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Smart Harvesting Decision System for Date Fruit Based on Fruit Detection and Maturity Analysis Using YOLO and K-Means Segmentation

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Abstract: The date palm (*Phoenix dactylifera*) is a large palm with exotic fruits measuring up to 30 meters in height. The date palm produces fruits rich in nutrients provides a multitude of secondary products, and generates income necessary for the survival of a large population. Losses attributed to manual harvesting encompass both quantitative and qualitative aspects, with the latter measured through attributes such as appearance, taste, texture, and nutritional or economic value. These losses, in terms of both quantity and quality, are influenced by practices across all phases of the harvesting process. On the other hand, the risks of work accidents are high because of the length of the date palms. To reduce the losses and reduce risks, it is essential to propose a decision system for robotic harvesting to help farmers overcome the constraints during the harvest. The assessment of quality and maturity levels in various agricultural products is heavily reliant on the crucial attribute of color. In this study, an intelligent harvesting decision system is proposed to estimate the level of maturity based on deep learning, K-means clustering, and color analysis. The decision system's performance is assessed using the dataset of date fruit in the orchard and various metrics. Based on the experimental results, the proposed approach has been deemed effective and the system demonstrates a high level of accuracy. The system can detect, locate, and analyze the maturity stage to make a harvest decision.

Keywords: Deep Learning, Date Harvest, Yolo, Maturity Analysis, K-Means Segmentation

Introduction

Dates are edible fruits that come from (*Phoenix dactylifera*, L.), also known as the date palm. They are highly energetic berries that contain a high percentage of carbohydrates, primarily sugars. Date fruit is rich in water and micronutrients such as vitamins, minerals, and fibers. Dates are predominantly rich in vitamins from the B family. They also naturally contain antioxidant vitamins, particularly vitamins C and E (Al-Shahib and Marshall, 2003).

In addition to their ecological and social significance, there are currently over five thousand date palm varieties worldwide. Date palms play a significant role in the agricultural income of farmers, providing dates as well as a variety of by-products utilized for commercial and domestic uses.

The height of date palms can reach 15-25 m. According to the Food and Agriculture Organization (FAO) (Alotaibi *et al.*, 2023), the production of date palms covers an area of 1.11 million hectares, for a total production of 8.53 million tons. Date palm cultivation is widespread, with Asia accounting for 648,372 hectares, Africa for 435,763 hectares, Europe for 947 hectares, and the Americas for 7,022 hectares.

In the majority of date farms, the conventional practice involves human experts manually categorizing the stage of maturity. These trained workers utilize external cues like shape and color. However, this approach is susceptible to human error. It is more and more difficult to ensure the harvest in time because of the shortage of qualified climbers and the high cost of this operation. Harvesting dates is a laborious task typically carried out by hand by the farmers themselves, requiring great care and significant physical effort, but also posing a risk of severe falls.

The ripening period of dates exhibits significant variations. It is during this stage that the organoleptic qualities of the fruit develop, including the accumulation of sugars and acids, production of aromas, and color changes. Color serves as a crucial parameter that influences consumer acceptability and preference. On the other hand, the period during which the product maintains its optimal quality is short. Therefore, it is imperative to exert control over the harvesting process to determine the ideal moment for harvest.

The ripening process initiates at the onset of color change and continues until the fruit reaches full maturity. Color plays a significant role in the visual appeal of dates, influencing the initial impression formed by consumers, whether positive or negative. Additionally, color serves as a quality criterion, enabling the categorization of dates into distinct segments and providing consumers with easily relatable options when making their selection.

Harvesting dates involves picking them at various stages of maturity, depending on the specific variety, which necessitates different processing methods before they can be stored. Assessing the maturity level is crucial, especially in the context of robotic harvesting, but current analysis techniques are time-consuming and require significant labor input. Automated color grading has the potential to address the challenge of correlating date maturity with color. This is because color strongly correlates with date maturity.

Intelligent harvesting decision systems for date fruit offer several advantages over manual harvesting they can improve efficiency, quality, safety, and consistency while reducing waste and time and also increase production and income (Aggarwal *et al*., 2022).

Explorations within this domain continue to be restricted due to a variety of challenges presented by unstructured environments and ever-changing lighting conditions (Kapach *et al*., 2012), which make date detection and maturity analysis a challenging task to the extent of our knowledge, no prior research has addressed the challenge of detecting and precisely localizing date fruits within an orchard. Although certain studies have employed classification techniques to categorize the complete image, they have not tackled the essential mission of locating the precise coordinates of date fruit within the image. This information is indispensable for the functioning of robots. In this research, an intelligent harvesting decision system that utilizes deep learning and K-means segmentation to create an automated harvesting system capable of detecting and estimating the maturity stage of date fruit is proposed.

