancing early detection accuracy and providing spatial information for targeted treatments.

The primary objective of this study is to evaluate and compare YOLOv8 and U-Net in detecting and segmenting diseased palm trees using UAV-captured imagery from the Figuig oasis. A dataset consisting of 400 annotated UAV images was employed, divided into training (70%), validation (20%), and test sets (10%) to ensure rigorous model assessment. Performance metrics including accuracy, precision, recall, and F1-score were analyzed to identify the strengths and limitations of each approach.

The outcomes of this research significantly contribute to the expanding domain of AI-driven agricultural monitoring, illustrating the potential of deep learning models to improve early disease detection and support sustainable farming practices (Zhang et al., 2021). Integrating UAV technology with advanced AI techniques presents automated, scalable, and cost-effective solutions for palm health assessments (Liu et al., 2021). Future research will aim to further optimize model performance, expand the dataset, and investigate advanced architectures to enhance detection accuracy and reliability.

2. Materials And Methods

The Material and Methodology section introduces the structured approach employed in this study, initially presenting the geographical context of the study area the Figuig oasis, Morocco. Subsequently, it outlines the comprehensive identification framework (Figure 1), which systematically covers all critical phases of the research. This framework involves sequential steps, including data acquisition, meticulous annotation and labelling, preprocessing techniques for enhancing data quality, model training procedures, rigorous model evaluation, and ultimately, prediction and mapping of diseased palm trees.

2.1. Study Area

Figuig, a charming oasis town in the Oriental region of Morocco (Figure 1), is situated at approximately 32°06′N, 1°14′W near the Algerian border (Teixidor-Toneu et al., 2017). Nestled within the Sahara Desert, it is surrounded by arid mountains and features expansive palm groves covering around 5,000 hectares (Msanda et al., 2021). These groves, vital to the local economy, are sustained by ingenious traditional khettara irrigation systems. Figuig's desert climate is marked by hot summers exceeding 40°C (104°F), mild winters ranging from 5°C to 20°C (41°F to 68°F), and scarce rainfall, which averages less than 200 mm annually (Teixidor-Toneu et al., 2017).

Home to about 12,000 residents, Figuig thrives on agriculture, with date farming as its main activity. The town is renowned for producing premium-quality dates, including the sought-after "Aziza" variety (Msanda et al., 2021). The palm trees not only provide economic sustenance but also contribute to the town's scenic beauty and ecological balance (Talley et al., 2012).

Figuig is composed of seven historic ksour (fortified villages) interconnected by narrow alleys and characterized by traditional adobe architecture (Msanda et al., 2021). These ksour reflect the town's deep cultural roots and its role as a historic crossroads for trade and cultural exchange. Festivals, including the annual date celebration, showcase the community's vibrant heritage and agricultural achievements (Teixidor-Toneu et al., 2017).

Figuig's unique combination of natural beauty, historical significance, and agricultural wealth makes it a fascinating and resilient oasis in Morocco's desert landscape.

