Sustainable Wastewater Management in Agriculture: A Deep Learning-based Olive Classification for Resource Efficiency in Water-Scarce Regions

Walid Karamti
Department of Computer Science, College of Computer, Qassim University, Buraydah, Saudi Arabia
w.karamti@qu.edu.sa (corresponding author)

Salim El Khediri
Department of Information Technology, College of Computer, Qassim University, Buraydah, Saudi Arabia
s.elkhediri@qu.edu.sa

Tarek Moulahi
Department of Information Technology, College of Computer, Qassim University, Buraydah, Saudi Arabia
t.moulahi@qu.edu.sa

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ABSTRACT

Efficient sustainable wastewater management combined with resource recovery represents a critical challenge for water-deprived areas, such as the Qassim region in Saudi Arabia. The effective integration of wastewater reuse into agricultural practices, particularly olive cultivation, requires advanced technological solutions to maximize yield, quality, and resource efficiency. This research investigates Deep Learning (DL)-based automatic olive classification systems as a vital component for optimizing post-harvest sorting operations, directly contributing to improved water efficiency by ensuring the appropriate allocation of wastewater resources to different olive varieties. The You Only Look Once (YOLO) object detection models—YOLOv5, YOLOv7, and YOLOv8—were employed to enhance accuracy and operational efficiency by classifying olives based on physical characteristics, including color, shape, and texture. A dataset of 2,025 images covering seven olive varieties was collected from publicly available sources, annotated using Roboflow, and preprocessed by resizing, rotation, scaling, and color adjustments. The YOLOv8 model achieved the best results, with a Recall of 99%, Precision of 99.1%, and mean Average Precision (mAP) of 99.4%, computed across thresholds [0.5:0.95] and [0.5:0.85]. These findings underscore the role of AI-powered classification in facilitating sustainable wastewater management, supporting more efficient water usage, and enhancing agricultural sustainability in arid regions.

Keywords-ANNs; sustainable wastewater management; deep learning in agriculture;YOLO; Object Detection; olive classification; sorting; resource efficiency in water-scarce regions

I. INTRODUCTION

Saudi Arabia is significantly developing its olive industry, particularly in the Al-Jouf region. In areas such as the Qassim region, sustainable agricultural practices face the scarcity of water resources, positioning wastewater reuse as an essential strategy for resource management. Different olive varieties possess distinct nutritional profiles, culinary uses, and cosmetic and medicinal applications, prompting increased market demand for premium olive products. Consequently, accurate sorting and efficient classification systems are increasingly crucial for maximizing product value and minimizing resource waste [1, 2]. Historically, classification methods predominantly relied on manual inspection or traditional Machine Learning (ML) approaches, such as Multilayer Feedforward Neural Networks (MFNNs) and basic Artificial Neural Networks (ANNs). These methods generally required extensive manual feature extraction and preprocessing, resulting in limitations related to accuracy, speed, and scalability. Moreover, such conventional techniques did not seamlessly integrate with modern wastewater management strategies, leaving a critical gap in creating sustainable agricultural frameworks [3-5]. Due to this situation, consumers and farmers demonstrate minimal understanding of different olive varieties along with their distinct characteristics. A widespread belief suggests that all olives have unacceptable pH values, fats, and sugars, which make them unsuitable for human consumption [6, 7]. To overcome these limitations, recent advancements in DL have provided significantly more efficient tools, capable of automatically extracting powerful image features. Specifically, the YOLO object detection model has emerged as highly effective due to its capability to integrate feature extraction, object localization, and classification in a single computational step. YOLO models (including YOLOv5, YOLOv7, and YOLOv8) demonstrate remarkable accuracy and operational speed, making them ideally suited for real-time agricultural applications [7-9].

The present research adopts the latest versions of YOLO-based models to efficiently classify olives, leveraging physical characteristics, such as color, shape, and texture. By doing so, this study contributes directly to sustainable agricultural practices in water-scarce regions, like Qassim, reducing post-harvest waste, optimizing water use, and enhancing the economic and ecological sustainability of the olive industry.

A. *Motivation*

- The wide variation in olive types, differing in color, shape, and texture, necessitates an efficient classification system to address this variability.
- Manual classification and sorting of olives is time-intensive and error-prone, emphasizing the need for automated and reliable solutions.
- Accurate post-harvest classification and sorting are critical for improving efficiency and reducing waste in the olive industry, making technological advancements essential.