Maturation is the stage of development that achieves physiological or horticultural maturity. The critical factor is the level of maturity during harvest, which dictates both the preservation duration and the ultimate quality of the fruit. Siddiqui (2017) spans from 5-8 months after the fruit set, the maturation period encompasses a progressive sequence of alterations in the fruit's attributes, beginning from flowering and culminating in maturity and senescence. These modifications encompass shifts in shape and structure, as well as changes in biochemical, physiological, and color attributes, distinctly showcasing the evolving appearance of the fruit throughout the ripening process (Djaoudene *et al*., 2019).

We can classify the previous works into two categories: The first is color-based and uses traditional methods such as color histograms or machine learning models while the second is intelligent solutions based on deep learning.

Regarding color-based approaches, (Zhang *et al*., 2014) introduced a classification method rooted in color analysis. This method relies on 2D histograms of colors within each grading category, enabling the assessment of co-occurrence frequencies. Diverging from the color grading methods introduced by Zhang *et al*. (2014). Lee *et al*. (2008) introduced an alternative approach. Their solution involves converting color spaces and analyzing the distribution of color indices for the automated assessment of date fruit maturity. This method is specifically tailored for efficient deployment in commercial production. Additionally, the proposed technique simplifies the task for human operators to define and fine-tune color preference settings across various color groups, each signifying different stages of maturity. Continuing along the same lines, (Avila *et al*., 2015) introduced a method aimed at generating a color scale. Their proposed approach involves employing multidimensional regression through support vector regression to produce these color scales. The experimental phase centers around two instances of color scales: The initial example pertains to grape seeds, while the subsequent one focuses on olives.

In the context of deep learning-based approaches, multiple research investigations have been carried out to classify and harvest various fruits beyond date fruits. For instance, (Worasawate *et al*., 2022) performed a comparative analysis involving four machine learning classifiers: K-means, Naive Bayes, support vector machine, and the Feed-Forward Artificial Neural Network (FANN). Their primary aim was to categorize the maturity stage of mangoes during the harvesting process. Nagaraju *et al*. (2021) introduced a detection and classification system tailored for strawberries and cherries, employing the MobileNet convolutional neural network architecture. This MobileNet CNN was engineered to effectively discern and classify distinct types of strawberries and cherries. Most of the previous methods for date maturity classification use images with a white background after harvesting, rather than in an orchard with natural background and conditions. In a recent study Altaheri *et al*., (2019a), two pre-trained Convolutional Neural Network (CNN) models, specifically AlexNet and VGG-16, were studied. The evaluation process involved employing an image dataset

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containing five different date types across various maturity stages. Notably, the pre-trained CNNs demonstrated the capability to achieve strong classification outcomes for date fruits even without the need for prior image preprocessing.

Materials and Methods

Throughout its growth and development, a date fruit undergoes distinct stages. At each phase, the fruit exhibits diverse characteristics that serve as potential indicators of its maturity. Features like size, color, and skin texture change as the fruit advances. Notably, the color attribute is particularly significant, as dates assume varying colors corresponding to different maturity statuses.

According to the literature, the works with high accuracy are about images taken in specific conditions such as the position of the camera and lighting conditions. These solutions are made for the classification of fruits in the packing stations. The other solutions, especially those based on deep learning, analyze real images for robotic harvesting. The image analysis is done on the whole image. To have good precision, the processed information must be only the fruit.

The proposed solution consists of eliminating all the details of the image that are not about the fruit. In the first phase, the proposed system starts with detecting and recognizing the types of dates and in the second phase, the system must determine the stage of maturity so that the harvesting robot can make a decision. Figure 1 illustrates the depiction of the robotic harvesting system. This system integrates a neural network for both detection and recognition purposes, along with a color-based analysis of date maturity. Within this framework, the system is designed to quantify the number of ripe fruits and assign them corresponding labels. A ripeness percentage is calculated and ultimately, the decision to harvest the dates is made based on both the category and the calculated maturity percentage.