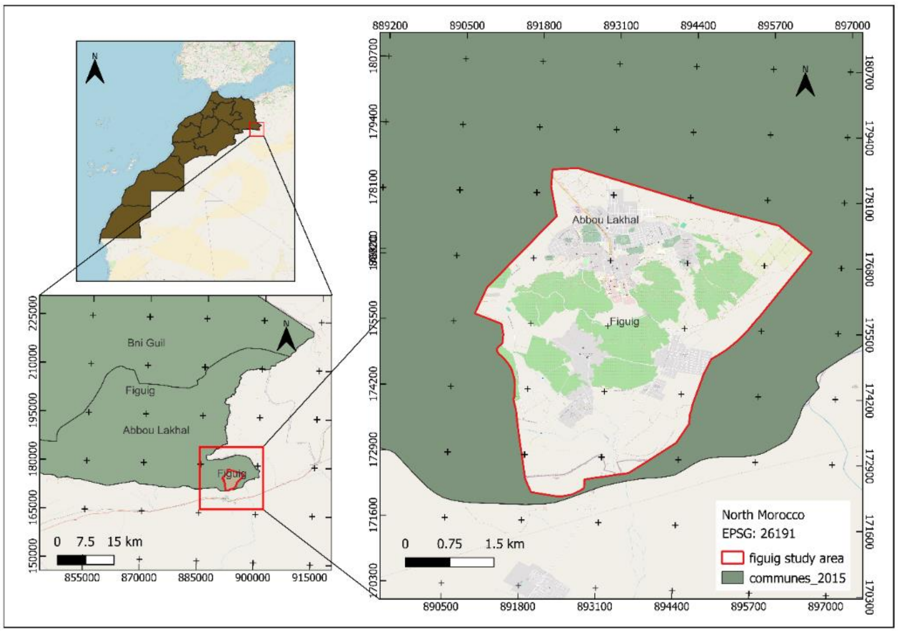

Figure 1: Geographic Context of the Study Area.

2.2. Data Used

The study utilized two primary forms of data: UAV (Unmanned Aerial Vehicle) imagery and annotated datasets. These datasets were crucial for achieving the study's objectives, ensuring high accuracy in detecting and segmenting diseased palm trees, and enabling robust model training and evaluation.

2.2.1. UAV Imagery

High-resolution UAV imagery formed the foundation of this study. The UAV images were captured over palm plantations in the Figuig oasis, Morocco, under consistent lighting and altitude conditions to ensure uniformity and clarity [[File]]. These images provided detailed views of both healthy and diseased palm trees, enabling precise analysis of canopy conditions and disease symptoms. The UAV platform was equipped with advanced sensors capable of capturing RGB and multispectral data, which are essential for identifying early signs of palm tree diseases (R. S et al., 2024).
After capturing the UAV images, photogrammetric processing was performed using Agisoft Metashape , a state-of-the-art software for photogrammetry ,Agisoft Metashape aligned the individual drone images to create a single cohesive image, resulting in high-resolution orthophotos with a ground resolution of 1 cm per pixel ,This process ensured that the images were geometrically corrected and suitable for further analysis.

2.2.2. Orthophoto Splitting and Dataset Preparation

The orthophotos generated by Agisoft Metashape were subsequently split into smaller, manageable tiles using a custom Python script. (Pahari, n.d.) This step was necessary to divide the large orthophotos into smaller sections that could be efficiently processed by the AI models. The splitting process also helped standardize the dataset for consistent input sizes during training
Once the orthophotos were split, the resulting images were uploaded to Roboflow, a platform designed for managing and annotating machine learning datasets. In Roboflow, the images were annotated to prepare them for supervised learning tasks.

2.2.3. Annotated Datasets

To facilitate supervised learning for both YOLOv8 object detection and U-Net segmentation, the UAV imagery was meticulously annotated using the Roboflow platform (R. S et al., 2024). The annotation process involved:

- Bounding Boxes: For YOLOv8, individual palm trees were labeled as either "healthy" or "diseased," enabling the model to learn localized disease detection.
- Pixel-wise Masks: For U-Net, precise pixel-level masks were created to delineate diseased regions within the tree canopies, supporting accurate segmentation tasks.

The annotated dataset was divided into three subsets (R. S et al., 2024):

Training Set (70%): Used to train the AI models.
Validation Set (20%): Employed for hyperparameter tuning and model validation.
Testing Set (10%): Reserved for final performance evaluation, ensuring an unbiased assessment of model accuracy and reliability (R. S et al., 2024).

2.2.4. Metadata

In addition to the UAV imagery, metadata was collected to provide contextual information about the data acquisition process. This metadata included:

- UAV flight parameters such as altitude, speed, and camera settings.
- Geographical coordinates of the palm plantations within the Figuig oasis.
- Environmental conditions during image capture, including weather patterns and lighting conditions.(Pahari, n.d.)

This metadata played a vital role in understanding the conditions under which the data was collected and ensured the reproducibility of the study.

2.2.5. Data Preprocessing

Before feeding the data into the AI models, several preprocessing steps were performed to enhance data quality and model performance:

- Image Cropping: Individual tree crowns were extracted from UAV imagery to focus on specific areas of interest.
- Normalization: Pixel values were adjusted to ensure consistency across images.
- Augmentation: Techniques such as rotation, flipping, and contrast adjustments were applied to increase dataset diversity and reduce overfitting.

