Cultivar Identification of Pistachio Nuts via Deep Learning

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Abstract

Background: This study presents a deep learning approach for identifying pistachio cultivars using sophisticated image classification techniques.

Materials and Methods: We utilized the YOLOv8 convolutional neural network, recognized for its swift training and testing capabilities, as well as its outstanding single-object classification accuracy. Unlike conventional methods that assess individual pistachio nuts, our strategy analyzes images with multiple nuts at once, greatly improving both efficiency and speed.

Results: We rigorously tested this method on a detailed dataset of images featuring five commonly grown Iranian pistachio cultivars: *Badami*, *Fandoghi*, *Kalleh Ghoochi*, *Ahmad Aghaei*, and *Akbari*. Our findings revealed an impressive average classification accuracy of 99.8% on the test set, highlighting the robustness and effectiveness of our approach.

Conclusion: This method marks a significant advancement over traditional techniques, providing a highly reliable, automated, and efficient solution for identifying pistachio cultivars, with extensive practical applications in agricultural sorting systems and the food processing quality control industry.

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1. Introduction

Pistachios are one of Iran's key agricultural exports, playing a significant role in the nation's economy [1]. The most prominent cultivars include Ahmad Aghaei, Fandoghi, Akbari, Badami, and Kalleh Ghoochi. Accurately identifying these cultivars is essential for quality control, pricing, and market distribution. However, current methods for identifying pistachio cultivars, such as sound reflection and traditional image analysis, have limitations regarding scalability and accuracy. These methods typically involve classifying pistachios individually, which is time-consuming and requires precise measurements for each kernel. This problem becomes even more challenging when dealing with bulk quantities, highlighting the need for more efficient and scalable solutions. Recent advancements in intelligent methods for pistachio cultivar identification present promising alternatives [2]. One interesting method is sound reflection analysis, which is primarily used to differentiate between open and closed-shell pistachios. These techniques typically operate on an individual kernel basis, analyzing the acoustic signals produced when pistachios are subjected to specific impacts or sound waves. For instance, one system introduced the use of convolutional neural networks (CNNs) to classify pistachios based on their shell status, achieving high accuracy. This system analyzes the sound waves reflected from the nut's shell to determine whether it is closed. Similarly, another study examined a method in which the sound generated when pistachios strike a metal surface was processed through neural networks to classify the main export cultivars: Kalleh Ghoochi, Akbari, Fandoghi, and Ahmad Aghaei. Additional research has applied acoustic analysis to distinguish between open and closed pistachios [3, 4, 5, 6].

Although sound-based methods are accurate in certain situations, they have several limitations. Primarily, these methods are designed to detect the shell status of pistachios rather than to identify the cultivar. Additionally, they analyze individual pistachios, which can be time-consuming and impractical for large-scale operations. This single-kernel approach restricts their effectiveness in commercial settings where high-throughput solutions are necessary. Furthermore, sound reflection methods provide limited information about the physical characteristics that distinguish different cultivars, such as size, shape, and surface texture. For example, Omid et al. proposed an expert system that successfully sorted pistachios based on shell status, but it was not intended for cultivar differentiation. Similarly, Pearson's real-time sorting system effectively separated open and closed-shell pistachios but did not extend its functionality to cultivar classification. While these methods are effective for their specific purposes, they fall short in identifying particular pistachio cultivars, which is crucial for market pricing and quality assessment. As a result of these limitations, there is growing interest in alternative methods such as machine vision and deep learning. These techniques enable the simultaneous processing of multiple pistachios while accurately identifying different cultivars. Image-based approaches are more suitable for large-scale industrial applications and provide greater accuracy in distinguishing between cultivars such as Kalleh Ghoochi, Akbari, Badami, and Ahmad Aghaei [7, 8].

Unlike sound reflection techniques, machine vision-based methods leverage image analysis and neural networks for pistachio identification. Various studies have highlighted the potential of these approaches. For example, [9] developed a system to classify pistachios based on their shell characteristics, successfully categorizing them into multiple grades. In another study [10], color features were used to classify pistachios based on shell openness, while deep learning models such as AlexNet, VGG16, and VGG19 were applied in [11] to classify pistachio cultivars with high accuracy, achieving up to 98.84% accuracy with VGG16. However, despite the reported high accuracies in controlled environments, most methods still focus on individual kernels, which limits their scalability for industrial applications. For example, a study [12] demonstrated that models trained on desktop data achieved only 61.75% accuracy when applied in an industrial setting, highlighting the challenge of translating laboratory results to real-world scenarios. Moreover, even studies that have achieved high classification accuracy with models such as VGG16 and AlexNet in controlled environments, such as [13], still face bottlenecks because they rely on individual kernel analysis. Processing pistachios one by one is not feasible for large-scale operations, where rapid bulk classification is critical. In response to these challenges, our research presents significant advancements. By employing deep learning techniques that process multiple pistachios simultaneously, we overcome the scalability issues inherent in current methods. Our approach is optimized for large-scale industrial applications, offering high classification accuracy for different cultivars while maintaining efficiency in bulk processing. Despite these advancements, a critical limitation of most existing methods is their reliance on processing individual pistachio kernels, which is inefficient for bulk quantities. Methods based on image analysis or sound reflection require significant time and precision for single-kernel processing. Therefore, a method that can process multiple pistachios simultaneously is essential. In [14], images of groups of pistachios were classified into five categories—*Badami*, *Fandoghi*, *Kalleh Ghoochi*, *Ahmad Aghaei*, and *Akbari*—using Gabor filters and the K-Nearest Neighbors (KNN) classifier. As this study utilized a similar database, we compare its results with those of our proposed method. Similarly, [15] applied the EfficientNet deep learning model to classify pistachio cultivars from images of multiple pistachios, aiming to improve the accuracy of cultivar identification. Given the relevance of their findings, we will include a comparison in the results section.

