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Next-Generation Computing Systems and Technologies
http://dx.doi.org/10.62762/NGCST.2025.936740

RESEARCH ARTICLE

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# AI-Powered Detection and Quantification of Local Date Varieties Using YOLO: Toward Intelligent Supply Chain Integration in Agri-Food Technology

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## Abstract

**This study presents an AI-powered approach to enhance quality control and traceability in the agri-food sector, focusing on the automated detection and classification of two Tunisian date varieties: Deglet Nour and "Bsir". The main objective is to develop a smart system that can quantitatively and qualitatively determine the proportion of any contamination of one variety by the other within a batch. To achieve this, state-of-the-art object detection YOLO models, v8 and v12, have been employed, trained on a custom annotated dataset which includes a wide range of real-world images, capturing the variability in the studied date fruit size, shape, and presentation. Both YOLO models were fine-tuned over 50 epochs using transfer learning techniques, allowing them to adapt effectively to the specific classification task. Training step consisted of a thorough analysis of bounding box distributions and samples clustering, taking into account natural variations in date morphology based on their 2D images. Evaluation showed that both models achieved high detection accuracy, with YOLOv12 outperforming slightly in precision and speed, making it well-suited for real-time applications. By estimating the relative variety proportions within a mixed batch, the developed smart system supports the intelligent decision-making across the supply chain. This work lays the groundwork for embedding deep learning models into portable smart optical devices that can assess date mixtures on-site, from farms to packaging centers. Future developments will focus on expanding detection to additional date varieties and integrating the system into commercial post-harvest processes.**

**Keywords**: AI-ML, classification, date fruits, intelligent detection, YOLO.

**Submitted:** 02 September 2025
**Accepted:** 25 September 2025
**Published:** 22 October 2025

**Vol.** 1, **No.** 1, 2025.
10.62762/NGCST.2025.936740

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**Citation**
Raboudi, F., Rebai, O., Ben Amara, S., Fattouch, T., & Fattouch, S. (2025). AI-Powered Detection and Quantification of Local Date Varieties Using YOLO: Toward Intelligent Supply Chain Integration in Agri-Food Technology. *Next-Generation Computing Systems and Technologies*, 1(1), 33–42.

## 1 Introduction

Quality control and traceability represent critical challenges in the agri-food sector, especially for valuable crops such as date fruits (Phoenix dactylifera), which hold significant cultural and economic importance in several countries, including Tunisia. Automated variety detection systems are increasingly needed as valuable tools for better monitoring and quality assurance in date products. These smart systems help ensure the purity and consistency of raw materials, thereby maintaining quality throughout the production chain of dates and their derivatives [1]. In this context, accurate identification and quantification of date varieties, especially when batches of raw material are accidentally cross-contaminated or intentionally adulterated, are essential not only to ensure consistent product quality and meet consumer expectations but also to support official quality control processes, which are critical for factory operations. Traditional manual sorting methods are often slow, laborious, and prone to error, emphasizing the need for effective automated solutions [2].

## 2 Related Work

Artificial intelligence and machine learning technologies have been shown to revolutionize agricultural practices by enabling more precise crop monitoring, quality assessment, and sorting automation [3]. Among these, deep learning models demonstrate strong capabilities in recognizing complex visual patterns, making them well suited for object detection tasks in agricultural applications [4]. During the last years, other deep learning architectures have been applied to fruit detection. Two-stage detectors like Faster R-CNN have been recognized for their high accuracy in complex orchard settings, while single-shot detectors like SSD (Single Shot MultiBox Detector) was found to offer a strong balance of speed and precision [5]. Furthermore, traditional machine learning approaches, using simple features such as color, texture, and shape with classifiers like Support Vector Machines (SVM) or Random Forests (RF), have also been used for fruit identification and classifying [6].