B. *Highlights*

- The study utilized YOLOv5, YOLOv7, and YOLOv8 models to classify and identify olives based on high-quality image datasets, achieving state-of-the-art results.
- YOLOv8 demonstrated superior accuracy with 99% Recall, 99.1% Precision, and 99.4% mAP, highlighting its effectiveness for olive classification.
- The findings show the potential for implementing these models to streamline the olive sorting process, handling variations in fruit ripening rates and optimizing multi-harvest operations.

Classification of olive tree cultivars by the type of olive fruits is a standard problem. It intends to sort novel inputs utilizing the patterns obtained through the training data. The relevant literature is rather limited. The current trend is more inclined to DL algorithms, especially Convolutional Neural Networks (CNNs) due to their capability to automatically determine parameters from the data. The model proposed in [10] classified eight types of popular olives in Saudi Arabia with high accuracy. Consequently, the authors extended a deep neural network model that employs about 1,750 private image samples, with 204-240 samples per variety, including techniques, such as reduced learning rate, model checkpointing, image enlargement, and dropout.

The system developed in [2] utilized MFNNs, for establishing the distinction of individual olive tree varieties from images of the leaves. The system used scanned images of the leaves at a resolution of 300 dpi, compressed to 50 × 20 pixels, normalized, and segmented. The Canny frond function was used to segment the edges of the leaves from which 10 primary characteristics were then calculated. The used back propagation feedforward ANN had 10 input neurons, 2 hidden layers with 10 neurons in each, and 12 neurons in the output layer that represented the varieties. The dataset consisted of images of olive types, with 60 images from each of the 12 olive types for training and 60 for testing. The system was quite effective with approximately 91 % accuracy. Authors in [11] paid attention to the differentiation of apple cultivars. They suggested the use of Deep Convolutional Neural Networks (DCNNs) to classify apple cultivars using only images of the leaves. The proposed network recorded satisfying overall classification accuracy of 97.11%.

In conclusion, when analyzing the state of the art, one can find relatively few publications pertaining to the olive classification problem, while there is a comparatively low availability of the corresponding end-user tools. Furthermore, most datasets are private, small in size, and often without very clear images. Even specific features, such as small surface cracks and material texture are usually not discernable, which makes the classification even more difficult. The number of olive varieties analyzed in current research varies [7, 12, 13]. Additionally, some utilized classification algorithms are characterized by high time consumption [14]. Based on the fact that YOLO has been proved effective in object detection and classification in previous studies, including general object detection, landing spot detection [15], and poultry recognition, the current study aims to compare different YOLO versions and to determine their suitability in detecting and classifying olives.

ML and DL have been utilized to predict the efficient use of water for sustaining olive orchards. An effective water management approach, combining high-resolution satellite imagery with DL, was proposed in [16]. This method helps minimize water loss and ensures precise irrigation by delivering the optimal amount of water to olive orchards. Authors in [17] developed a framework for optimizing economic profit prediction in olive trees. They focused on preprocessing input data, comparing ML algorithms, and selecting the most accurate predictive model. Another application of satellite imagery is presented in [18], where DL is utilized to process satellite images as input, enabling the early prediction of accurate crop yield data at the beginning of the cropping season.

DL techniques have also been utilized to strengthen the security of smart agriculture by detecting intrusions and identifying malicious activities [19]. The trade-off between energy efficiency and spectral efficiency in UAV-based irrigation systems to optimize water usage for efficient olive irrigation is addressed in [20]. To ensure a secure irrigation system for olive orchards, the use of IoT technology based on 5G communications to achieve this goal is proposed in [21].

II. MATERIALS AND METHODS

A. Materials

The present study involved finding a dataset of olive fruits cultivated in Saudi Arabia. The Fruit Image Dataset in Controlled Environment [2], was considered. It includes 1,735 high-quality JPEG images, each representing a single olive type, featuring seven prominent olive varieties grown in the region: 'Arbequina,' 'Corbella,' 'Coratina,' 'Empeltre,' 'Koroneiki,' 'Picual,' and 'Morrut', as illustrated in Figure 1. The distribution of the classes can be seen in Figure 2. As portrayed in Figure 4, each of the classes has images of the representing objects and in some cases, people.

Fig. 1. Data samples from seven olive varieties at the medium stage of ripeness.