This study addresses the challenge of classifying bulk pistachio cultivars using advanced deep learning techniques. We hypothesize that YOLOv8, due to its superior speed and accuracy, can surpass traditional methods such as Gabor filters in recognizing pistachio cultivars. Specifically, we expect that YOLOv8 will provide enhanced scalability, higher classification precision, and significantly faster inference times, making it more suitable for real-time bulk classification in agricultural processing environments. Unlike conventional approaches that classify each kernel individually, our method allows for the simultaneous classification of multiple pistachios, significantly improving efficiency and scalability for large-scale industrial applications. Preliminary results show classification accuracies ranging from 99.8% to 100%, outperforming previous studies [14, 15]. This research not only enhances the speed and accuracy of pistachio cultivar identification but also has broader applications in agricultural automation. The structure of the paper is as follows: Section 2 details the materials and methods, Sections 3 and 4 present the results and discussion, respectively, and Section 5 concludes with the findings and future research directions.

2. Materials and methods

In recent years, deep learning technologies have found wide-ranging applications across various industries, leading to rapid advancements in object detection algorithms. YOLO (You Only Look Once) is one such algorithm developed for real-time object detection and recognition in images and videos. It employs a deep neural network to detect and classify multiple objects within an image simultaneously. A key advantage of YOLO is its ability to operate at high speed, making it suitable for time-sensitive applications. Originally introduced by Joseph Redmon in 2015, YOLOv1 gained popularity due to its superior speed and accuracy compared with other models, such as R-CNN, MobileNet, and AlexNet [16]. Subsequent improvements led to the development of YOLOv8 by Glenn Jocher in 2023, which further enhanced its performance and efficiency [17].

This study aims to develop a deep learning-based approach for the bulk classification of pistachio cultivars, addressing the limitations of traditional methods in scalability, speed, and accuracy. We hypothesize that YOLOv8, due to its superior computational efficiency and precision, can outperform conventional techniques in terms of both classification accuracy and inference speed. The architecture of YOLOv8m introduces several significant advancements, particularly in its classification head. This design allows for efficient image classification by treating the entire image as a single object. The classification phase is pretrained on ImageNet, which enhances the model's ability to generalize across diverse datasets. Additionally, YOLOv8m is anchor-free, simplifying the detection process by eliminating the need for predefined anchor boxes. This innovation accelerates training and improves the model's adaptability to various image scales and orientations.

The use of YOLOv8m is particularly advantageous in real-time agricultural applications, such as automated sorting, where rapid and accurate decision-making is essential. The model comprises three core components: a backbone for feature extraction, a neck for feature aggregation, and a head for classification. In our research, the model was fine-tuned on a pistachio cultivar dataset, leveraging its classification head to distinguish between five pistachio varieties: *Badami*, *Fandoghi*, *Kalleh Ghoochi*, *Ahmad Aghaei*, and *Akbari*. To enhance the model's generalization ability, we applied common data augmentation techniques, including random rotations, scaling, and brightness adjustments.

YOLOv8m is useful in agricultural settings, where it excels in tasks requiring real-time object classification, such as livestock tracking, pest detection, and crop sorting. For pistachio classification, the model effectively treats each image, comprising multiple pistachios of the same cultivar, as a single object, streamlining the process of identifying and sorting different varieties. This approach is particularly well-suited for automated agricultural systems, where maintaining both accuracy and computational efficiency is crucial.

Deep learning has been widely used in agriculture for tasks such as crop disease detection and yield estimation. However, its application in bulk classification is still limited. Traditional classification models typically focus on identifying individual objects in controlled environments, while real-world agricultural processes often require the ability to distinguish and categorize multiple overlapping instances at once. This includes tasks like sorting grains, seeds, or harvested produce in bulk. This study aims to address that gap by utilizing YOLOv8, a state-of-the-art object detection model, to improve the accuracy and efficiency of bulk classification. YOLOv8 is particularly well-suited for high-throughput agricultural applications due to its capability to detect and classify multiple objects in real-time, where both precision and speed are essential. By demonstrating the potential of deep learning for bulk classification, this work lays the groundwork for more scalable and automated sorting and quality control systems. These advancements could reduce labor dependency and enhance efficiency throughout agricultural supply chains.

Figure 1 presents the architecture of YOLOv8, highlighting its key components. The backbone extracts hierarchical feature maps at different scales (C_1 to C_5), which are further refined and aggregated via a feature pyramid network (FPN). The processed features are passed through several convolutional blocks to form the final feature pyramid (P_3 to P_5), which is then fed into the heads for object detection and classification. The loss function incorporates classification loss, L1 loss for bounding box regression, and objectness loss. YOLOv8's architecture is designed with multiple convolutional layers for feature extraction, supplemented by upsampling blocks that increase feature map resolution. The use of concatenation and injection points enhances its ability to handle objects of varying sizes and improves classification accuracy. This combination of speed and precision makes YOLOv8 highly suitable for real-time tasks, including both object detection and image classification.

