Olive Protection using Artificial Intelligence

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1 Introduction

The olive tree, a plant of immense historical, cultural, and economic significance in the Mediterranean basin and particularly in Tunisia, is a vital component of global agriculture [2]. However, the health of these trees is constantly under threat from a wide range of phytopathogens, including fungi, bacteria, and viruses, as well as various insect pests. Diseases such as peacock spot (Spilocaeaoleagina), olive knot (Pseudomonassavastanoi), and Auculus Olearius can severely impact tree health [5], leading to reduced yields, decreased olive oil quality, and in some cases, the death of the tree itself. The economic ramifications of these diseases are substantial, threatening the livelihoods of countless farmers and the stability of the olive oil supply chain.

Traditionally, the detection and diagnosis of these diseases have been performed through manual inspection by agricultural experts [8]. This process, while effective in the hands of a seasoned professional, is inherently inefficient. It is labor-intensive, requiring extensive on-site visits, and time-consuming, often leading to significant delays between the onset of symptoms and the implementation of a treatment plan. The scarcity of expert plant pathologists and the sheer scale of olive groves make this approach impractical for widespread, continuous monitoring. Furthermore, manual diagnosis is susceptible to human error, particularly in the early stages of infection where symptoms may be subtle or ambiguous. The limitations of these traditional methods can lead to delayed intervention, allowing diseases to spread unchecked and causing irreversible damage.

The motivation behind this project is to develop a scalable, accurate, and timely solution to the critical problem of olive tree disease detection. We seek to address the shortcomings of conventional diagnostic practices by harnessing the power of artificial intelligence (AI) and computer vision. The core objective of this work is to create an AI-driven application capable of analyzing digital images of olive tree leaves and branches to automatically identify and classify diseases. This approach is inspired by the successful application of deep learning in other agricultural contexts, such as the detection of diseases in grapevines [4, 6], tomatoes [9], and apples [1, 3].

This report presents a novel methodology for the automated diagnosis of olive tree diseases using a custom-built convolutional neural network (CNN) model. We detail the entire process, from the collection and preprocessing of a comprehensive image dataset to the training and validation of our AI model. The system is designed to provide rapid and non-invasive disease detection, offering a significant improvement over manual methods. By providing farmers and agricultural organizations with an accessible and powerful diagnostic tool, our application aims to facilitate proactive and precision agriculture. This will enable earlier intervention, optimized use of treatments, and ultimately, enhanced crop resilience and sustained profitability for the olive sector.

2 Methodology

Our proposed pipeline aims to detect and classify both branches and leaves of olive trees to assess their health status. We designed a two-stage detection-classification framework as shown in Fig. 1 using a fine-tuned YOLOv8 object detection model [7]. We operate directly on RGB images of parts of olive trees captured in natural field conditions.

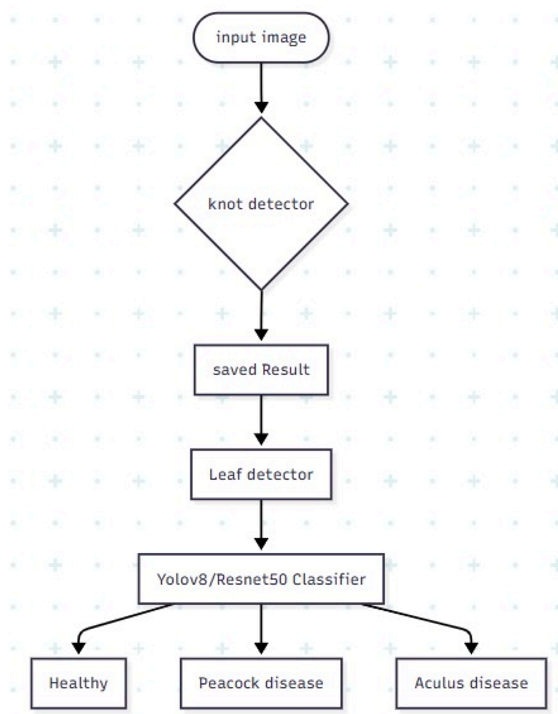

Fig. 1: Proposed model architecture.

2.1 Inference Pipeline

During inference, each input image undergoes sequential processing through a three-stage pipeline:

1. **Knot Detection:** The first model identifies and localizes olive knots within the entire image.
2. **Leaf Detection:** The second model detects all visible leaves in the original image.
3. **Leaf Disease Classification:** Detected leaves are cropped and individually processed by the third model, which classifies each leaf as either *Healthy* or affected by two diseases: Olive Peacock or Aculus olearius.

