

RESEARCH ARTICLE



A Machine Learning–Based Quality Control Algorithm for Tangerines Using Descriptors Derived from Peel Sectorization

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Abstract: Tangerines must fulfill specific quality control requirements established by major importing countries such as peel tone and ripeness, which are analyzed through visual inspection. This conventional evaluation is subjective since it depends on human perception; hence, automated solutions based on computer vision are considered, using different types of cameras, color models, adaptive thresholds, transforms, and convolutional neural networks (CNNs). In the state of the art, the proposed solutions are focused on determining peel defects by applying image processing and machine learning techniques with performance levels above 85%. In this work, an alternative solution is presented using RGB cameras with a resolution of 640×480 pixels and descriptors designed to characterize peel-tone variations by sectors, simulating human visual assessment for quality determination. These descriptors are used as inputs to classifiers based on support vector machines and multilayer perceptron neural networks, achieving accuracy levels above 92%. Finally, a comparative analysis between the proposed algorithm and CNN-based quality classifiers such as YOLOv11 and ResNet50 is done, proving that the proposed method outperforms CNN-based classifiers.

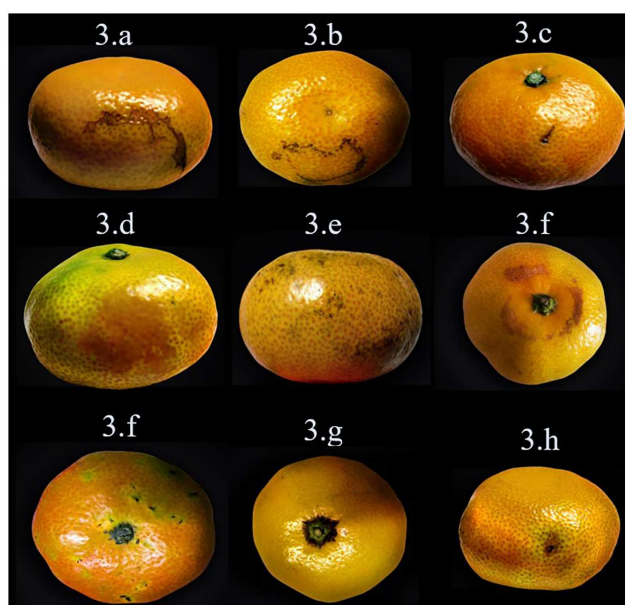
Keywords: tangerine, quality control, image processing, descriptors, machine learning

1. Introduction

Global production of tangerines, including clementines, satsumas, and tangerines, has shown moderate fluctuations, with China leading the way with a global supply accounting for over 70%. Furthermore, according to the United States Department of Agriculture (USDA), production in 2022 reached approximately 44.2 million tons, while, considering the 2022–2023 season, it stood at around 36.9 million tons, with China contributing nearly 72% of the total. For the 2023–2024 season, production had an increase especially due to yield improvements in China, Turkey, South Africa, and Morocco. For example, countries such as Morocco, the United States, and South Africa reflect high production between 1.15 million and 759,000 tons, showing increasing international demand. In South America, according to the USDA, Peru has become one of the main suppliers of tangerines; in 2024, the Peruvian citrus sector recorded tangerine exports exceeding 300,000 tons and US\$300 million, consolidating its position [1]. The determining characteristics required by trade standards and consumers are external qualities (peel) and ripeness, which must be fulfilled. At a regulatory level, international standards are focused on ripeness requirements (minimum juice content, soluble solids, and acidity ratio) and tolerances for external defects (peel damage, scarring, blemishes, and dehydration).

In Peru, the Instituto Nacional de Calidad (INACAL) issued the Technical Standard NTP 011.023:2014 [2], which describes several defects in tangerines, as shown in Figure 1 and Table 1.

Figure 1
Tangerine peel defects



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Table 1
Description of tangerine peel defects

Tangerine (Figure 1)	Name of defect	Description
3.a	Branched	Generated by branches
3.b	Application stains	Generated by fungus
3.c	Unhealed wounds	Generated by wounds
3.d	Hits	Generated by hits
3.e	Mites	Generated by mite
3.f	Thrips	Generated by thrip
3.g	Queresas	Generated by queresas
3.h	Sooty mold	Generated by fruit fly

As shown in Figure 1 and Table 1, visual peel features can be identified by localized contrast and variability in color tone.

Consumers identify tangerines' peel imperfections through visual perception, which makes the process subjective. Hence, image processing techniques replace this method by quantifying localized variance and applying sector-wise adaptive statistical thresholds.

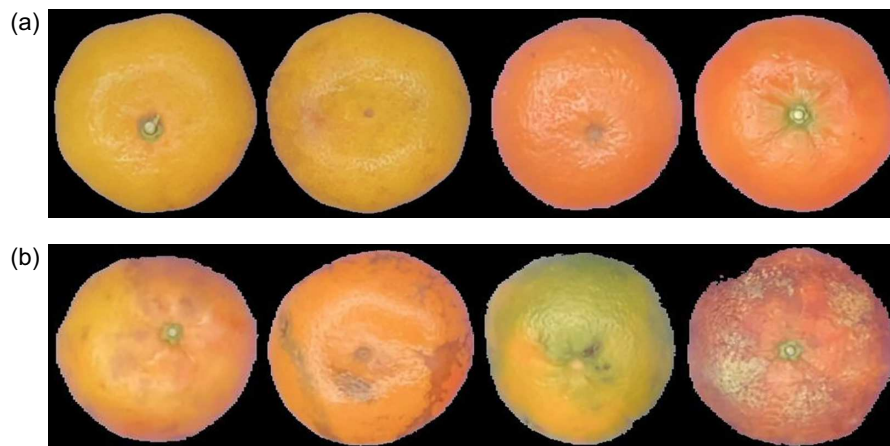
Figure 2 shows two groups of tangerines classified by consumers as "good quality" and "poor quality" using visual inspection, where the uniformity of hue and color on the tangerine peel are the identified features, which, together with the presence of few and small green regions, tend to lead consumers to select the "good-quality" option (see Figure 2(a)). On the other hand, for "poor-quality" samples, consumers observe gradual or abrupt changes in hue and coloration across different peel regions or the presence of extensive green regions. These features can be translated as high variance, which indicates the sample is still unripe (see Figure 2(b)).

The selection of only two quality levels aims to construct a supervised dataset that is not affected by the subjectivity of consumer decisions. In this context, a tangerine is defined as "good quality" if its peel does not show any of the defects illustrated in Figure 1 and described in Table 1. In contrast, the presence of a minimal visible defect leads to its classification as "poor quality." Based on these criteria, and including consumer input, the supervised dataset was compiled and used to develop the proposed algorithm.

On the other hand, for applications that process large quantities of tangerines, quality control based on visual inspection becomes time-consuming and inefficient; thus, an automated process solution for quality determination is required, which is one of the key motivating factors for the development of the present work.

In the state of the art, several approaches use image processing techniques, choosing different types of cameras with a performance level above 85%. These techniques apply color models, transforms, adaptive thresholding, and trained classifiers to detect damage and defects on the peel. This work proposes an alternative solution based on image processing using RGB cameras with a resolution of 640×480 pixels, descriptors designed to characterize, at a regional level, the color variations of the tangerine peel, thereby resembling consumers' quality evaluation criteria. These descriptors are used as input to classifiers based on support vector machines (SVMs) and backpropagation neural networks (NNs), which achieve a classification accuracy exceeding 92%. In addition, a comparative analysis is presented between the proposed algorithms' results and those achieved by tangerine quality classifiers based on YOLOv11 and ResNet50 convolutional neural networks (CNNs). Moreover, this work can be adapted to different quality requirements depending on the training provided to the classification algorithms (restricted to two levels). However, it will have the best performance for the tangerines with a uniform orange peel color as it is for the Clementine variety and lesser for the Satsuma variety.

Figure 2
Quality classification groups: (a) "good quality" and (b) "poor quality"



It is relevant to mention that the proposed algorithm is meant for solutions that employ an enclosed setup with controlled illumination for image acquisition. This setup is applied in industrial applications for fruit classification due to its high detection and classification performance, which ensures high-quality images while minimizing unwanted artifacts that could adversely affect fruit classification, as presented in [3, 4].

2. Literature Review

The state-of-the-art proposals focused on algorithms and the automation of the tangerine quality control process are detailed in Table 2 with their strengths and weaknesses. The ones with an accuracy around 80% apply color models, thresholds, and

transforms, while the others, despite using hyperspectral cameras and CNNs for classification and detection of specific problems with tangerines, involve high computational and implementation costs in automation processes.

The proposal of the present work is based on descriptors computed by sectors of the tangerine peel; therefore, the classifiers used, such as multilayer perceptron neural networks with back-propagation training (NN-MLP-BP) and SVMs, can be trained using the hue variations captured by these sector-based descriptors. The descriptor computation and the NN-MLP-BP and SVM classifiers do not require high computational load compared to CNN-based approaches and can be efficiently executed on small-board computers for continuous quality control of large quantities of tangerines.

Table 2
State of the art

Category	Technique	Strengths	Weaknesses	Refs.
Traditional computer vision and geometric analysis	Sliding window, histogram statistics, adaptive threshold, morphological operations, and shape and tone characteristics	Its local segmentation based on classification reduces threshold calculations by 80%, ensuring accuracy and robustness in the face of light variations	It focuses on defect segmentation algorithms, which involve a high computational load. Furthermore, it omits details about the acquisition system	[5]
	Computer vision, Blob analysis, morphology, Halcon software, and Fourier transform	The system integrates high-precision industrial hardware with Halcon, achieving 87.5% accuracy through Fourier analysis	It has a high computational cost, requiring the processing of 30 images per tangerine. In addition, it relies on high-speed cameras and is governed by Chinese standards	[6]
	It uses an image analysis and machine learning methods to identify and classify four types of defects in Kinnow tangerine through adaptive thresholding, RGB, HSV, CIELAB, Random Forest, and neural networks	Two machine learning techniques were trained: Random Forest classifier and neural networks, achieving accuracies of 93.5% and 89.3%, respectively	The highest misclassification rates occurred for wind and thrip scars due to similar texture and color characteristics. A dataset of tangerine images with defects was prepared under controlled laboratory conditions	[7]
Deep learning	YOLO architecture optimized with attention mechanisms Three-Dimensional Coordinate Attention (TDCA) and multiscale mechanisms Focusing Diffusion Pyramid Network (FDPN), Hybrid Dilated Residual Attention Block (HDRAB)	High accuracy in detecting variable defects (84.2% to 98.7% mAP). Parameter reduction and efficiency in small objects	They are limited exclusively to defect detection, omitting classification by technical standards. They require models with high computational load	[8, 9]
	Deep CNNs (ResNet, EfficientNet, MobileNet) with transfer learning and K-Medoids segmentation	Maximum classification accuracy (99% to 99.53%) with low inference latency (54 ms), ideal for real-time processes	Despite their speed, they have high latency in the training and deep execution phase. They only focus on three maturity categories	[10, 11]
	Gradient ensembles (XGBoost, LightGBM) and color quantification in CIELAB spaces with YOLO	Nondestructive volume estimation capability ($R^2 = 0.971$) and objectivity in color indices at high speed (25 fps)	They do not assess the overall quality of citrus fruits according to standards. They require expensive hardware (two high-resolution cameras)	[12, 13]

