A YOLO-Based Approach for Detection of Olive Knot Disease through UAV and Computer Vision Technologies

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***Abstract*—This work presents an approach for detecting olive knot disease in olive trees, utilizing Computer Vision (CV), Unmanned Aerial Vehicle (UAV) based imagery, and Machine Learning (ML) within the context of Precision Agriculture (PA). The study focuses on applying the You Only Look Once (YOLO) deep learning architecture to develop a model capable of identifying trees affected by the disease with accuracy and speed. By integrating UAV technology with object detection algorithms, this approach enables real-time monitoring of olive plantations, supporting early detection and targeted interventions. This study emphasizes the potential of combining drone imaging and ML to drive sustainable and practical solutions in PA. Results show that this method can potentially improve crop management by reducing human labor and contributing to the enhancement of disease control strategies.**

***Index Terms*—Unmanned Aerial Vehicle, Disease Detection, Olive Knot, YOLO, Computer Vision, Deep Learning**

I. Introduction

Precision Agriculture (PA) has established itself as a foundation of modern farming, combining advanced technologies to optimize productivity, enhance sustainability, and address global food security challenges [1]. By leveraging GPS, sensors, drones, and robotics solutions, PA enables farmers to make data-driven decisions that minimize resource waste and environmental impact while maximizing crop yields [2]. These technologies work together to provide precise insights into soil health, crop conditions, and ecological factors, paving the way for more efficient and sustainable agricultural practices [3].

Unmanned Aerial Vehicles (UAVs) (combined with Computer Vision (CV)) have emerged as powerful tools in PA, particularly for the detection and monitoring of plant diseases. High-resolution cameras and advanced sensors can capture detailed aerial imagery of large agricultural areas in a fraction of the time required for manual inspections [4]. CV algorithms process this imagery to identify patterns, anomalies, or symptoms indicative of diseases, such as discoloration, wilting, or lesions on leaves and stems [5].

For instance, UAVs equipped with Red-Green-Blue (RGB) and multispectral cameras have been effectively used for precise disease identification and monitoring, as highlighted in recent studies [2], [6]. By integrating machine learning models, such as deep learning architectures, these systems can accurately identify specific diseases, even in complex and heterogeneous environments [7]. The combination of UAVs and CV not only enhances the scalability and efficiency of disease detection but also reduces reliance on labor-intensive methods, contributing to more sustainable and precise crop management practices [8].

Applying CV algorithms for disease detection demonstrates significant potential for economically important crops, such as olive trees in Portugal.

Olive cultivation plays a crucial role in the Portuguese economy, with a production of 1194990 tons in 2023 [9], producing olive-derived products, such as olive oil, one of the key exports of the country [10]. However, this essential crop faces serious threats from diseases like olive knot, which directly impact its productivity and quality, which is a bacterial disease characterized by the formation of small tumors or knots on the trunks and branches of olive trees [11]. These

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growths weaken the tree and can lead to its death in severe cases [12]. In addition, olives from infected trees often result in substandard products, such as olive oil with a salty taste and unpleasant odor [13]. Infection typically spreads through wounds caused by pruning or other physical damage to the tree, and favorable environmental conditions increase its rapid spread throughout olive groves [14].

A. State of the Art and Related Works

The rapid advancements in PA have paved the way for innovative solutions to address critical challenges in crop management, such as plant disease detection and monitoring.

Among these, UAVs combined with CV and ML algorithms have gained prominence for their ability to provide scalable, efficient, and accurate disease detection [15].

Though effective in localized scenarios, traditional manual inspection methods are labor-intensive, time-consuming, and limited in coverage [16]. In contrast, UAV-based systems equipped with advanced sensors and deep learning models offer a transformative approach by enabling real-time monitoring of large plantations with high precision. Recent studies have explored various methodologies, architectures, and sensor technologies to optimize UAV-based disease detection systems, showcasing their potential to revolutionize agricultural practices.

Given this scenario, several works have explored using UAVs in PA under the scope of disease detection, often using YOLO algorithms to enhance accuracy and efficiency. Paper [17] proposed a novel approach to detecting and classifying olive tree diseases using UAVs and deep learning. The authors developed a dataset of 14000 annotated images representing seven classes of diseases, all collected by UAVs, and employed a transfer learning technique to enhance detection accuracy while reducing training time. Their model achieved a validation accuracy of 99%. The results demonstrated that transfer learning significantly improves the efficiency and precision of disease detection, offering a scalable solution for PA.