Dataset

To evaluate the proposed solution, it is necessary to have a dataset that contains real images that have not been preprocessed Fig. 2. Therefore, the dataset published by Altaheri *et al*. (2019b) is a good choice for detection and Maturity analysis in an orchard. The dataset comprises 8079 images originating from 29 date palm trees. These images encompass date bunches from five distinct date varieties: Naboot Saif, Khalas, Barhi, Meneifi, and Sullaj. The image captures were conducted using two RGB cameras, namely Canon EOS-600D (camera-1) and EOS1100D (camera-2) from Tokyo, Japan. These cameras were operated in automatic mode with varying focal lengths. The respective resolutions of the cameras were 5184×3456 and 4272×2848. The images were taken under varying natural daylight conditions: During the morning hours (9:00-11:00) and afternoon hours (3:005:00). Moreover, the images were captured in challenging illumination conditions, with the cameras positioned at different angles relative to the sun.

The imaging sessions encompassed snapshots of date fruits across the six distinct stages of maturity: Immature, Khalal, Rutab, and Tamar. Due to non-uniform maturation, dates within each session might exhibit multiple maturity stages. The initial session generally featured immature dates, while the concluding session featured dates in the Tamar stage. The dataset was meticulously annotated to account for the variety, maturity level, and harvesting determination.

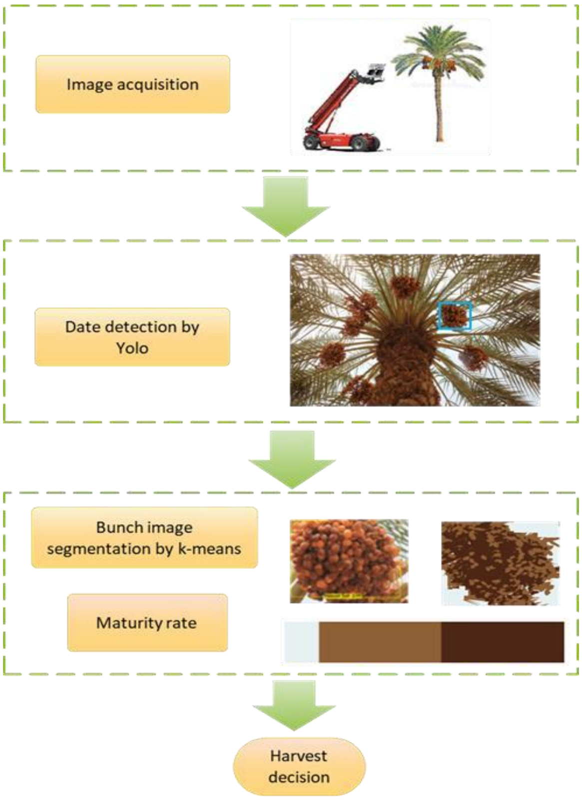


Fig. 1. Intelligent decision system for robotic harvesting

Fig. 2: Examples of dataset images

This comprehensive dataset of date fruits holds value for the research community, serving various purposes such as automated harvesting, visual yield estimation, and classification endeavors.

Yolo Detection

The "You Only Look Once" (YOLO) algorithm is designed to identify and classify diverse objects within an image. In YOLO, object detection is approached as a regression task, yielding the class probabilities for the detected objects (Redmon *et al*., 2016). Utilizing Convolutional Neural Networks (CNN), the YOLO algorithm is capable of real-time object detection (Fang *et al*., 2020). As its name suggests, this algorithm necessitates a single forward propagation through the neural network to accomplish object detection.

The YOLO algorithm encompasses multiple variations. It functions as a real-time object detection and recognition system for diverse objects within an image. In YOLO, object detection is treated as a regression task, delivering class probabilities for the detected objects.

Based on the latest advancements in detection research (Liu *et al*., 2020; Krishna *et al*., 2022; Gai *et al*., 2023; (Alghyaline, 2022; Ponraj, 2023), the YOLO algorithm holds significance for several reasons.

YOLO enhances detection speed by enabling real-time object prediction. This algorithm operates as a predictive technique, yielding precise outcomes while minimizing background errors. The algorithm boasts remarkable learning capabilities, allowing it to grasp object representations and apply them effectively in object detection.

YOLOV8 is the latest version in the YOLO family of object detection models similar to YOLOV5 (Jocher *et al*., 2020) the architecture of the model consists of a backbone, neck, and head. The backbone used in ImageImageYOLOV8 is Darknet-53 it's a convolutional neural network for features extraction, the neck component consists of a sequence of convolutional layers that iteratively enhance the extracted features, while the head component comprises fully connected layers responsible for generating predictions of bounding boxes and class probabilities. YOLOV8 includes new features like segmentation, classification, pose estimation, and tracking making it a top choice for real-time object detection.