These preprocessing steps ensured that the models could generalize effectively to real-world scenarios.(M. Ahmed & Ahmed, 2023)

2.3. Methodology

This study follows a structured approach combining data acquisition, preprocessing, model training, and evaluation to assess the effectiveness of deep learning models in detecting and segmenting diseased palm trees in the Figuig oasis-Morocco.

2.3.1. Data Acquisition

UAV (Unmanned Aerial Vehicle) imagery was collected over palm plantations in the Figuig oasis, capturing both healthy and diseased palm trees. A total of 400 high-resolution images were obtained under consistent lighting and altitude conditions to ensure uniformity.

2.3.2. Data Annotation and Preparation

The dataset was manually annotated using Roboflow platform, labeling individual palm trees as either "healthy" or "diseased" for object detection tasks (YOLOv8), and creating pixel-wise masks for segmentation tasks (U-Net). The annotated dataset was then split into training (70%), validation (20%), and testing (10%) subsets.

2.3.3. Model Selection and Implementation

Two deep learning architectures were employed:

- YOLOv8 for object detection, aimed at identifying and localizing individual palm trees and classifying their health status.
- U-Net for semantic segmentation, designed to delineate the exact regions of disease presence within the canopy.

2.3.4. Model Training

The models were trained on the prepared datasets using Python frameworks. Data augmentation techniques such as rotation, flipping, and contrast adjustments were applied to enhance model generalization. Hyperparameters (learning rate, batch size, number of epochs) were optimized through experimental tuning.

2.3.5. Evaluation Metrics

- For YOLOv8, performance was assessed using Accuracy, Precision, and Recall to measure detection quality.
- For U-Net, segmentation performance was evaluated using Precision, Recall, and F1-score at the pixel level. Confusion matrices and visual inspection of predictions were used to validate model outputs.

2.3.6. Analysis and Comparison

Results from both models were compared to assess their strengths and limitations. While YOLOv8 provided efficient detection of palm trees, U-Net offered detailed segmentation of diseased areas, making the models complementary.

2.3.7. Tools and Platforms

- **Annotation:** Roboflow
- **Model Training:** Google Colab
- **Visualization:** Matplotlib, OpenCV