(Continued)

Table 2
(Continued)

Category	Technique	Strengths	Weaknesses	Refs.
Spectral analysis	Use of hyperspectral images and Visible and Near-Infrared (Vis-NIR) with variable selection Competitive Adaptive Reweighted Sampling (CARS), Successive Projections Algorithm (SPA), Iteratively Retaining Informative Variables (IRIV), Principal Component Analysis (PCA), and Linear Discriminant Analysis (LDA)	They achieve accuracies of 94.9% to 97.27% using only 5 key bands, which simplifies the processing of complex data	High cost of the acquisition system and high latency in capture. In addition, the models have a high computational load and are limited to non-domestic varieties	[14–17]
	Integration of fluorescence images with complex architectures Graph Convolutional Neural Network-Long Short-Term Memory-Attention (GCNN-LSTM-AT) and CNN (ResNet50)	They achieve up to 100% accuracy in invisible bruises and an R^2 of 0.9885 in internal quality Soluble Solid Content (SSC), processing 10 fruits per second	High computational and hardware costs due to the use of hyperspectral or fluorescence cameras. They focus only on internal aspects, omitting external quality	[18, 19]
	Implementation in TinyML (ESP32/ESP8266) with 18-channel Vis-NIR sensors and dynamic control with Proportional-Integral-Derivative (PID)/Node-RED	High efficiency in low-cost devices (R^2 of 0.9956 in sugar) and batch optimization, increasing classification by an additional 11.09%	It does not address quality by simulating human visual inspection, limiting itself only to maturity stages and chemical parameters that are difficult to integrate into industrial lines	[20, 21]

3. Materials and Methods

The present study focuses on two main components: the acquisition of tangerine images and the design of a quality classification algorithm based on image processing and machine learning (its block diagram is shown in Figure 3). The input image, acquired in the RGB primary components format, goes through a sequence of processing stages and yields the final classification output.

The materials and methods used and developed for each component and processing stage are described in the following sections.

3.1. Image acquisition and dataset

The image acquisition process was performed in a closed chamber with dedicated lighting, where a blue conveyor belt positioned the tangerines on the image acquisition surface (see

Figures 4 and 5). The chamber dimensions were 360 mm (length) $\times$ 300 mm (width) $\times$ 220 mm (height), and its purpose was to ensure a uniform environment during the sampling process and to isolate the system from external light. Moreover, the interior illumination was provided by two 12 V LED rows installed along the upper corners of the chamber (see Figure 4).

In addition, an RGB camera was mounted at the top of the chamber, and a laser emitter with a photodetector was installed at the acquisition surface level in order to detect the presence of tangerines and automatically trigger the image capture (see Figure 4). This camera's settings were configured to capture images with a resolution of 640×480 pixels using the RGB color model.

On the other hand, the use of the blue conveyor belt (see Figure 6) enabled proper separation and segmentation of the background from the fruit and its conversion to a black background (see Figure 5), which facilitated the processing of the images by the proposed algorithm.

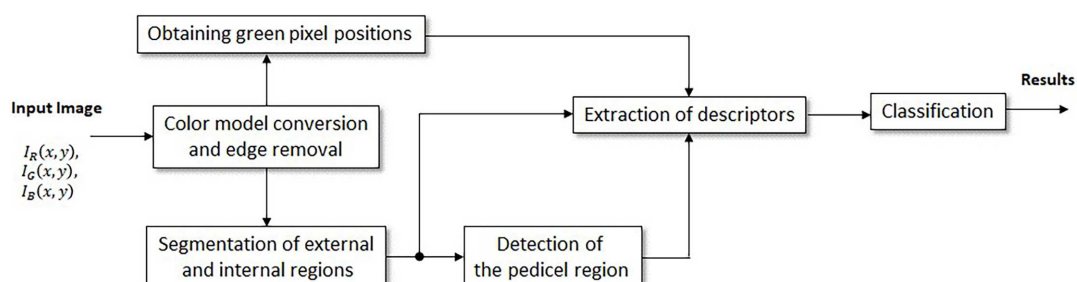
Figure 3
Block diagram of the proposed algorithm

Figure 4
Internal section of the image acquisition chamber

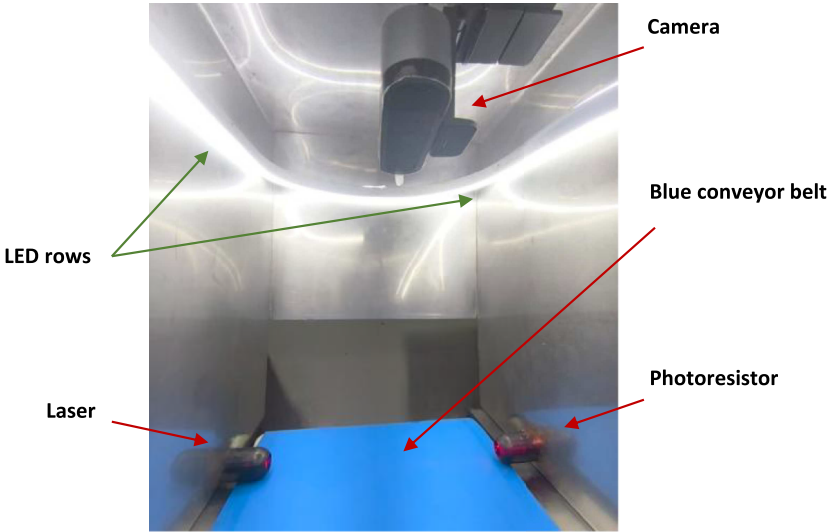


Figure 5
(a) Original tangerine image acquired in the RGB color model and (b) original tangerine image with background separation and segmentation in the RGB color model

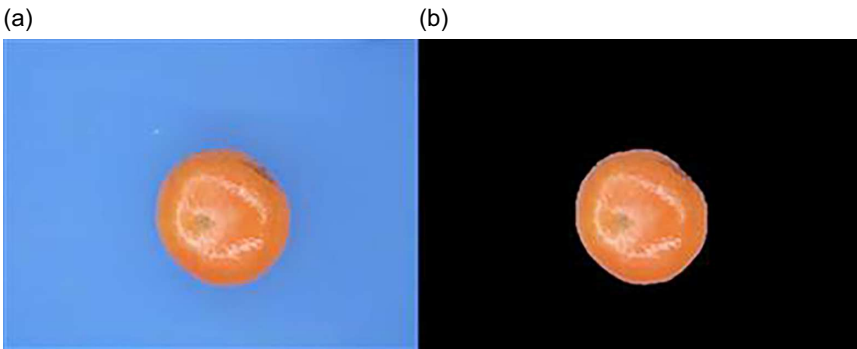
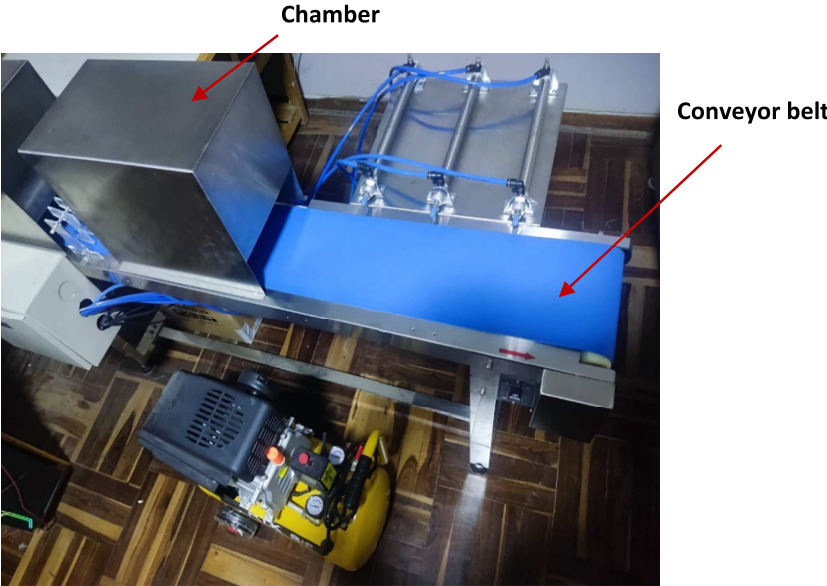


Figure 6
External view of the chamber above the conveyor belt



The black background (see Figure 5(b)) image is used as the input to the proposed algorithm (see Figure 3). This image can be expressed in its primary RGB components as $I_R(x, y)$, $I_G(x, y)$ and $I_B(x, y)$, where (x, y) denote its spatial coordinates for $x = 0, 1, 2, \dots, M - 1$ and $y = 0, 1, 2, \dots, N - 1$. In this case, $M = 480$ and $N = 640$.

A total of 170 tangerines were considered during the acquisition process, yielding 340 original images where, in this case, two images were captured per tangerine, corresponding to its two faces.

A supervised dataset was constructed based on consumer evaluation using these images. Each tangerine was assessed by visual inspection and assigned to one of two classes: “good quality” or “poor quality.” With this classification, 148 additional images of “good-quality” tangerines and 148 additional images of “poor-quality” tangerines were generated using data augmentation techniques to obtain more generalized results and enhance the reliability of the proposed method.

The dataset was grown using seven specific augmentations: horizontal/vertical flips, brightness and contrast tweaks, hue shifts, gamma correction, CLAHE (local adaptive contrast), and affine transformations like translation and rotation. The criteria used for setting thresholds focused on keeping photometric changes light rather than drastic. It is important to mention that “poor-quality” tangerines exhibit greater variability in peel manifestations. Therefore, they were represented in a larger proportion in the dataset compared to “good-quality” tangerines, which exhibit higher uniformity in terms of tonalities and textures. In addition, the proposed method employs machine learning techniques, such as NN-MLP-BP and SVM, which do not require large datasets to achieve satisfactory results, in contrast to deep learning-based models. Table 3 presents the final composition of the dataset used in this work.

Table 3
Number of images in the supervised dataset

“Good quality”	“Poor quality”	Total
266	370	636

Finally, it should be noted that the process of obtaining tangerine samples and images required close coordination with specialists, as well as the consideration of specific design and configuration aspects. In this regard, the following elements were considered:

- 1) Continuous coordination with tangerine producers and quality control specialists to ensure the appropriate selection of samples comprising the dataset.
- 2) The positioning, uniform distribution, and intensity adjustment of the internal illumination system (both lateral and overhead) were carefully optimized to minimize undesired shadows and specular highlights.
- 3) The speed of the conveyor belt was adjusted to reduce motion blur in the images, considering both the camera shutter speed and the processing capabilities of the hardware.