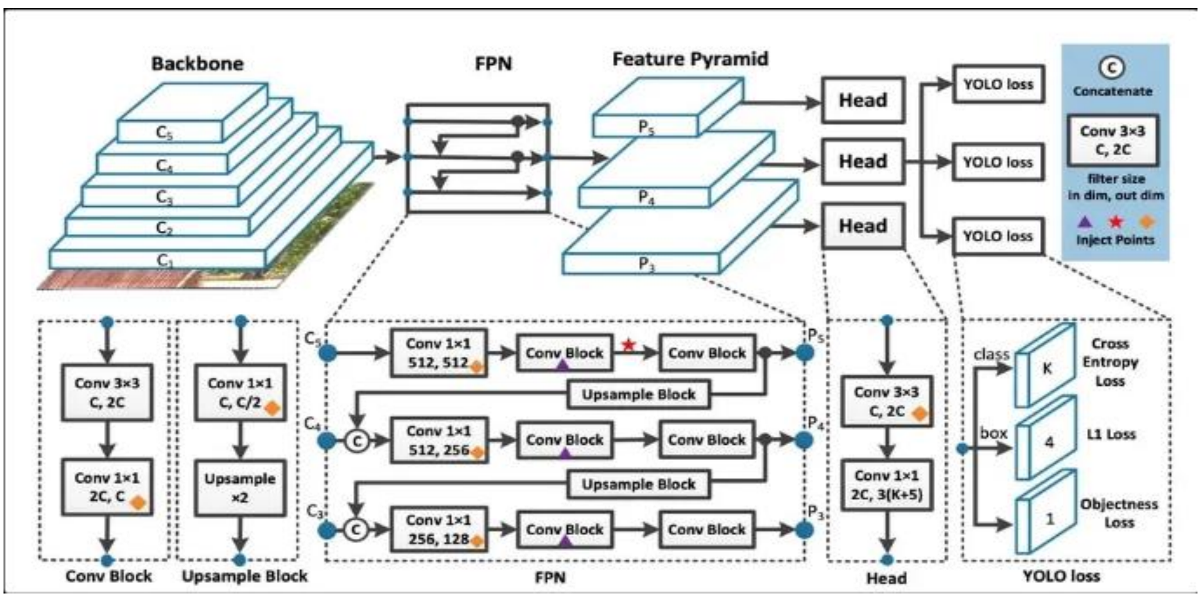

Fig 1. The YOLOv8 architecture illustrates the backbone for feature extraction, the FPN for feature aggregation, and the head used for object detection and classification.

In this study, YOLOv8m was specifically employed to classify pistachio images into five categories, with each image being treated as a single entity. This method effectively addresses the research objective of classifying entire images rather than individual objects, making it a practical and efficient solution for automated pistachio sorting systems.

3. Results

The proposed method was implemented via the Python programming language and executed on Google Colab with a GPU processor. This section presents the dataset, evaluation metrics, and experimental results.

3.1. Dataset Preparation

Image collection

To evaluate the proposed method, we utilized the dataset from reference [14], which comprises 15 color images for each of five distinct Iranian pistachio cultivars—*Badami*, *Fandoghi*, *Kalleh Ghoochi*, *Ahmad Aghaei*, and *Akbari*, resulting in a total of 75 images. Each image was captured at a resolution of 2542×3498 pixels. To ensure consistent and high-quality imaging, the pistachios were placed in a glass container that precisely fit the scanner bed. This container was positioned on an HP ScanJet 6300c scanner, and images were scanned at a resolution of 300 dpi. Consistent lighting conditions during scanning further ensured uniformity across all the images. Figure 2 provides representative examples of pistachio images from different varieties.

In this study, each class consists of pistachios from a specific cultivar, yet there is significant intra-class variability in terms of visual characteristics. This includes closed-shell pistachios, deformed pistachios, kernel-only samples, empty shells, and even broken shell fragments. Such intra-class diversity may pose challenges for the model, as the visual features within a single class can vary considerably. However, this variability enhances the generalizability of the model in real-world scenarios, where input samples exhibit a wide range of shapes and conditions.

(a) Badami *(b) Fandoghi* *(c) Kalleh Ghoochi*

(d) Ahmad Aghaei *(e) Akbari*

Fig 2. Sample images of different pistachio varieties: (a) *Badami*, (b) *Fandoghi*, (c) *Kalleh Ghoochi*, (d) *Ahmad Aghaei*, and (e) *Akbari*.

Given that the color information for all pistachio cultivars is identical, with primary differences arising from variations in size, the color images were first converted to grayscale to reduce computational complexity. To further increase the classification accuracy, random subimages of 2048×2048 pixels were extracted from the grayscale images and subsequently resized to 512×512 pixels. The choice of these dimensions was based on two key factors: smaller subimages may not capture sufficient detail within a single window, potentially reducing classification accuracy, whereas larger subimages increase computational demands, potentially slowing down the system. In total, 2000 subimages, each measuring 512×512 pixels (400 subimages per pistachio cultivar), were generated for the analysis.

Data splitting

Data splitting is the process of dividing a dataset into distinct subsets—typically training, validation, and test sets—ensuring that machine learning models are trained, validated, and evaluated in a manner that accurately reflects their performance. This practice is essential to prevent overfitting, where a model performs well on the training data but struggles to generalize to unseen data. By using separate datasets for training and evaluation, we can obtain a more reliable assessment of the model's ability to generalize and perform effectively on real-world data.

In this study, the dataset comprises 2000 subimages, with 400 subimages per class representing five pistachio cultivars, extracted from 15 high-resolution images. The data were split as follows:

Training set: 200 subimages per pistachio type extracted from the first 7 images.

Validation set: 100 subimages per pistachio type extracted from the next 4 images.

Test set: 100 subimages per pistachio type extracted from the final 4 images.

To ensure that there was no overlap between the different subsets, the data were split such that each subset was constructed independently. As a result, the dataset included 1000 training subimages (200 per pistachio type), 500 validation subimages (100 per type), and 500 test subimages (100 per type). This structured approach to data splitting ensures comprehensive coverage of the dataset while minimizing the risk of data leakage, thereby enhancing the reliability and robustness of the model evaluation.