To train YOLOv8 for the date detection task, the model YOLOV8S was configured with specific parameters. The image size was set to 640 pixels, the batch size to 16, the learning rate to 0.001, and the number of epochs to 100. The training process was trained on Google Colab, utilizing the A100 Nvidia graphics card.

Fig. 3: Example of detection result on the

Fig. 4. Bunch image detected by YOLO

After detecting the dates by YOLO Fig. 3. The next phase is the analysis of the region that contains the date bunch. The mature date pixels and the immature date pixels often represent more than 90% of the region bunch, background pixels represent less than 10% of the region Fig. 4. A method of segmentation is necessary to separate the immature dates, the immature dates, and the background.

K-means Segmentation

The k-means algorithm (Likas *et al*., 2003) is a well-known clustering method employed to minimize clustering errors, it is an efficient way to solve the clustering problem. The objective of image segmentation using K-means is to partition pixels into k distinct regions, where the value of k is predetermined by the user. Color intensity serves as the basis for segmentation. The process initiates with the random allocation of each pixel to a region, followed by iterative steps: Recalculating the centroids of various groups and reassigning each pixel to a group based on its proximity to the center. The convergence criterion is met when the centroids cease to change.

In terms of minimization, the pixels $x_1, x_2, x_3,..., x_n \in IR^3$ are divided into k groups at each iteration. Let C_i (i is the class index) denote the set of centers of the classes. Their coordinates are recalculated by averaging those of the points in the group. A pixel x_i is assigned to group j if:

$$\|x_i - C_i\| = \min_u \|x_i - C_u\|$$

Due to the unsuitability of randomly selecting initial cluster centers from image data (Ouhda *et al*. 2018; Moftah *et al*. 2014), an alternative approach involves utilizing histogram peaks. In this context, histograms have been constructed for each color component, as illustrated in Fig. 5.

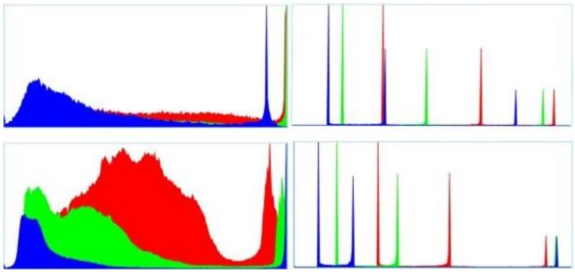
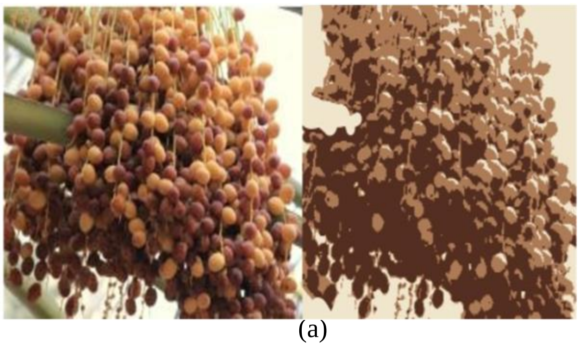


Fig. 5: Example of bunch image histogram before and after segmentation



(a)

(b)

Fig. 6: Example of bunch image segmented; (a) Bunch image; (b) Segmented image into three regions

The natural agriculture environment is a complex scene. The detection and segmentation steps eliminate too many details. The segmented bunch image contains three regions: The region of mature dates, the region of immature dates, and the background Fig. 6. The next step is to analyze the regions.

The significance lies more in the relative disparities between colors within separate regions of interest, rather than the precise color values. Additionally, many fruits such as dates and apples exhibit only a few noteworthy colors, leading to a constrained spectrum of observed colors during the grading process. This subset usually comprises a minute fraction of the extensive 32 million color possibilities

Here 2581 images of palm trees dated at different levels of maturity and different varieties were used for a static study. Each image of this sample contained many date bunch. Moreover, bunch detection is done by YOLOv8. Note that 11055 is the number of bunch images. These images contain three regions, the mature dates, the immature dates, and the background as depicted in Fig. 7.

In agriculture, color scales serve as a potent instrument for gauging the maturity of fruits. Assessing fruit maturity holds crucial significance in determining optimal harvest timing. Traditionally, an expert evaluator visually links the fruit's color with a corresponding hue on the scale to determine its maturity level. Given that a fruit's representative color corresponds to a vector within the three-component RGB color model, the static analysis of data samples across varying maturity stages results in a collection of points within the three-dimensional space (R_3). Subsequently, various parametric indices are computed from this dataset. (Table 1) corresponds to the mature region obtained from the date bunch dataset. While (Table 2) corresponds to the immature region and (Table 3) corresponds to the background region.