The research detailed by authors from [18] investigates the use of the YOLOv5 deep learning model to detect Verticillium wilt in olive trees through UAV-captured RGB imagery. The research aims to evaluate the performance of different YOLOv5 architectures (medium, small, and nano). Results demonstrate that YOLOv5 achieved high accuracy and efficiency in detecting infected trees, with specific architectures excelling in precision, recall, and mAP metrics. The study concluded that UAVs combined with YOLO provided a scalable, cost-effective solution for early disease detection, reducing reliance on labor-intensive manual inspections and enabling timely interventions.

In another significant study in the YOLO architecture application on disease detection, Robi et al. [19] did a comparative analysis of various YOLO models, where they explore the application of those models for detecting and classifying diseases in rock melon plants using UAV imagery. They showed that these models provide scalable and efficient solutions for disease management, highlighting the potential of integrating Artificial Intelligence (AI)-driven technologies to improve crop health and yield.

Not all diseases exhibit distinct features that sufficiently differentiate them from the surrounding vegetation to be detected in images captured at high altitudes. Some diseases require imagery collected at lower altitudes to ensure their characteristics can be accurately identified. In this scenario, Okole et al. [20] investigated the use of UAVs and deep learning to assess the incidence of virus yellows in sugar beet fields. The study achieved accurate disease incidence scoring by integrating remote sensing data with ground-truth measurements, demonstrating the effectiveness of UAV-based systems for large-scale agricultural monitoring. The results highlighted the potential of this technology to replace traditional manual assessments, offering a faster, scalable, and also highlighting the importance of low-altitude flights in capturing detailed features that often are not distinguishable at higher altitudes.

More related works in the field of disease detection using UAV imagery can be found in works [21]–[25].

B. Contributions

As mentioned before, this work presents interesting research for olive disease detection. Many works detected problems raised in those plantations, but not specific to knot disease. Taking this into account, the main scientific contributions of this work are:

- Integration of UAVs and Deep Learning for olive knot disease detection;
- Validation of the YOLOv11 Framework for Disease Detection;
- Advancement of PA practices;
- Development of a novel dataset for the olive knot disease.

II. Methodology Formulation

A. Dataset Creation

There are limited studies specifically focused on the detection of olive knot disease, which has resulted in a lack of publicly available datasets with sufficient images to train deep-learning models. Consequently, it was necessary to collect images directly from infected olive groves and create a dedicated dataset to facilitate the training and evaluation of neural networks for this research.

1) UAV Platform: The UAV system used in this study was a DJI Mini 3, which features a compact design with a takeoff weight of 248g [26]. It has a 1/1.3-inch CMOS camera capable of capturing 48 MP still images and recording 4K videos at up to 30 fps. The UAV offers a maximum flight time of 38 minutes. Additionally, its downward vision system ensures stable hovering, while the three-axis gimbal provides smooth image stabilization, making it ideal for aerial data collection in agricultural applications.

2) Data Sample Collection: The images were collected on December 5, 2024, at Mirandela (coordinates 41.514016º N, -7.175772º W), Portugal, between 15 and 16:00.

The aerial view of the olive plantation is presented in Fig. 1:

Fig. 1. Aerial view of the olive plantation, situated in Mirandela, Portugal.

The dataset was composed of 665 high-resolution RGB images, which cover the disease in different backgrounds, lighting conditions, and angles, striving to reflect the environment's complexity and improve the model's generalization ability. Some collected images can be observed in Fig. 2:

Fig. 2. Demonstration of olive knot disease.

3) Data Annotation: The Roboflow online platform was used to manually label objects within the images and create annotations for the dataset, where, in this specific case, it was used to create bounding boxes on the pictures [27]. This tool streamlines tasks related to deep learning applications in the CV. It was chosen due to its accessibility, free use, non-installation requirement, and ability to be accessed directly through a web browser.

4) Data Augmentation: An insufficient number of images in a dataset can often lead to bad detection and evaluation metrics. As stated by Shu [28], data augmentation is a great solution to avoid this problem, which is also a great way of improving the model's generalization ability. Also, the augmentation measures taken in this dataset can be observed in Table I:

TABLE I
AUGMENTATION PARAMETERS USED IN THE DATASET.

