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Nondestructive Detection of Hazelnut Defects Using X-ray Imaging and Deep Learning-Based Segmentation

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ABSTRACT
The hazelnut (Corylus avellana L.) is a strategic agricultural product of high economic and nutritional value. Turkiye is the world leader in hazelnut production and export. The quality of hazelnuts is critically essential for international competitiveness and economic returns. The most common method for determining quality in the literature and industry is calculating the percentage of hazelnut kernels based on the ratio of sound kernels. However, this method relies on human observation, which can lead to errors and inconsistencies. In particular, this observation-based method sometimes fails to detect defects in the hazelnut kernel. Recently, nondestructive quality determination methods, particularly X-ray imaging technology, have allowed for the quick and accurate detection of internal and external defects in food products. However, the hazelnut industry has only recently started to adopt these technologies and deep learning–based computer vision methods. Significant advantages in terms of accuracy and efficiency for analyzing the quality of hazelnuts, recognizing objects, and detecting defects are offered by nondestructive food processing technologies and artificial intelligence-based approaches. This study created and made publicly available a unique dataset of X-ray images for defect detection in hazelnut kernels. Defect detection was performed using deep learning–based object detection algorithms, including YOLOv5, YOLOv8, Faster R-CNN, and SSD, whereas segmentation was achieved using K-means clustering, yielding successful results. Consequently, with joint usage of defect detection and segmentation, the developed method provides a more objective, accurate, and reliable process for assessing hazelnut quality.

Keywords: Hazelnut, Deep Learning, Defect Detection, Nondestructive Quality Assessment, Image Segmentation

1. Introduction

Hazelnuts (*Corylus avellana* L.) are a significant agri-product with high economic value around the globe and are widely utilized in the food industry. With their high production volume, they rank third in the global tree nut market and attract significant consumer demand due to their rich nutritional content and positive health effects (Król & Gantner 2020; Romero-Aroca et al. 2021). Turkiye accounts for approximately 73% of the world's hazelnut cultivation area (about 734 409 hectares), meets around 70% of global production, and exports 75% of this output (FAO 2023). With an average annual production of 776,046 tons, Turkiye is the world leader in hazelnut production, which enables the country to play a strategic role in both its economy and agricultural sector (Ayyildiz et al. 2023). Furthermore, Turkiye, along with countries such as Italy, the United States, and Spain, makes significant contributions to the global economy through hazelnut production and exports (Baki 2023). The ability of countries to maintain and strengthen their positions in the international market is directly linked to hazelnut quality. In this context, hazelnut quality is a critical parameter that not only determines domestic market and export potential but also enhances competitive strength in the international market and directly shapes post-sale economic returns.

Although various methods are available for determining hazelnut quality, the most commonly used approach in the literature and industry is based on calculating the sound kernel percentage (Karakaya et al. 2023; Bostan & Karakaya 2024). Studies show that the hazelnut kernel percentage is the most decisive parameter in determining quality among the physical properties analyzed in hazelnuts (İsbakan & Bostan 2020). Hazelnut Kernel percentage is calculated by dividing the acceptable kernel hazelnut weight by the total shelled hazelnut weight, and the result is expressed as a percentage value (Equation 1). This calculation is defined as yield calculation in the literature and industry and is accepted as a basic indicator in quality determination.

$$Kernal\ percentage\ (\%) = \frac{Hazelnut\ kernal\ weight}{Hazelnut\ weight}\ x\ 100 \quad (1)$$

In hazelnut purchasing centers, quality assessment is carried out according to the percentage of intact hazelnuts in a 250-gram sample of shelled hazelnuts selected at random (Gülsoy et al. 2019; Turan 2023). Hazelnut purchasing centers often rely on traditional evaluation methods where expert evaluators perform visual inspections to determine kernel percentages (Turan 2023). However, such approaches lead to inaccuracies in hazelnut quality determination due to human and subjective judgment errors. Particularly challenging is the identification of subtle defects that cannot be detected by manual visual inspection, creating significant evaluation challenges (Figure 1). These limitations directly affect kernel percentage calculations and subsequently affect critical factors such as storage time, industrial practices, and fair pricing mechanisms for hazelnut products (Yılmaz et al. 2025).



Figure 1- Hazelnut kernel and processed hazelnut kernel

Accurate defect detection is a fundamental requirement for generating reliable hazelnut yield calculations. Regional growing conditions and agricultural practices significantly influence defect occurrence rates, which show significant annual variations of between 1% and 15% across different production areas (Valeriano et al. 2022). Global hazelnut production statistics from FAO (2023) indicate that annual output exceeds 1 million tonnes, and defective product volumes can reach between 10 000 and 150 000 tonnes annually. This significant amount underlines the critical need for accurate defect detection methodologies in hazelnut quality assessment processes.

Most of the defects in hazelnut kernels are caused by sucking and piercing insects (Saruhan & Şen 2016). These insects can cause "stained kernel" damage in hazelnut production (Arciuolo et al. 2020). Especially in recent years, the increasing brown marmorated stink bug (Halyomorpha halys), infestation damages hazelnut development, causing early shedding, developmental disorders, and stained kernels (Ozdemir et al. 2023; Kan et al. 2024). Such damages can lead to complaints during the export and hazelnut sales process. Spotted kernels formed in hazelnut production can sometimes be difficult to detect because the damage from sucking insects or external damages can remain under the hazelnut shell.

Quality problems seen in hazelnuts can occur both in the outer shell and in the kernel (Bostan 2019; Kan et al. 2024). While defects in the hazelnut shell can be easily detected by visual inspection, problems in the hazelnut kernel may not be easily detected. The ripening of the hazelnut kernel ends with the formation of the brown outer shell. However, before this stage, environmental factors can cause damage that remains hidden under the shell (Bostan 2019; de Benedetta et al. 2023). Even when the kernels are cut for analysis, some problems between the kernel center and the kernel membrane may not be visible (Bostan 2019; de Benedetta et al. 2023). Therefore, visual methods for calculating kernel percentage are slow, costly, limited, and ineffective in detecting lipid oxidation or inner kernel defects (Pannico et al. 2015). Additionally, since traditional approaches depend on human factors, the margin of error cannot be standardized and is extremely difficult to control (Mahanti et al. 2022). In this situation, the use of nondestructive techniques has become a necessity for more efficient determination and standardization of defects in hazelnut kernels (Ropodi et al. 2016).

In recent years, nondestructive quality assessment methods have gained popularity. These nondestructive quality determination approaches enable food quality evaluation processes to be conducted rapidly, non-invasively, reliably, and without causing damage. Such methodologies accomplish quality measurements while preserving the product's physical integrity completely intact. Nondestructive quality determination technologies are increasingly replacing traditional methods since they can spot defective regions without complex sample prep or damaging the specimens (Arendse et al. 2018). There's a whole range of methods being used for nondestructive food processing nowadays, and these techniques bring some real advantages to food quality control (Abasi et al. 2018; Shakiba et al. 2022). This technique is particularly effective in X-ray imaging for identifying damage, including visible surface issues and internal defects in agricultural products (Xue et al. 2022). Research findings also reveal that X-ray technology doesn't pose any health threats to humans, which means food processing facilities can implement it without worrying about safety issues (Zehi et al. 2020).

There has been a noticeable increase in the use of machine learning, computer vision, and AI technologies in nondestructive food processing recently (Kayakuş et al. 2024; El-Mesery et al. 2019). Such methods bring impressive accuracy and reliability to food quality and safety evaluations, making quality assessment processes much more effective (Zhu et al. 2021). This integration is expected to be particularly useful when applied to hazelnut classification and quality analysis studies.

Food quality assessment has seen improvements through machine learning and computer vision applications, with studies showing these approaches deliver better accuracy than conventional techniques (Manavalan, 2020). Wang et al. (2024) obtained successful results when they used X-ray imaging alongside machine learning to spot kiwi fruit problems without damaging the fruit. Ma et al. (2025) examined various deep learning models with X-ray imaging to detect internal defects without causing harm and demonstrated that their approach could function in industrial environments.

Deep learning methods have become more common recently, and scientists report good results from using these tools. By adopting these methods for classifying and recognizing hazelnuts, significant benefits are achieved regarding labor requirements, time efficiency, and cost savings. Classification of 17 distinct in-shell hazelnut varieties was accomplished by Taner et al. (2021) through convolutional neural network implementation. Gençtürk et al. (2023) developed a mobile application for hazelnut variety classification by implementing InceptionV3 and ResNet50 architectures. Ünal & Aktaş (2023) designed a system for sorting defective hazelnuts employing InceptionV3 and EfficientNet architectures. In another study, Dönmez et al. (2024) created a dataset of three different hazelnut varieties and performed classification using BigTransfer (BiT) models. Although studies employing nondestructive quality assessment methods for classifying hazelnuts according to quality levels are less common than studies utilizing RGB (Red, Green, Blue) cameras, such research is also present in the literature (Maier et al. 2021; Khosa & Pasero 2014; Erbaş et al. 2022). However, current studies remain insufficient for the regional detection of defects in hazelnuts. Yet, in the processes of kernel percentage calculation and quality assessment, it is crucial to accurately detect and classify the regions where defects are present.