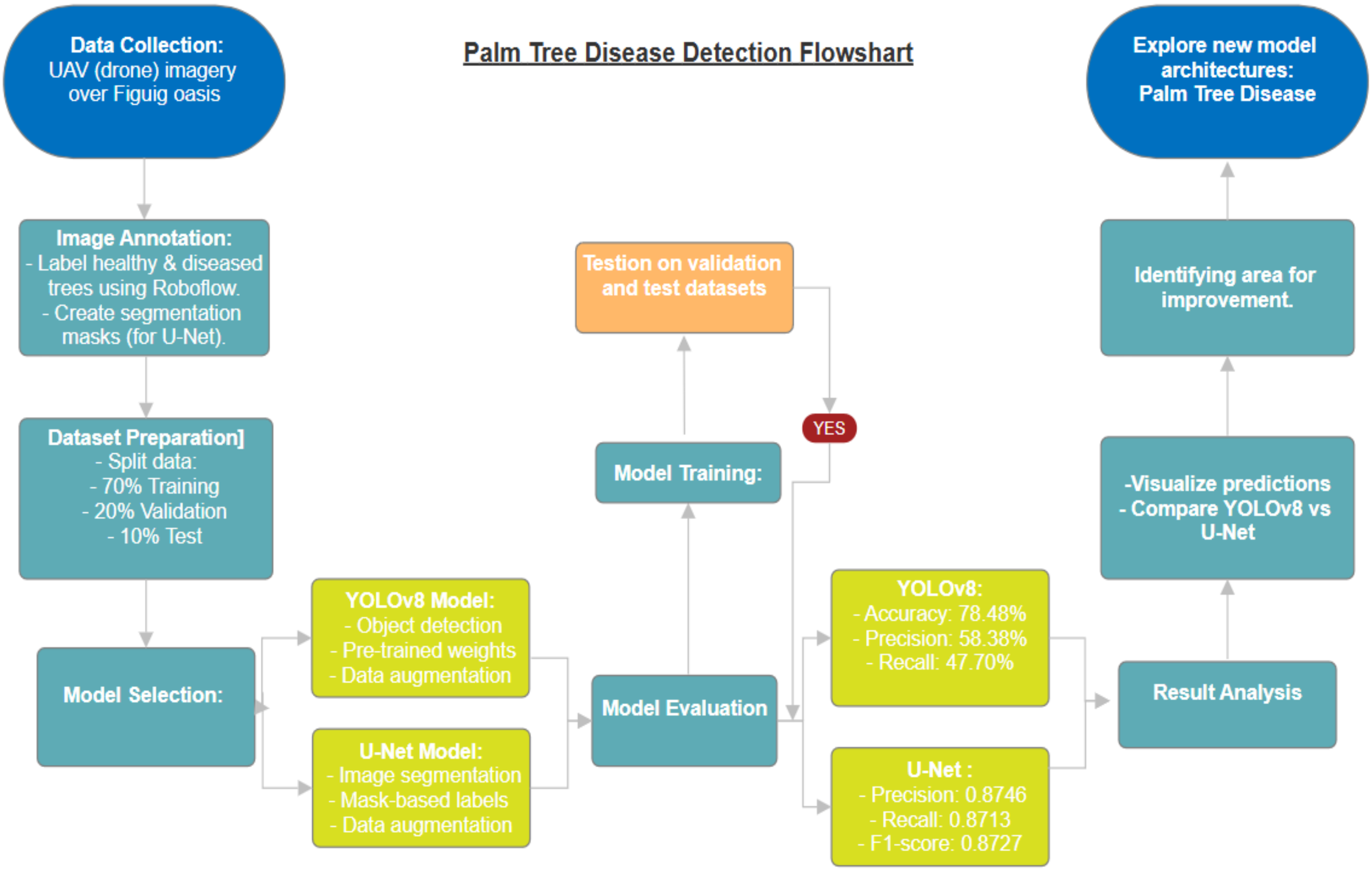

Figure 2: Methodology for Palm Tree Disease Detection and Segmentation Using Deep Learning and UAV Imagery.

This flowchart (Figure 2) outlines a complete deep learning workflow for palm tree disease detection and segmentation using UAV imagery from the Figuig oasis. Two models were implemented: YOLOv8 for object detection and U-Net for image segmentation. The evaluation results show that YOLOv8 achieved a good accuracy of 78.48% but had moderate precision (58.38%) and lower recall (47.70%), indicating a tendency to miss diseased trees (false negatives). In contrast, U-Net delivered strong performance in segmentation with high precision (0.8746), recall (0.8713), and F1-score (0.8727), making it more effective for detailed health assessment. Overall, the models are complementary: YOLOv8 is efficient for fast detection, while U-Net offers more accurate and fine-grained segmentation. Future improvements will focus on enhancing YOLOv8's recall and testing advanced architectures for better overall performance.

3. Results

This section presents the evaluation results of the two deep learning models applied in this study: YOLOv8 for object detection and U-Net (with a ResNet101 backbone) for semantic segmentation. Both models were trained and tested on UAV imagery collected from the Figuig oasis, with the goal of detecting and segmenting healthy and diseased palm trees. Performance metrics such as precision, recall, F1-score, and mAP were used to assess model accuracy and reliability.

3.1. YOLOv8 Object Detection Results

The YOLOv8 model was trained to detect and classify healthy and diseased palm trees from UAV imagery collected over the Figuig oasis. It achieved a precision of 58.38%, recall of 47.70%, and an overall accuracy of 78.48%. The model performed well in identifying healthy palm crowns, consistently drawing bounding boxes with high confidence scores. However, detecting diseased trees proved more challenging due to their lower representation in the dataset and the visual similarity between diseased and healthy trees.

As illustrated in Figure 4, the distribution of detected instances reveals a strong class imbalance: over 6,000 healthy instances were annotated compared to fewer than 1,000 diseased ones. This imbalance likely led to a reduced ability to generalize the characteristics of diseased palms, resulting in lower recall and missed detections. The detection previews also show this limitation—while YOLOv8 successfully outlines most healthy palms with confidence scores often exceeding 0.70, diseased trees are either misclassified or identified with lower confidence levels.

Despite these challenges, YOLOv8 remains a highly efficient tool for large-scale palm monitoring. Its speed and ability to rapidly assess tree health status make it ideal for field deployment. For future improvement, integrating class balancing strategies, targeted data augmentation, or combining detection with segmentation could significantly enhance its performance in detecting rare disease patterns.