3.2. Color model conversion and edge removal

Despite choosing enclosed environments with appropriately positioned and calibrated lighting, image acquisition chambers often exhibit some non-uniform lighting, which introduces

shadows, global darkening, and thin dark streaks along object boundaries. Hence, it can yield false positives, leading to the fruit being misclassified as “poor quality” despite not warranting that label. To reduce lighting-related artifacts at object boundaries, a thin rim is detached from the perimeter of each processed tangerine (Figure 7). This operation was integrated into the pre-processing pipeline to ensure that subsequent segmentation and classification stages were not affected by shadowing or dark streaks that are unrelated to intrinsic fruit quality. Specifically, the input RGB image (Figure 7(a)), with channels $I_R(x, y)$, $I_G(x, y)$, $I_B(x, y)$, was transformed into the HSV color space to obtain $I_H(x, y)$, $I_S(x, y)$, $I_V(x, y)$ with each component in the integer range $[0, 255]$ [22]. A binary mask $Z1(x, y)$ was then derived by thresholding the value component $I_V(x, y)$ (Figure 7(b-c)); $\mu_1 = 0$ was adopted because $I_V(x, y) = 0$ corresponds to pixels not belonging to the tangerine, thereby promoting a conservative separation of foreground from background. Subsequently, $Z1(x, y)$ was processed with a Canny edge detector using a Gaussian smoothing filter of variance 2 [23], producing an edge map $Z2(x, y)$ that delineates the tangerine boundary (Figures 7(d) and (e)).

Finally, pixels on the detected boundary were removed from $Z1(x, y)$ (obtaining the mask $Z3(x, y)$) and from the original RGB image, yielding the corrected image with primary components $I_R(x, y)$, $I_G(x, y)$, $I_B(x, y)$ and HSV components $I_H(x, y)$, $I_S(x, y)$, $I_V(x, y)$. Consequently, the resulting tangerine no longer exhibits darkened borders that could otherwise bias the classification stage (Figure 7(f)).

3.3. Obtaining green pixel positions

Defects in tangerines are predominantly manifested within the orange-toned regions of the peel, whereas the green areas typically exhibit consistent texture, color, and shading. As a result, green regions do not introduce substantial confounders for the classification stage beyond their chromatic identity, and the analysis can focus on distinguishing orange from green pixels without confusing artifacts with pathologies.

Therefore, green is discriminated from orange pixels using the hue component $I_H(x, y)$ obtained in the preceding procedure. In particular, $I_H(x, y)$ was thresholded at $\mu_2 = 34$, a value selected after systematic visual inspection across tangerines containing both orange and green sectors. This choice separated the chromatic modes associated with each class and improved label reliability. Figure 8 summarizes the workflow. Specifically, Figure 8(a) shows the input image with components $I_R(x, y)$, $I_G(x, y)$, $I_B(x, y)$, Figure 8(b) depicts the identified green sector, and Figure 8(c) presents the histogram of $I_H(x, y)$, where the applied threshold delineates the orange versus green distributions. Consequently, the result is the set of spatial positions of pixels classified as green, expressed as:

$$S_{green} = \{(x_i, y_i) \in Z^2 \mid i = 0, 1, \dots, N_{green} - 1\} \quad (1)$$

Where:

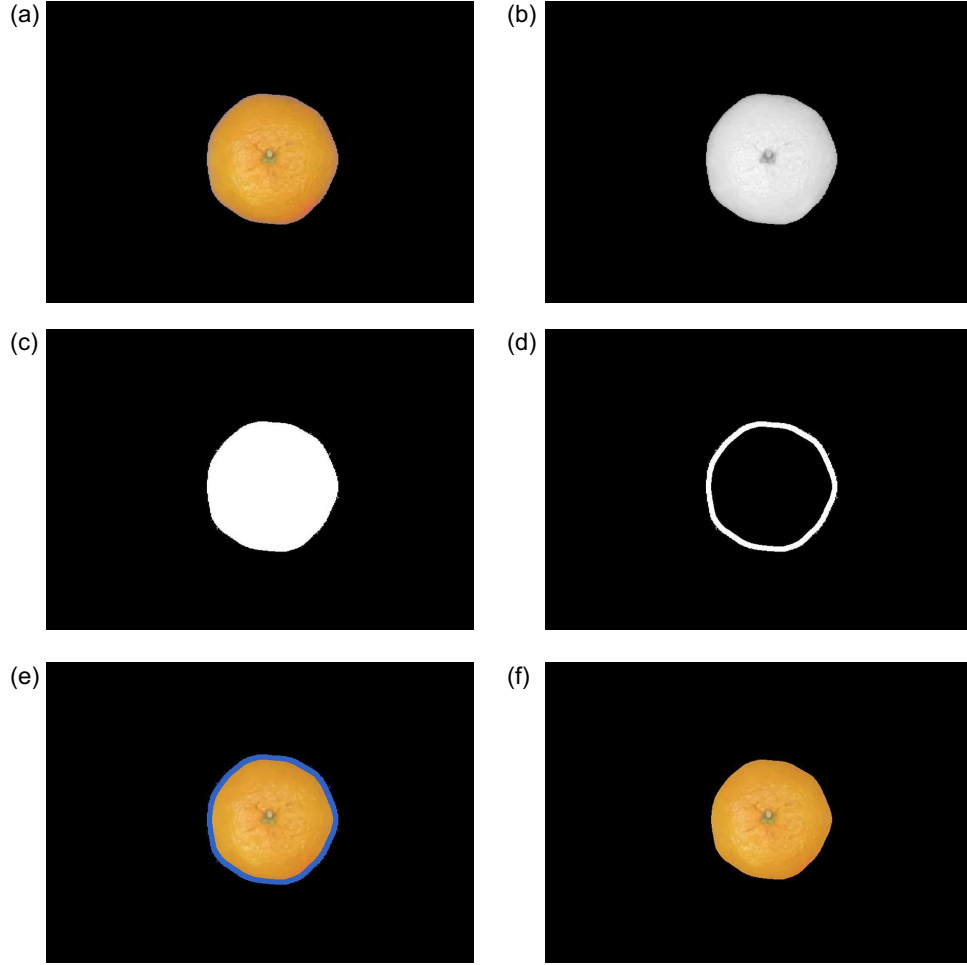
N_{green} : Number of pixels classified as green.

3.4. Segmentation of external and internal regions

For the targeted analysis of peel chromaticity, the tangerine was segmented into two concentric regions: an internal region and an external region. This segmentation supports the

Figure 7

Edge removal: (a) input image, (b) value component, (c) binarized value component, (d) binary mask of the edge to be removed, (e) input image with the edge marked for removal, and (f) input image after edge removal



extraction of local descriptors that quantify hue variance within each zone, reflecting the sector-wise evaluation implicitly performed by human inspectors during visual assessment.

Segmentation was driven by the detection of specular highlights generated under controlled illumination in the image acquisition enclosure. As shown in Figure 9(a), these highlights typically occur nearly concentric with the geometric center of the fruit; this characteristic was exploited to define the boundary that delineates the internal and external regions.

The segmentation begins with 3×3 median filtering of $I1_G(x, y)$ and $I1_B(x, y)$ to attenuate minor unwanted contrasts [24], yielding $I2_G(x, y)$ and $I2_B(x, y)$ (see Figures 9(b) and 9(c)). These channels are preferred since, on the tangerine peel, they present greater contrast and more intense specular highlights than alternative components. Subsequently, the contrast of $I2_G(x, y)$ and $I2_B(x, y)$ was enhanced using histogram stretching [23], producing $I3_G(x, y)$ and $I3_B(x, y)$ (Figures 9(d) and (e)). This operation further amplifies the highlight points relative to the surrounding peel, thereby simplifying subsequent detection and segmentation. Contrast may however be further improved by using a composite of $I3_G(x, y)$ and $I3_B(x, y)$, given by:

$$I3_{BG}(x, y) = I3_G(x, y) \times I3_B(x, y) \quad (2)$$

In this case, $I3_{BG}(x, y)$ was then normalized to the image range $[0, 255]$ (see Figure 9(f)). Note that the specular highlights exhibit much higher intensity than the rest of the tangerine surface. This eases the thresholding of $I3_{BG}(x, y)$ (with threshold $\mu_3 = 50$) to produce the binary mask $Z4(x, y)$, which isolates only the most significant specular points (see Figure 9(g)).

Next, the center of mass (x_c, y_c) of $Z4(x, y)$ is determined, and—along the vertical and horizontal directions—the largest distance $d1$ from (x_c, y_c) to the position of the last white pixel encountered is computed. Subsequently, a binary mask $Z5(x, y)$ with a hexagonal shape (approximating an ideal circular shape), centered at (x_c, y_c) and with circumradius $d1$ is generated. The mask $Z5(x, y)$ represents the detected internal region of the tangerine (see Figure 9(h)).

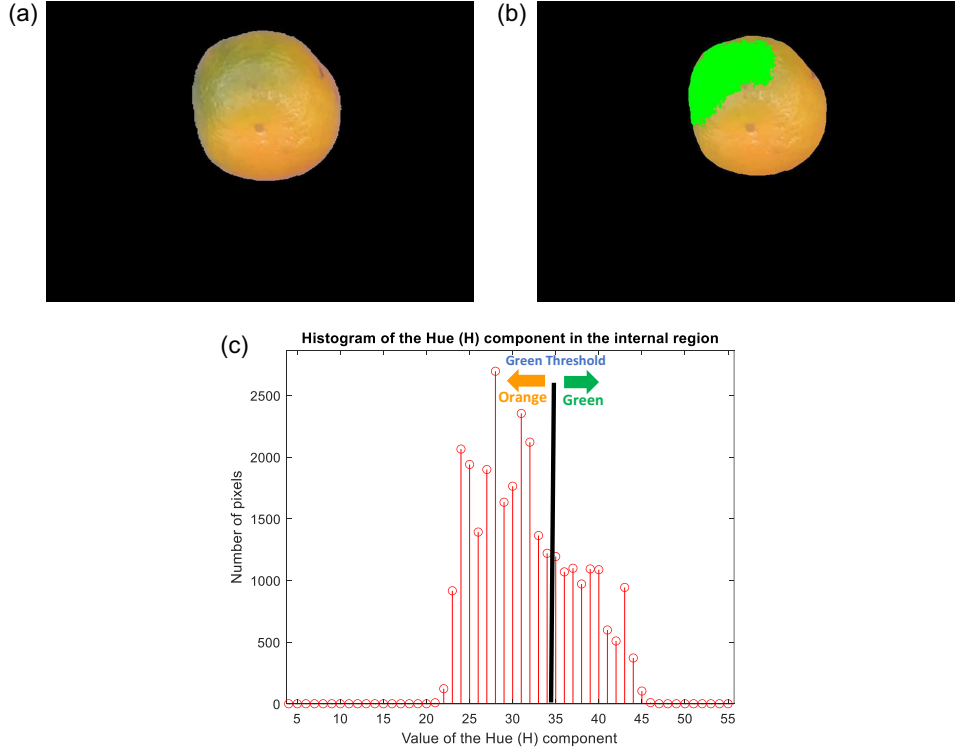
Finally, to obtain the external region, a binary mask $Z6(x, y)$ (see Figure 9(i)) is generated as follows:

$$Z6(x, y) = Z3(x, y) \times (1 - Z5(x, y)) \quad (3)$$

Then, using $Z5(x, y)$ and $Z6(x, y)$, the internal and external regions of the RGB image with components $I1_R(x, y)$, $I1_G(x, y)$, and $I1_B(x, y)$ are segmented (see Figures 9(j) and (k), respectively). In this case, the RGB image of the segmented internal region is denoted as $II_R(x, y)$, $II_G(x, y)$, $II_B(x, y)$. For the

Figure 8

Green area detection and marking: (a) input image, (b) input image with the detected green area marked, and (c) global histogram of hue component



segmented external region, it is denoted as $IE_R(x, y)$, $IE_G(x, y)$, and $IE_B(x, y)$.