Machine learning and computer vision advancements have made nondestructive food quality assessment methods easier, more precise, and faster. However, the limited adoption of these methods in the hazelnut industry remains a notable shortcoming. The detection of defects in hazelnuts during the procurement stage (kernel percentage measurement) directly affects their intended use, storage processes, and pricing. Accurate quality assessment for the classification of hazelnuts intended for industrial use after export is crucial for the efficiency of subsequent processes. Identifying such defects at the procurement stage not only provides economic benefits but also reduces the workload. In particular, detecting physical defects located within the internal regions of hazelnuts is challenging, and traditional observation-based methods are prone to human error. This issue can be readily addressed using X-ray imaging and computer vision techniques (Figure 2).

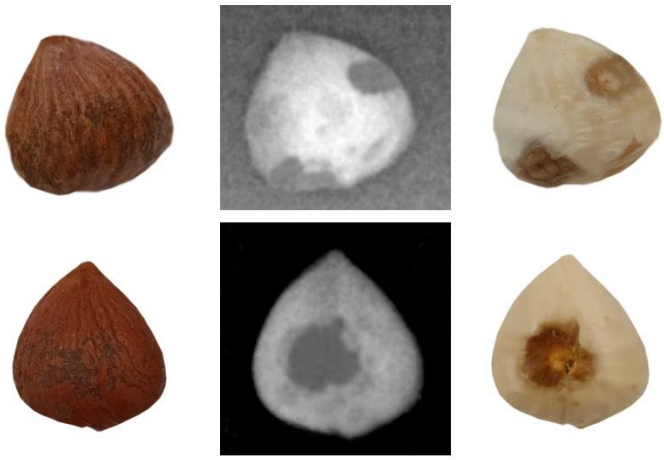


Figure 2- Hazelnut kernel, X-ray of hazelnut kernel, and processed hazelnut kernel images

In the literature, no study reports the use of nondestructive quality assessment and deep learning methods for hazelnut kernel percentage estimation or defect detection based on X-ray imaging. The present study employed X-ray imaging to detect defective regions in hazelnuts. No X-ray datasets specific to hazelnuts are available in the literature or open-access sources. In this context, one of the main innovations of our study is the creation of an X-ray hazelnut kernel dataset.

In this study, X-ray imaging and bounding box-based deep learning methods were employed to detect all defects, including those arising from human error, in the assessment of hazelnut quality. An X-ray hazelnut image dataset was created for defect detection, and this dataset has been made publicly available for future research applications. Defect detection in hazelnut images was performed using bounding box-based deep learning methods, specifically YOLOv5 (You Only Look Once version 5) (Terven et al. 2023), YOLOv8 (You Only Look Once version 8) (Terven et al. 2023), Faster R-CNN (Faster Region-Based Convolutional Neural Network) (Pham et al. 2020), and SSD (Single Shot MultiBox Detector) (Liu et al. 2016), and their performances were evaluated. The proposed preprocessing method achieves more effective feature extraction. One of the main objectives of this

study is to perform the segmentation process based on location information obtained after object recognition. In this context, the K-means clustering algorithm was utilized to achieve detailed and accurate segmentation of defective areas. As a result, defective regions and their respective areas within the hazelnut kernels were clearly identified in the quality assessment process. Consequently, more consistent, objective, and highly accurate quality measurements were achieved in the hazelnut industry.

Considering all these factors, the main contributions of this study are as follows:

- A unique X-ray hazelnut image dataset was created,
- Anchor-based deep learning methods with high accuracy were utilized,
- All hazelnut defects were detected using nondestructive X-ray imaging and deep learning methods,
- The performance of the employed deep learning methods was analyzed,
- Segmentation was performed using the proposed image preprocessing and segmentation method.

2. Material and Methods

2.1. Dataset collection and preparation

In recent years, the increasing proportion of defective hazelnuts has diminished the effectiveness of traditional quality assessment methods. In particular, detecting defects located beneath the inner shell of hazelnuts is extremely challenging with conventional techniques (Figure 1). This situation has necessitated the adoption of new nondestructive technologies. The X-ray imaging method offers an effective solution for identifying such defects (Figure 2). However, due to the lack of an existing dataset for detecting hazelnut defects using X-ray imaging, it has become necessary to create an original dataset.

During dataset preparation, the most common hazelnut varieties -Çakıldak, Foşa, Mincane, Sivri, Tombul, and Palaz- grown in Samsun, Ordu, and Giresun, which are the central hazelnut-producing regions in Turkiye, were used (Balık & Beyhan 2014). A total of 75 kg of hazelnuts was collected by obtaining 15 kg from each city's hazelnut groups. To ensure class balance among the labeled categories, 1320 hazelnuts were randomly selected from the collected samples for inclusion in the dataset. The in-shell hazelnuts were processed to obtain kernels, and X-ray imaging was performed using an X-ray device to create the dataset. All single hazelnut radiographs were acquired at a resolution of 480×480 pixels (Figure 3). In order to achieve accurate and reliable visualization of the hazelnut kernels, a low-dose soft X-ray imaging system was utilized. The device features an adjustable tube voltage capability ranging from 40 to 150 kV, making it well-suited for delicate sample imaging. It is equipped with a digital flat-panel detector, offering an approximate spatial resolution of 100 micrometers per pixel. The detector's performance is enhanced by a Detective Quantum Efficiency (DQE) of approximately 70% and a 16-bit dynamic range, which together ensure clear, high-contrast images even under minimal exposure conditions. The constructed dataset has been made publicly available for future studies (https://drive.google.com/drive/folders/1nH9bXsBKBDuXfKysPnC43VfDETRKp3zq?usp=sharing.).

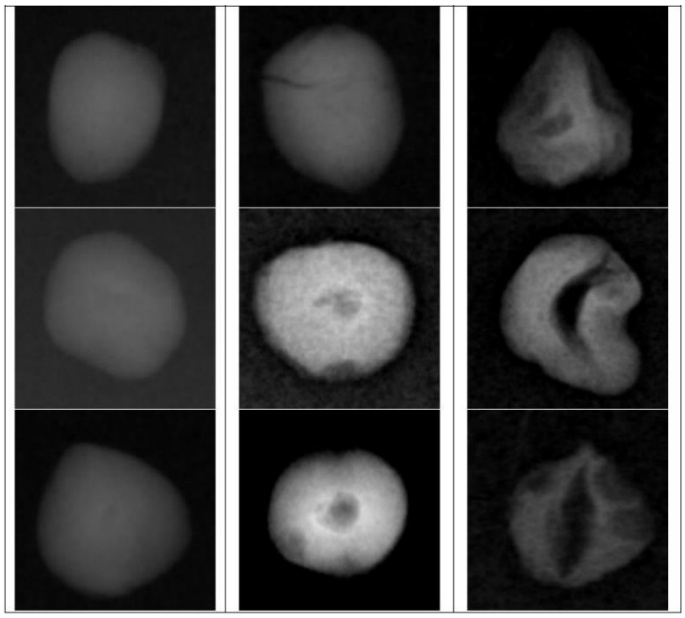


Figure 3- Hazelnut X-ray images

The acquired X-ray images of hazelnuts (Figure 3) were labeled into three categories: defective, slightly defective, and non-defective, resulting in a comprehensive dataset for model training. The labeling process was conducted with the assistance and expert judgment of an agricultural engineer specialized in hazelnuts. Labeling was performed by comparing the X-ray images

with the actual physical appearance of the hazelnut kernels. Defect classification was based on the size and extent of the flaws observed in the X-ray images. Hazelnuts without any detectable defects were labeled as "non-defective" Those with defects were categorized into "slightly defective" or "defective" classes depending on the severity and size of the defective regions. Based on the hazelnut expert's opinion, samples with a defect ratio below 5% were classified as "slightly defective," those above 5% as "defective," and those without defects as "non-defective". The entire dataset image distributions are shown in Table 1. Soft X-ray imaging was employed to obtain more sensitive and accurate radiographs.

Table 1- All X-Ray hazelnut images class range

Class	*Images*	*Instances*
all	1320	2349
defective	465	973
non-defective	440	440
slightly defective	415	936

A 5-fold cross-validation method was employed to determine the most appropriate training and testing partitioning of the constructed dataset. In this context, the dataset consisting of 1 320 X-ray images and 2 349 labeled object instances was divided into five equal subsets (folds); in each iteration, four folds were used for training and one fold for testing. This approach ensured that all data were utilized in both training and testing phases, allowing for a more robust evaluation of the model's generalization capability. The YOLOv8 architecture was trained for 200 epochs using default training parameters during the 5-fold cross-validation process to identify the optimal results. The number of images and instances in each fold are detailed in Table 2. Additionally, performance metrics including accuracy, precision, recall, F1-score, and mAP@50 for each fold are also presented in the Table 2. This comprehensive presentation enabled a detailed assessment of the model's performance across each subset. Upon examining the results, the highest performance was achieved in the second fold.