Fig. 7: An example of a bunch image detected by YOLOv8

Table 1: A descriptive analysis of mature regions

	Red	Green	Blue
Mean	73.511905	68.277778	59.25198400
std	12.457321	15.894062	19.36100500
Min	30.000000	33.000000	18.00000000
25%	66.250000	56.250000	44.25000003
50%	77.500000	74.000000	60.00000000
75%	82.000000	80.500000	76.25000000
Max	94.250000	98.000000	93.00000000

Table 2: A descriptive analysis of immature regions

	Red	Green	Blue
Mean	133.936508	132.500000	114.472222
std	22.414904	19.802828	24.123872
Min	70.000000	78.000000	66.000000
25%	120.250000	119.000000	95.000000
50%	134.000000	133.500000	117.000000
75%	154.750000	148.750000	131.750000
Max	174.000000	165.000000	161.000000

Table 3: A descriptive analysis of background region

	Red	Green	Blue
Mean	203.791667	213.896825	212.776786
std	30.551248	29.614034	34.671911
Min	144.000000	146.000000	144.000000
25%	180.250000	192.250000	182.750000
50%	214.000000	222.500000	228.500000
75%	228.000000	237.750000	243.000000
Max	248.000000	251.000000	253.000000

Fig. 8: Date colors at different maturity levels

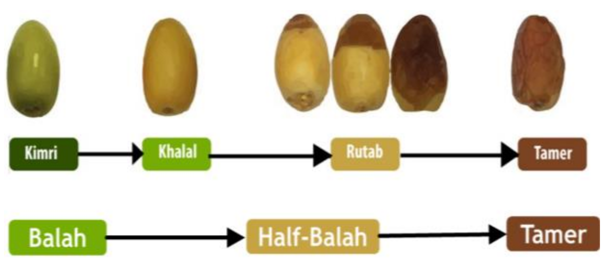


Fig. 9: The maturity level of dates; (Altaheri, 2019; Alsaed *et al.*, 2013)

Most varieties change the color of dates from green to yellow or orange during June, this change depends on the variety and the geographical area. The final maturity of dates begins in July and ends in November (Sedra, 2003; Manickavasagan *et al*., 2014). The experiments are made on image areas that contain the bunch, the statistics show that, the colors of interest range from light yellow to dark brown Fig. 8.

Harvest Decision

Date fruits can be harvested using two methods: The first involves selective harvesting, where individual mature dates are picked, while the second method entails cutting the entire bunch when a majority of the dates are mature (referred to as bunch-based harvesting). However, selective harvesting is highly tasked expensive, and slow. Harvesting by cutting the entire bunch is used on large date farms. Hence, the focus of this study is on the harvesting decision linked to bunch-based harvesting, specifically in the context of the eastern or northern regions of Africa. The maturity stages for date fruits include Kimri, Khalal, Rutab, and Tamar as identified by (Altaheri, 2019), or alternatively, Blah, Half-Blah, and Tamer as indicated by Alsaed *et al*. (2013) Fig. 9.

The decision regarding the optimal harvesting stage depends on various factors, including the type of date fruit and prevailing climatic conditions (Alsaed *et al*., 2013). The proposed system makes harvesting decisions for date bunches by considering both the date type and the calculated rate of bunch maturity:

$$MR = \frac{Mature}{Mature + IMmature} \tag{1}$$

MR : Maturity Rate
Immature : The pixel number corresponds to the immature date's region
Mature : The pixel number corresponds to the mature date's region

Results and Discussion

Figure 10 Presents some of the visualization results obtained by YOLOv8 detection. The model effectively recognized date bunches in varying maturity stages, exhibiting different colors (green, yellow and brown), sizes, textures, and types. Furthermore, the model demonstrated accurate date bunch detection, even in challenging scenarios such as when date fruits were covered by bags, exhibited blurriness, or were of small sizes.

The outcomes of the model's performance are showcased in (Table 4). The model was trained using 2065 images, with 258 images designated for testing and an additional 258 images for validation. The images were sized at 640 pixels and trained during 100 epochs. The training was executed on an NVIDIA A100 graphics card with 40 GB of VRAM. Notably, the achieved mean average precision (mAP50) stands at an impressive 99.1%.