The YOLO (You Only Look Once) family of models has gained widespread adoption due to its exceptional balance of speed and accuracy, allowing real-time processing which is essential for practical deployments such as fruit detection and classification [7]. Significant evolution of YOLO models has taken place over recent years [8, 9]. Earlier versions, such as YOLOv5, introduced streamlined architecture and enhanced training methods, resulting in improved efficiency and accessibility [10]. The latest iterations, YOLOv8 and YOLOv12, incorporate advanced features including improved backbone networks, anchor-free detection heads, and enhanced multi-scale feature fusion, which boosted model performance [11, 12]. These advancements position the models as ideal candidates for integration into portable optical devices and edge computing systems used in modern workflows, including agriculture [13]. Over the past decade, numerous studies have explored the use of AI-based detection systems to support automated fruit harvesting, with a primary focus on fruit localization, maturity classification, and yield estimation in field environments [14]. These works have employed object detection YOLO models trained on datasets featuring date clusters on trees, aiming to enhance real-time performance for robotic harvesting and precision agriculture. However, most of these efforts remain limited to pre-harvest applications, with little attention given to post-harvest quality assessment or variety cross contamination [13]. Thus, the present study addresses this gap by developing an AI-powered detection and classification system using a model based on the economically important Tunisian date Deglet Nour variety, and the “Bsir” dates (as known in the Tunisian dialect, and referred to as “Bisr” in the Middle East) as a cross contaminant. A custom-annotated dataset was created using LabelImg, and both YOLOv8 and YOLOv12 models were fine-tuned to capture the natural variability in fruit size, shape, and appearance. Their performance was evaluated to determine the most effective model for real-time deployment. This work enables the quantitative and qualitative assessment of variety contamination in commercial batches, supporting enhanced traceability, quality control, and compliance in the agri-food supply chain. This novel approach is designed for post-harvest environments and can be integrated into portable optical devices to perform on-site evaluations at farms, packaging centers, and distribution hubs [15]. This approach is expected to support improved smart decision-making across the supply chain, from farm to fork.

## 3 Methodology

### 3.1 YOLO Based Model for Local Date Fruit Classification and Detection

In this work, YOLOv8 and YOLOv12 were adopted, both of which introduced several architectural

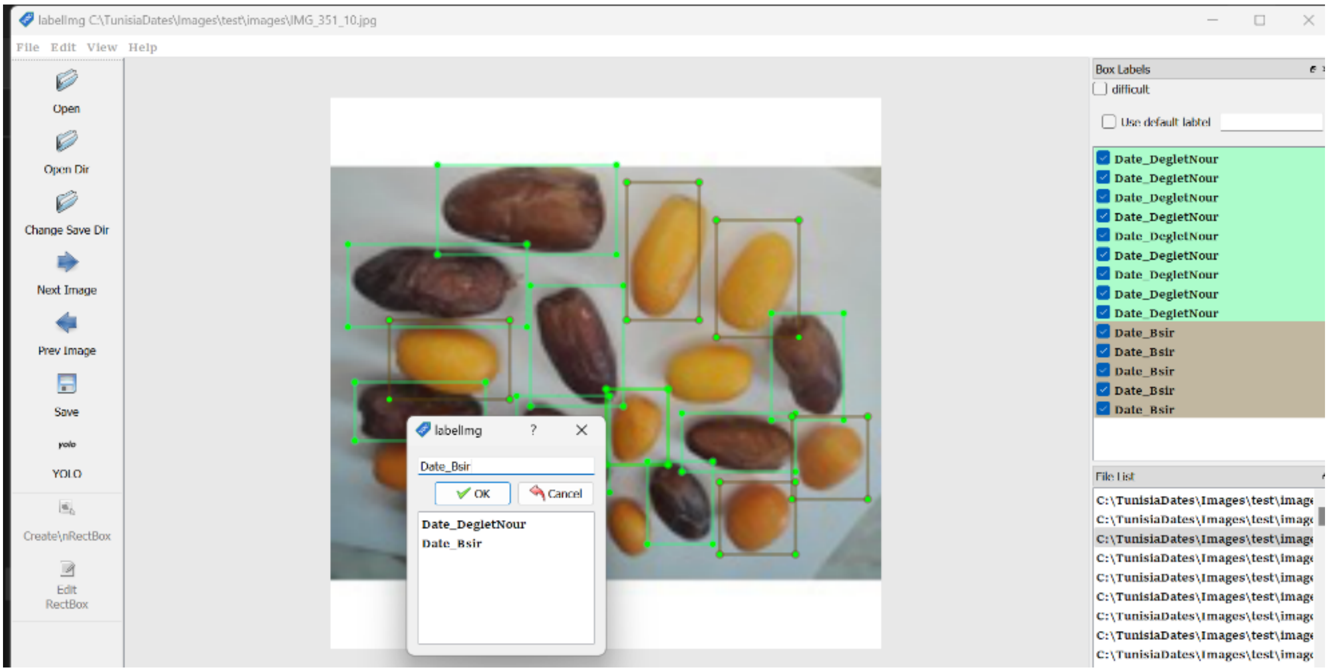


**Figure 1.** Manual annotation of date fruits using LabelImg software, showing the generated bounding boxes and class labels.

improvements over previous versions in the YOLO family. These include the replacement of the C3 module with the more efficient C2f module for better gradient flow, a simplified up-sampling process, and an anchor-free decoupled detection head which separates classification and localization branches to improve precision and training stability [16]. These models' architecture is composed of a backbone for feature extraction, a neck (PANet) for multi-scale feature aggregation, and a detection head that handles object prediction tasks without relying on predefined anchor boxes [16].