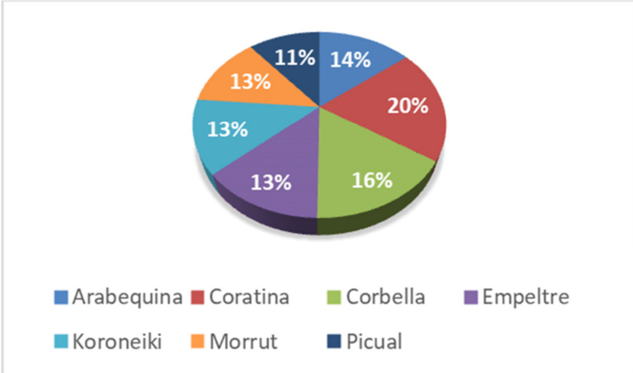

Fig. 2. Distribution of olive fruit types within the dataset.

1) Data Processing

Roboflow was utilized to preprocess the dataset and prepare it for use in the model. To ensure dataset consistency, preprocessing steps were applied, including resizing images to 640 × 640 pixels, the optimal input size for the YOLO model. Additionally, re-orientation was performed to align all images uniformly, facilitating accurate analysis and interpretation.

2) Data Annotation

Roboflow, an online platform for dataset management and augmentation, was utilized to create bounding boxes, ensuring that the smallest rectangles accurately fit each object in the dataset.

3) Data Augmentation

To enhance the YOLO dataset and improve the model's generalization capabilities, several augmentation processes were applied. Since the original images were collected, with objects placed in a horizontal orientation, random rotations were conducted. Additionally, techniques, such as scaling, and color adjustments, were employed to further diversify the dataset. These transformations helped create a more robust model by increasing its ability to generalize across different object positions, sizes, and lighting conditions. This not only mitigated the risk of overfitting, but also enhanced the model's accuracy and robustness.

4) Data Splitting

The dataset was divided into training, validation and testing subsets using Roboflow. For training, a total of 70% of the data (training set) was used to train and fine-tune the YOLOv5, YOLOv7, and YOLOv8 models, and 20% of the data (validation set) was used to tune the hyperparameters. The test set (10%) was utilized for model testing.

B. Methods

1) You Only Look Once

YOLO is a single stage object detection model, widely applied in complicated image annotation in fruit recognition problems [22]. While in most of the existing systems, bounding boxes and class probabilities are predicted and estimated separately, YOLO's regional proposal network outputs bounding boxes along with probabilities of various classes in a single pass through the neural network.

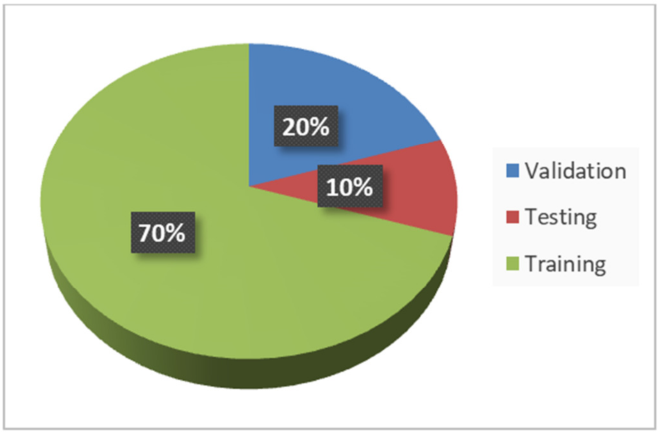

Fig. 3. Utilized data partitioning.

First proposed in [23], YOLO is well known for its tremendous speed of detecting and identifying objects in real-time. The model presents a new solution for object detection, where the latter is translated into a regression question, thereby leading to lesser computations, and thus giving a higher speed than common methods. There are more advanced versions, such as YOLOv5, YOLOv6, YOLOv7, and finally, YOLOv8, all of which improved model performance and kept the speed issue in mind. Moreover, authors in [24] found that not only these newer versions provide high frame rates, but also feature high mAP, which makes YOLO a perfect candidate for real-time object detection.

In this study, the YOLO was chosen as a DL model due to its balance between speed and accuracy, which makes it suitable for specific applications, such as sorting or grading along a production line. The achievement of real-time monitoring is important, requiring a high frame rate.

2) Model Development

The details of the proposed model are depicted in Figure 4.

3) Training Process

The training process for all YOLO models followed a standardized methodology, utilizing the hyperparameters outlined in Table I.