The YOLO detection model's evaluation metrics encompass precision, reacall, and F1-score. Additionally, discrimination values consist of True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN). The F1 score combines precision and recall through the following equations:

$$precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1 - score = \frac{TP}{TP + \frac{1}{2}(FP + FN)} \quad (4)$$

$$IoU = \frac{Precision \times Recall}{Precision + Recall - Precision \times Recall} \quad (5)$$

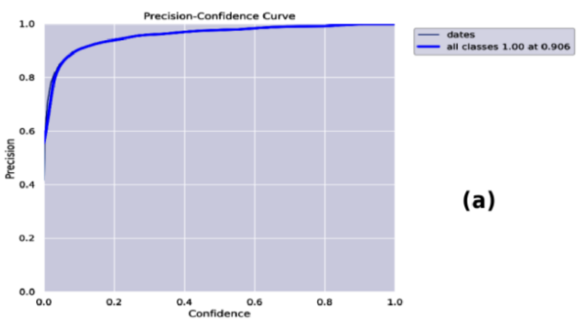
Fig. 10: Detection results of dates under different conditions on the testing set

Table 4: Shows the training performance of YOLOv8

Total number of images	2581 images
Training	2065 images (80%)
Testing	258 images (10%)
Validation	258 images (10%)
Image size	640
Epochs	100
Training time (h)	9
Graphics card	A100 Nvidia 40Go VRAM

Table 5: Yolov8 performance

Precision	0.97557
Recall	0.98598
F1-score	0.98000
mAP@0.5	0.99123
mAP@0.5-0.95	0.81806
Average time(s)	0,015.00000



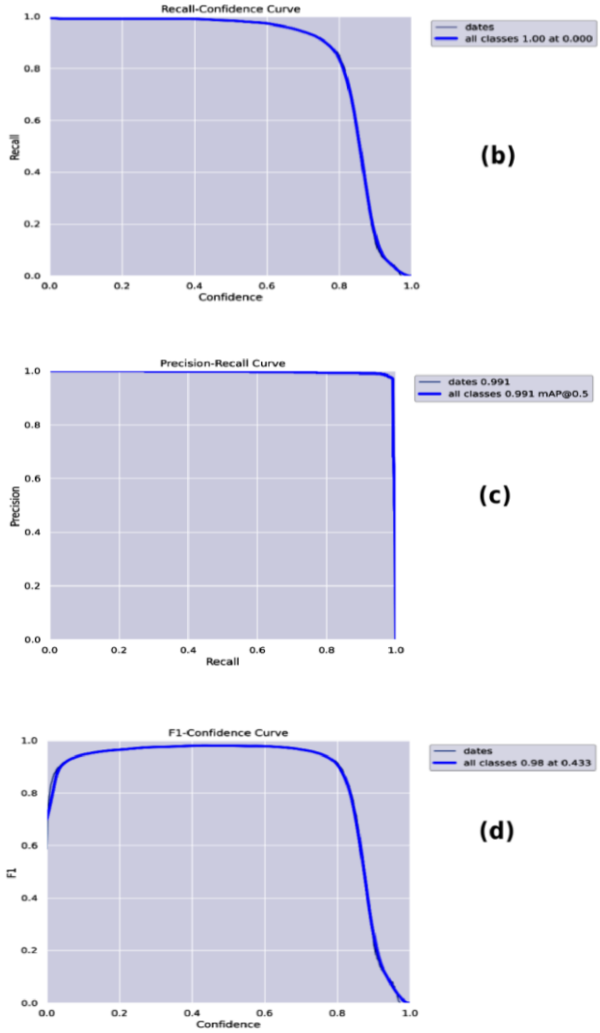


Fig. 11: Date fruit detection results achieved with YOLOv8 model; (a) Precision-confidence curve; (b) Recall confidence curve; (c) Precision recall curve; and (d) F1 confidence curve

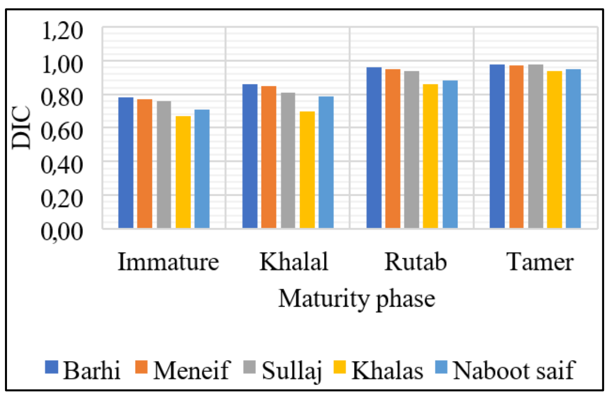


Fig. 12: The measure of dice in the different stages of maturity

The results of the model are depicted in Fig. 11. The mean Average Precision (mAP) value is 0.99 in Fig. 11(c) at a threshold of 0.5. Fig. 11(d) displays the F1 confidence curve, where an F1-score of 0.98 is achieved at a confidence threshold of 0.43. The model demonstrates a high F1 score, indicating superior performance in terms of precision and recall. These outcomes provide valuable insights into the model's performance and its ability to detect bunches of dates in orchard images.