To tailor the pretrained models on different fruits to both date varieties specific application, YOLOv8 and YOLOv12 were trained on a labeled dataset containing two indigenous Tunisian varieties, Deglet Nour variety and "Bsir". The experiments were conducted on a computer equipped with an Intel Core i5 processor (4 cores, 8 threads, 2.9 GHz base frequency, up to 4.2 GHz), 8 GB DDR4 RAM, an Intel Iris Xe Graphics, and a 512 GB SSD. The system operated under Windows 11 Pro 64-bit. During training, the model was configured with several key parameters: it ran for 50 epochs to ensure sufficient learning cycles, with multi-scale input enabled using image sizes of 320 by 700 pixels to improve robustness across varying resolutions. A batch size of 16 was chosen to balance speed and hardware capacity, and 4 workers were used to efficiently load data in parallel. Several graphical user interfaces (GUI) were developed using Tkinter to allow users to easily select model and image files and visualize the results. PyTorch served as the underlying framework for model loading and inference execution. Data handling and visualization were managed using pandas and NumPy for numerical operations, and Matplotlib for plotting training and evaluation charts.

### 3.2 Dataset Description

The dataset comprises 2,750 annotated images of date fruits, constructed to ensure model robustness and diversity. The fruit samples were sourced from the Boudjebel VACPA Company (Nabeul, Tunisia) and were all selected at a uniform, commercially ripe maturity stage to minimize variability unrelated to cultivar type. This final dataset was built using a pipeline of data augmentation, incorporating random rotation and horizontal flipping, to expose the model to a wide range of fruit orientations and enhance its ability to learn generalizable features.

### 3.3 Image Acquisition Setup

Images were captured using a 13-megapixel smartphone camera. The setup included a ring light providing white light at 480 lumens, mounted on a foldable tripod to ensure consistent, natural, and shadow-free illumination. A standardized background was used throughout to minimize visual noise and simplify the object detection task.

### 3.4 Data labelling for training the model

The annotation process was performed manually using the LabelImg software (version 1.8.1), an open-source graphical image annotation tool widely used for computer vision tasks (Figure 1). This tool allows for the creation of bounding boxes and supports saving annotations directly in the YOLO format [17]. For this study, each image was labeled with bounding boxes corresponding to individual date fruits, assigning a class label based on fruit variety.

### 3.5 Evaluation metrics

Metrics including precision, recall, F1 score, ROC AUC, and related curves were calculated using scikit-learn to thoroughly assess the model's classification performance. A user-friendly environment based on the PIL libraries was used to load models, visualize training progress, and quantitatively evaluate their effectiveness across multiple metrics.

**Accuracy**: calculated as $(TP+TN)/(TP+TN+FP+FN)$ which represents the proportion of all correct predictions made by the model, combining both true positives ($TP$) and true negatives ($TN$). It provides a general sense of how well the model performs overall.

**Precision**: equals to $TP/(TP+FP)$, and measures how many of the instances predicted as positive by the model are positive, therefore, reflecting the model's ability to avoid false positives ($FP$).

**Recall**: calculated as $TP/(TP+FN)$, quantifies the model's ability to correctly identify all actual positive instances. In this context, recall would show how effectively the model detects all Deglet Nour and Bsir dates present, without leaving many undetected.

**F1 Score**: $= 2 \times [(Precision \times Recall)/(Precision + Recall)]$, therefore balancing precision and recall into a single measure. It is especially useful when the dataset has class imbalance between the two date varieties.

**ROC AUC**: the Receiver Operating Characteristic – Area Under Curve summarizes the model's ability to distinguish between positive and negative classes at various threshold settings. A score closer to 1 indicates excellent discrimination, while a score $\approx$ 0.5 suggests no better than random guessing.

**Intersection over Union (IoU)**: is the ratio $(Area\ of\ Overlap/Area\ of\ Union)$ which measures how well the predicted bounding boxes overlap with the ground truth boxes. A higher IoU means the model localizes objects more precisely, which is critical for accurately identifying fruit locations, especially in images with overlapping or closely clustered fruits.

## 4 Experiments

For this study, YOLOv8 and YOLOv12 were fine-tuned using the labeled dataset of both indigenous Tunisian date fruit varieties. Training was conducted using pre-trained checkpoints for both YOLO versions.