4) Validation

Precision (P): Precision is defined as the percentage of the actual positives observed in the dataset by the system out of all the hopefully positive outputs given by the system. It measures the performance of the classifier in correctly predicting positive cases while avoiding the high likelihood of false positives:

$$P= TP/ (TP +FP)$$

Recall (R): Measures how many of the actual positives (true positives) the classifier acquired in the total positives, which includes true positives and false negatives. It measures the classifier sensitivity:

$$R = TP/ (TP + FN)$$

F1-score: Is the harmonic mean of R and P:

$$F1 =(R * P)/(R + P)$$

mAP: Summarizes the performance by averaging across P for all the R levels for each class. The closer the mAP value is to 1, the better is the detection system:

$$m_{Ap} = \frac{1}{(k-n)} \sum_{k=1}^{\infty} AP *_k$$

Confidence: Confidence indicates the model's certainty that an object exists within a predicted bounding box and is correctly classified. It is the product of the objectness score and class probability. Higher confidence values suggest stronger prediction certainty. This metric is visualized in Figures 8 and 9 to analyze classification reliability.

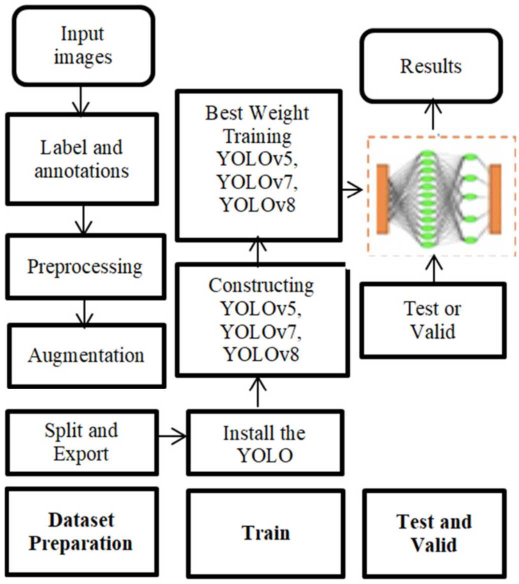

Fig. 4. Specifics of the proposed methodology.

TABLE I. OVERVIEW OF THE HYPER-PARAMETERS EMPLOYED DURING TRAINING

Hyper-parameters	All YOLO architectures
Epochs	100
Batch size	16
Image size	650 × 650

III. RESULTS AND DISCUSSION

Several YOLO models (YOLOv5, YOLOv7, and YOLOv8) were trained and compared using the open-source public dataset in [2]. The results of mAP, Precision, and Recall can be seen in Figure 5. YOLOv8 achieved superior Precision (99.1%) and Recall (99.7%), demonstrating its strength in accurately detecting and classifying olive varieties. YOLOv7 also provided high accuracy (Precision 98.4%, Recall 99.3%) and mAP scores, showing a strong ability to localize objects effectively. YOLOv5, while still robust, demonstrated comparatively lower performance. This structured comparison clarifies the relative strengths of each YOLO version, focusing explicitly on essential performance metrics and avoiding redundancy.

A. Training and Validation

Further assessment of YOLOv5, YOLOv7, and YOLOv8 models was performed using confusion matrices during both training and validation phases (Figure 6). As summarized in Table III, all models achieved high accuracy, with YOLOv8 demonstrating the highest Precision (99.1%), Recall (99.7%), and minimal false-positive rates, making it the most effective for olive detection tasks. While YOLOv7 obtained slightly higher mAP scores (0.995 during training), indicating excellent object localization capabilities, YOLOv8's ability to detect all classes (Recall = 1.0) and maintain high Precision renders it the preferred model.

Figures 7–8 and Tables II-VII further illustrate model performance through Precision-Recall curves and F1 scores. YOLOv8 showed consistent performance across most olive classes, reflected by stable F1 scores (~0.99). Although some classes, such as Sugaey and Meneifi, exhibited slightly lower recognition rates, this minor variation indicates opportunities for dataset expansion and image quality enhancement to further improve classification performance. Overall, by clearly delineating key differences without repetition, the refined analysis emphasizes each YOLO version's distinctive strengths and potential areas for future improvement.