Augmentation	**Amount (%)**
Brightness	-15 and 15
Saturation	-25 and 25

Through data augmentation, the dataset was expanded by 3 times over the original size, and the specific data is shown in Table II:

TABLE II
DATASET COMPOSITION AND KNOT DETECTION INSTANCES.

	Train 80%		**Val** 20%
Images	**532 (Original)**	**1596 (Expanded)**	**133**
Instances	8128	24369	1843

The images were randomly divided in the dataset to ensure the effectiveness and authenticity of the model training and evaluation, following a split of 80% for the training set and 20% for the validation set.

B. Evaluation Metrics

To thoroughly assess the model's performance in detecting the olive knot disease, this study utilized some widely accepted evaluation metrics in object detection, such as precision (P), recall (R) $mAP50$, $mAP50-95$ and $F1$-Score. More details in those metrics can be found in Japkowics and Shah [29], and Pustejovsky and Stubbs [30].

Precision (P) measures the accuracy of the model's predictions, specifically the proportion of instances identified as olive knots that are correct. High precision indicates that the model can accurately detect olive knots while minimizing false positives, such as misclassifying other tree features or objects as knots. Its calculation formula is expressed in (1):

$$P = \frac{TP}{TP + FP}, \tag{1}$$

where TP (True Positive) represents cases where the model correctly identifies actual olive knots, FP (False Positive) refers to instances where the model incorrectly classifies non-olive knot features as knots.

Recall (R) evaluates the proportion of actual olive knots in the dataset correctly detected by the model. It reflects how comprehensive the model is in identifying all instances of olive knots, reducing missed detections. A high recall metric ensures that most olive knots are being identified, with its formula expressed in (2):

$$R = \frac{TP}{TP + FN}, \tag{2}$$

where FN (False Negative) refers to cases where actual olive knots are incorrectly classified as non-knots or other objects.

The Intersection over Union (IoU) is a metric that measures the overlap between two boundaries. It is normally used to measure how much the predicted boundary overlaps with the real object boundary, shown in (3):

$$IoU = \frac{|A \cap B|}{|A \cup B|}, \tag{3}$$

where $|A \cap B|$ is the area of overlap between bounding boxes, and $|A \cup B|$ is the area of union of the bounding boxes.

The mean Average Precision (mAP) (presented in (5)) combines both precision and recall to provide a comprehensive measure of model performance. The Average Precision (AP) ranges from 0 to 1, where high values indicate better detection capabilities. In other words, the definition of AP is finding the area under the precision-recall curve, shown in (4):

$$AP = \int_0^1 P(R)dR, \tag{4}$$

$$mAP = \frac{\sum_{i=1}^{N} AP_i}{N}, \tag{5}$$

where two specific metrics were considered in this work:

- mAP50: Calculates the mAP at an IoU threshold of 0.5 to evaluate how well detections align with ground truth boxes;
- mAP50-95: Averages mAP value cross IoU thresholds from 0.5 to 0.95 in increments of 0.05, offering a broader assessment of model performance under varying conditions.

The $F1$ score is another widely used evaluation metric in ML. It combines precision and recall into a single value by calculating their harmonic mean. It ranges from 0 to 1, where 1 represents perfect precision and recall, and 0 indicates the worst performance. This metric emphasizes the importance of balancing precision and recall by penalizing models that perform well on one metric but poorly on the other, making it a robust and useful measure for evaluating performance. Its formula is expressed in (6):

$$\text{F1} = \frac{2PR}{P+R}. \tag{6}$$

In practical applications, it is essential for the model to not only detect olive knots but also accurately pinpoint their locations for precise interventions. The mAP is a comprehensive metric for evaluating overall model performance in detecting and localizing olive knots under different conditions.

C. Computer Vision Algorithm

As the latest iteration of the YOLO framework, YOLOv11 represents a significant advancement in real-time object detection. This version highlights itself upon its predecessors by introducing new architectural improvements such as the C3k2 block and the C2PSA (Cross Stage Partial with Spacial Attention) module, improving spatial attention on more complex images and, consequently, its capacity to extract information from these images [31]. These advancements make YOLOv11 more effective in detecting small or overlapping objects, addressing a few limitations observed in earlier framework versions [32].