### 4.1 Bounding Box Distribution Analysis

The *labels.jpg* file generated during the training process provides a scatter plot showing the proportions of both date fruit classes (Figure 2, panel A), revealing a roughly balanced dataset. A uniform spread of points across the entire area of the Y vs. X plot (Figure 2, panel B) indicates that the annotated objects are well distributed throughout the analyzed images, rather than being concentrated in corners or confined to specific regions of the frame. Furthermore, the distribution of bounding box widths versus heights across the annotated dataset (Figure 2, panel C) shows a diverse range of object scales, including small, medium, and large-sized date fruits. A positive correlation between bounding box width and height was observed, implying that the studied date fruits are generally elliptical or circular in shape rather than elongated or irregular. This well-distributed range of object sizes supports the model's ability to generalize across varying scales, which is crucial for robust fruit detection and classification in real-world scenarios with variable 2D image conditions.

### 4.2 Metrics evaluation of the trained models

Final trained models were saved in ".pt" format under the filenames "trained_Yolo8.pt" and "trained_Yolo12.pt". Each trained model demonstrates strong performance across all evaluation metrics and could serve as the foundation for further experiments and deployment in practical date fruit classification tasks. Obtained data (Table 1) show that both YOLOv8 and YOLOv12 models demonstrated strong performance in detecting and classifying both Tunisian date fruit varieties. The overall classification accuracy was approximately identical for both models (92-94%), with perfect recall 1.0000, F1 score of 96%, and an IoU of 85%, indicating high precision in object localization and complete detection of relevant instances. Notably, YOLOv12 outperformed YOLOv8 in precision, achieving $\approx$ 0.99 compared to $\approx$ 0.93, suggesting a significant reduction in false positive detections. ROC AUC scores were perfect

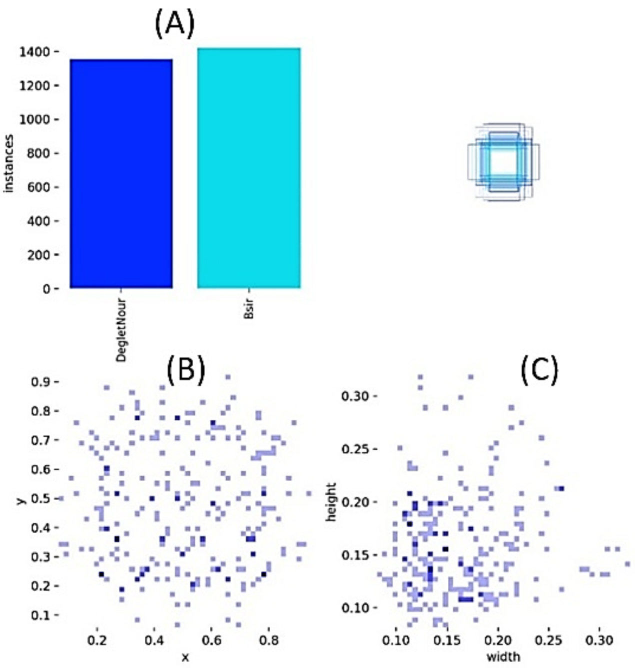

**Figure 2.** Output file (*labels.jpg*) generated to visually analyze the dataset distribution.

(1.0000) for both models, confirming excellent class separability. Obtained results align with previous studies reporting the effectiveness of YOLO models in detecting and classifying date fruits [18]. Despite identical confusion matrices, YOLOv12 demonstrated more confident classification decisions, likely due to its enhanced architecture. These results validate the effectiveness of both models, with YOLOv12 offering a slight advantage in precision-critical scenarios.

**Table 1.** Metrics of trained models using Yolo v8 and Yolo v12.

| Metric | Values | |
|---|---|---|
| | **YOLO8** | **YOLO12** |
| Accuracy | 0.9286 | 0.9412 |
| Precision | 0.9286 | 0.99937 |
| Recall | 1.0000 | 1.0000 |
| F1 Score | 0.9697 | 0.9630 |
| ROC AUC | 1.0000 | 1.0000 |
| IoU | 0.8594 | 0.8544 |
| FLOPS in MMac | 255.38 | 186.41 |
| FLOPS in B | (0.51) | (0.37) |

The analysis of FLOPS (Floating Point Operations Per Second), which measures the computation required by each model, showed that YOLOv8 demands 255.38 Mega Multiply-Accumulate operations (0.51 Billion FLOPS), while YOLOv12 is more efficient at 186.41 MMac (0.37 Billion FLOPS). Higher FLOPS indicate greater computational cost, potentially slowing processing. These results highlight the suitability of the more efficient YOLOv12 model for integration into portable optical devices, enabling real-time, on-site agri-food applications and improved supply chain decision-making.