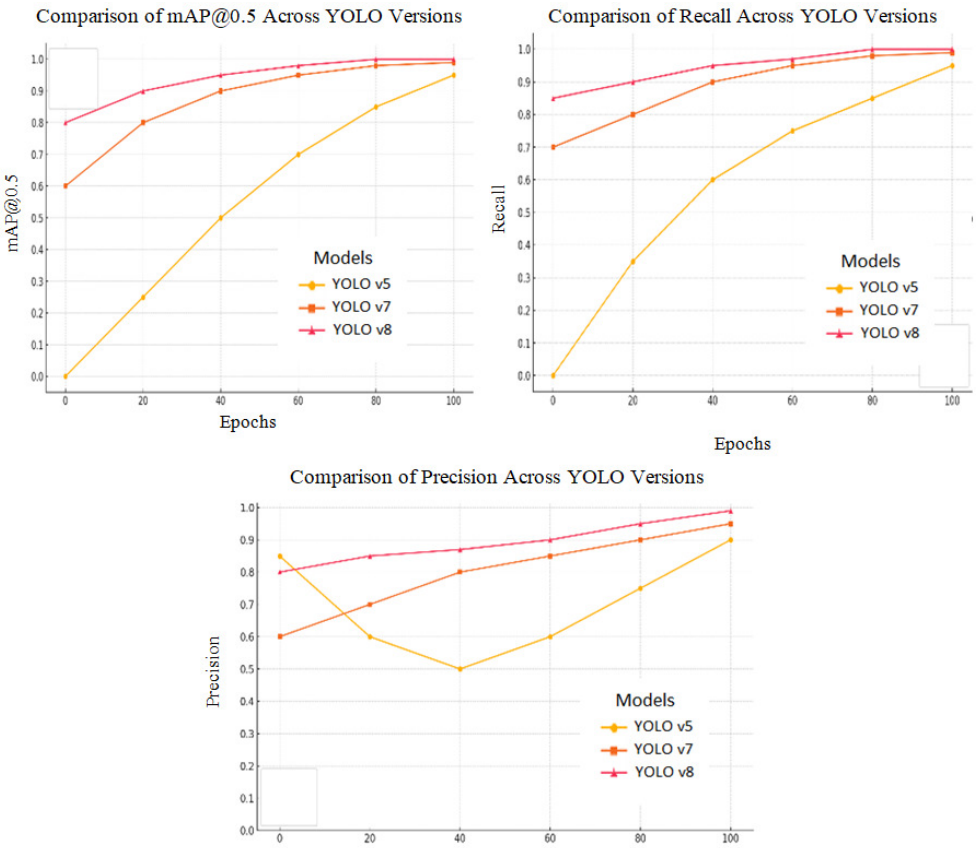

Fig. 5. The training curves for: (a) mAP@0.5, (b) Recall, and (c) Precision, corresponding to YOLOv5, YOLOv6, YOLOv7, and YOLOv8, respectively.

B. K-Fold Cross-Validation

This work examines the appropriate value of k in K-Fold cross validation, to ascertain the effect of data distribution on validation results. The results of four YOLO algorithms were tested based on distinct k values of 3, 7, and 10 to identify the best k value on the Precision and mAP@0.5. Table VII displays the mean of all the k values for each group in this performance comparison analysis. The findings reveal that for equal P, the output of algorithm YOLO increases in convergence with the computation of k. For example, the mAP@0.5 was stable at 0.994 in all tested k values on YOLOv7, whereas Precision slightly decreased for YOLOv8, when k ranged from 3 to 10. Notably, it was proposed that k = 3 was the optimal value for YOLOv7 in identifying the categories of olive fruits that were being predicted. On the other hand, YOLOv8 was at its best when k=7, while for YOLOv5 the best k value was determined to be 10. Such results indicate that the validation performance of YOLO architectures depends on the selected k value in part. Besides, the division of the dataset into k folds was a way to have an equal distribution of the classes of data, further rendering the models more consistent and credible when implemented. These problems were reduced with the help of the K-Fold Cross validation, whereby it was possible to train on a single substrate of the data and to test the model/them on another subset of the data. The benefits of this approach include designing global models that have more consistent and stable performance compared to other datasets, and using the greatest amount of accessible data.