3.5. Detection of the pedicel region

The pedicel is the green region of the tangerine peel (approximately located at the center of the internal region) that should not be considered for quality classification. Thus, detecting the position of the pixels that constitute the pedicel helped to prevent their inclusion in the calculation of descriptors, avoiding the influence of undesired contrasts or hues that do not correspond to genuine quality defects in the tangerine. To obtain the positions of these pixels, the hue component of the internal region was computed (see the example in Figure 10(a)), which was denoted as $II_H(x, y)$. Then, the spatial position of pixels was extracted to satisfy the condition $II_H(x, y) > \mu_4$ (with $\mu_4 = 30$), that is, pixels exhibiting green hues (see Figure 10(b)). Using these positions, a binary mask $Z7(x, y)$ was formed, where a value of 1 corresponds to pixels meeting the above condition (white region in Figure 10(c)). Next, the center of mass of $Z7(x, y)$, denoted as (x_{c1}, y_{c1}) was computed.

From this center, a hexagonal binary mask $Z8(x, y)$ centered at (x_{c1}, y_{c1}) was generated (white region in Figure 10(d)) with circumradius $d2 = 30$, an appropriate value to define the pedicel's domain in the acquired tangerine images. Pixel positions were identified to fulfill $\mu_5 \leq II_H(x, y) \leq \mu_4$ (with $\mu_5 = 27$) and set those positions to 1 in $Z7(x, y)$.

This step marks pixels that belong to the pedicel but exhibit a transitional coloration from green to orange. Consequently, the mask $Z9(x, y)$ that delineates the pedicel (see the white region in Figure 10(e)) can be expressed as:

$$Z9(x, y) = Z7(x, y) \times Z8(x, y) \quad (4)$$

It is important to highlight the purpose of the hexagonal mask $Z8(x, y)$, which is to retain only the green pixels located in the vicinity of the center of the internal region. This design choice is motivated by the very high probability—established through extensive testing—that pixels in this area that accomplish the specified conditions belong to the pedicel.

3.6. Extraction of descriptors

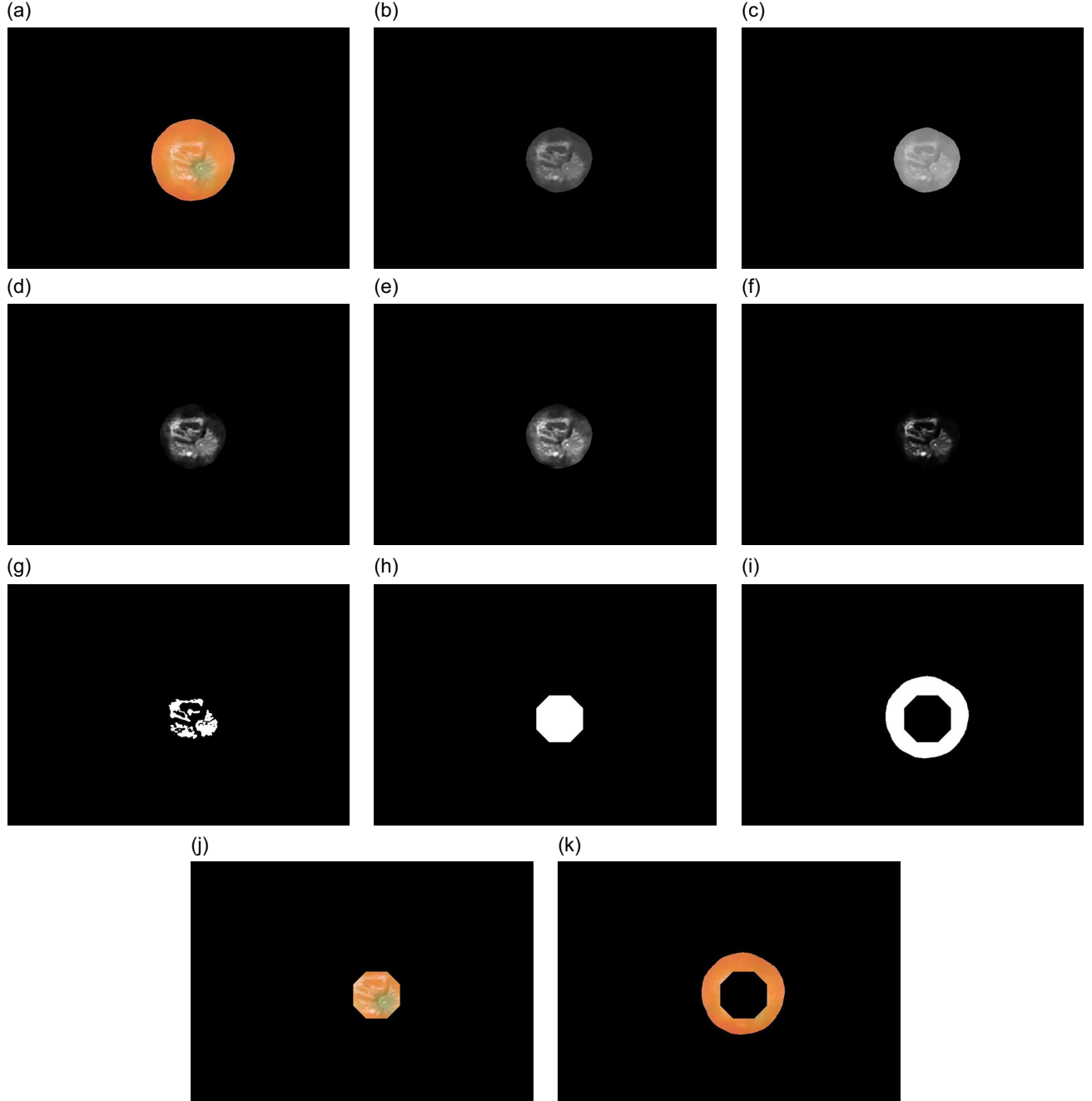
As previously mentioned, the computation of the tangerine descriptors was performed in a sectorized manner to quantify the variance of color and tonal variations by region. This approach is supported by Bhagwat and Dandawate [25], demonstrating that handcrafted features are often more effective for characterizing local surface defects and lesions. The division was carried out as follows:

- 1) External region: The external region was divided into four parts, and four descriptors were obtained (one for each part). Figures 11 and 12 illustrate this process for a “good-quality” tangerine and a “poor-quality” tangerine, respectively.
- 2) Internal region: A single descriptor of tonal variation was computed (excluding the pedicel region). Figures 13 and 14 illustrate this process for a “good-quality” tangerine and a “poor-quality” tangerine, respectively.
- 3) Global evaluation: The entire surface visible to the camera was divided into sectors in the form of concentric rings (excluding the pedicel region), and two descriptors were obtained. Figures 15 and 16 illustrate this process for a “good-quality” tangerine and a “poor-quality” tangerine, respectively.

The details of each case are described below:

Figure 9

Segmentation of external and internal regions: (a) input image; (b, c) B and G components; (d–f) B, G, and their product (BxG) after contrast enhancement; (g) thresholded product; (h, i) internal and external segmentation masks; and (j, k) resulting internal and external regions



1) External region

For the external region, it was verified that the primary components R (red) and G (green) most clearly revealed the intensity variations of the peel; therefore, the computation of the photometric descriptors was performed from a combined component $IE_{RG}(x,y)$ defined as:

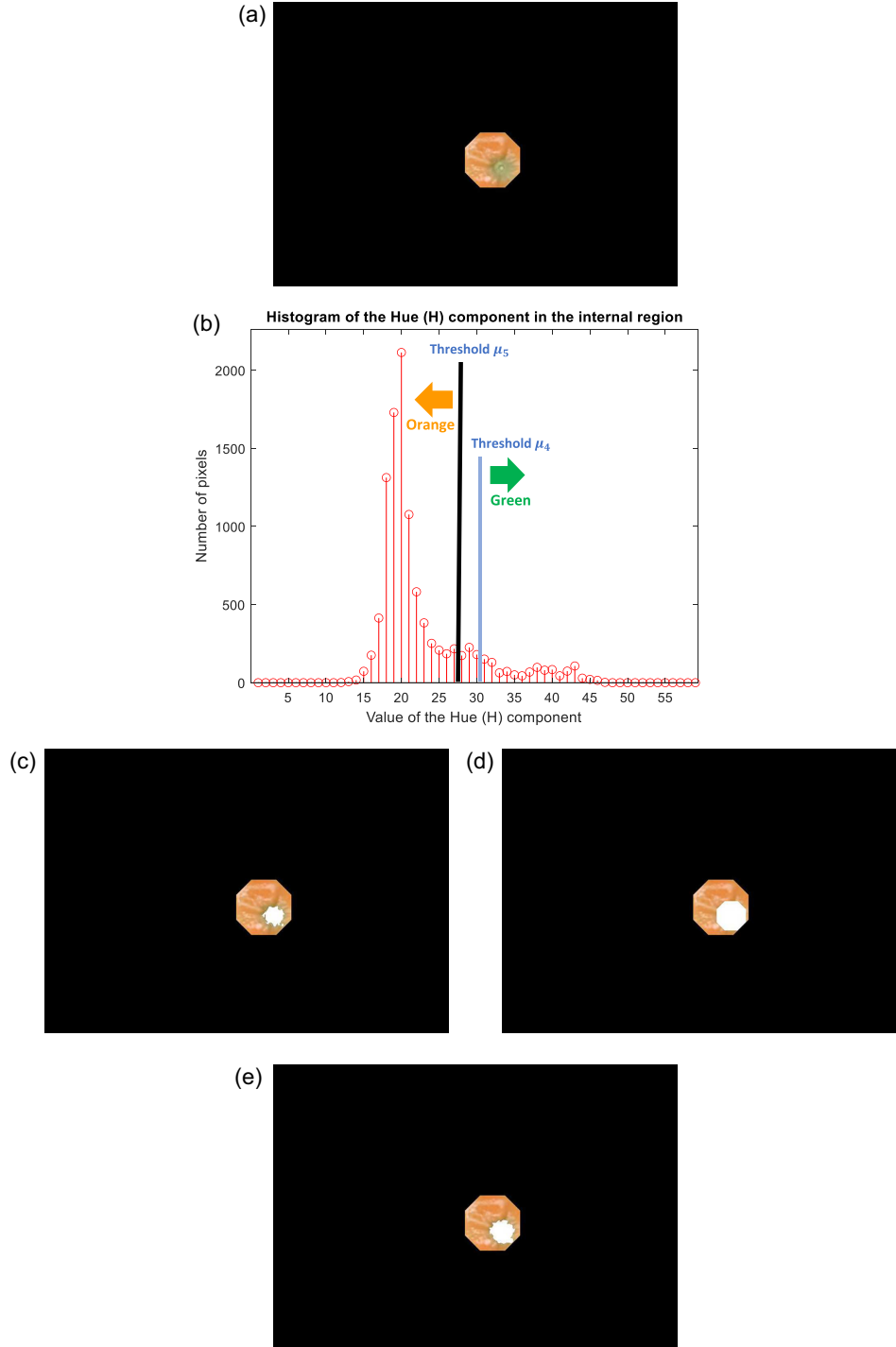
$$IE_{RG}(x,y) = 0.7 \times (IE_R(x,y))^2 + 0.3 \times (IE_G(x,y))^2 \quad (5)$$

Then $IE_{RG}(x,y)$ was normalized to the range [0,255] (8 bits per pixel) so that it could be processed as an image (see

Figures 11(b) and 12(b)) and divided into four parts: upper, left, right, and lower. Each part was subjected to gamma correction [23] with $\gamma = 1.5$ and requantized to 5 bits per pixel (32 gray levels in the range [0,255]) to enhance and highlight small contrasts that may be present in that sector of the tangerine (see Figures 11(c, e, g, i) and Figures 12(c, e, g, i)).