The presented metrics demonstrate that both models achieved high performance on the independent test set, with YOLOv12 reaching a near-perfect Precision of 0.999 and YOLOv8 also demonstrating a strong Precision of 0.929 (Table 1). With regard to the exceptional score of YOLOv12, it is important to underline the potential risk of overfitting, where a model memorizes training data rather than learning generalizable features. The robustness of this result is confirmed by its consistent high performance of both models on the final test data, which the models had never encountered before and was not used during training process at all. This consistency, supported by the strategic use of data augmentation, indicates that the models learned robust and invariant representations of the date fruit classes. Therefore, we conclude that the reported metrics, particularly for YOLOv12, are a reliable indicator of strong model generalization and not an artifact of overfitting.

### 4.3 Training and Validation Loss Analysis

The obtained chart (Figure 3) shows how the model's training and validation loss changed over time as it learned. Over successive epochs, a steady decrease in both curves has been observed which means that the model was improving and becoming more accurate in its predictions. The fact that the two lines (training loss, and validation loss) stay close to each other suggests the model learned patterns that also work well on new, unseen data. Overall, this shows that the training process was stable and effective.

The training and validation loss curves, while showing expected fluctuations, exhibit a clear and simultaneous descending trend, ultimately converging at a low value. This pattern indicates stable learning dynamics and a reduced risk of overfitting. This robustness was further promoted by the use of data augmentation techniques, specifically random rotation and horizontal flipping, which enhanced the model's ability to generalize.

### 4.4 Training and Validation Accuracy Analysis

The training and validation accuracy curves illustrate the performance of the YOLOv8 and YOLOv12 model across epochs (Figure 4). As observed, both metrics demonstrate a consistent upward trend, indicating that