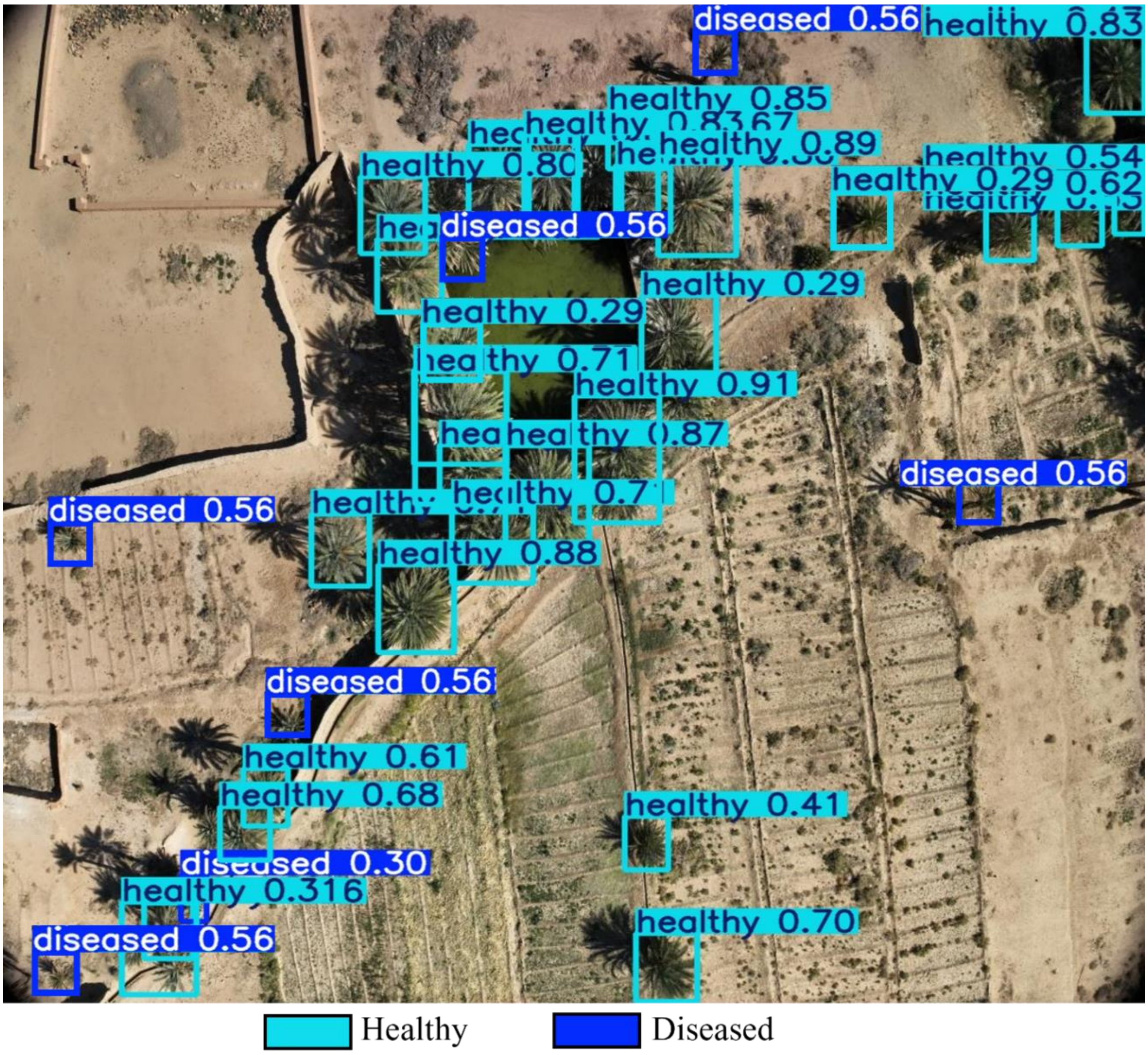

Figure 3: UAV image with YOLOv8 detection of healthy trees and confidence scores

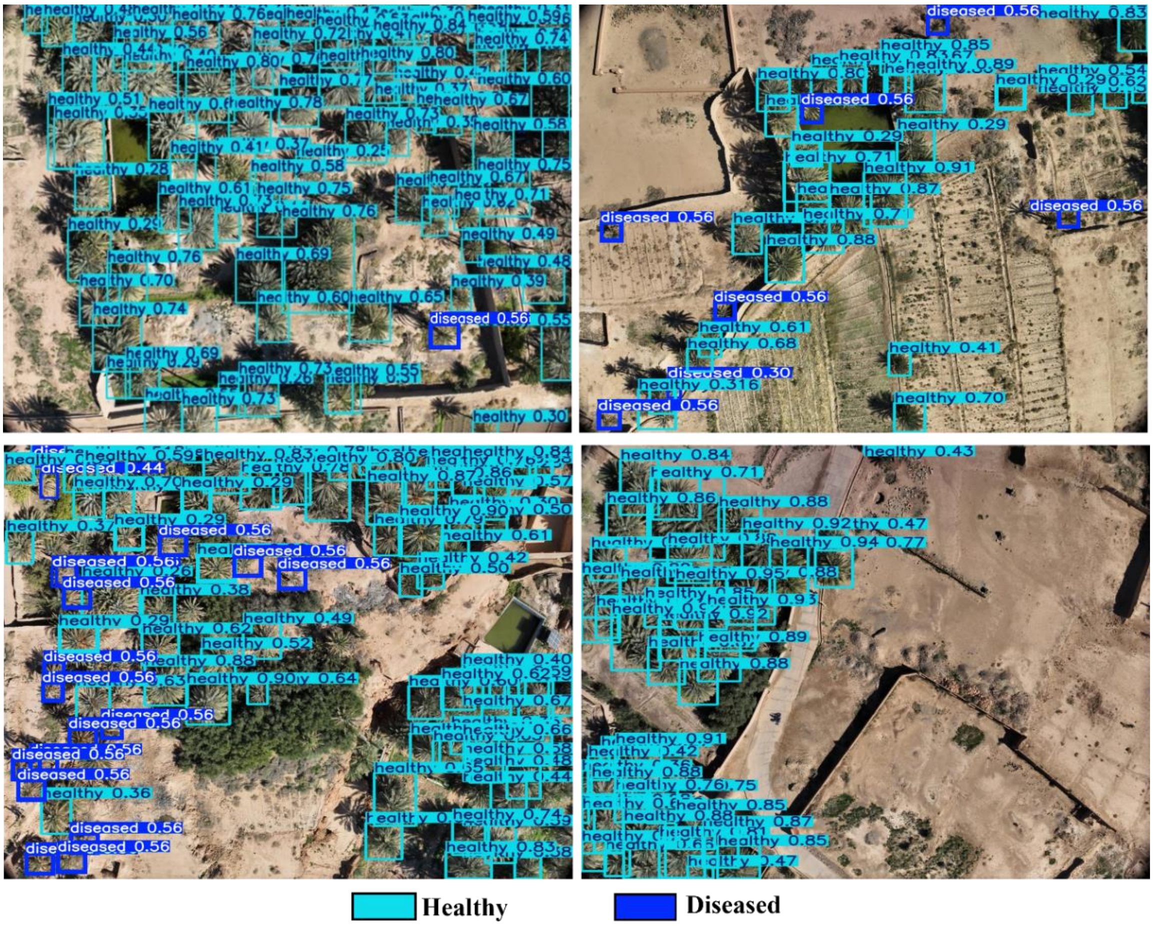

Figure 4: Overview of detection results across different UAV scenes.

3.2. U-Net Segmentation Results

The U-Net model, equipped with a ResNet101 encoder, demonstrated strong performance in segmenting palm crowns and identifying disease-affected regions across various UAV scenes. As illustrated in Figure 5, the model effectively distinguishes between healthy and unhealthy palm trees, producing clear and spatially coherent segmentation masks. In each example, the original UAV image is shown alongside its predicted segmentation output and the corresponding pixel count for each class. The bar charts reveal a consistent class imbalance, with a significantly higher number of healthy pixels compared to unhealthy ones. Despite this imbalance, U-Net succeeded in accurately localizing diseased areas, even in complex visual conditions such as overlapping canopies, shadows, or partial visibility. These results underscore the model's robustness in pixel-level analysis and its practical utility in monitoring disease distribution within dense palm groves. The clarity of spatial boundaries and the consistency of predictions across diverse environments further confirm the model's reliability for operational use in precision agriculture.