For each part, the histogram and its probability density function (PDF) were computed. Finally, the corresponding variances were obtained, which are defined as σ_{upper}^2 , σ_{left}^2 , σ_{right}^2 and σ_{lower}^2 (see Figures 11(d, f, h, j) and Figures 12(d, f, h, j)). Note that the variance values corresponding to a “good-quality” tangerine

Figure 10
Pedicle area detection and marking: (a) internal region, (b) histogram of hue component, (c) result with threshold 1, (d) dilated mask, and (e) final result



(Figure 11) are much lower than those of a “poor-quality” tangerine (Figure 9), showing that tonal uniformity is an important indicator for the classification process.

2) Internal region

For the internal zone (Figures 13(a) and 14(a)), the procedure is applied only to pixels that have not been classified

as green and that do not belong to the pedicle; these are referred to as eligible pixels. In this region, the R-G component was also employed, which was denoted as $II_{RG}(x, y)$. The contrast of $II_{RG}(x, y)$ is likewise enhanced by applying gamma correction with $\gamma = 2$ and requantization to 4 bits per pixel and 16 gray levels in the range [0,255] (see Figures 13(b) and 14(b)).

Figure 11

Extraction of external region descriptors for a good-quality tangerine: (a) input image; (b) R-G component of the external region; (c, e, g, i) upper, left, right, and lower parts after gamma correction and requantization; and (d, f, h, j) corresponding PDFs and variances for each part

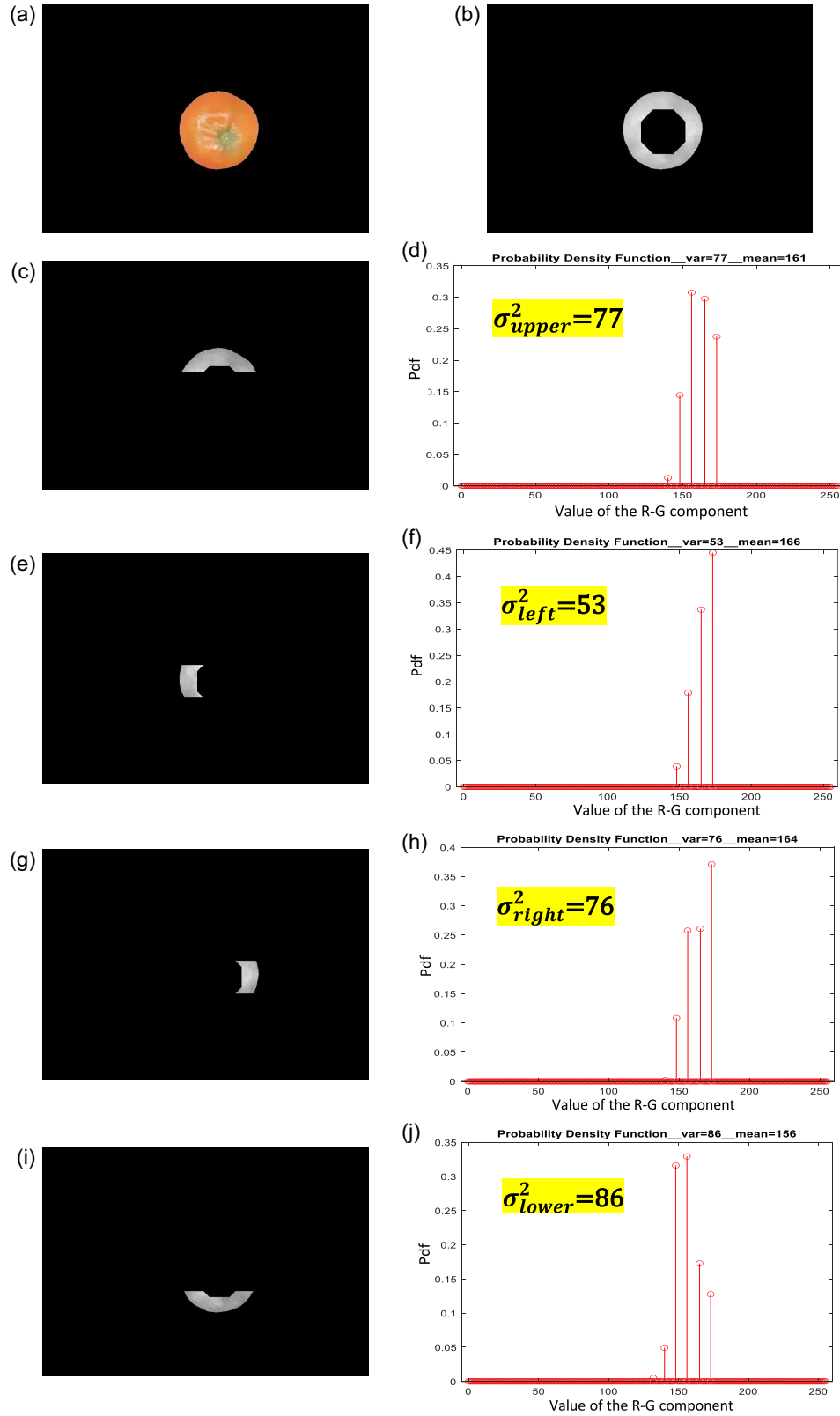


Figure 12

Extraction of external region descriptors for a poor-quality tangerine: (a) input image; (b) R-G component of the external region; (c, e, g, i) upper, left, right, and lower parts after gamma correction and requantization; and (d, f, h, j) corresponding PDFs and variances for each part

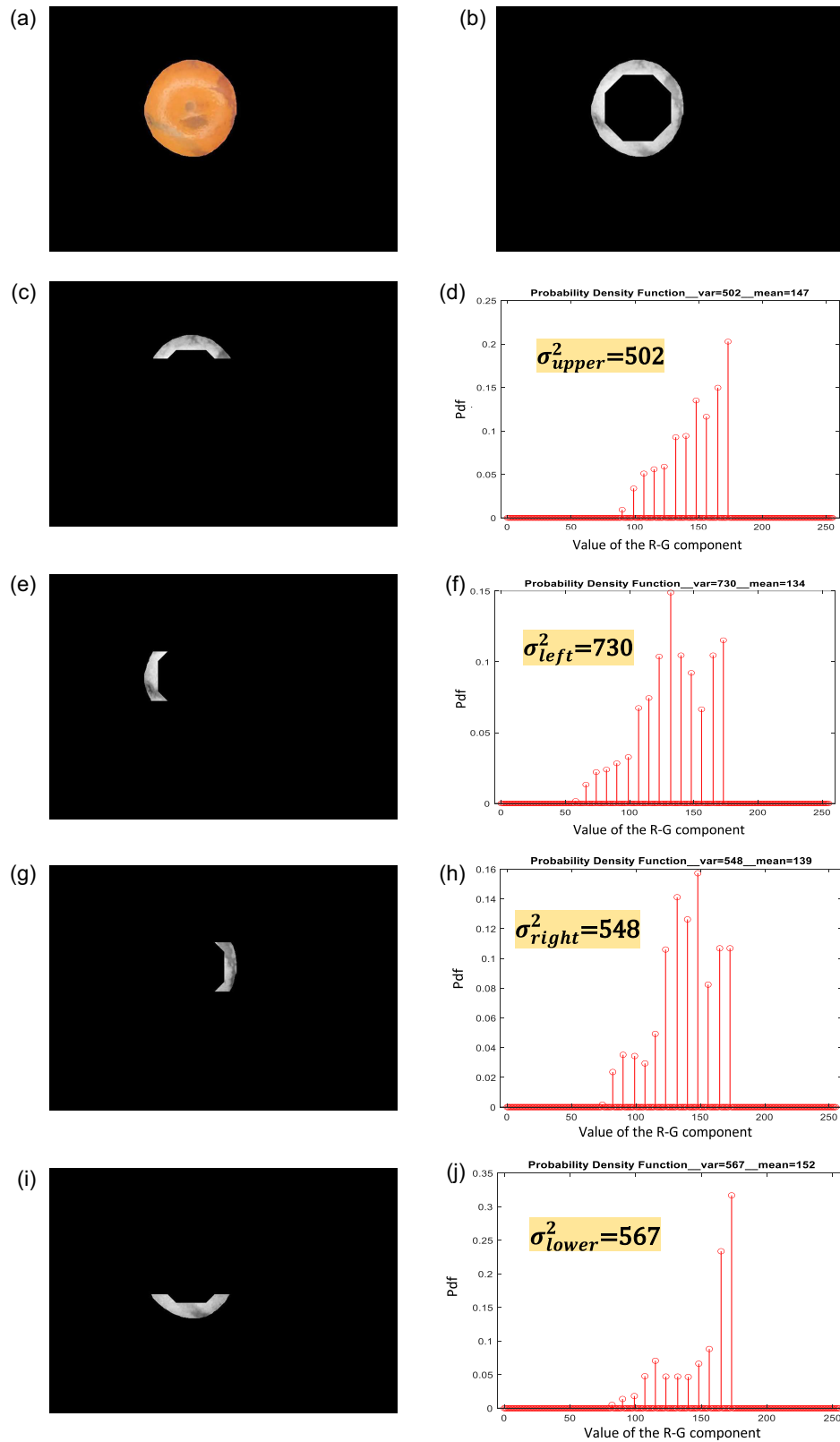
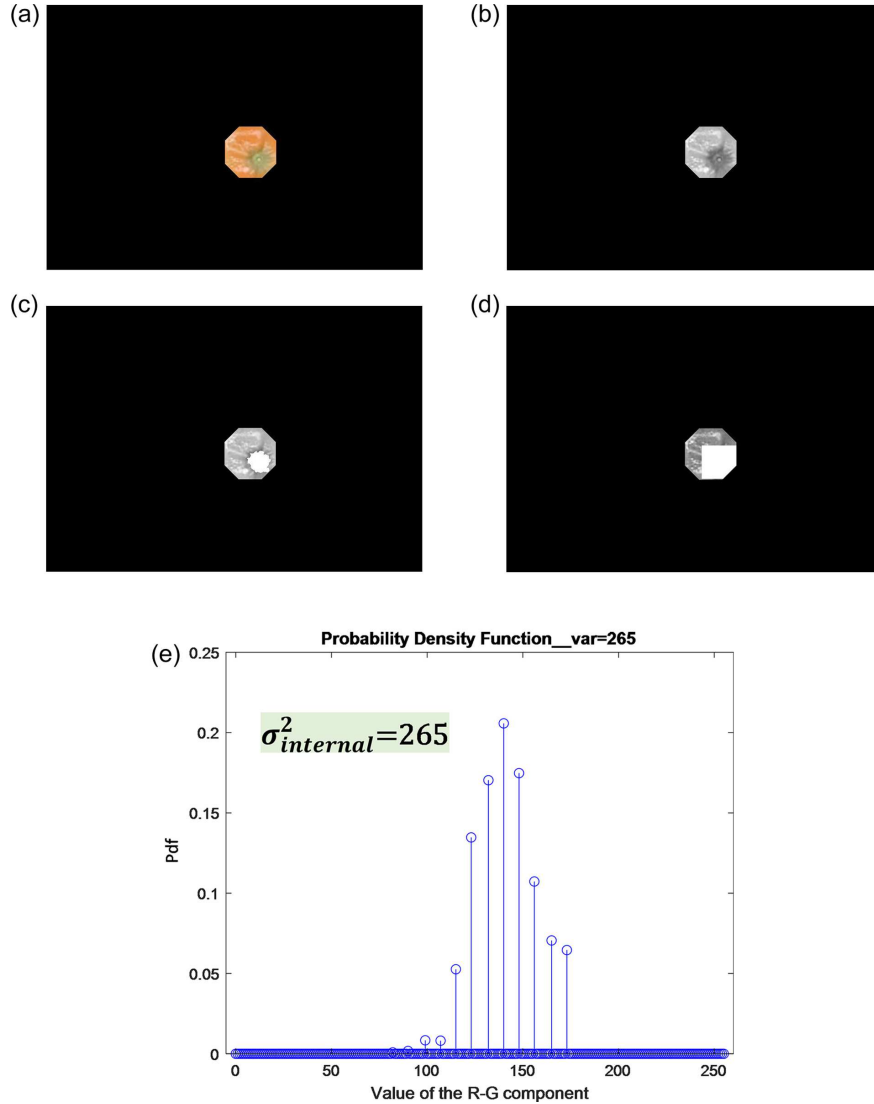