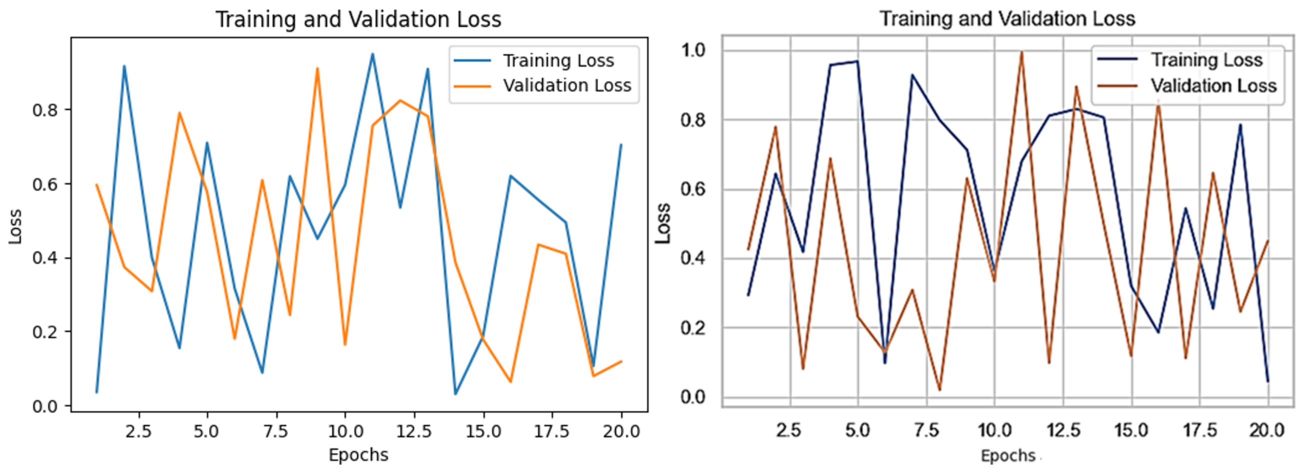


**Figure 3.** Training and validation loss of YOLOv8 (left) and YOLOv12 (right) models.

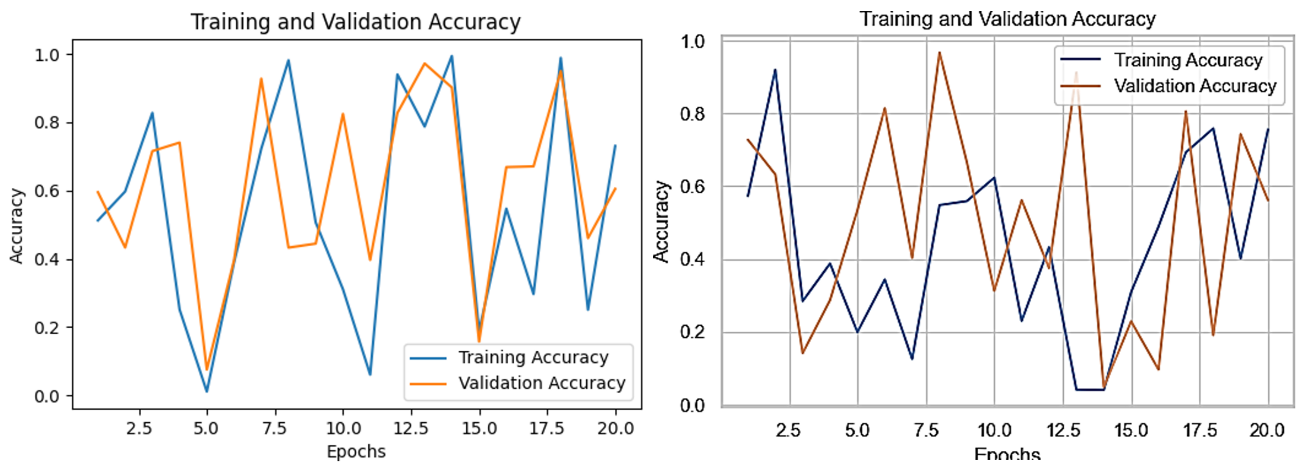


**Figure 4.** Training and validation loss of YOLOv8 (left) and YOLOv12 (right) models.

the model effectively learned discriminative features over time. The relatively close alignment between training and validation curves suggests minimal overfitting and good generalization to unseen data. This reflects the stability and robustness of the training process, thus, validating the model's suitability for the task of data fruit detection in the dataset.

The ROC curves for both YOLOv8 and YOLOv12 models exhibited ideal performance, achieving an AUC of 1.0000 (Figure 5). This indicates perfect class separability, with the models consistently assigning higher confidence scores to correct predictions across all thresholds. Such results confirm the robustness of the used models in distinguishing between the two date fruit varieties, independent of classification threshold.

Throughout training, the two models demonstrated steady improvements across key performance metrics (Figure 6). Precision and recall curves reached high values early and remained stable, with YOLOv12 showing slightly higher precision overall, suggesting fewer false positives. Curves of mAP@0.5 and map@0.5:0.95 followed similar trajectories, reflecting a strong balance between precision, recall and accurate localization.

As a real application of the retained YOLOv12 trained model, a new image containing a mixed batch of both varieties (Figure 7) was used; this image was not part of the training, testing, or validation datasets. The output shows detected object classes along with values displayed next to the bounding boxes. These values represent (i) the class label/name, indicating the category of the detected object, either "Deglet Nour" or "Bsir" varieties, and (ii) the confidence score (also called probability or confidence), which mostly approaches 1 confirming how certain the model is that the detected object belongs to the given class.

Furthermore, the developed AI-ML model accurately quantified the detected objects, providing both the absolute count and the relative percentage of each class within a sample. This detailed classification enables precise identification of any accidental mixing