3.2. Data Augmentation

In this study, a range of data augmentation techniques were employed to enhance model performance and increase the diversity of the training dataset. These augmentations were automatically applied by YOLOv8 during the training process. While the specific augmentation methods are handled internally by YOLOv8, analysis of the augmented images suggests the use of techniques such as random rotations, scaling, cropping, and adjustments to brightness and contrast. Figure 3 shows a batch of 16 augmented training images, showcasing the transformations applied, whereas Figure 4 presents a batch of 16 validation images, representing the original unaltered data.

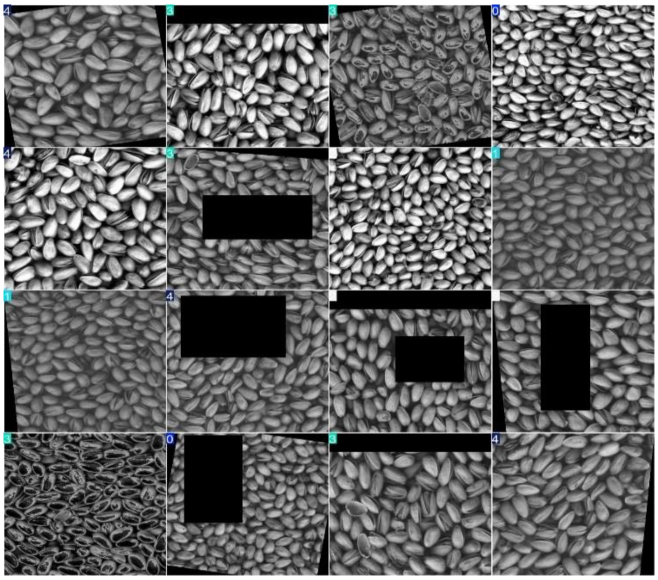

Fig 3. Samples of augmented images in the training set.

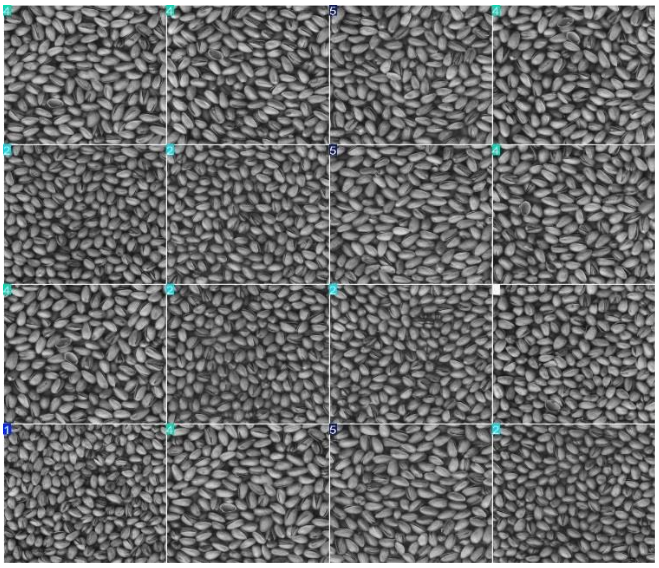

Fig 4. Samples of original images in the validation set.

3.3. Evaluation Metrics

To compare the performance of the proposed method with that of other methods, several metrics are used: precision, accuracy, sensitivity, and F1 score, which are defined by the following equations:

(1)

$$Percision = \frac{TP}{TP+FP}$$

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

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

(4) $$F1 - score = \frac{2\times Precision\times Sensitivity}{Presision+Sensitivity}$$

where TP Is the number of true positives, TN Is the number of true negatives, FP Is the number of false positives, and FN Is the number of false negatives.

In these equations:

TP (true positives) represents the number of images that correctly belong to a class and are classified as such.

TN (True Negatives) denotes the number of images that do not belong to a class and are correctly not classified as that class.

FP (false positives) indicates the number of images that do not belong to a class but are incorrectly classified as that class.

FN (false negatives) refers to the number of images that belong to a class but are incorrectly classified as not belonging to that class.

3.4. Results

The YOLOv8 network was trained on a dataset of 1000 subimages over 50 epochs, with accuracy evaluated at each epoch via a validation set. The model performance was monitored throughout training, and the best-performing version, which achieved a validation accuracy of 99.8% at epoch 5, was saved and subsequently tested on a dedicated test set.

Table 1 presents the confusion matrix for the test set, which consists of 500 subimages across five pistachio cultivars (100 subimages per cultivar), for the proposed method. The matrix visually represents the number of correct and incorrect classifications for each cultivar. The diagonal elements (i, i) indicate correctly classified subimages from cultivar *i*, whereas the off-diagonal elements (i,j) represent misclassified subimages from cultivar *i*, incorrectly predicted as cultivar *j*.

To assess the effectiveness of the YOLOv8 algorithm, its results are compared with those from Reference [14], which also uses the same dataset. The confusion matrix for Reference [14] is shown in Table 2, Table 1 highlights the proposed method's strong classification performance, which achieved near-perfect classification, with only one misclassified Ahmad Aghaei pistachio. In contrast, as shown in Table 2, the Reference [14] method showed notable misclassifications, particularly for Kalleh Ghoochi and Ahmad Aghaei cultivars. Specifically, 15 Ahmad Aghaei samples were misclassified as Kalleh Ghoochi, and 5 Kalleh Ghoochi samples were wrongly identified as Akbari. Additionally, 3 Kalleh Ghoochi samples were misclassified as Ahmad Aghaei. These results highlight the superior precision and reliability of the proposed approach.

Table 1. Confusion matrix using the proposed method.

True Class		Badami	Fandoghi	Kalleh Ghoochi	Ahmad Aghaei	Akbari
	Badami	100	0	0	0	0
	Fandoghi	0	100	0	0	0
	Kalleh Ghoochi	0	0	100	0	0
	Ahmad Aghaei	0	0	0	99	1
	Akbari	0	0	0	0	100
		Predicted Class				

Table 2. Confusion matrix of the method from Reference [14].