In this study, using a custom dataset, the YOLOv11x (extra-large) framework, the largest and most powerful variant of the yolov11 model series, was employed to detect olive knot disease. The training process utilized transfer learning by leveraging pre-trained weights from YOLOv11, which were initially trained on large-scale datasets such as COCO [33]. This approach enabled the model to inherit a robust understanding of general object features, significantly reducing training time and improving performance.

The dataset must be adjusted to be in the YOLO format to begin training, which includes images and corresponding annotation files specifying bounding boxes and class labels. During training, the framework optimizes its detection capabilities by adjusting its detection head to handle objects of varying scales. The metrics described in Section II-B are used during training to evaluate model performance [34].

III. Proposed Solution and Experimental Results

This paper proposes a practical approach for detecting olive knot disease by integrating UAV-based imagery with the YOLOv11 object detection framework. The solution leverages pre-trained weights from YOLOv11, fine-tuned on a custom dataset of high-resolution olive tree images captured in low altitudes with an UAV. The dataset includes annotated images and highlights knots, enabling the model to learn subtle disease characteristics that are often hard to distinguish from surrounding vegetation. After training the model and validating its ability to detect the olive knot disease accurately, a subsequent step in the solution would involve validating and integrating the model. Then, the UAVs flies in a new olive plantation under actual operating conditions, accounting for all associated environmental and operational variables.

A. Experimental Environment and Hyperparameters

This experiment was built on a PyTorch deep learning framework and executed in a PyCharm Virtual Environment. Table III shows the equipment used in the experimental environment and Table IV shows the main hyperparameter settings:

TABLE III
Experimental Environment Configuration.

Environment Configuration	Parameter
Operating system	Windows 10
CPU	AMD EPYC 7443 CPU@ 2.85GHz
GPU	GeForce RTX 4080 Super (16GB)
Development environment	PyCharm 2024.3
Language	Python 3.11.9
Framework	PyTorch 2.7.0
Operating platform	CUDA 11.8

TABLE IV
Hyperparameters Settings.

Hyperparameter	Parameter
Epochs	500
Batch	16
Optimizer	SGD
Learning rate	0.01
Momentum	0.9
Weight Decay	0.0005
Input image size	640

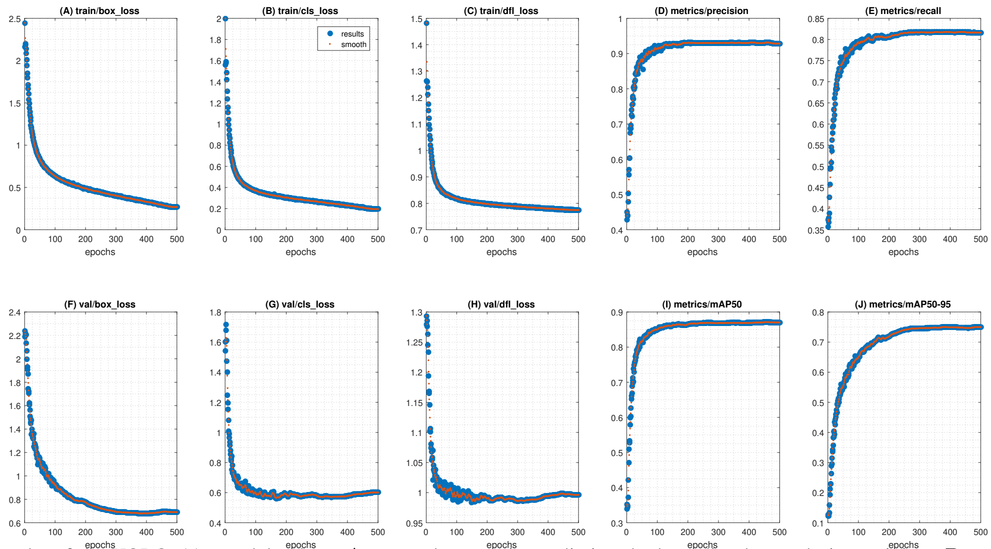

Fig. 3. Experimental results of the YOLOv11x model, where A means the error in predicting the bounding boxes during training; B means the classification loss during training; C measures the quality of bounding box regression; D measures the precision of the model; E measures the recall of the model; F means the error in predicting the bounding boxes during validation; G means the classification loss during validation; H indicates the capacity of the model to generate bounding boxes on unseen data; I measures the $mAP50$ metric; J measures the $mAP50-95$ metric.