Figure 13

Extraction of internal region descriptor for a good-quality tangerine: (a) internal region; (b–d) R-G component with gamma correction and requantization showing (b) the unmasked area, (c) the masked pedicel, and (d) the enlarged pedicel marking; and (e) PDF and variance of the R-G component excluding the pedicel area



The pedicel area (obtained in section 3.5) is also evaluated to determine whether it is less than 20% of the total area of the internal zone. If so, the pedicel region is expanded into a rectangular shape (see Figures 13(c, d) and 14(c)) until its area is equal to or greater than the indicated percentage (to further eliminate possible pedicel pixels that could affect the descriptor calculation). Once the final positions of the pixels comprising the expanded pedicel are defined, the histogram of the pixels classified as eligible and its corresponding PDF are computed to obtain the variance of the internal zone (see Figures 13(e) and 14(d)), which is denoted as $\sigma^2_{internal}$. Combining this result with the variances computed for the external region yields the descriptor **TotalVar**, which is defined as:

$$\text{TotalVar} = \sigma_{upper}^2 + \sigma_{left}^2 + \sigma_{right}^2 + \sigma_{lower}^2 + \sigma_{internal}^2 \quad (6)$$

3) Global evaluation

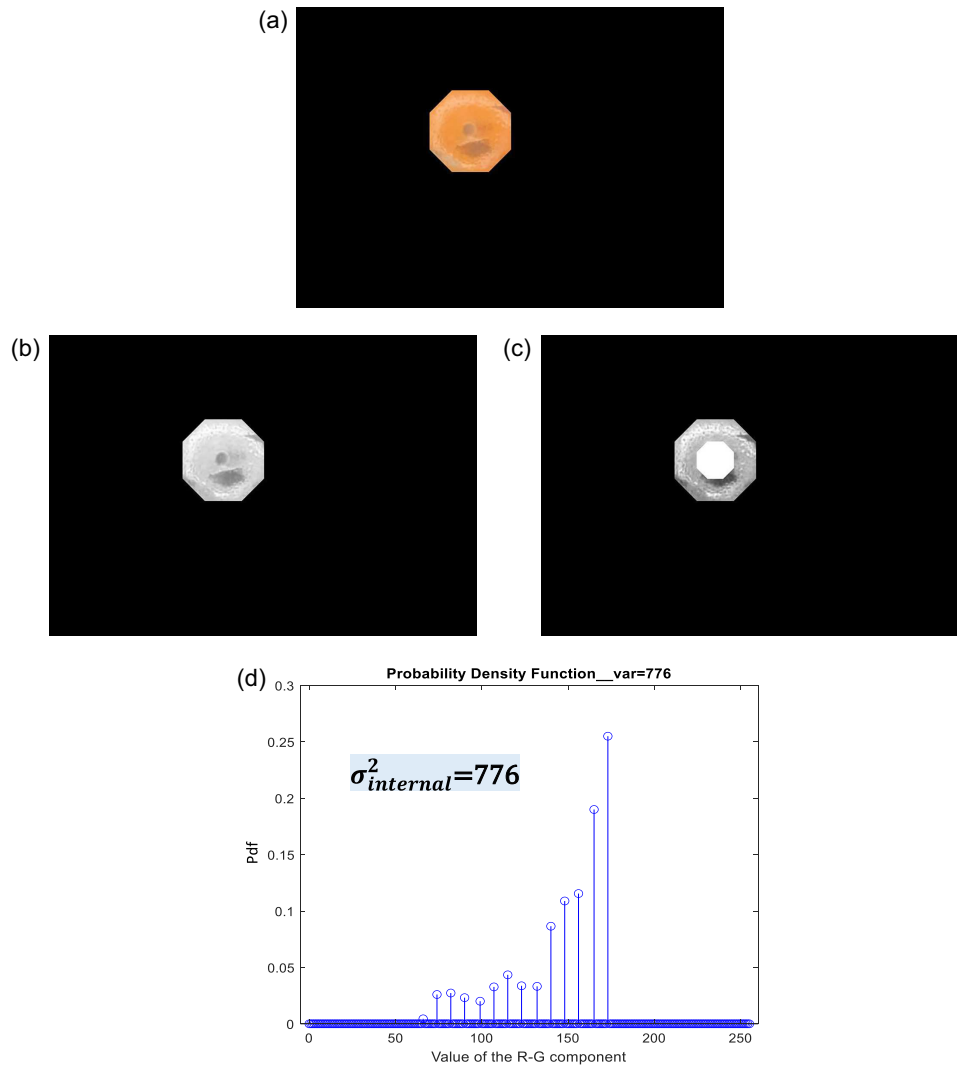
The global evaluation is performed over the entire visible surface of the tangerine through sectors shaped as concentric

rings (corresponding to the primary R component) whose radius decreases from the boundary toward the pedicel. In this case, the process concludes when most of the pixels that form the ring belong to the pedicel (see Figures 15 and 16).

On the other hand, the use of the $I_{IR}(x, y)$ component in this case is because it constitutes the most significant color component (in a healthy tangerine) with respect to $I_{IG}(x, y)$ and $I_{IB}(x, y)$. The R component enables the differentiation of dark spots that directly influence the perceived quality of a tangerine. The evaluation process begins by defining a binary mask $Z_{10}(x, y)$ (of the same size as the input image) in which all pixels are initially set to zero. Then, from $Z_1(x, y)$, the maximum diameter D_{max} of the tangerine is obtained, after which the thickness w of each ring is determined, defined as 10% of D_{max} , that is, $w = 0.1 \times D_{max}$. With this, there would be a maximum of five rings per tangerine; however, the real number of rings to be processed is conditioned by the size of the pedicel region. In this case, the expanded pedicel obtained in the derivation of the descriptor for the internal region is considered (see Figures 15(a) and 16(a)).

Figure 14

Extraction of internal region descriptor for a poor-quality tangerine: (a) internal region; (b–c) R-G component with gamma correction and requantization showing (b) the unmasked area and (c) the masked pedicel; and (d) PDF and variance of the R-G component excluding the pedicel area



4) Processing applied per ring

Each R ring is initially subjected to a 5×5 median filter (reference) to remove small undesired contrasts. Then, the mean value m_0 (derived from the PDF) of the R values that compose the ring is computed, from which the threshold $\mu_6 = 0.88m_0$ is obtained (with which the best classification results were achieved). Using this threshold, the positions of the ring pixels whose values fall below μ_6 are determined, that is, pixels that would be perceived as dark within the ring region.

The process concludes by setting to 1 the pixels in the mask $Z_{10}(x, y)$ located at the identified positions.

The procedure is applied iteratively to each ring until the cumulative total result is obtained in the binary mask $Z_{10}(x, y)$. Figures 15(b–f) and 16(b–f) show, highlighted in purple, the pixels that have a value equal to 1 in the resulting mask $Z_{10}(x, y)$.

Finally, by applying the labeling algorithm [23] to $Z_{10}(x, y)$, two descriptors are obtained: the total affected area, **TAffArea** (counting the pixels with value equal to 1), and the area of the largest object, **LOArea** (in number of pixels).

Table 4 shows, as an example, the values of the descriptors obtained for the “good-quality” tangerine shown in Figures 11, 13, and 15. Likewise, Table 5 presents the values of the descriptors obtained for the “poor-quality” tangerine shown in Figures 12, 14, and 16.

Note that a “poor-quality” tangerine exhibits much greater variance in tonalities, a larger total affected area, and individual affected regions of much greater size than a “good-quality” tangerine.

Figure 17 shows the characteristic feature space of the descriptors TotalVar, TAffArea, and LOArea for the tangerines in the supervised dataset. Note that two distinct regions emerge to facilitate the classification process.

3.7. Classification

As mentioned before, the classification process considers two tangerine quality classes: “good quality” and “poor quality.”