True Class		Badami	Fandoghi	Kalleh Ghoochi	Ahmad Aghaei	Akbari
	Badami	100	0	0	0	0
	Fandoghi	0	100	0	0	0
	Kalleh Ghoochi	0	0	92	3	5
	Ahmad Aghaei	0	0	15	84	1
	Akbari	0	2	0	0	98
		Predicted Class				

A detailed evaluation of the classification performance is conducted via the following key metrics: sensitivity, precision, F1 score, and accuracy. These metrics are presented for both the proposed YOLOv8 method and the comparative method in Tables 3 and 4. The proposed model demonstrates exceptional performance, achieving nearly perfect scores across all classes, with an overall accuracy of **99.9%**. The only minor deviation is observed in the Ahmad Aghaei and Akbari cultivars, where accuracy is **99.8%** due to a single misclassification. In contrast, the comparative method exhibits significantly lower performance, particularly for Kalleh Ghoochi and Ahmad Aghaei cultivars, with sensitivities of **0.92** and **0.84**, respectively. The lower F1-scores for these classes (**0.888** and **0.898**) indicate notable misclassifications, as also reflected in the confusion matrix. The overall accuracy of the comparative model is **98.0%**, which, while relatively high, is notably lower than the proposed method's performance. These results highlight the superiority of the YOLOv8-based approach, particularly in handling challenging classifications and reducing misclassifications across all pistachio cultivars. This multidimensional evaluation is critical in agricultural applications, where accurate cultivar classification is essential for sorting and processing.

In this study, we evaluated model performance using precision, recall, F1-score, and accuracy, as these metrics effectively capture both classification accuracy and detection quality. Notably, AUC-ROC was excluded because all classes in the dataset were well-balanced, minimizing its relevance as a performance measure. Since AUC-ROC is particularly useful for assessing models on imbalanced datasets, where distinguishing between true positive and false positive rates is crucial, its omission does not impact the robustness of our evaluation. Instead, the selected metrics provide a more direct and interpretable assessment of the model's effectiveness in the given classification task.

Table 3. Evaluation Metrics for Pistachio Image Classification via the Proposed Method.

	Sensitivity	Precision	F1-Score	Accuracy
Badami	1.00	1.00	1.00	1.00
Fandoghi	1.00	1.00	1.00	1.00
Kalleh Ghouchi	1.00	1.00	1.00	1.00
Ahmad Aghaei	0.99	1.00	0.995	0.998
Akbari	1.00	0.99	0.995	0.998
All Five Classes	0.998	0.998	0.998	0.999

Table 4. Evaluation Metrics for Pistachio Image Classification via the Method from Reference [14].

	Sensitivity	Precision	F1-Score	Accuracy
Badami	1.00	1.00	1.00	1.00
Fandoghi	1.00	0.98	0.99	0.996
Kalleh Ghouchi	0.92	0.859	0.888	0.954

Ahmad Aghaei	0.84	0.965	0.898	0.960
Akbari	0.98	0.94	0.96	0.984
All Five Classes	0.948	0.948	0.948	0.980

3.4.1. Result Analysis

Bar charts have been generated for each metric, providing a visual comparison of the performance between the proposed and reference methods and offering a clear perspective on their relative strengths.

Sensitivity (Recall)

Sensitivity, also known as recall, evaluates a model's ability to correctly identify positive instances of each class. High sensitivity indicates the model's effectiveness in capturing all relevant instances for a given class. As shown in Tables 3 and 4 and the bar chart of this metric in Figure 5:

The proposed method achieves very high sensitivity overall (0.998). However, it perfectly classifies all instances except for *Ahmad Aghaei*, where 1% of these pistachios are not correctly identified.

In comparison, the method from Reference [14] shows lower sensitivity for some classes. The sensitivity for *Ahmad Aghaei* is only 0.84, which means that 16% of pistachios in this class are not identified correctly. Similarly, the *Kalleh Ghouchi* class has a sensitivity of 0.92, implying an 8% miss rate.

The overall sensitivity for all five pistachio classes combined is 0.998 for the proposed method, whereas it is 0.948 for the method in Reference [14]. This demonstrates the robustness of the proposed method in minimizing missed detections across all classes, offering a more reliable performance for pistachio classification than that of Reference [14].

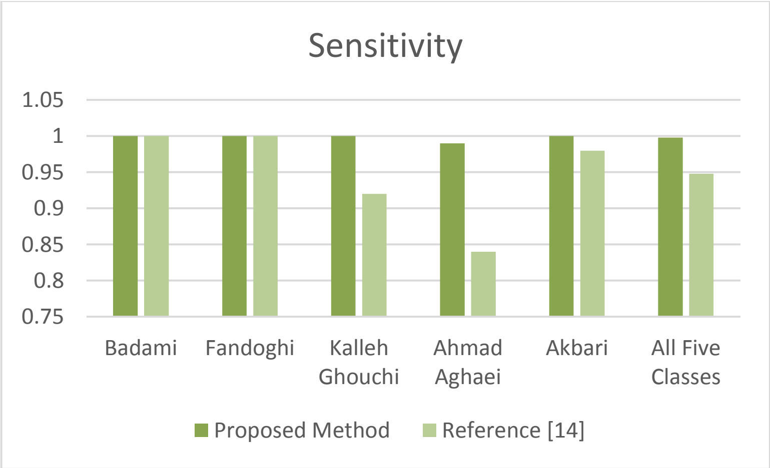

Fig 5. Comparison of model sensitivity for the proposed method and the method from reference [14].