TABLE II. A DEPICTION OF THE CONFUSION MATRIX ON THE TEST SET ACROSS DIFFERENT MODELS: YOLOV5

Predicted labels	Morrut	0.66	0.06	0.08	0.00	0.00	0.00	0.00	0.00	0.00
	Picual	0.00	0.90	0.06	0.27	0.00	0.00	0.00	0.00	0.00
	Koroneiki	0.03	0.02	0.78	0.00	0.00	0.00	0.00	0.00	0.00
	Empeltre	0.00	0.00	0.00	0.84	0.08	0.00	0.00	0.00	0.00
	Coratina	0.02	0.06	0.14	0.00	1.00	0.03	0.10	0.00	0.00
	Corbella	0.00	0.00	0.00	0.00	0.04	0.90	0.06	0.00	0.00
	Arbequina	0.05	0.10	0.03	0.00	0.08	0.00	0.96	0.00	0.24
	Background FN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.00
	Background FP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50
		Morrut	Picual	Koroneiki	Empeltre	Coratina	Corbella	Arbequina	Background FN	Background FP
True Labels										

TABLE III. A DEPICTION OF THE CONFUSION MATRIX ON THE TEST SET ACROSS DIFFERENT MODELS: YOLOV7

Predicted labels	Morrut	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Picual	0.00	1.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00
	Koroneiki	0.00	0.00	0.96	0.00	0.00	0.00	0.00	0.00	0.00
	Empeltre	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
	Coratina	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
	Corbella	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
	Arbequina	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00
	Background FN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.50
	Background FP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50
		Morrut	Picual	Koroneiki	Empeltre	Coratina	Corbella	Arbequina	Background FN	Background FP
True Labels										

TABLE IV. A DEPICTION OF THE CONFUSION MATRIX ON THE TEST SET ACROSS DIFFERENT MODELS: YOLOV8

Predicted labels	Morrut	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Picual	0.00	1.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00
	Koroneiki	0.00	0.00	0.96	0.00	0.00	0.00	0.00	0.00	0.00
	Empeltre	0.00	0.00	0.00	0.92	0.00	0.00	0.00	0.07	0.42
	Coratina	0.00	0.00	0.00	0.00	1.00	0.05	0.00	0.00	0.17
	Corbella	0.00	0.00	0.00	0.00	0.00	1.00	0.03	0.00	0.00
	Arbequina	0.00	0.00	0.00	0.00	0.00	0.00	0.90	0.00	0.17
	Background FN	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.50	0.00
	Background FP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50
		Morrut	Picual	Koroneiki	Empeltre	Coratina	Corbella	Arbequina	Background FN	Background FP
True Labels										

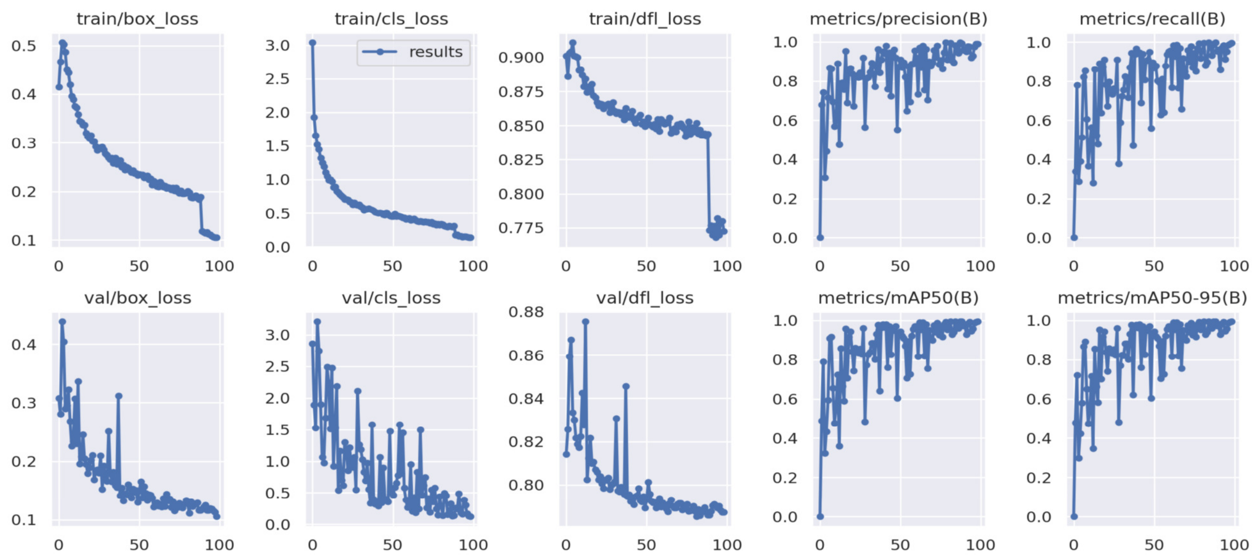

Fig. 6. Visualization of YOLOv8's performance throughout the training and validation phases.