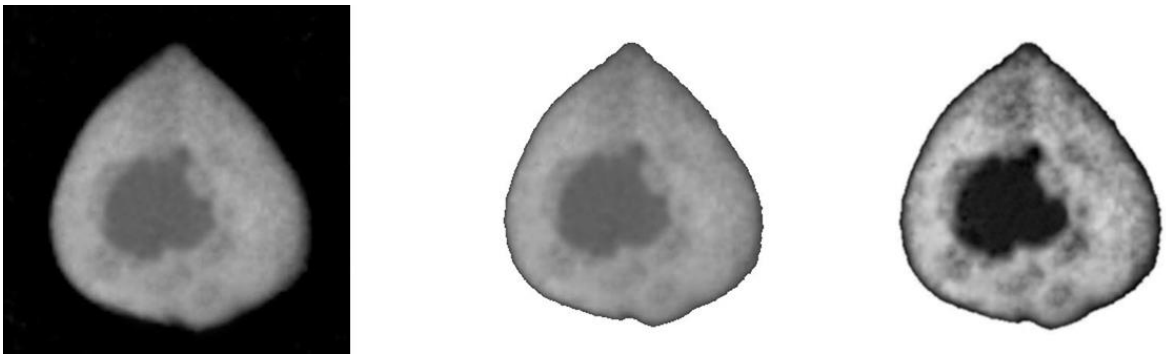
Table 2- 5-fold cross-validation performance metrics

Fold	*Class*	*Images*	*Instances*	*Accuracy*	*P*	*R*	*F1-score*	*mAP@50*
1	all	263	373	0.8695	0.8636	0.8576	0.8667	0.8816
	defective	112	191	0.9195	0.8416	0.8726	0.9167	0.9316
	non-defective	74	74	0.9919	0.987	1.000	0.9891	0.994
	slightly defective	77	108	0.8205	0.7786	0.8236	0.8177	0.8326
2	all	262	372	0.9092	0.9056	0.907	0.9063	0.9112
	defective	110	192	0.9275	0.8506	0.9586	0.9247	0.9396
	non-defective	74	74	0.9919	0.9919	1.000	0.9891	0.994
	slightly defective	78	106	0.8495	0.8446	0.8376	0.8467	0.8516
3	all	262	372	0.8645	0.8636	0.8516	0.8617	0.8666
	defective	110	193	0.8945	0.8696	0.8386	0.8917	0.9066
	non-defective	74	74	0.9879	0.989	0.989	0.9851	0.99
	slightly defective	78	105	0.8175	0.8176	0.7936	0.8047	0.8196
4	all	263	375	0.8505	0.8316	0.8606	0.8477	0.8526
	defective	109	196	0.8985	0.8136	0.9136	0.8957	0.9106
	non-defective	74	74	0.9749	0.967	0.966	0.9721	0.977
	slightly defective	80	105	0.8235	0.8176	0.8266	0.8207	0.8256
5	all	263	372	0.9015	0.8826	0.8936	0.8987	0.9036
	defective	111	189	0.9565	0.8306	0.9356	0.9537	0.9686
	non-defective	74	74	0.9919	0.988	1.000	0.9891	0.994
	slightly defective	78	109	0.8105	0.8246	0.8086	0.8477	0.8326

2.2. Image preprocessing

In deep learning methods, to better extract the features of defective hazelnut X-ray images and to enable more effective clustering for the subsequent segmentation process, all areas outside the hazelnut in the images were converted to pure white. A multi-step approach was employed for this purpose. First, the contrast quality of the image was enhanced using histogram equalization. Second, three different thresholding methods were applied to identify hazelnut regions: automatic threshold selection by the Otsu method, percentile-based thresholding, and local adaptive thresholding. The combined results of these three methods were used

to reduce false detections. In the cleaning stage, small noise particles were removed, holes were filled, and the largest object region was identified through morphological operations. In the final step, Gaussian filtering was applied to smooth object edges, ensuring that areas outside the hazelnut were thoroughly cleaned (Figure 4(b)).



(a) (b) (c)

Figure 4- (a) X-ray image, (b) cleaned X-ray image, (c) filtered X-ray image

2.3. Deep learning algorithms

2.3.1. SSD

Single Shot MultiBox Detector (SSD) represents a swift and efficient deep learning technique employed within object recognition fields (Liu et al. 2016). SSD architecture comprises two principal components: the backbone and the head. The backbone uses pre-trained image classification networks, such as ResNet or VGG, to extract detailed features from input images. The SSD head predicts bounding box coordinates and object classes through convolutional layers. By leveraging feature maps of various scales, the SSD can effectively detect objects of different sizes. The prediction of box coordinates and class labels is allowed by assigning potential object locations to each cell within the feature maps using anchor boxes. SSDs are characterised by their ability to process classification and localization in a single pass, a feature that facilitates rapid inference (Figure 5).

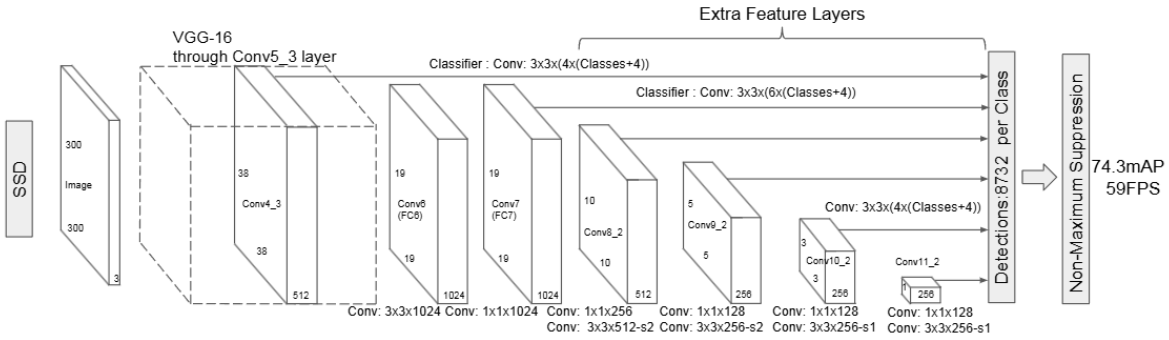


Figure 5- SSD architecture (Liu et al. 2016)

2.3.2. Faster R-CNN

Faster R-CNN represents an advanced approach that offers significant improvements in speed and efficiency over previous R-CNN architectures for object detection and classification tasks (Pham et al. 2020). The model integrates region proposal and feature extraction stages into a unified structure, optimizing the object detection process (Figure 6). Its key innovation, the Region Proposal Network (RPN), employs a fully convolutional architecture to rapidly and accurately identify potential object locations within visual data. By sharing convolutional feature maps between the RPN and the detection network, computation time is significantly reduced, resulting in faster outputs. The regions proposed by the RPN are forwarded to the classification and localization network, where each region is assigned a class label, and its bounding box dimensions are precisely refined.

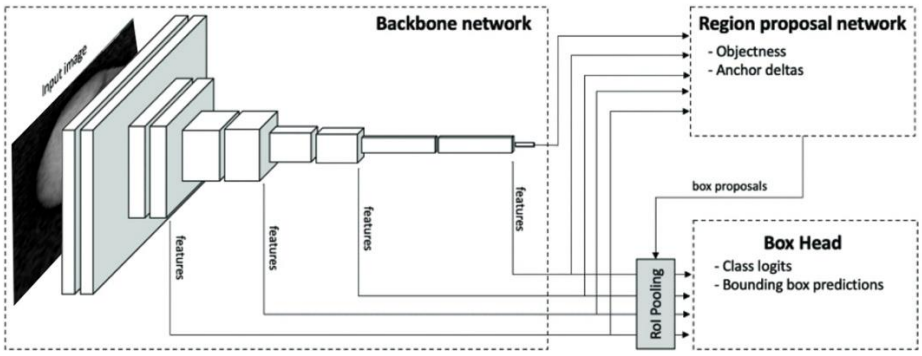


Figure 6- Faster R-CNN architecture (Pham et al. 2020)

2.3.3. YOLOv5 and YOLOv8

The YOLO series occupies a prominent position in object detection due to its real-time and high-speed performance. YOLOv5 employs a CSPDarknet53-based backbone and utilizes the Path Aggregation Network (PANet) to enhance object detection capabilities (Terven et al. 2023). The model minimizes information loss by integrating feature maps at different levels and detects objects of various sizes through its head, which contains three multi-scale output layers (Figure 7). YOLOv5 divides the input image into grid cells, generating bounding boxes for each cell. For every bounding box, it predicts the objectness score, coordinates, width, height, and class probabilities. The anchor box generation process is automated, allowing more accurate detection across different object sizes.