Precision

Precision reflects the proportion of correct positive predictions, with higher values indicating fewer false positives. As demonstrated in Tables 1 and 2 and depicted in the bar chart in Figure 6:

The proposed method achieved perfect precision (1.00) for four out of five cultivars, with only a slight reduction for *Akbari* (0.99), indicating minimal misclassification.

In contrast, the method from Reference [14] showed more variability, with the lowest precision observed for *Kalleh Ghouchi* (0.859), reflecting a higher rate of false positives for this class.

Overall, the proposed method maintains an excellent precision of 0.998, whereas the reference method's precision is 0.948.

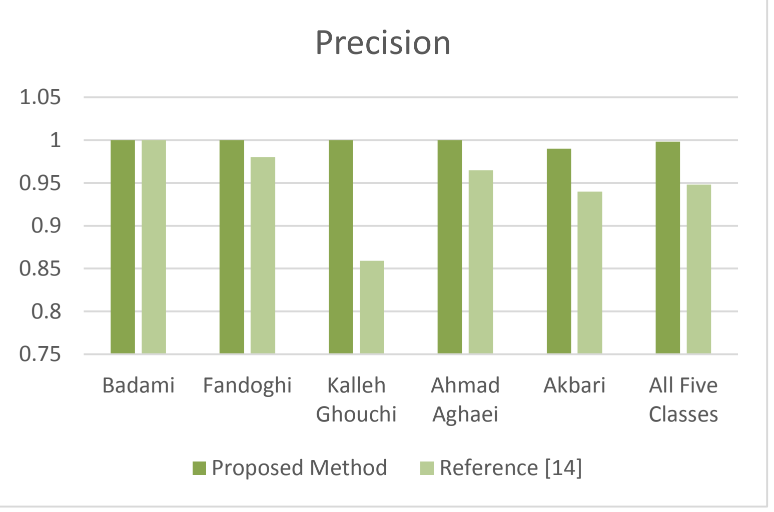

Fig 6. Comparison of model precision for the proposed method and the method from reference [14].

F1 score

The F1 score balances precision and sensitivity, making it particularly useful for imbalanced datasets or when both false positives and false negatives are important. As shown in Tables 3 and 4 and Figure 7:

The proposed method achieves a perfect F1 score (1.00) for *Badami*, *Fandoghi*, and *Kalleh Ghouchi*, with only slightly lower scores for *Ahmad Aghaei* and *Akbari* (0.995), indicating a strong balance across all classes.

The method from Reference [14] showed significant variation, with weaker performance for *Kalleh Ghouchi* (0.888) and *Ahmad Aghaei* (0.898), highlighting their struggle to maintain a balance between precision and sensitivity.

The overall F1 score of 0.998 for the proposed method underscores its superior balance and reliability for pistachio classification compared with the 0.948 F1 score of the reference method.

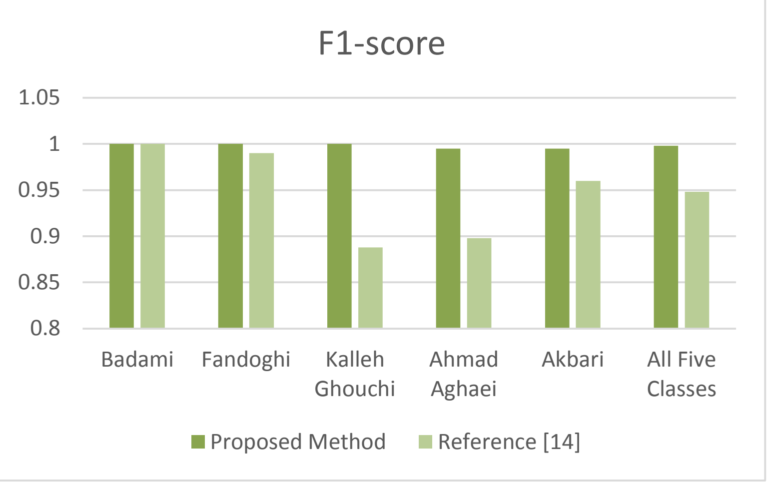

Fig 7. Comparison of model F1 scores for the proposed method and the method from reference [14].

Accuracy

Accuracy measures the proportion of correct predictions out of the total instances, but it can be misleading in imbalanced datasets. As displayed in Tables 3 and 4 and illustrated in Figure 8:

Both methods achieve perfect accuracy (1.00) for *Badami*.

The proposed method outperforms the reference method for *Kalleh Ghouchi*, with an accuracy of 1.00 compared with 0.954.

For Ahmad Aghaei, the proposed method achieves an accuracy of 0.998, slightly surpassing the reference method's accuracy of 0.960.

Overall, the proposed method achieves an accuracy of 0.999, compared with 0.980 for the reference method, reinforcing its superior performance in pistachio classification.

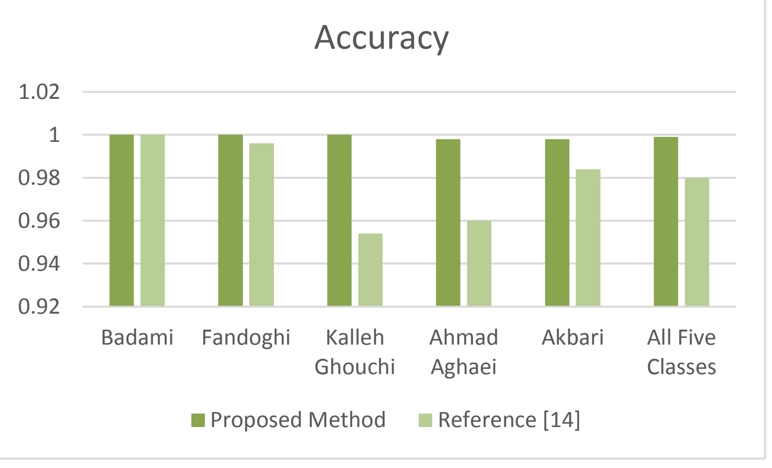

Fig 8. Comparison of model accuracy for the proposed method and the method from reference [14].