TABLE V. QUANTITATIVE CLASSIFICATION OUTCOMES

Version type	Precision	Recall	mAP@0.5	mAP@ [0.5:0.95]
YOLOv5	0.941	0.923	0.985	0.997
YOLOv7	0.984	0.993	0.995	0.995
YOLOv8	0.991	0.997	0.994	0.994

(a)
(b)
(c)

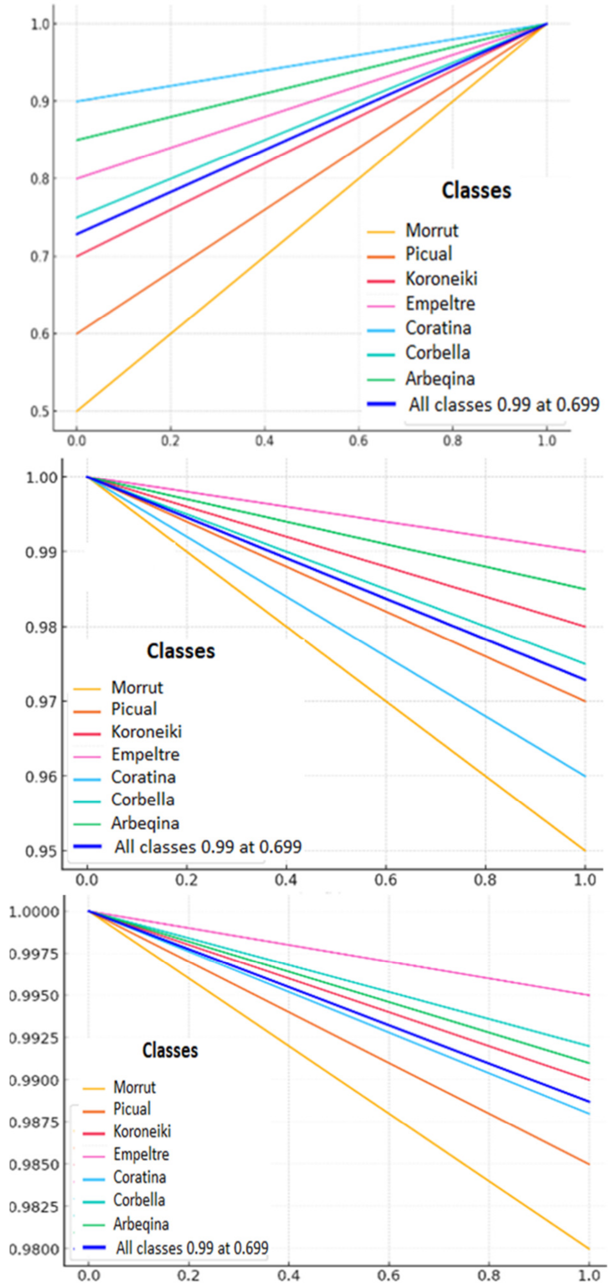

Fig. 7. Visual representations of validation results versus confidence in classification performance using YOLOv8: (a) F1-score, (b) Precision, and (c) Recall.

(a)
(b)
(c)