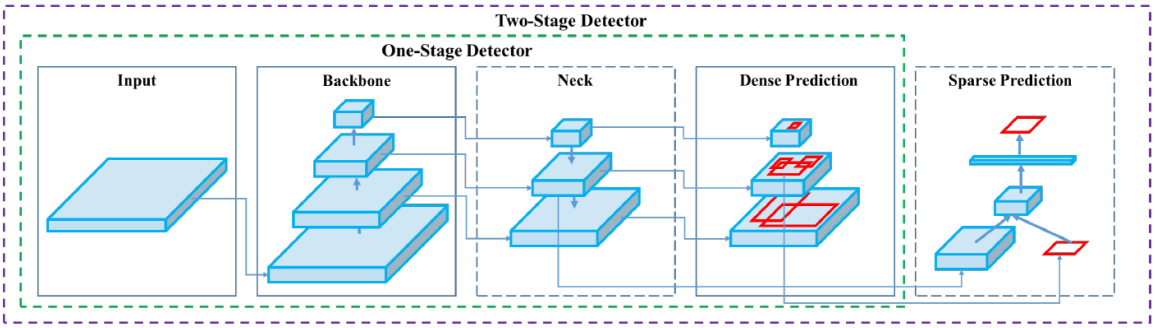


Figure 7- YOLO v5 architecture (Khanam & Hussain, 2024)

YOLOv8 incorporates a C2f (cross-stage partial bottleneck with two convolutions)-based backbone and combines a Feature Pyramid Network (FPN) with PANet to provide advanced feature extraction (Terven et al. 2023) (Figure 8). Its head supports both anchor-based and anchor-free models, offering structural flexibility. The anchor-based approach predicts bounding boxes based on predefined anchor sizes, while the anchor-free approach directly estimates object centers and dimensions without relying on predefined references. This flexibility improves detection performance, particularly for small and complex objects.

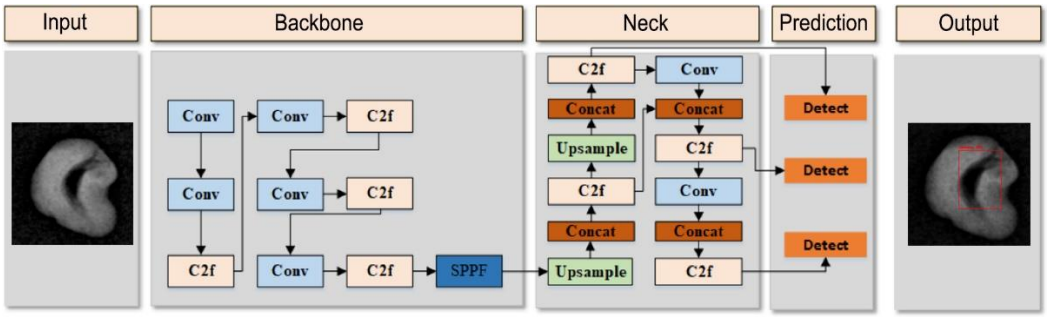


Figure 8- YOLO v8 architecture (Herfandi et al. 2024)

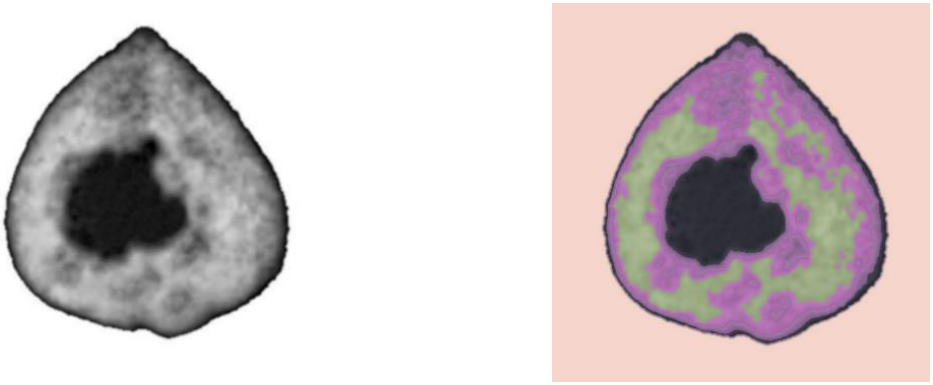
Both YOLOv5 and YOLOv8 are recognized for their high-speed detection capabilities. YOLOv5 offers fast training and inference through its optimized PyTorch-based architecture. Despite its deeper and more complex design, YOLOv8 achieves efficient performance through attention mechanisms and a refined architecture. While YOLOv5 delivers strong accuracy across many object detection applications, YOLOv8 further enhances precision, especially in detecting small and challenging objects,

due to its architectural improvements and integrated attention modules. Both versions provide high accuracy and efficiency for specialized applications such as X-ray imaging and hazelnut defect detection.

2.3.4. Segmentation

In the segmentation process, deep learning–based object detection results were combined with clustering methods based on grayscale intensity levels to accurately identify defective and slightly defective regions in X-ray hazelnut images.

During the segmentation stage, the preprocessed images obtained from the X-ray hazelnut dataset (Section 2.1) were subjected to the K-means clustering algorithm. Pixels were clustered exclusively according to their grayscale intensity levels. Through experimental evaluation and analysis of the intensity histograms of the dataset, the number of clusters was set to k = 5, as this configuration provided sufficient separation between the target regions (defective and slightly defective areas) in terms of both intensity variation and size. Each cluster corresponded to pixel regions sharing similar intensity characteristics. The clustering results were visualized by mapping each cluster to distinct color schemes, and the outcomes were assessed through expert visual inspection. Following clustering, small and isolated noise regions were identified, which could potentially reduce segmentation accuracy. To address this, a morphological closing operation was performed, filling small gaps and producing more cohesive and regularly shaped clusters. This refinement improved the overall integrity, interpretability, and accuracy of the segmented regions (Figure 9). The step-by-step segmentation process is also depicted in Figure 10. Furthermore, object location data obtained from deep learning–based detection methods were utilized, and within each detected region, the largest cluster was designated as the segmentation area.



(a) (b)

Figure 9- (a) The preprocessed image, (b) the image resulting from the K-Means clustering and segmentation process

As illustrated in Figure 10, the segmentation process begins with acquiring the preprocessed images. These images are converted to grayscale format and represented as two-dimensional matrices. Subsequently, the K-means clustering algorithm is applied based on the matrix values, with the number of clusters set to k = 5, partitioning the pixels into regions of similar intensity. To eliminate small and isolated noise clusters that may arise after clustering, a morphological closing operation is performed. This step ensures that the clusters become more coherent and regularly shaped. Finally, using the coordinates of bounding boxes obtained from deep learning-based object detection algorithms, the largest cluster within each bounding box is identified and designated as the segmentation region.

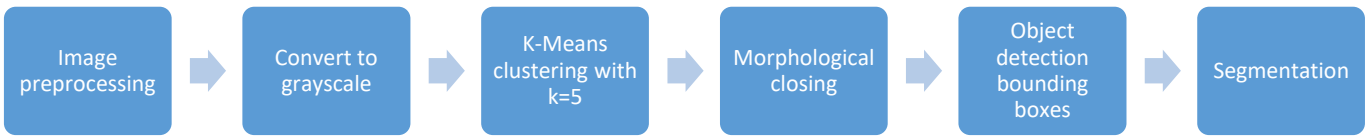


Figure 10- Steps of defect segmentation in hazelnuts

To determine the optimal number of clusters for the segmentation process, tests were conducted with k values ranging from 2 to 15 (Table 3). For k values smaller than 5, the predicted clustering regions were larger than the ground truth masks (GT), resulting in relatively low Dice Similarity Coefficient (DSC) and Intersection over Union (IoU) values. For k values greater than 5, the predicted clusters became smaller due to over-segmentation, and the DSC and IoU values gradually decreased. These observations indicate that k = 5 provides an optimal balance between under-segmentation and over-segmentation; therefore, k = 5 was selected as the optimal cluster number for the proposed segmentation method.

Table 3- Segmentation Performance for Different Cluster Numbers (k)

Method	*k=2*	*k=3*	*k=5*	*k=7*	*k=9*	*k=11*	*k=13*	*k=15*
IoU	0.16	0.49	0.72	0.61	0.46	0.24	0.14	0.08
DSC	0.17	0.51	0.78	0.63	0.48	0.26	0.15	0.09

2.4.5. Performance evaluation and hyperparameters

All deep learning methods were developed using the Python 3.11 programming language and the PyTorch 2.1.0 library. The implementations were carried out on a system equipped with an Intel i5-1340P processor, an NVIDIA RTX 4050 GPU, and 16 GB DDR5 RAM. The input image size for all deep learning models was set to 480×480 pixels.

All deep learning models (SSD, Faster R-CNN, YOLOv5, and YOLOv8) were trained using their default hyperparameters. The learning rate was set to 0.001, a value chosen to ensure both stable and rapid convergence. Stochastic Gradient Descent (SGD) was employed as the optimizer for all models due to its widespread use and strong generalization capability. The batch size was fixed at 64, and training was performed over 200 epochs. Learning rate scheduling strategies varied depending on the model architecture: cosine annealing was applied for YOLOv5 and YOLOv8, whereas step decay was used for SSD and Faster R-CNN. To ensure fair and consistent comparisons, similar hyperparameter settings were adopted across all models.