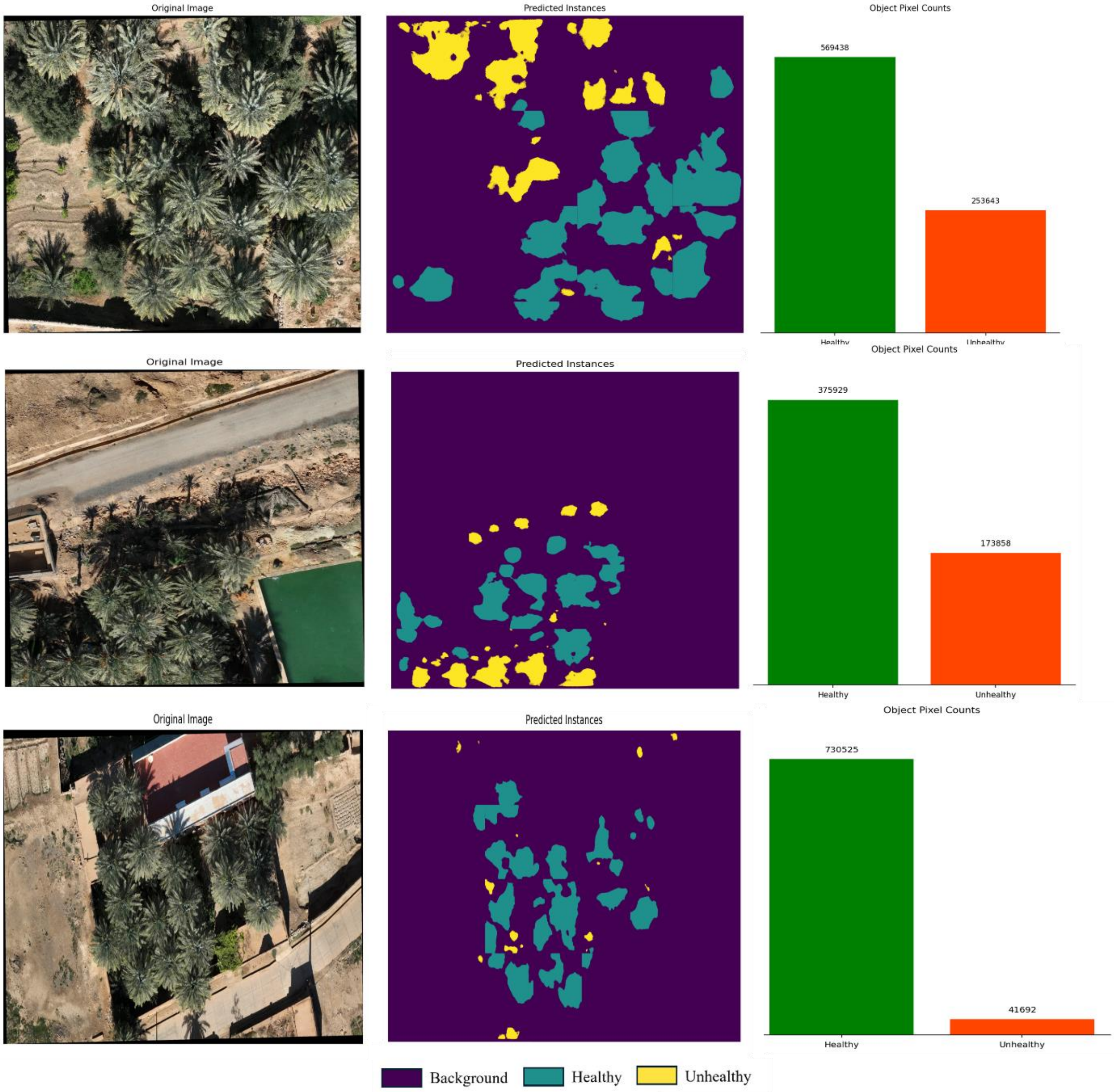

Figure 5: U-Net Segmentation Results with Pixel Counts

4. Discussion

The performance of both YOLOv8 and U-Net models was evaluated on a reserved test set representing 10% of the total UAV imagery dataset. The analysis focused on key evaluation metrics, including precision, recall, F1-score, and accuracy, to determine how well each model could detect and segment healthy and diseased palm trees.