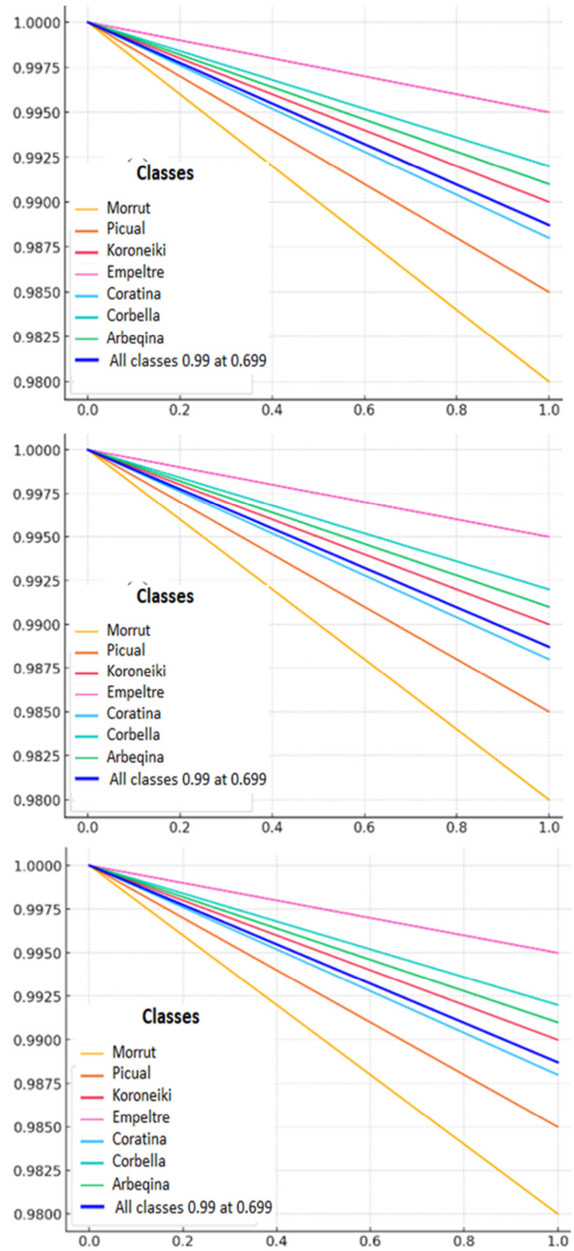

Fig. 8. Visual representations of validation results versus confidence in classification performance using YOLOv7: (a) F1-score, (b) Precision, and (c) Recall.

TABLE VI. COMPARATIVE SUMMARY OF VALIDATION METRICS FOR ALL K-VALUES

k	Model	Precision	Recall	mAP@ 0.5	mAP@ [0.5:0.95]
3	**YOLOv5**	0.891	0.904	0.956	0.887
3	**YOLOv7**	0.98	0.983	0.987	0.998
3	**YOLOv8**	0.908	0.887	0.984	0.976
7	**YOLOv5**	0.913	0.911	0.965	0.977
7	**YOLOv7**	0.917	0.984	0.988	0.988
7	**YOLOv8**	0.893	0.88	0.994	0.99
10	**YOLOv5**	0.941	0.919	0.984	0.954
10	**YOLOv7**	0.904	0.951	0.988	0.979
10	**YOLOv8**	0.941	0.907	0.982	0.984

The evaluation of the proposed model was conducted on a workstation running Python on an Intel i7 processor with 16 GB of RAM. While the current results provide valuable insights, they can certainly be further enhanced over time when utilizing more powerful hardware, such as high-performance GPUs or more advanced computational resources. With access to such systems, improvements in processing speed, model accuracy, and the ability to handle larger datasets are anticipated, ultimately leading to better real-world deployment outcomes.

C. Learning Rate Sensitivity Analysis

To further justify the selection of 0.01 as the learning rate, a comparative analysis was conducted using different values (0.001, 0.005, and 0.01). The results showed that:

- The value of 0.001 led to slower convergence, requiring more epochs to achieve comparable accuracy.
- The value of 0.005 improved stability but resulted in slightly lower mAP scores compared to 0.01.
- The value of 0.01 provided the best balance, ensuring rapid convergence while maintaining high Precision and Recall.

This analysis confirms that 0.01 is the optimal choice, as it prevents overshooting while allowing efficient model training.

IV. CONCLUSION

This paper presented a robust Deep Learning (DL)-based model for identifying and categorizing fully ripe olive fruits into edible and pressing types using multiple YOLO models. The proposed approach significantly enhances the efficiency and accuracy of sorting, classification, and quality control processes compared to traditional manual or conventional Machine Learning (ML)-based systems. Specifically, the YOLOv8 model achieved superior performance, attaining a Precision rate of 99.8% on the olive image dataset. This surpasses previous models, such as the MobileNetV2 architecture utilized in [10], where lower accuracy was reported, and the Multilayer Feedforward Neural Networks (MFNN) employed by earlier studies [2], which achieved an accuracy of approximately 91%. Moreover, the current work demonstrates improved Precision and speed compared to recent YOLO models (YOLOv5 and YOLOv7), highlighting the progression in DL capabilities for agricultural applications. These comparative results underscore the novelty and significant contribution of the present study, emphasizing its potential for practical deployment in sustainable wastewater management and Precision agriculture.

However, some limitations remain, including restricted camera positioning and limited dataset samples. Future improvements will involve expanding the dataset to include a broader range of olive varieties and increased image samples, thereby enhancing the model's generalizability and overall performance.

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