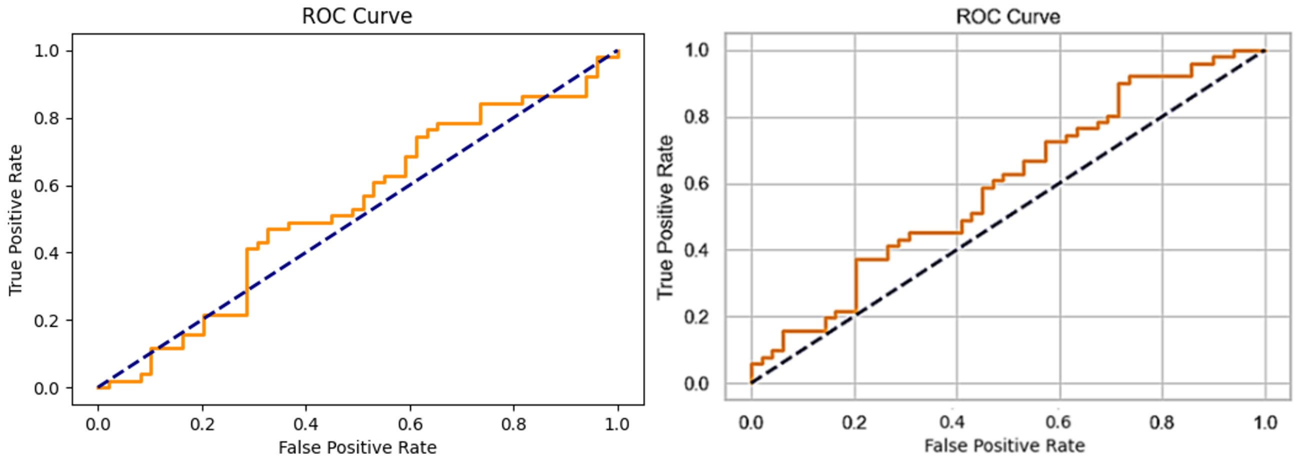


**Figure 5.** ROC curve of YOLOv8 (left) and YOLOv12 (right) models.

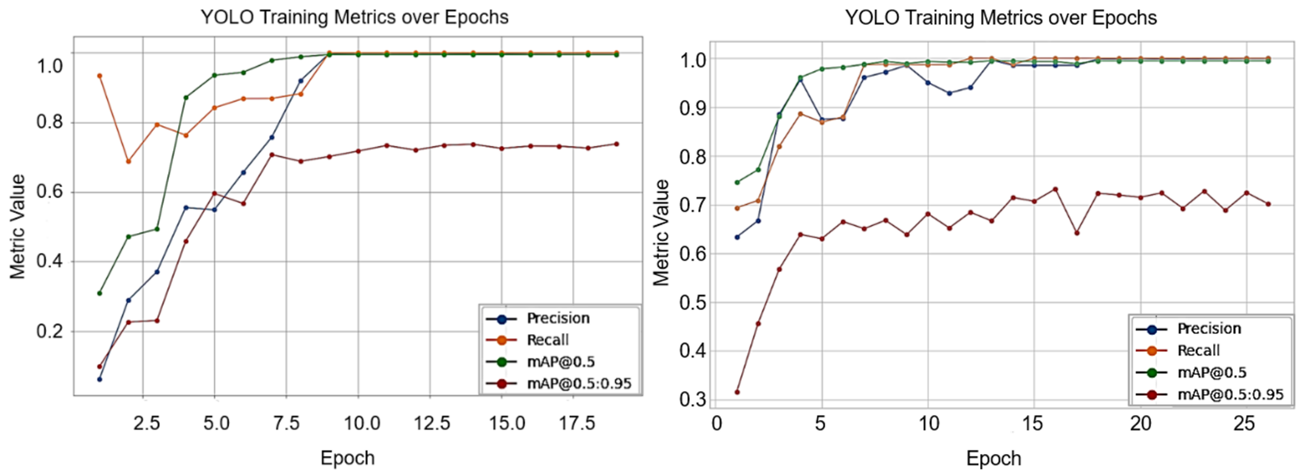


**Figure 6.** Evolution of metrics for YOLOv8 (left) and YOLOv12 (right) models on validation.

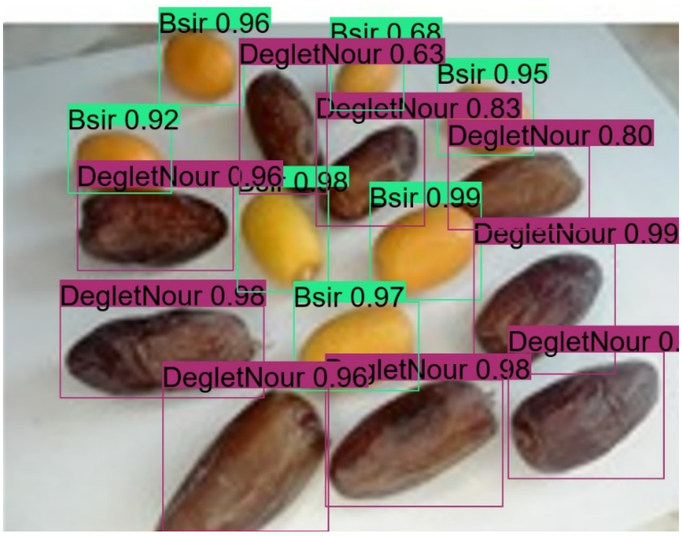


**Figure 7.** Typical real application result to detect date varieties using Yolov12 trained model.

or "contamination" of date variety lots by detecting the presence of extraneous varieties (Figure 8).

The results obtained in this work are significant, confirming the robustness of the developed AI-driven system to accurately qualify and quantify cross-mixed date varieties, which greatly benefits both farming and the food industry. High accuracy reduces the time and cost associated with manual sorting, making the entire supply chain faster and more efficient. It also ensures that date fruits are packed and labeled correctly, which is crucial for quality control. Early detection of cross-contaminated fruit prevents the need for later interventions, ensures product authenticity [19] and guarantees that only the best products reach customers, thereby improving satisfaction and trust. Moreover, by automating these processes, farmers and distributors can respond more quickly to market demands and optimize inventory management, benefiting the entire agricultural economy.