The X-ray hazelnut kernel dataset created in this study was partitioned into training and testing groups using 5-fold cross-validation to enable a reliable evaluation of model performance. The training-test ratios for each fold are presented in Table 2. Each model was independently trained and tested in every fold, and performance metrics were calculated accordingly. This approach ensured that the most appropriate training and testing subsets were used for an accurate and robust assessment of model accuracy and generalization capability.

The performances of the deep learning methods were evaluated using commonly used metrics for measuring classification and segmentation accuracy: Accuracy (Equation 2), Precision (Equation 3), Recall (Equation 4), and F1-Score (Equation 5), in addition to mAP50 (mean Average Precision) (Equation 6) and FPS (Frames Per Second).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

$$F1 - Score = 2x\frac{Precision\ x\ Recall}{Precision + Recall} \quad (5)$$

$$mAP50 = \frac{1}{N}\sum_{i=1}^{N} AP_i^{IoU \geq 0.50} \quad (6)$$

In the equations, TP (True Positive) denotes true positives, TN (True Negative) denotes true negatives, FP (False Positive) denotes false positives, and FN (False Negative) denotes false negatives, and *AP* represents the Average Precision for class *i* at a given Intersection over Union (IoU) threshold.

$$IoU = \frac{A \cap B}{A \cup B} \quad (7)$$

$$DSC = \frac{2x(A \cap B)}{A + B} \quad (8)$$

n the evaluation of segmentation performance, the IoU, derived from the Jaccard similarity index, and the DSC were used in addition to the Precision and Recall metrics. These metrics measure the overlap between the segmentation mask predicted by the model (A) and the ground truth mask (B) generated by an expert (Ataş, 2023). IoU represents the ratio of the intersection area to the union area of the two masks and is presented in Equation 7. DSC evaluates the accuracy of the model by dividing twice the intersection area by the total number of positive pixels in both masks, as shown in Equation 8. Both metrics take values between 0 and 1, where values closer to 1 indicate a high degree of overlap with the ground truth and reliable segmentation performance.

This approach quantitatively demonstrates both the accurate detection of defective regions within the hazelnut kernels and the overall performance of the model.

3. Results and Discussion

This study utilized open-source object detection algorithms, namely YOLOv5, YOLOv8, Faster R-CNN, and SSD, and all images in the constructed dataset were trained using these methods. The obtained training results are presented in Table 4. Among all methods, Faster R-CNN achieved the highest values in terms of accuracy (92.65%), precision (92.63%), recall (92.77%), F1-score (92.70%), and mAP (92.88%), thus demonstrating superior detection performance. However, since Faster R-CNN is a two-stage deep learning method, it offers this high level of accuracy with a significant drawback: its frame processing rate (10 FPS) is quite low, and its training time is much longer compared to the other methods. Therefore, this method is more suitable for applications where accuracy is prioritized over real-time requirements. The YOLOv8 model demonstrated the second-best performance after Faster R-CNN with an accuracy of 90.92% and mAP of 91.12%; moreover, it achieved the highest FPS (39) and the shortest training time, providing an optimal balance between speed and accuracy. In this respect, YOLOv8 stands out as the most suitable method for real-time object detection applications. YOLOv5 exhibited an average performance with an accuracy of 88.95% and 35 FPS, offering a reasonable trade-off between speed and accuracy; its training time was longer than YOLOv8 but shorter than Faster R-CNN. On the other hand, the SSD model demonstrated lower performance than the other methods in terms of accuracy (78.66%) and speed (19 FPS) and required a considerably longer training time of 362 minutes.

The findings suggest that Faster R-CNN and YOLOv8 are better suited for tasks demanding high accuracy, whereas YOLOv5 and YOLOv8 offer advantages in scenarios where shorter training times are critical. On the other hand, SSD presents a viable alternative in applications where moderate accuracy is acceptable and rapid training is not a priority.

Table 4- Performance of deep learning methods

Deep learning Method	*Accuracy %*	*Precision %*	*Recall %*	*F1-Score %*	*mAP %*	*FPS*	*Training Time*
YOLOv5	88.95	88.93	89.08	89.01	89.41	35	174 minute
YOLOv8	90.92	90.56	90.70	90.63	91.12	39	130 minute
Faster R-CNN	92.65	92.63	92.77	92.70	92.88	10	724 minute
SSD	78.66	78.49	78.76	78.63	78.74	19	362 minute

The performance analysis graph of training models is presented in Figure 11. Throughout the training duration, the YOLOv5 model gradually increased accuracy rates, reaching a plateau of 88.95% accuracy. The YOLOv8 model began the training process with rapid accuracy improvement, achieving 90.92% levels and demonstrating stable performance within a short timeframe. While the Faster R-CNN model initially showed moderate accuracy improvement, it subsequently accelerated to reach the highest accuracy rate of 92.65% and exhibited stable performance. The SSD model displayed more fluctuating accuracy improvements during training and achieved a 78.66% accuracy rate.

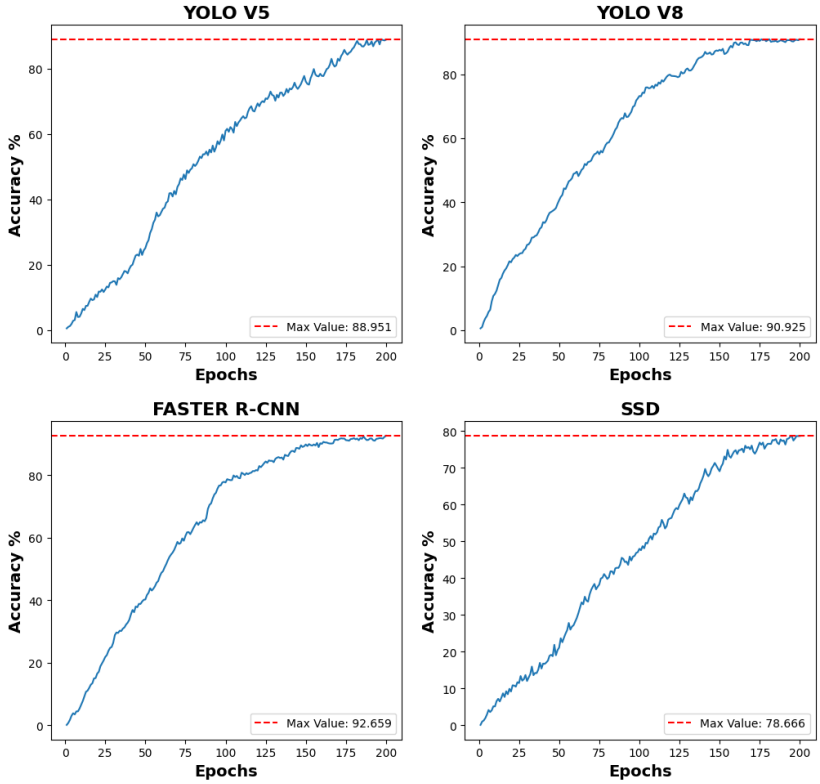
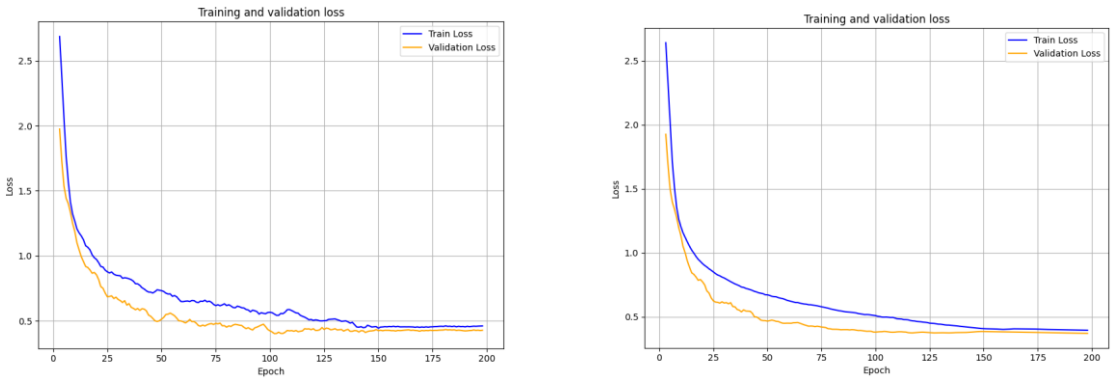


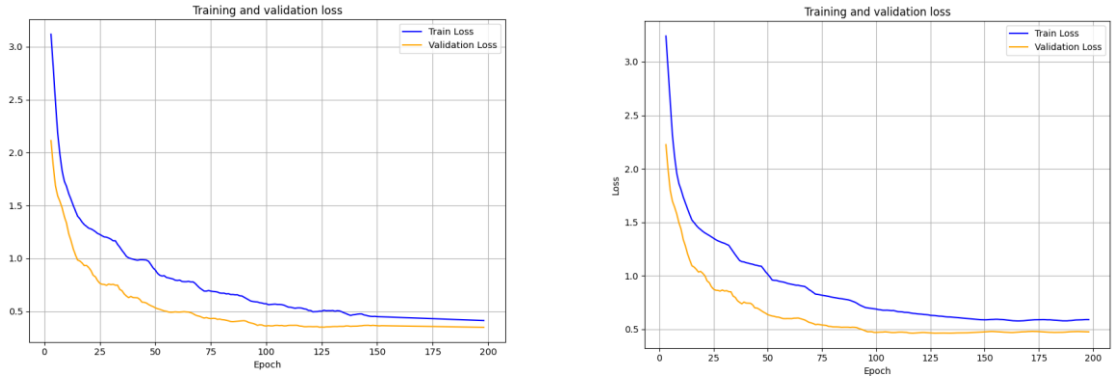
Figure 11- Accuracy comparison graph of all models

An examination of the graph reveals that the Faster R-CNN model exhibits the least fluctuation during training, whereas the SSD model shows the greatest variability. The consistently low training loss values for Faster R-CNN suggest effective learning and stable convergence throughout the training process. YOLOv5's steady increase in accuracy reflects a gradual and consistent improvement without significant spikes in loss. Conversely, YOLOv8 achieves rapid accuracy gains and stabilizes quickly, indicating a fast learning rate and swift reduction in training losses. In contrast, the fluctuating accuracy and higher loss values observed in the SSD model imply instability during training and challenges in minimizing errors effectively.