As displayed in Table 5, the outcomes from the analysis of 258 test images indicated that the comprehensive precision and recall rates reached 97% and 98%, respectively. The primary sources of errors in fruit detection stemmed from factors like inaccuracies in image labeling during training. Additionally, certain image features remained undetected due to factors like noise, varying illumination, occlusion, or the camera angle.

In conclusion, the detection outcomes are remarkably satisfactory. Notably, it was observed that YOLOv8 consistently produced the most optimal results (achieving an F1-score of 98%), irrespective of the level of data maturity.

Although manual segmentation is not an absolute reference, Table 6 presents the DICE coefficients obtained by segmentation estimated by adaptive k-means as well as the segmentation results obtained by different stages of maturity.

We note in Fig. 12 that the average values of DICE are 0.76 for the immature stage, 0.8 for the stage Khalal, 0.91 for the stage rutab and finally 0.96 for the stage tamer. The increase in DICE is explained by a large change in the date color in the harvesting stages (Rutab and Tamer) compared to the immature stage, where the color of date green is the most dominant. The k-means algorithm adopted is very responsive to this problem because the adaptive algorithm is based on the initialization of the centers from the histogram peaks.

The outcomes generated by the k-means algorithm distinctly revealed boundaries between different regions, visually depicted in Fig. 6, which favors the k-means method. This adaptive method was adequate to separate the mature region's data from the immature and background.

During the classification phase, the Red (R) and Green (G) values of individual pixels within the segmented date bunch region are extracted. The average color values (R, G, and B) for the three segmentation regions are illustrated in Fig. 13. According to statistical analysis (Tables 1-3) of the different data types in different maturity steps and from Fig. 13, each mature data region is assigned a color interval in the range from 30-94 for the R component, from 30-98 for the G component and from 18-93, for the B component. Thus, the immature date region has a color interval in the range of 70-174 for the R component, from 78-165 for the G component, and from 66-161 for the B component, while the background region has a color interval in the range from 144-248 for the R component, from 146-251 for the G component and from 144-253 for the B component. The overlapping of a color component from one region with a color channel from another is rarely noticed. Moreover, the overlapping of the three components of the different regions is never observed.

In some cases, when date fruits in an image have a high degree of confusion, it is difficult to classify the fruit in the bunch into maturity classes. For this, we chose to calculate the maturity rate based on the rate of pixels at the tamer maturity stage. The table represents the maturity rate for a different variety of dates in maturity classes.

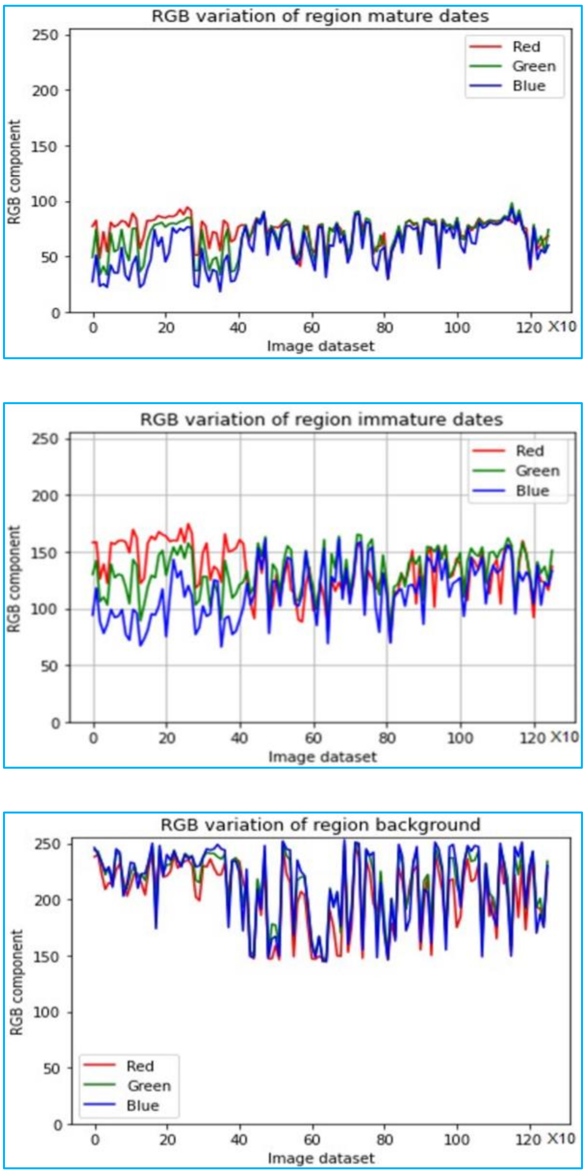


Fig. 13: RGB variation in three regions of bunch images

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Table 6: Date Maturity Rate (MR) at different maturity levels