Figure 15

Affected area and largest object extraction for a good-quality tangerine: (a) input image, (b–e) concentric rings 1–4 showing the marked affected areas (0, 80, 7, and 33 pixels, respectively), and (f) total affected area (132 pixels) highlighting the largest object (50 pixels)

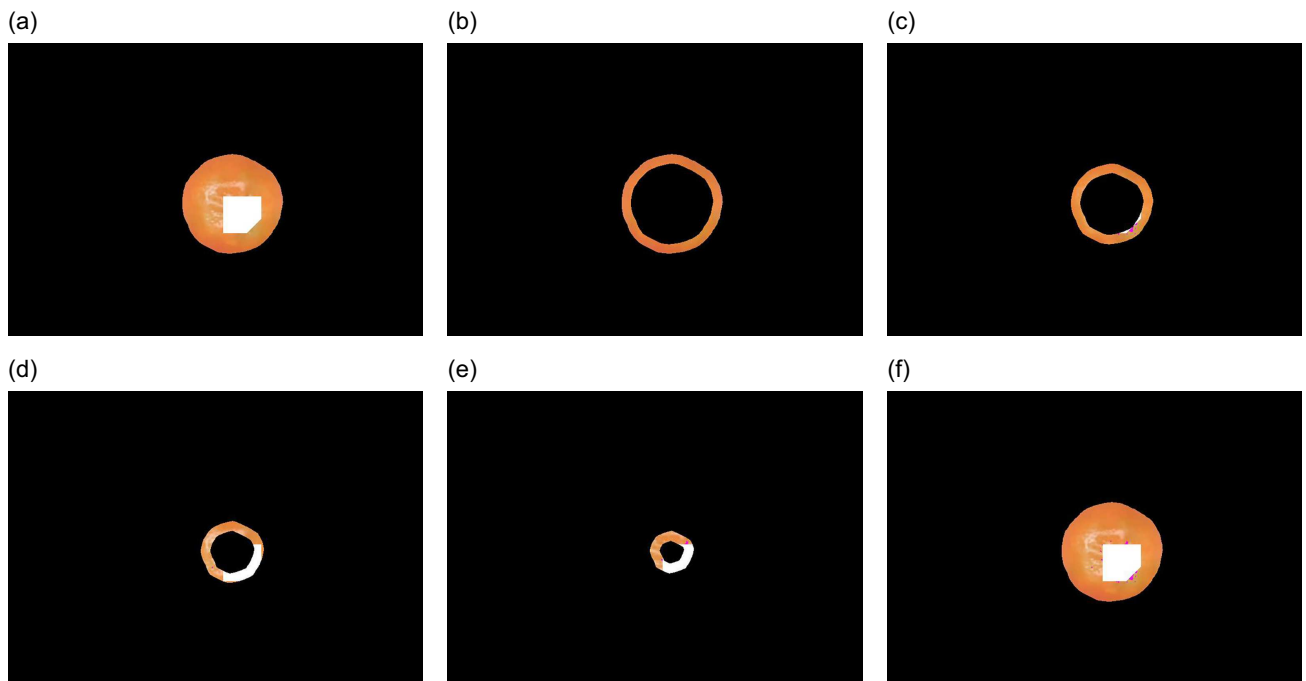


Figure 16

Affected area analysis for a poor-quality tangerine: (a) input image, (b–e) concentric rings 1–4 showing marked affected areas (1469, 336, 425, and 339 pixels, respectively), and (f) total affected area (2569 pixels) and largest object (759 pixels)

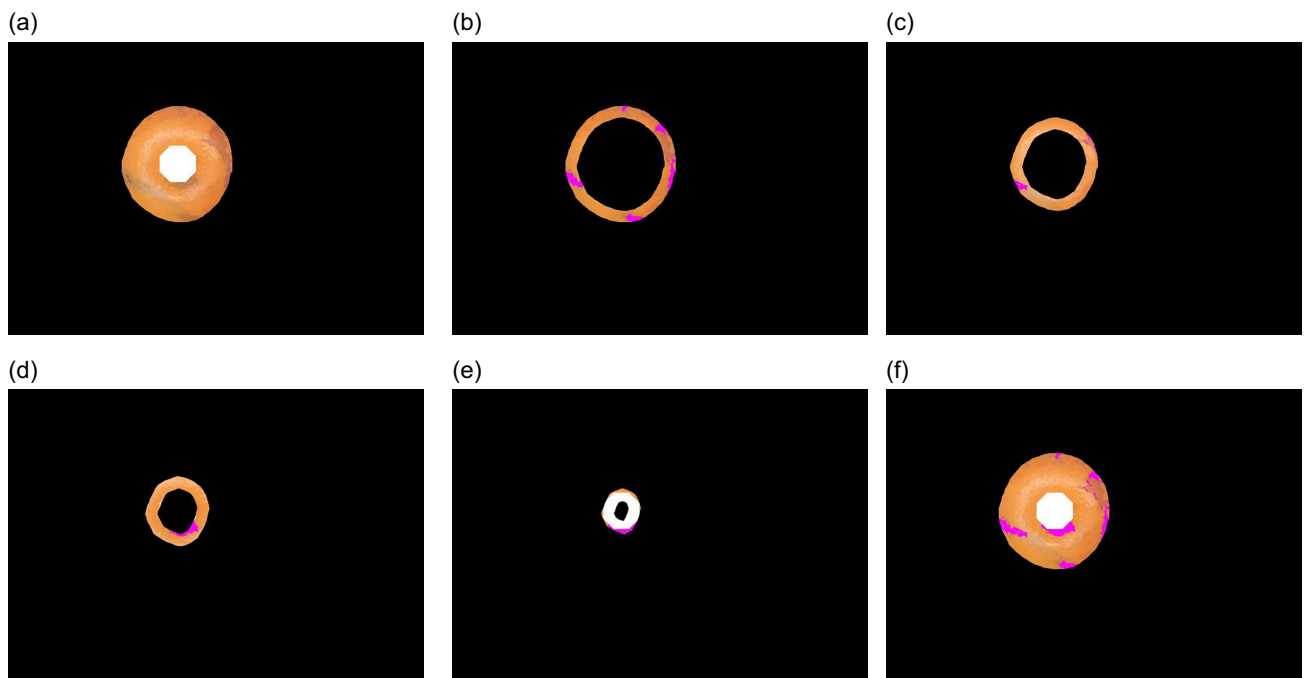


Table 4
Descriptor values for the “good-quality” tangerine

Internal region		External region			TotalVar
$\sigma_{internal}^2$	σ_{upper}^2	σ_{left}^2	σ_{right}^2	σ_{lower}^2	
0	77	53	76	86	292
Total affected area (in pixels): TAffArea = 132					
Area of the largest object (in pixels): LOArea = 50					

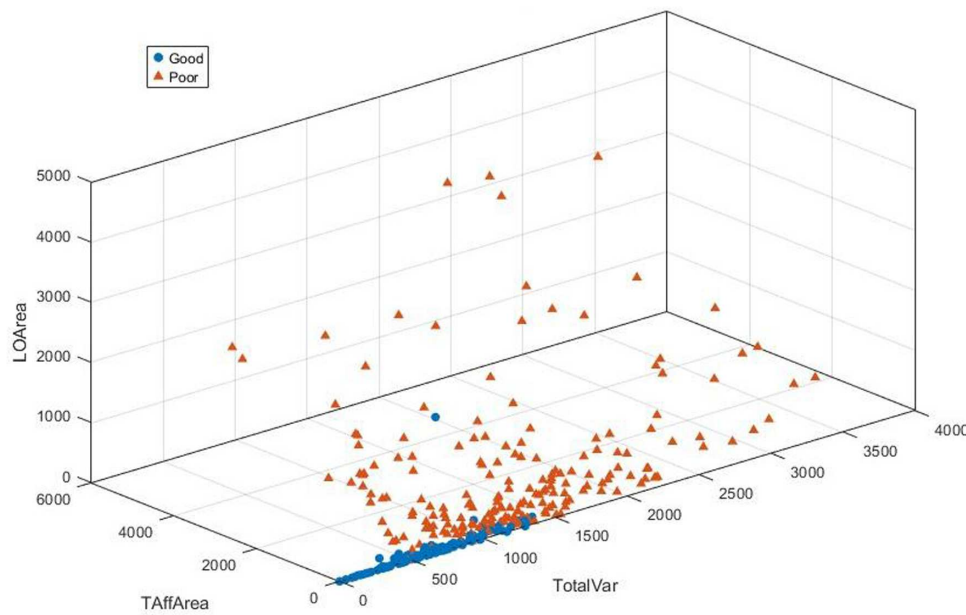
Note: The corresponding measurements are illustrated in Figures 11, 13, and 15

Table 5
Descriptor value for the “poor quality” tangerine

Internal region		External region			TotalVar
$\sigma_{internal}^2$	σ_{upper}^2	σ_{left}^2	σ_{right}^2	σ_{lower}^2	
776	502	730	548	567	3123
Total affected area (in pixels): TAffArea = 2569					
Area of the largest object (in pixels): LOArea = 759					

Note: The corresponding measurements are illustrated in Figures 12, 14, and 16

Figure 17
Feature space of TotalVar, TAffArea, and LOArea descriptors



The process is focused on quality control and not strictly on the identification of any specific defect.

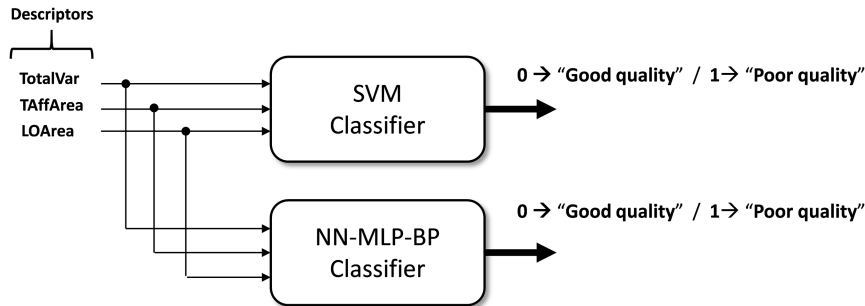
The evaluated classifiers were the SVM and the NN-MLP-BP. As noted in [26], traditional classifiers like SVM or Random Forest coupled with robust feature extraction often yield better stability and generalization than complex deep learning architectures. Figure 18 shows the process with the input descriptors and the output classes. In this case, for both classifiers, the value “0” was assigned to the “good-quality” class and the value “1” to the “poor-quality” class.

The values of the configuration parameters that yielded the best results for both SVM and NN-MLP-BP are shown in Tables 6 and 7, respectively. The remarks presented in Table 6 aim to

justify the SVM configuration used. In the case of Table 7, the values assigned to the configuration parameters were determined from multiple classification trials in which both classification performance and the resulting computational load were considered. The latter implies that a configuration was discarded when only a small improvement in classification was obtained at the cost of an excessive increase in the computational load of the NN-MLP-BP. The training, validation, and testing percentages used for both the SVM and the NN-MLP-BP were 60%, 10%, and 30%, respectively. The distribution and number of images in the dataset used for these three processes are shown in Table 8.

For training, validation, and testing, two methods were used: circular-shift cross-validation and K-fold [27]. In the first case,

Figure 18
Classification process



two buffers are established: buffer 1 containing the identification numbers of the 266 images classified as “good quality” and buffer 2 containing the same information for the 370 images classified as “poor quality.”

Then, $N_i = 636$ iterations were established to vary the position of the identifiers in the buffers. In each iteration, a circular shift of one position is applied to both buffers, and the training, validation, and testing processes are executed by taking, for training, the first 160 values of buffer 1 and the first 222 values of

buffer 2. For validation, the next 26 values of buffer 1 and the next 37 values of buffer 2 were used.