Figure 12 presents the training and validation losses of all models. In the train and validation loss graphs for all methods, it was observed that both training and validation losses decreased steadily throughout the training process and reached similarly low values after approximately 200 epochs. For the YOLOv5 and YOLOv8 models, the losses dropped rapidly and plateaued in the early epochs, with the difference between them remaining minimal; notably, the low validation loss of YOLOv8 indicates a strong generalization capability. In Faster R-CNN, both training and validation losses converged to similarly low levels, suggesting that the model did not exhibit an overfitting tendency. In the SSD model, although the losses generally followed a similar decreasing trend, the validation loss curve remained higher than the training loss, indicating that the model's generalization performance may be relatively lower compared to the others. Overall, the graphs demonstrate that all models were successfully trained, but the best generalization performance was achieved by YOLOv8 and Faster R-CNN.



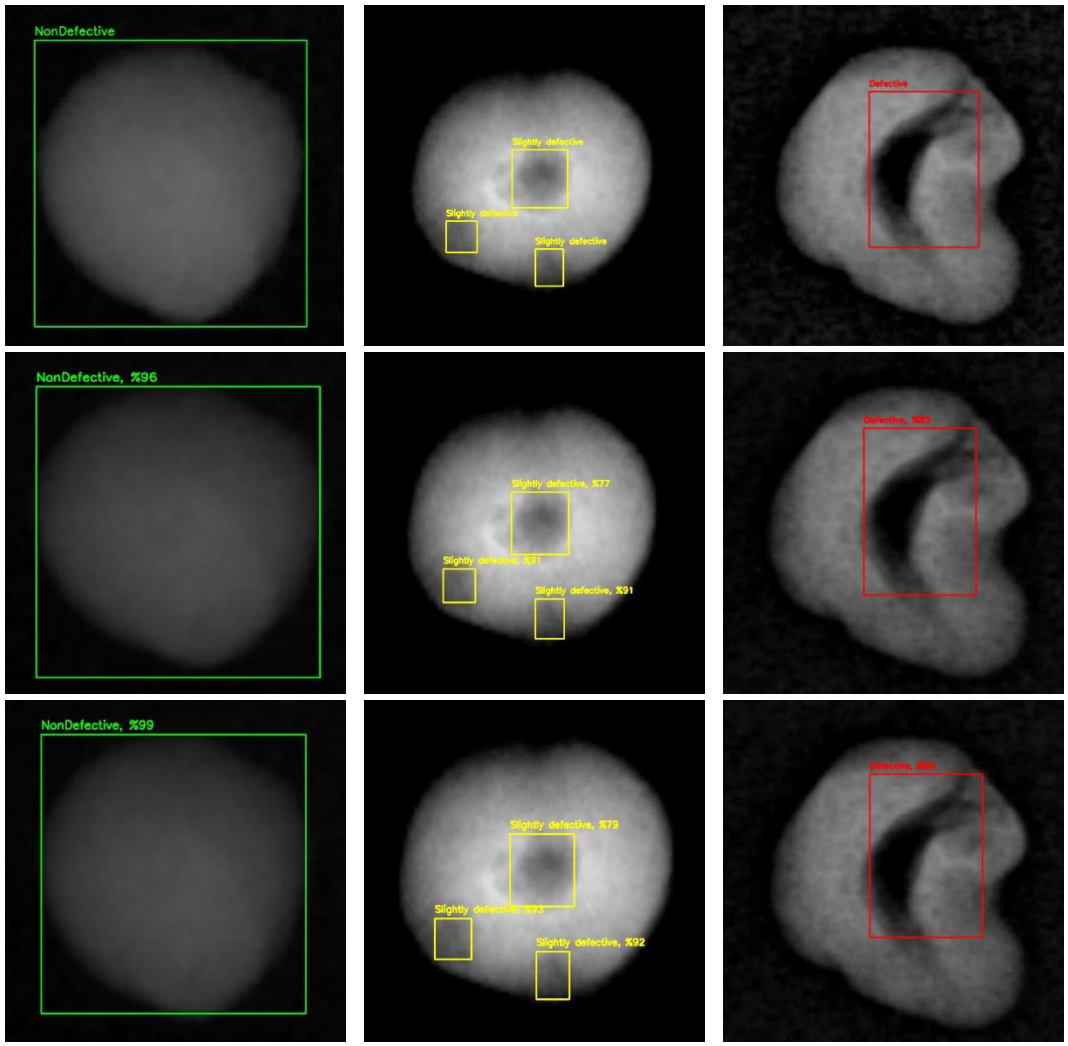
(a) (b)



(c) (d)

Figure 12- Training and validation loss curves for each model: (a) YOLOv5, (b) YOLOv8, (c) Faster R-CNN, (d) SSD

As a result of the training processes, a trained model was generated for each method. The hazelnut images subjected to these trained models are presented in Figure 13.



(a)

(b)

(c)

(d)

(**e**)

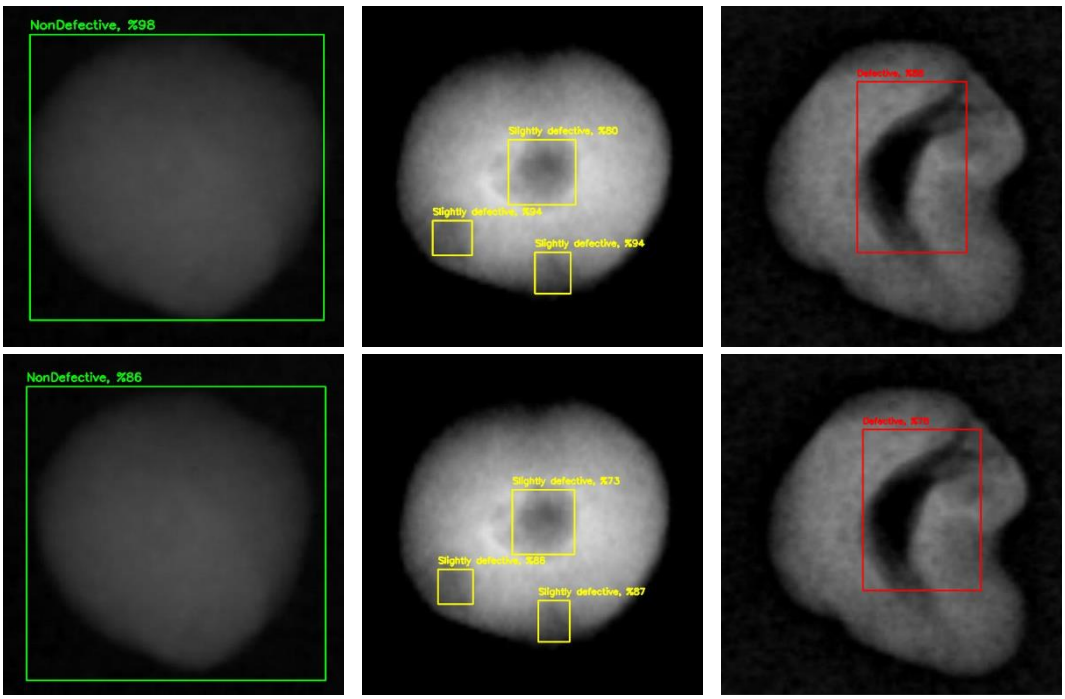


Figure 13- The result images for all models are as follows: (a) Ground truth (expert-annotated), (b) YOLOv5, (c) YOLOv8, (d) Faster R-CNN, (e) SSD

The obtained results reveal that, despite its lengthy training time, the Faster R-CNN model provides the highest accuracy and lowest losses among all methods. YOLOv8, on the other hand, stands out with its high accuracy, short training time, low losses, and highest FPS, thus offering an optimal solution for real-time object detection applications. YOLOv5 is notable for its acceptable accuracy, reasonable training time, and balanced overall performance, while the SSD model, despite its lower accuracy and more fluctuating losses, may be considered for applications that require faster results and where accuracy is less critical. In light of these evaluations, when the key performance criteria -such as speed, accuracy, and generalization capability- are considered together, the YOLOv8 model emerges as the most suitable method for scenarios that demand both high accuracy and real-time performance.