3.4.2. Statistical analysis of the performance metrics

To further validate the results, a comprehensive statistical analysis of the performance metrics was conducted for both the proposed method and the reference method from Reference [14]. The metrics analyzed—sensitivity, precision, F1 score, and accuracy—were evaluated via 95% and 99% confidence intervals (CIs), and the relevant statistics are summarized in Table 5. The narrower CIs for the proposed method suggest higher reliability across all the metrics.

Sensitivity: The proposed method achieved a 95% CIs of (0.992, 1.003) and a 99% CIs of (0.989, 1.007), indicating consistent performance, whereas the reference method showed more variability with wider CIs.

Precision: Compared with the wider CIs for the reference method, the proposed method's 95% CIs of (0.992, 1.003) and 99% CIs of (0.989, 1.007) further affirm its reliability.

F1 score: Compared with the reference method's broader CIs, the proposed method maintains a strong balance with CIs of (0.994, 1.001) and (0.992, 1.004), indicating superior performance.

Accuracy: The proposed method's accuracy CIs of (0.998, 1.000) and (0.997, 1.001) suggest very high reliability, in contrast to the reference method's wider intervals.

Table 5. Confidence intervals for the proposed method and the reference method [14].

		Sensitivity	precision	F1-Score	Accuracy
95% CIs	Proposed Method	(0.992, 1.003)	(0.992, 1.003)	(0.994, 1.001)	(0.998, 1)
	Reference [14]	(0.863, 1.033)	(0.881, 1.017)	(0.883, 1.011)	(0.953, 1.005)
99% CIs	Proposed Method	(0.989, 1.007)	(0.989, 1.007)	(0.992, 1.004)	(0.997, 1.001)
	Reference [14]	(0.806, 1.089)	(0.836, 1.061)	(0.841, 1.054)	(0.936, 1.022)

3.4.3. Time analysis

Most studies on pistachio classification focus on single kernels, but this work uses images of multiple kernels. In addition to Reference [14], another study [15] used EfficientNet for classifying pistachios, achieving 98% accuracy. However, the YOLOv8 algorithm outperforms EfficientNet, not only in accuracy but also in speed. On Google Colab, using a GPU, the YOLOv8 network took approximately 39 s per epoch for a test dataset containing 1000 images and a validation set containing 500 subimages with a size of 512×512 (262,144 pixels). In contrast, the EfficientNet deep network, which uses a GPU on Google Colab, took approximately 172 seconds per epoch for a test dataset containing 2000 images and a validation set containing 500 subimages with a size of 300×300 (270,000 pixels).

YOLOv8 achieved classification in 0.1 milliseconds per image, significantly outperforming EfficientNet (21.5 milliseconds per image) and the Gabor filter-based approach (approximately 30 milliseconds per sample). These results demonstrate that YOLOv8 is not only more accurate but also far more efficient, making it highly suitable for real-time agricultural sorting and bulk classification applications.

3.5. Impact of Mixed-Cultivar Scenarios on Model Performance

To evaluate the robustness of the proposed model in **mixed-cultivar classification scenarios**, we conducted controlled experiments in which test images contained varying proportions of the primary class alongside secondary class interference. Four conditions were simulated: Case 1 (84% primary class, 4% each secondary class), Case 2 (68% primary class, 8% each secondary class), Case 3 (52% primary class, 12% each secondary class), and Case 4 (36% primary class, 16% each secondary class). In each case, 10 images per class were generated, and the model's performance was analyzed using confusion matrices. The classification performance was assessed using confusion matrices in Table 6 to 9, highlighting how the increasing presence of non-primary classes influenced the model's decision-making.

The results indicate that as the proportion of secondary classes increased, the model's classification accuracy gradually declined, with a noticeable rise in misclassification rates, particularly for visually similar classes. In Case 1, where the primary class dominated the image, classification performance remained high across all classes, with minimal errors. However, as the secondary classes occupied a larger portion of the image (Cases 2–4), the model exhibited progressive confusion, particularly in distinguishing cultivars with similar texture, shape, or color characteristics. Kalleh Ghoochi and Ahmad Aghaei cultivars were increasingly misclassified in cases with higher levels of mixture, suggesting that the model relies heavily on global image features rather than extracting fine-grained, class-specific details. Furthermore, the results highlight a decline in classification confidence, particularly in Case 4, where the primary class constituted only 36% of the image. This suggests that the model is highly sensitive to class proportions, and its performance deteriorates when no single dominant class is present.

Table 6. Confusion matrix for Case 1: Images with 84% primary class and 4% each from other classes.

True Class`s		Badami	Fandoghi	Kalleh Ghoochi	Ahmad Aghaei	Akbari
	Badami	**10**	**0**	**0**	**0**	**0**
	Fandoghi	0	10	0	0	0
	Kalleh Ghoochi	2	0	7	1	0
	Ahmad Aghaei	1	0	0	9	0
	Akbari	0	0	0	0	10
		Predicted Class				

Table 7. Confusion matrix for Case 2: Images with 68% primary class and 8% each from other classes.

True Class		Predicted Class				
		Badami	Fandoghi	Kalleh Ghoochi	Ahmad Aghaei	Akbari
	Badami	**10**	**0**	**0**	**0**	**0**
	Fandoghi	2	8	0	0	0
	Kalleh Ghoochi	4	0	5	1	0
	Ahmad Aghaei	2	0	0	7	1
	Akbari	1	0	0	2	7

Table 8. Confusion matrix for Case 3: Images with 52% primary class and 12% each from other classes.