The final visualization combines outputs from all stage, using in particular `matplotlib`'s text rendering capabilitie.

2.2 Dataset Preparation

These images were collected and merged from multiple public datasets :Kaggle-Leaf Detection , Kaggle-Olive Leaf Image Dataset , Inference Images from google., ensuring a wide range of geographic variability, tree cultivars, and disease presentations. The images include various views of olive trees, with some containing only branches, only leaves, and others containing both structures simultaneously.

For branches, we defined two classes: Healthy and Olive Knot disease. For leaves, we defined three classes: Olive Peacock, Aculus olearius, and Healthy. Samples of these images are given in Fig. 2. Images were split into training, validation, and testing subsets using an 80/10/10 split, ensuring class balance across sets.

2.3 Branch Detection and Classification

We trained a YOLOv8 model specifically for detecting olive knots in olive tree branches and trunks. This model was initialized with Ultralytics YOLOv8's COCO pre-trained weights and fine-tuned on our annotated branch dataset.

To enhance robustness to environmental variability, we applied a variety of data augmentation techniques including random flipping and rotation, Hue, Saturation and contrast adjustment. The model was trained using the AdamW optimzer for 150 epochs with a learning rate of 0.001 and a batch size of 22. The best model checkpoint was selected based on validation set performance.

2.4 Leaf Detection and Classification

A second YOLOv8 model was trained for the task of leaf detection and classification, targeting three classes: Healthy, Olive Peacock Disease, and Aculus olearius. The model's performance is evaluated through confusion matrices for different approaches, shown in Figure 3.

3 Experiments and Results

3.1 Olive Knot Detection

To address the limited size of the Olive-Knot dataset, we generated synthetic data consisting of center-positioned olive knot images against randomized noise backgrounds. This approach removes complex environmental distractions, focusing the model on disease features while reducing computational requirements which helped the model improve by $\simeq 0.8$ in mAP. Figure 4 shows a representative sample of our synthetic images.

3.2 Leaf Detection

The first stage of the pipeline involved using YOLOv8 to detect leaves within full-branch images. This approach mimics real-world usage scenarios where a user captures a picture of an entire branch or tree rather than an isolated leaf. As shown in Figure 5 , qualitative inspection indicates that YOLOv8 consistently and accurately identifies leaves by drawing bounding boxes around them, even in dense branches. This detection step is a critical precursor to the second stage of the pipeline, ensuring that the classification model receives clean, focused inputs.

3.3 Multi-Class Classification

Model performance in the second stage was evaluated using accuracy, macro-precision, macro-recall, and macro-F1-score metrics chosen to reflect balanced performance across all classes given the minor class imbalance. The proposed YOLOv8 model achieved 95.33% accuracy, 96.15% macro-precision, 95.70% macro-recall, and 95.92% macro-F1-score. In fact, the confusion matrix (Figure 6) displays a strong diagonal, indicating consistent correct classification across all four classes.

For benchmarking, we compared our model against ResNet50 and ResNet18 trained under the same conditions. As shown in Table 1, our model outperformed both, with ResNet18 achieving 85.16% accuracy and ResNet50 reaching 94.92%.

Table 1: Benchmark comparison between YOLOv8, ResNet18, and ResNet50

Model	**Accuracy (%)**	**Macro-Precision (%)**	**Macro-Recall (%)**	**Macro-F1 (%)**
YOLOv8	**95.33**	**96.15**	**95.70**	**95.92**
ResNet18	85.16	87.46	86.95	86.71
ResNet50	94.92	95.85	95.81	95.70

Overall, the proposed approach outperformed the smaller baseline ResNet18 and marginally surpassed the deeper ResNet50, demonstrating both efficiency and robustness in classification.

4 Discussion and Conclusion

The results of our study demonstrate the effectiveness of a two-stage YOLOv8-based detection and classification pipeline for automated diagnosis of olive tree diseases. The proposed system achieved high performance across all evaluation metrics, outperforming traditional deep learning baselines. Data augmentation and synthetic image generation hugely improved model accuracy, particularly in olive knot disease detection.

Despite these promising results, several limitations remain. First, although the dataset was diverse, it is possible that it is still not representative of the complete spectrum of environmental conditions and disease variations encountered in all regions where olives are cultivated. Second, real-world deployment can be impacted by issues like image blur, occlusion, or changing illumination, which were alleviated partially in this work through augmentation but could still limit generalization.