To evaluate segmentation performance, the proposed segmentation method was compared with the default segmentation outputs of YOLOv8. Dice Similarity Coefficient (DSC), Intersection over Union (IoU), precision, and recall metrics were used in the assessment, and the average values for these metrics were calculated. This approach statistically demonstrates the overall accuracy and consistency of the proposed method and enables a reliable evaluation of the segmentation outcomes. In this way, both the correctness of defect localization within the hazelnut kernels and the performance trend of the model across the entire dataset can be clearly observed.

The ground truth masks required for segmentation performance evaluation were generated through a systematic annotation process under the guidance and expert judgment of an agricultural engineer specialized in hazelnuts. Each X-ray hazelnut image was meticulously examined to identify defective regions within the kernel. Defect classification was based on both the size and extent of flaws observed in the X-ray images. Hazelnuts without any detectable defects were labeled as "non-defective," while those containing defects were further categorized as "slightly defective" or "defective," depending on the severity and proportion of the defective areas. Specifically, samples with defective regions covering less than 5% of the kernel area were classified as "slightly defective," whereas those with defective regions exceeding 5% were labeled as "defective." Using these criteria, the expert carefully marked the defective areas, and validation masks were generated for each image to provide accurate ground truth references for segmentation performance evaluation.

The results of the segmentation performance evaluation are presented in Table 5. As shown, the proposed segmentation method achieved average values of 0.72 for IoU and 0.78 for DSC, while the precision and recall scores were measured as 80.68% and 81.35%, respectively. In comparison, the default segmentation outputs of YOLOv8 exhibited slightly higher performance, with IoU of 0.74, DSC of 0.79, precision of 80.42%, and recall of 81.28%. These findings demonstrate that both methods achieve high accuracy in identifying defective regions within hazelnut kernels. Although YOLOv8 shows a slight advantage in IoU and DSC metrics, the proposed method offers comparable precision and recall values, confirming its reliability in segmentation tasks. Overall, the close performance between the two approaches indicates that the proposed method can serve as an effective alternative to YOLOv8 for hazelnut defect segmentation.

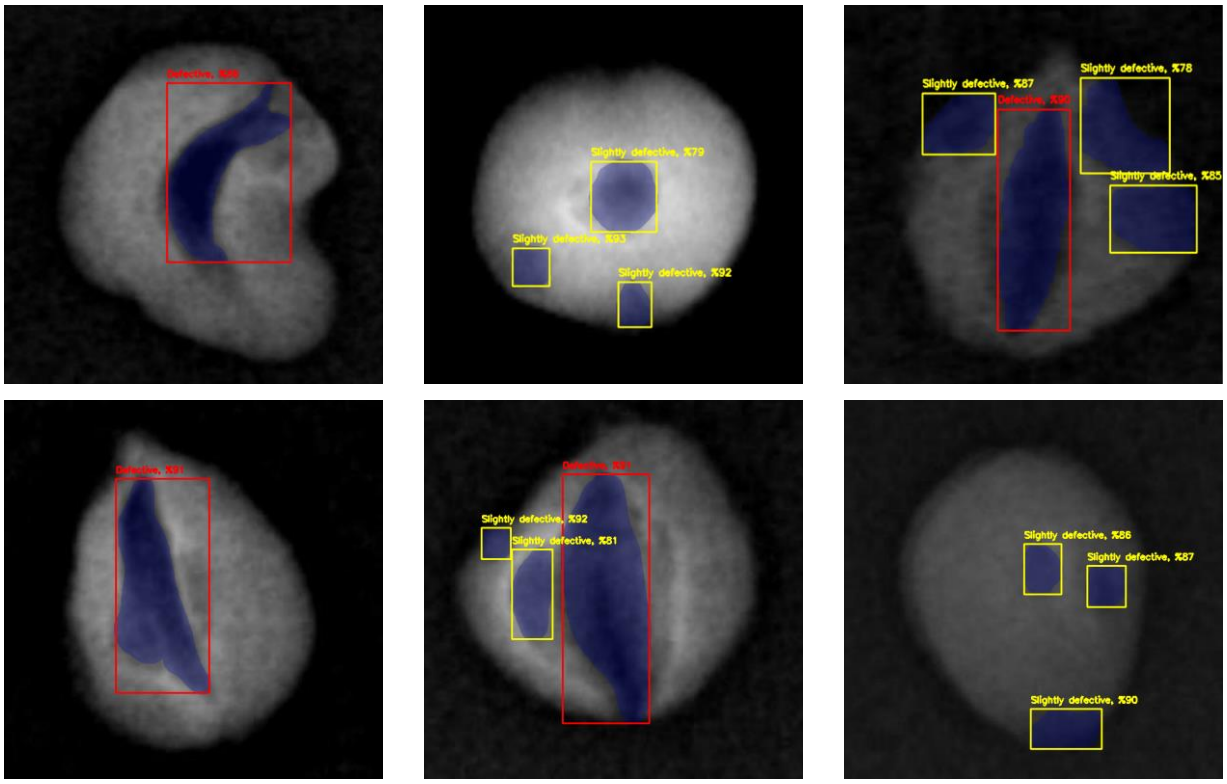
Table 5- Comparison of Segmentation Performance Metrics for the Proposed Method and YOLOv8

Segmentation Methods	*IoU*	*DCS*	*Precision %*	*Recall %*
Proposed Segmentation Method	0.72	0.78	80.68	81.35
YOLOv8	0.74	0.79	80.42	81.28

The core component of the proposed segmentation approach is built upon the bounding box outputs obtained from an object detection model (Figure 10). In this study, various deep learning-based detection models, including SSD, YOLOv5, Faster R-CNN, and YOLOv8, were applied for the object detection stage in hazelnut images. Comparative evaluation showed that YOLOv8 achieved the highest performance and was therefore selected for the object detection step in the segmentation process. The proposed system uses the bounding box coordinates provided by YOLOv8 as the initial region and performs the masking process entirely through an image processing and clustering-based framework.

During the segmentation process, the steps illustrated in Figure 10 were applied sequentially, reducing both computational cost and annotation dependency. This approach significantly minimizes the need for ground truth masks, offering notable advantages in terms of time, labor, and cost, particularly for large-scale datasets. In conventional deep learning-based segmentation methods, model training can be highly demanding due to high computational requirements, long training times, and intensive annotation needs. The proposed method eliminates these training-related time and cost burdens, providing a faster, lightweight, and more practical alternative. Furthermore, thanks to its image processing-based hierarchical structure, it can accurately segment defective regions in X-ray images independently of any model, offering an interpretable, low-cost, and efficient solution compared to deep learning-based segmentation approaches. Collectively, these features make the proposed method a robust alternative for both practical applications and scenarios where model training is difficult, time-consuming, or costly.

In the segmentation stage, object detection was performed using the YOLOv8 model. Subsequently, the images obtained during the preprocessing step were grouped using the K-means clustering algorithm, as detailed in Section 2.4. As a result of the clustering process applied within each object region detected by YOLOv8, the area corresponding to the largest cluster was assigned as the segmentation region for the respective object. This approach enabled not only the precise determination of the general locations of the objects but also the accurate delineation of their boundaries and shapes (Figure 14). In conclusion, the combined use of YOLOv8's rapid and high-accuracy detection capability with clustering-based segmentation has significantly contributed to achieving more consistent, reliable, and meaningful segmentation results in image analysis.



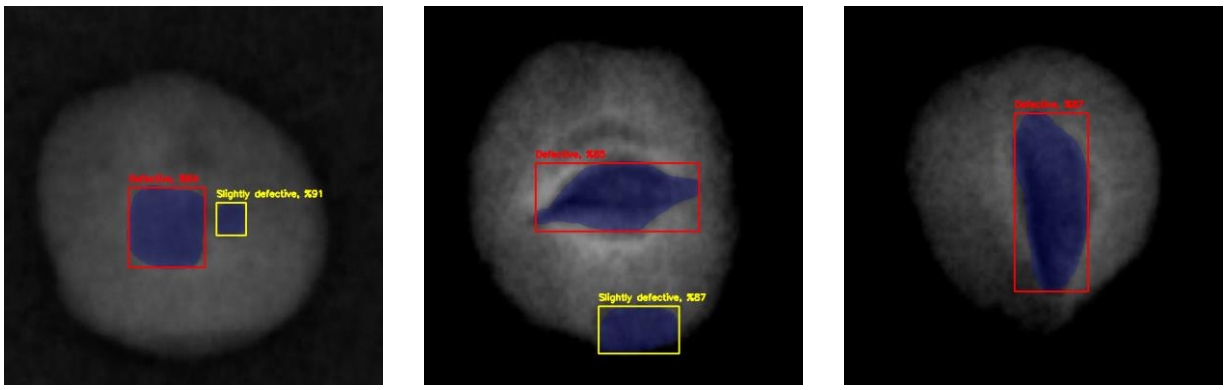


Figure 14- The proposed segmentation process (using YOLOv8)

The classification of agricultural products using technology offers significant advantages in terms of efficiency and quality management. Technological methods enable the characteristics and quality criteria of agricultural products to be determined more accurately and reliably, thereby contributing to the improvement of production processes and the enhancement of market value. In the literature, several studies have focused on the classification of hazelnuts.