True Class		Predicted Class				
		Badami	Fandoghi	Kalleh Ghoochi	Ahmad Aghaei	Akbari
	Badami	**10**	**0**	**0**	**0**	**0**
	Fandoghi	2	6	0	2	0
	Kalleh Ghoochi	6	0	2	2	0
	Ahmad Aghaei	1	0	0	9	0
	Akbari	3	0	0	1	6

Table 9. Confusion matrix for Case 4: Images with 36% primary class and 16% each from other classes.

True Class						
	Badami	**10**	**0**	**0**	**0**	**0**
	Fandoghi	7	2	0	1	0
	Kalleh Ghoochi	5	0	1	4	0

	Ahmad Aghaei	3	0	0	7	0
	Akbari	7	0	0	2	1
		Badami	Fandoghi	Kalleh Ghoochi	Ahmad Aghaei	Akbari
	Predicted Class					

4. Discussion

The proposed YOLOv8m-based classification approach achieves an optimal balance between accuracy, speed, and computational efficiency, making it highly suitable for real-time agricultural applications. Compared to traditional models, such as the Gabor-KNN approach in Reference [14], which relies on manual feature extraction and CPU-based processing, YOLOv8 m significantly reduces both training time and computational demands while maintaining superior accuracy. The GPU-accelerated architecture enables real-time image processing, which is crucial for high-throughput agricultural sorting systems.

Additionally, the model's ability to operate efficiently on resource-constrained hardware, including edge devices, enhances its practical applicability in on-site agricultural environments. This is particularly beneficial for real-time decision-making in automated sorting lines, where rapid classification is essential to maintain operational efficiency.

Broader Applicability and Industrial Integration:

Beyond pistachio cultivar classification, the proposed method can be extended to a wide range of agricultural products that require automated sorting and quality control, including:

Nuts (e.g., almonds, walnuts, hazelnuts) – For variety classification and defect detection.

Fruits and vegetables (e.g., apples, citrus fruits, tomatoes) – For ripeness assessment, size grading, and external defect identification.

Grains and legumes – For sorting high-quality grains from defective or contaminated samples.

Tea leaves and coffee beans – For grading based on quality and appearance.

The ability to efficiently classify multiple categories makes this approach particularly valuable for food processing and packaging industries, where fast and precise automated sorting is crucial.

To further enhance scalability, this classification system can be seamlessly integrated into industrial automation, including:

Conveyor belt sorting systems – The model can be deployed in high-speed sorting lines, where rapid decision-making is required for maintaining throughput in food processing plants.

Robotic arms for automated selection and packaging – Machine vision-guided robotic systems can automatically separate defective or lower-grade products.

Edge computing devices for on-site classification – Optimizing the model for low-power hardware (e.g., Raspberry Pi, NVIDIA Jetson) will enable real-time, field-deployable quality assessments without requiring cloud-based processing.

Challenges and Future Improvements:

Despite its strong performance, deploying the model at commercial scale presents some challenges that require further research:

1. Dataset Expansion and Diversity

The current dataset, while effective for controlled conditions, lacks diversity in factors such as lighting variations, mixed-cultivar scenarios, and real-world environmental conditions.

Future work will focus on collecting a larger and more diverse dataset to improve robustness and generalization.

2. Generalization Across Different Environments

While the model achieves high accuracy, its performance may vary in unseen environmental conditions.

Techniques such as domain adaptation and transfer learning will be explored to allow the model to generalize across different datasets and imaging setups.

3. Hardware Constraints and Optimization

Deploying YOLOv8m in low-resource environments (e.g., mobile devices or edge computing platforms) may require model compression or pruning to maintain efficiency.

Future research will explore lightweight architectures that retain high accuracy while reducing computational costs.

Comparative Analysis of Computational Efficiency:

From a computational standpoint, YOLOv8 m significantly outperforms traditional methods, such as the Gabor-KNN approach. While the Gabor-KNN method is computationally lightweight during training, its reliance on manual feature extraction and CPU-based processing makes it inefficient for large-scale datasets and real-time applications.

In contrast, YOLOv8m benefits from GPU acceleration, reducing training time while enabling real-time inference, processing images within milliseconds. This makes it far more suitable for practical agricultural applications, where both speed and accuracy are critical. While the Gabor-KNN approach may be effective for smaller datasets, it is unsuitable for large-scale automated sorting systems, where computational efficiency is essential.

5. Conclusion

This study presents a deep learning-based method for classifying pistachio cultivars using YOLOv8m, highlighting its effectiveness for real-time automated sorting applications. The model was tested on a dataset of 500 sub-images representing five common pistachio cultivars, achieving an impressive average classification accuracy of 99.8%. Unlike traditional methods that handle single-instance classification, this approach allows for the simultaneous classification of multiple pistachios within a single image. This significantly boosts both speed and efficiency. The ability to process multiple items at once makes it highly suitable for industrial-scale sorting systems, reducing the need for manual labor while maintaining high precision.

Broader Impact and Future Directions:

Beyond pistachio sorting, the model's high performance suggests its applicability to other agricultural products, including fruits, nuts, vegetables, and grains. By integrating with automated processing lines, robotic sorting systems, and real-time quality control mechanisms, this approach has the potential to enhance throughput, reduce waste, and improve the efficiency of agricultural supply chains.

To further improve scalability and adaptability, future research will focus on:

Expanding dataset diversity by incorporating images from different lighting conditions, regions, and real-world industrial settings.

Exploring domain adaptation and transfer learning to improve generalization across different crops and environments.

Optimizing for edge computing to enable low-latency, on-device processing for portable and field-deployable systems.

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