B. Experimental Results of the Trained Model

Fig. 3 illustrates the model's performance during training and validation. The summary highlights the evolution of various loss indicators during training and validation over the number of epochs. These metrics demonstrated a consistent decrease, indicating effective learning and improved generalization. Additionally, the precision, recall, and mAP metrics were plotted, all of which jointly reflect the model's overall performance in detecting olive knots.

Fig. 4 demonstrates the $F1$-Score obtained after training. It highlights the balance achieved between precision and recall during the training process. The steady increase in the score throughout the epochs demonstrated that the model effectively optimizes this trade-off, ensuring both accurate identification of TP and minimization of FN:

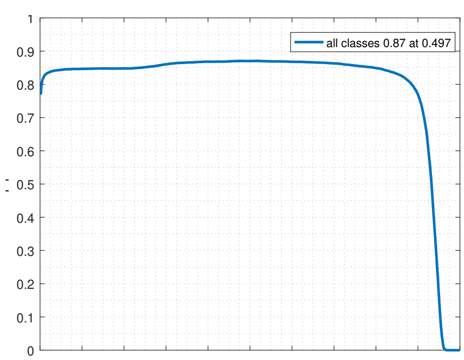

Fig. 4. F1 confidence curve of the YOLOv11x model.

C. Visual Validation of Test Results

Fig. 5 illustrates the performance of the trained model in identifying the olive knot disease. The first image demonstrates the ground truth, where no object detection has been applied, while the second image displays the results after predicting with the YOLOv11x model. This comparison reflects the model's ability to detect and localize the disease accurately in complex environments while maintaining robustness across diverse conditions. However, the training dataset mainly included images of the disease in advanced stages and under good lighting. As a result, the model struggles to detect less pronounced cases. Furthermore, under extreme shading conditions, the model fails to detect the disease altogether.

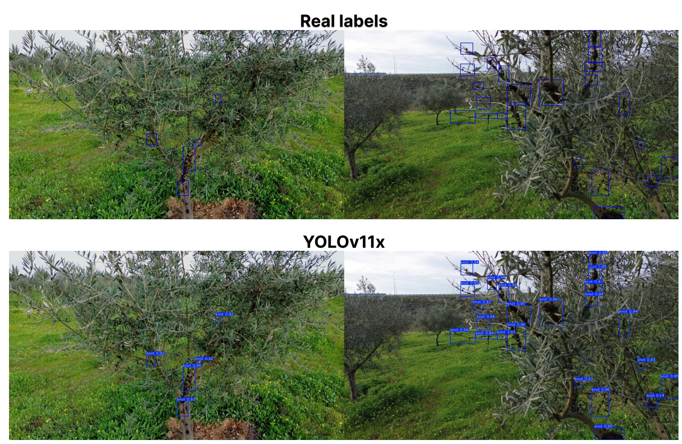

Fig. 5. Detection results of the YOLOv11x model.

A further model validation (in the format of a validation video) can be found in CeDRI Youtube Channel.

IV. Conclusions

This work demonstrated the effectiveness of integrating UAV-based imagery with the YOLOv11 framework for detecting olive knot disease. The proposed approach successfully utilized pre-trained weights, enabling the model to identify olive knots under diverse environmental conditions, including varying lighting, angles, and perspectives.

Also, the results showed that the model achieved a strong balance between precision and recall, as evidenced by the $F1$ score of 0.87 at a threshold of 0.497, the $mAP50$ of 0.85, and a $mAP50-95$ of 0.75.

Furthermore, the visualization of detection results highlighted the robustness of the model in accurately localizing and classifying the disease symptoms.

As future work, this project aims to validate the proposed model in real-world scenarios by deploying it on UAVs operating in real-time environments. This allows for a comprehensive assessment of its performance and feasibility under practical conditions. Additionally, the project intends to expand the olive knot dataset by collecting more images. Another important direction is to include images of other diseases affecting olive trees in the dataset and train new models capable of detecting multiple diseases, enhancing the system's versatility. Furthermore, the implementation of autonomous flight capabilities is planned, enabling the system to process images at the end of each flight and generate a detailed technical report diagnosing diseases in the olive plantation.

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