	Immature %	Khalal (Balah) %	Rutab (Half-Balah) %	Tamer %	Harvest decision %
Barhi	8	30	47	95	Harvest if MR >40
Meneifi	5	27	40	89	Harvest if MR >80
Sullaj	3	28	39	92	Harvest if MR >80
Khalas	7	33	43	96	Harvest if MR >40
Naboot saif	4	30	39	94	Harvest if MR >80

Table 7: Comparison of performance metrics between the proposed system and previous solutions

Proposed system	Dataset	Model	Accuracy %	F1-score %	Precision %	Recall %
Altaheri *et al.*	Date fruit bunches in orchard	YOLOv8	99.10	98.00	97.55	98.59
(2019a)	(Altaheri *et al*., 2019b)	VGG-16	97.25	89.56	96.10	97.20
Faisal *et al*. (2020)		Alexnet	94.98	86.14	93.50	94.90
		VGG-19	98.30	98.60	98.90	98.24
		NASNet	97.70	98.10	98.80	97.80
Nasiri *et al*. (2019)	Singles dates with uniform background	VGG-16	98.49	-	97.33	97.33

Considering the type of date fruits, certain varieties such as Barhi and Khalas are consumed at every stage of maturity, whereas others like Meneifi, Naboot Saif, and Sullaj are typically consumed during the Rutab or Tamer stages (Nasiri *et al*., 2019). The harvest depends on the variety and the maturity class. For that, the harvesting decision depends on the maturity rate and date variety.

To authenticate the effectiveness of the suggested system, other preceding detection methods were assessed for comparative analysis. The evaluation comparison relies on performance metrics utilized in various research studies, including the F1-score, accuracy, recall, and precision. Table 7 directly contrasts the evaluation criteria between the proposed system and the works by Altaheri *et al*. (2019a); Nasiri *et al*. (2019); Faisal *et al*. (2020).

The proposed system excelled beyond the other models, delivering remarkable results across all performance metrics in the realm of maturity detection systems. This superiority can be attributed to YOLO's proficiency as an efficient and swift detector. Moreover, the maturity analysis is carried out on the date bunch area and not on the whole image. The systems in the literature (Altaheri *et al*., 2019b; Nasiri *et al*., 2019; Faisal *et al*., 2020) are based on maturity levels. According to them, these maturity levels can range from 4-7 levels, while the proposed solution is based on the maturity rate metric and the data type.

Conclusion

In this study, an effective intelligent decision-making system is presented for the robotic harvesting of date fruits within an orchard, employing deep learning techniques. The solution consists of three steps: Detection, segmentation, and harvesting decision. We investigated a deep learning model, You Only Look Once version 8 (YOLOv8), to detect dates in the images. We used a rich image dataset containing date bunches of five varieties taken during the harvesting season under different daylight conditions in an orchard. The model achieves high accuracy, with a detection time of 0.015 sec and a mean Average Precision (mAP) of 99.1%. The model can successfully detect and locate date bunches under different light conditions, which is important information for the robot. K-means was used for segmentation and the harvest decision is based on the maturity rate and the type of dates.

The system introduced in this study was contrasted with three alternative systems outlined in the literature and it was observed to outperform the others. The maturity rate metric can provide better accuracy than making a decision based on maturity classes alone. Future work includes creating a dataset that contains more varieties of dates. Moreover, while the proposed research is dedicated to the total harvesting of date bunches, it would be interesting to propose a method to analyze the maturity of each date in the bunches for individual date harvesting.

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Author’s Contributions

Mohamed Ouhda: Conceptual design, model design, analysis of the experiment results and written a manuscript.

Zarouit Yousra: Participated in all experiments, coordinated data analysis and contributed to manuscript written.

Brahim Aksasse: Proofread and analysis and interpretation of results.

Ethics

This study is original and contains unpublished material. The authors have read and approved the manuscript and no ethical issues are involved.

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