YOLOv8, which was trained for object detection and classification, achieved an accuracy of 78.48%, with a precision of 58.38% and a recall of 47.70%. These results indicate the model's reliability in identifying palm crowns, particularly healthy trees, across diverse scenes. However, the comparatively lower recall suggests that some diseased trees went undetected, likely due to subtle symptoms, overlapping crowns, or the underrepresentation of diseased instances in the training dataset. Despite this, YOLOv8 offers a significant advantage in terms of speed and scalability, making it particularly well suited for real-time field assessments and rapid monitoring over large areas.

The U-Net model, based on a ResNet101 encoder, exhibited stronger segmentation performance. It achieved a precision of 87.46%, recall of 87.13%, and an F1-score of 87.27%, reflecting the model's ability to capture the spatial extent of disease symptoms within the palm canopy. The high precision highlights its strength in minimizing false positives, while the balanced recall demonstrates that most diseased areas were successfully identified. Visual inspections further validated these outcomes, with the model accurately segmenting disease-affected crowns even in visually complex scenes where YOLOv8 showed limitations. This makes U-Net particularly effective for detailed crown-level analysis and supports its use in precision treatment planning.

Together, the two models demonstrate complementary strengths. YOLOv8 enables rapid detection and initial localization of palms, whereas U-Net provides detailed semantic segmentation necessary for disease quantification and progression analysis. Their integration presents a promising two-stage pipeline: initial detection using YOLOv8 followed by high-resolution segmentation with U-Net. This combined approach enhances both the scalability and precision of disease monitoring in palm groves.

Table 1: Comparative Evaluation of YOLOv8 and U-Net Performance in Palm Tree Health Analysis

Model	Task	Precision	Recall	F1-Score	Accuracy
YOLOv8	Object Detection	58.38%	47.70%	58.5%	78.48%
U-Net	Semantic Segmentation	87.46%	87.13%	87.27%	89.51%

While both models delivered strong results (table 1), some areas for improvement remain. YOLOv8's recall could benefit from more balanced class representation and targeted data augmentation. Likewise, improving model generalization across different palm varieties and environmental contexts requires a more diverse and expansive training dataset. Future developments could include the use of multispectral or hyperspectral imagery, domain-specific pretraining, and hybrid detection-segmentation models to further enhance performance.

These findings also align with previous work in the field. Bouthina et al. (2024) demonstrated the potential of CNNs in palm disease classification, achieving accuracy rates of up to 98%. However, their study focused solely on classification and lacked spatial disease localization, limiting early detection capabilities. Similarly, Yarak et al. (2021) employed Faster R-CNN with high-resolution UAV imagery, obtaining F1-scores of 95.09% for detection and 92.07% for healthy tree classification. Yet, the model's performance dropped for unhealthy palms, particularly in early disease stages or where crown visibility was limited. In contrast, the integrated approach in this study addresses both detection and segmentation, providing spatially precise, actionable outputs for more effective disease monitoring.

5. Conclusion

This study underscores the transformative potential of integrating UAV imagery with advanced deep learning models for the early detection and monitoring of palm tree diseases in agricultural environments such as the Figuig oasis. By comparing YOLOv8 for object detection and U-Net for semantic segmentation, the research highlights the complementary strengths of each model. YOLOv8 demonstrates high efficiency and real-time detection capabilities, making it suitable for large-scale, rapid assessments. In contrast, U-Net excels in accurately delineating diseased regions, proving to be more effective for precise health monitoring and targeted interventions.

Despite promising results, challenges such as class imbalance, limited dataset variability, and moderate recall in YOLOv8 detection remain. Addressing these through dataset expansion, enhanced augmentation techniques, and model fine-tuning will be vital in future research. Furthermore, integrating these models into a unified pipeline could offer a robust, scalable solution for automated palm disease diagnosis, supporting sustainable agricultural practices and reinforcing the resilience of vulnerable ecosystems like those in Figuig.

In conclusion, this comparative analysis not only demonstrates the viability of AI-powered monitoring systems in precision agriculture but also sets a foundation for future advancements aimed at increasing accuracy, scalability, and field readiness of intelligent crop health management systems.

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