Future work can explore expanding the dataset with higher numbers of actual-field images and additional disease classes. Incorporating temporal data and mobile deployment optimization could further enhance the utility and impact of the system for real-time field use. We could also incorporate context-driven advice for users.

Overall, our approach is an important step toward scalable, accessible, and accurate disease detection in olive agriculture, giving useful support to farmers and agronomists in managing crop health.

5 Team Contributions

- **Author 1**: Provided mentorship and coordinated group activities.
- **Author 2**: Led the development of the model architecture and contributed to app deployment.
- **Author 3**: Assisted in data collection, performed model testing, and app development.
- **Author 4**: Conducted model testing and contributed to report writing.
- **Author 5**: Collected data.
- **Author 6**: Assisted with AI generated synthetic data and contributed to report writing.

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A Figures

In this appendix we collect most figures referenced in the text.

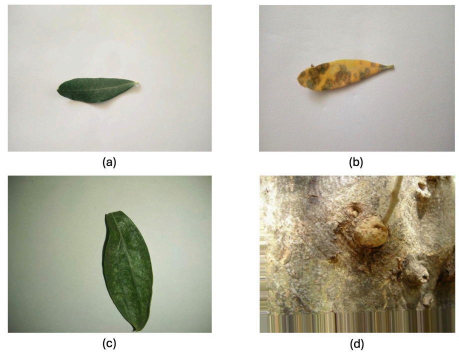
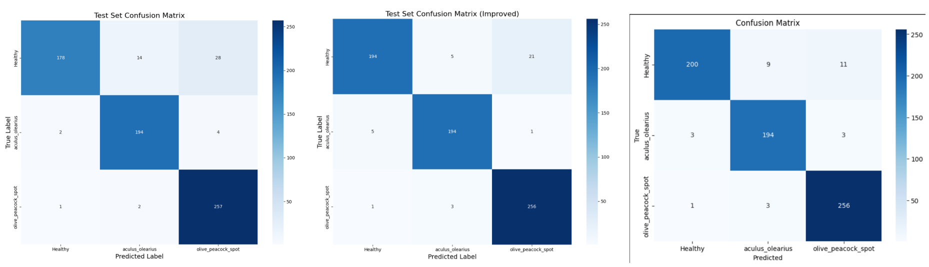


Fig. 2: Representative image patches from olive tree samples showing: (a) healthy foliage, and (b) foliage affected by Peacock disease (c) with Aculus disease (d) with knot disease.



(a) Simple Training (b) Class weighting (c) Freezing Layers

Fig. 3: Different approaches for training

Fig. 4: Example of synthetic training images: Olive knot disease feature isolated against a random noise background

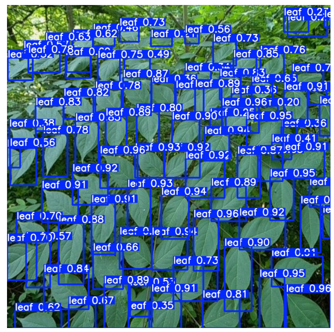


Fig. 5: YOLOv8 leaf detection model detects leaves and identifies them with bounding boxes.

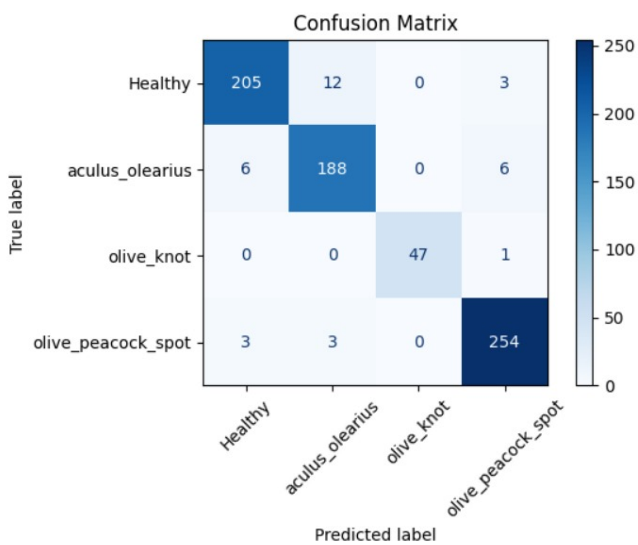


Fig. 6: YOLOv8 Confusion matrix showing a strong diagonal