Kayakuş et al. (2024) made a general classification of hazelnuts with and without shells using optical sensors and machine learning methods based on the mechanical properties and deformation energy of hazelnuts. However, this study did not include regional defect detection and deep learning-based analyses. In contrast, in our study, defects on hazelnuts were detected regionally with deep learning methods and classified in detail, thus contributing more to quality control processes.

Erbaş et al. (2022) proposed an artificial intelligence-based classification system using the AlexNet architecture and modern deep learning techniques to detect hazelnut quality. However, this study aimed to separate hazelnuts only into general quality categories, and a more detailed segmentation, such as defect detection or regional analysis, was not performed.

Dönmez et al. (2023) classified hazelnut varieties grown in different regions using deep learning-based BigTransfer (BiT) models. Similarly, in this study, the performance of deep learning methods was examined, and their contribution to quality control processes was revealed through regional defect detection.

In the study conducted by Ünal & Aktaş (2023), advanced deep learning architectures such as EfficientNet and InceptionV3 were employed to successfully distinguish different classes (whole kernel, damaged kernel, shell, undersized) during the sorting process in the hazelnut industry. However, this study primarily focused on general class separation rather than the regional detection of defects. In contrast, our proposed model enables not only the identification of defect types but also the determination of their locations on the hazelnut kernels, thereby offering a more detailed and precise evaluation of quality control and automation processes.

Most of the studies in the literature related to hazelnuts have focused on the classification of hazelnut varieties. There are also studies addressing the classification of hazelnut defects. In the majority of these works, hazelnut images have been classified using RGB cameras. Studies utilizing nondestructive imaging techniques such as X-ray imaging are relatively rare. Khosa et al. (2014) performed real-time automatic detection and classification of hazelnuts using X-ray images and image processing techniques. While previous research predominantly employed traditional image processing techniques, they did not utilize deep learning-based methods. In contrast, our study applies deep learning for regional detection and detailed visualization of defects in hazelnuts through segmentation.

A review of the comparisons summarized in Table 6 indicates that most existing studies have concentrated on species identification or general defect classification, and no relevant studies addressing segmentation tasks in depth have been encountered in the literature reviewed. Most of these studies have employed various deep learning architectures, such as VGG16, ResNet50, InceptionV3, BigTransfer, or machine learning methods. In contrast, this study emphasizes the regional detection and classification of defects in hazelnuts by applying X-ray imaging techniques. Unlike previous works, our study focuses on local defect detection and segmentation, enabling the precise identification of both the location and size of defects within individual hazelnuts. In addition, the performances of advanced deep learning-based object detection algorithms, YOLOv5, YOLOv8, Faster R-CNN, and SSD, were compared, and the segmentation process was successfully performed. Consequently, not only the overall condition of the hazelnut but also the precise location and size of defects were accurately determined. Furthermore, our approach demonstrates how integrating X-ray imaging with deep learning allows for more precise and reliable quality control compared to conventional methods. This approach provides a more detailed and effective analysis of quality control processes. As shown in Table 6, our study provides a more comprehensive and innovative solution, highlighting the added value of region-based defect analysis and segmentation over existing approaches in the literature.

Table 6- Comparison of similar studies in the literature

Ref.	*Imaging Method*	*Number of Images*	*Number of Classes*	*Classification Objective*	*Methods*	*Segmentation*
(Taner et al. 2021)	RGB Camera	4250	17	Species Classification	Lprtnr1i, VGG16, VGG19, ResNet50 and InceptionV3	Not applied
(Gencturk et al. 2023)	RGB Camera	3627	3	Species Classification	InceptionV3 + ResNet50	Not applied
(Ünal & Aktaş, 2023)	RGB Camera	2094	4	Defect Classification (All regions on hazelnut)	InceptionV3 and EfficientNe	
(Dönmez et al. 2024)	RGB Camera	3627	3	Species Classification	BigTransfer (BiT)-M R50 × 1, BiT-M R101 × 3 ve BiT-M R152 × 4	Not applied
(Maier et al. 2021)	Optic Sensors	-	2	Defect Classification (All regions on hazelnut)	Machine Learning Methods	Not applied
(Khosa & Pasero, 2014)	X-ray	788	3	Defect Classification (All regions on hazelnut)	Image Process (Feature Extraction)	Not applied
(Kayakuş et al. 2024)	The mechanical properties of hazelnuts	120	2	Species Classification	Machine Learning Methods	Not applied
(Erbaş et al. 2022)	RGB Camera	461	5	Defect Classification (All regions on hazelnut)	AlexNet	Not applied
Ours	X-ray	1320	3	Defect Classification (Local regions on hazelnut)	YOLOv5, YOLOv8, Faster R-CNN, SSD	Applied

In the assessment of hazelnut quality, it is more important to determine factors such as the type, size, and extent of defects rather than merely classifying the defects. An application capable of detecting defects is required to evaluate hazelnut quality accurately. Studies combining deep learning methods with X-ray imaging enable more precise and effective detection of hazelnut defects. In the current literature, such integrated approaches for hazelnut quality assessment have not yet been thoroughly investigated, and integrating these methods offers higher performance and accuracy. Therefore, increasing the number of studies that utilize both deep learning methods and X-ray imaging together will provide significant advancements in hazelnut quality evaluation.

4. Conclusions

This study offers a novel perspective on quality assessment processes in the hazelnut industry, presenting an innovative and effective quality control approach that overcomes the limitations of existing methods. Within the scope of the research, a novel X-ray hazelnut image dataset was created, and the samples were classified as defective, slightly defective, or non-defective. The performances of widely used bounding box–based deep learning models—YOLOv5, YOLOv8, Faster R-CNN, and SSD—were comprehensively evaluated. Furthermore, a segmentation-based method was proposed to enable more detailed examination of defective and slightly defective regions. The integration of X-ray imaging technology with advanced deep learning techniques offers an innovative approach for accurately, consistently, and rapidly determining hazelnut quality.

Experimental results demonstrate that the YOLOv8 model achieved the shortest training time and the highest FPS rate, while also delivering high accuracy and mean average precision (mAP) scores. The YOLOv5 model showed balanced performance, whereas the SSD method yielded the lowest results across all evaluation metrics. Although Faster R-CNN achieved high accuracy, its extended training duration and low FPS values limit its practical applicability. These findings indicate that YOLOv8 provides the most favorable trade-off between speed and accuracy for practical use. In addition, the proposed segmentation approach demonstrates the feasibility of performing segmentation alongside object detection on X-ray hazelnut images.

The proposed segmentation approach enables detailed and precise identification of defective, non-defective and slightly defective regions within hazelnuts. The method employs an image processing and clustering-based hierarchical framework to perform the segmentation process. This ensures accurate detection of defective areas while enhancing the reliability of the segmentation and significantly reducing annotation requirements and computational costs in large datasets. Additionally, the approach provides a fast, practical, and interpretable solution, allowing hazelnut quality to be assessed more accurately, consistently, and flexibly, and represents an effective alternative to existing segmentation methods.

The results highlight that integrating nondestructive X-ray imaging with deep learning techniques enables more accurate and consistent determination of hazelnut quality. This approach offers significant advantages for reliable storage management, fair pricing, and the precise identification of industrial application areas.

Future research will aim to develop novel quality assessment methods and devices by utilizing larger datasets and advanced computer vision techniques. Such technological advancements will allow hazelnut producers and processors to evaluate product quality in real time with high accuracy, thereby enhancing operational efficiency.

In conclusion, this study contributes a unique dataset to the literature and demonstrates the effectiveness of modern deep learning models in nondestructive quality assessment. The findings support improved decision-making processes in hazelnut production and processing, while also opening new opportunities for technological integration and optimization in future research.

Author Declarations

Authors' contributions: Conceptualisation: S.M.Y., S.Ç.K. and E.G.; Methodology: S.M.Y. and S.Ç.K.; Software: S.M.Y.; Visualisation: S.M.Y.; Validation: S.M.Y., S.Ç.K. and E.G.; Data collection: S.M.Y.; Analysis: S.M.Y., S.Ç.K. and E.G.; Writing—original draft preparation: S.M.Y.; Writing—review and editing: E.G.; Supervision: S.Ç.K. and E.G.; Project administration: S.M.Y. All authors reviewed and approved the final version of the manuscript.

Conflict of interest/Competing interests: The author(s) declare no conflict of interest.

Ethics approval/declarations: No need/ Not applicable.

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Consent to participate: No need/ Not applicable.

Consent for publication: No need/ Not applicable.

Data availability: The dataset used in this study was created by the researchers and has been made publicly available. It can be accessed via the following link:

https://drive.google.com/drive/folders/1nH9bXsBKBDuXfKysPnC43VfDETRKp3zq?usp=sharing

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