Looking forward, advances in computing such as edge AI devices, faster processors, and more efficient neural networks will enable real-time fruit classification directly in the field or packing lines

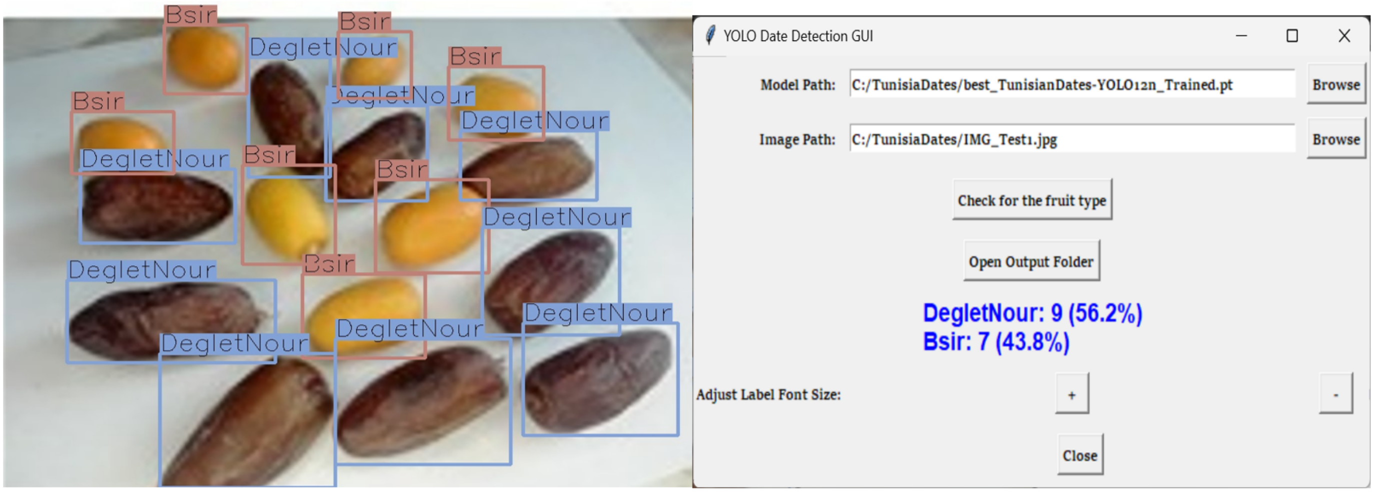


**Figure 8.** Quantitative analysis of a mixed batch of DegletNour and Bsir date varieties.

without relying heavily on cloud computing [20]. This will reduce latency and increase privacy and reliability. Integration with Internet of Things (IoT) systems and smart sensors will also create fully automated, intelligent supply chains capable of monitoring date fruit quality throughout transportation and storage [21]. Such developments promise to revolutionize agriculture by making it more precise, sustainable, and open to global food supply challenges [22].

### 4.5 Deployment Feasibility and Limitations

The high-performance metrics and robust training dynamics demonstrated in the above sections indicate strong potential for practical applicability. The lightweight nature of the best-performing YOLO model makes it highly feasible for use on cost-effective embedded systems or mobile devices, enabling portable, on-site quality control. A key limitation to consider is that the model's dependency on conditions similar to its training data; performance may degrade with the introduction of new date varieties or under significantly different lighting. For scaling this system to a commercial sorting line, future work would involve the establishment of a continuous data pipeline for model retraining to ensure long-term reliability and adapt to new scenarios.

## 5 Conclusion

Accurate date fruit classification is crucial in agriculture and the food industry for quality control and post-harvest processing. High classification accuracy reduces manual sorting errors and ensures consistency between package labeling and its content. Moreover, early detection of defective or mislabeled produce guarantees that only high-quality date fruits reach consumers. By enabling faster and more precise automatic sorting, this AI-based system optimizes inventory management. Besides, it paves the way for real-time monitoring and predictive analytics, further enhancing production efficiency and food quality standards.

This work demonstrated that AI systems, particularly trained YOLO models effectively detect and classify local Tunisian date varieties, accurately identifying cross mixed batches. YOLOv12 slightly outperformed in speed and precision, supporting its potential for real-time applications. Integrating these models into portable optical devices can significantly improve quality control and traceability across the date supply chain. Future work should focus on expanding to more varieties and embedding the system in commercial post-harvest processes to advance smarter farm-to-fork decision-making. Overall, AI-driven solutions promise to revolutionize agri-food monitoring and management.

## Data Availability Statement

Data will be made available on request.

## Funding

This work was supported by the PRIMA Program under Grant No. 2132.

## Conflicts of Interest

Sana Ben Amara is an employee of Boudjebel VACPA Company, Nabeul 8021, Tunisia.

## Ethical Approval and Consent to Participate

Not applicable.

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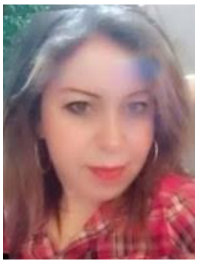

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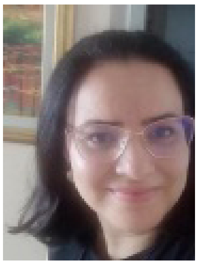

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