Finally, for testing, the next 80 values of buffer 1 and the next 111 values of buffer 2 were taken. Each iteration produces accuracy results for training, validation, and test. At the end of the process, for the test case, the maximum accuracy value, the average value, and the minimum value obtained in the 636 iterations are presented. For K-fold, $N_i = 7$ iterations were executed with $K = 3$, where in each iteration, a random permutation of each buffer was

Table 6
SVM configuration parameters

Parameter	Assigned value or configuration	Comment
Kernel	RBF	The RBF (radial basis function), or Gaussian kernel, performs a nonlinear mapping into a higher-dimensional space. Its use offered the best results in the classification process compared to other kernels. The RBF is highly suitable for similarity measurement in feature spaces defined by photometric and geometric image descriptors [28]
KernelScale	Auto	It performs automatic selection of the Gaussian RBF kernel's standard deviation (σ) to avoid overfitting or underfitting [28]
Standardize	True	It standardizes the influence of descriptors in similarity measurements when their scales differ substantially in range of variation [28]
BoxConstraint (hyperparameter C)	10	It controls the SVM margin size. High values (e.g., 100) heavily penalize errors, whereas low values (e.g., 1) tolerate them (reference). The best results were obtained with $C = 10$

Table 7
NN-MLP-BP configuration that yielded the best results

Parameter	Assigned value or configuration
Gradient computation method	Backpropagation
Number of epochs	500
Number of hidden layers	1
Activation function of the hidden layers	Sigmoid
Hidden layer: number of neurons	10
Early stopping	10
Damping factor (μ)	0.1
Factor to decrease μ	0.5
Factor to increase μ	10
Minimum gradient threshold	10^{-7}

Table 8
Distribution of the dataset for training, validation, and testing (circular-shift cross-validation)

Quality	Training	Validation	Tests	Total
Good	160	26	80	266
Poor	222	37	111	370

performed, segmenting each one into three blocks of the same size: two for training/validation (10% for validation) and one for testing.

The idea of using iterations with shifts and permutations in these processes aims to obtain as many combinations of data as possible for training, validation, and testing, achieving more generalizable accuracy results.

The accuracy value (Acc) is obtained from the following expression:

$$Acc = \frac{N_S}{N_T} \times 100 \quad (7)$$

Where:

N_S : It is the number of correctly classified images (one side of a tangerine per image).

N_T : It is the total number of processed images (one side of a tangerine per image).

4. Results and Discussion

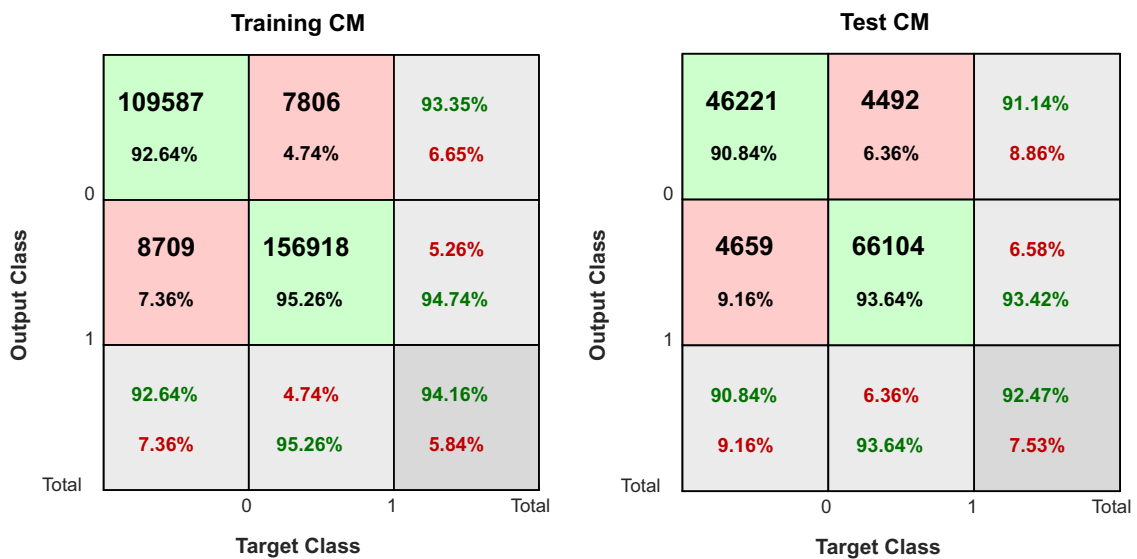
The performance evaluation of the tested models focused on standard metrics for the task of classifying the condition of the tangerine (good/bad) and a more in-depth analysis with extended confusion matrices.

The tests for deep NN algorithms such as YOLOv11 type “s” and ResNet50, which use libraries from the owner Ultralytics and the PyTorch framework, respectively, established the K-fold cross-validation method with $K = 6$. In addition, the data were divided into three sets: training (70%), validation (15%), and testing (15%). For the proposed algorithms of lower complexity, such as NN-MLP-BP and SVM, validation tests were performed using two methods: circular cross-validation and 3-fold cross-validation whose results for each one are detailed using performance metrics in Table 9.

Table 9
Comparison of the performance of descriptor-based and deep vision classification models

Model	Architecture type	Method	Precision	F1-score	Recall	Accuracy
SVM	Proposed/descriptors	Circular	0.9342	0.9353	0.9365	0.9248
		K-FOLD	0.9258	0.9239	0.9219	0.9240
NN-MLP-BP	Proposed/descriptors	Circular	0.9341	0.9359	0.9377	0.9254
		K-FOLD	0.9355	0.9292	0.9230	0.9296
YOLOv11s	CNN/deep learning	K-FLOD	0.8363	0.8606	0.8864	0.8420
ResNet50	CNN/deep learning		0.8082	0.8595	0.9179	0.8250

Figure 19
Confusion matrices for the SVM model using the circular validation method



Note: Validation method: Circular-shift cross-validation, $N_i = 636$. SVM (AccTest): Avg: 92.46%, Max: 97.38%, Min: 83.76%.

For SVM and NN-MLP-BP, an accuracy above 92% was achieved, showing better results with the proposed use of descriptors. On the other hand, highly complex computational models such as ResNet50 and YOLOv11, which are based on convolution processes, achieved an average accuracy of 82.5% and 84.2%, respectively.

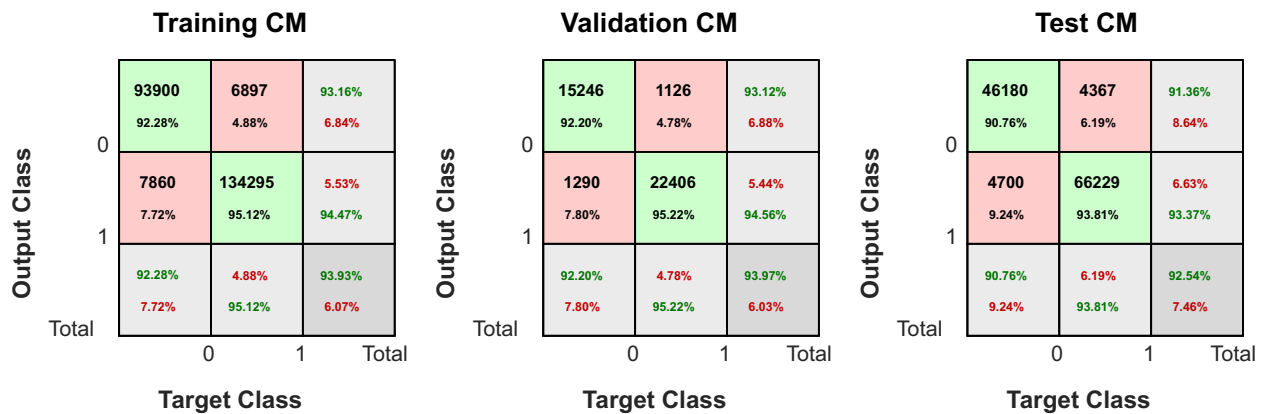
As part of the performance evaluation, confusion matrices were also created for each validation method, which can be seen in Figures 19, 20, 21, 22, 23, and 24. These figures show the quantification in percentages and quantities for the different groups in the dataset. For low-complexity models (SVM and NN-MLP-BP), a slight fluctuation between training and test values is shown, demonstrating that the models are reliable for implementation.

The results presented in Table 9 confirm that descriptors can characterize variations in tangerine peel color tone with high precision. An average precision of 93.5% was achieved using the SVM classifier (with RBF kernel). This level indicates that the extracted

characteristics are more relevant for determining tangerine quality than the information obtained with convolutional method algorithms. Likewise, deep network models require a greater volume of data to avoid overfitting the model, whereas proposals such as SVM and NN-MLP-BP are less susceptible to this problem. Moreover, the use of machine learning models presents minimal variation across evaluation metrics, discarding overfitting in these algorithms. Based on these characteristics, the presented work outstands more complex deep NN models and makes the implementation economical on affordable hardware devices, such as small-board computers (Raspberry Pi or Jetson Nano). Hence, it is a viable and accessible solution for the industry, unlike other state-of-the-art solutions that focus on complex models or use expensive equipment for data acquisition.

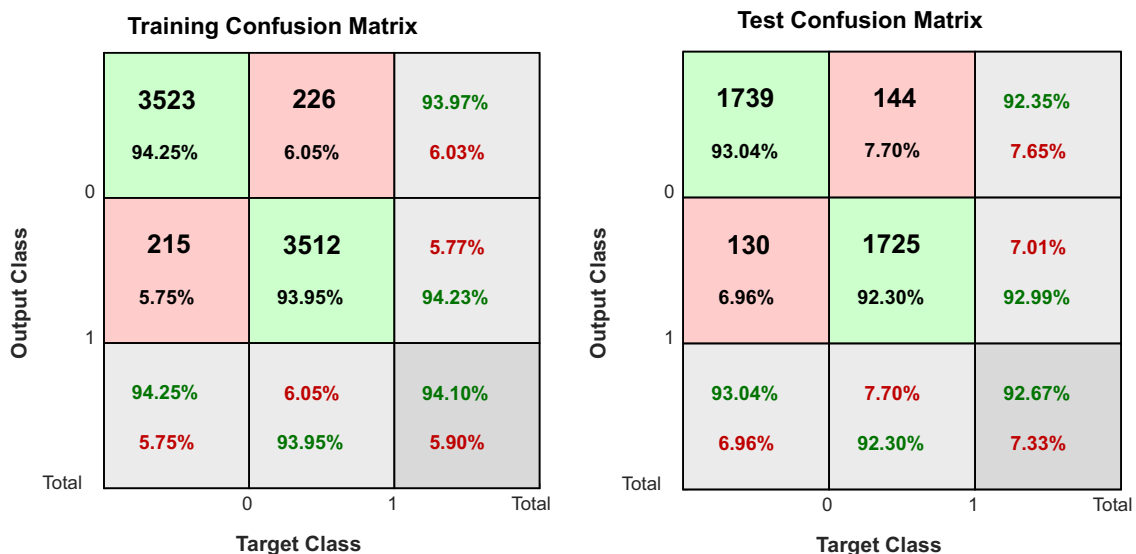
Although the system presented meets the requirements for accuracy and efficiency, the next phase of research will focus on overcoming challenges such as adapting to other types of citrus fruits with different colors and textures. The idea is to ensure that

Figure 20
Confusion matrices for the NN-MLP-BP model using the circular validation method



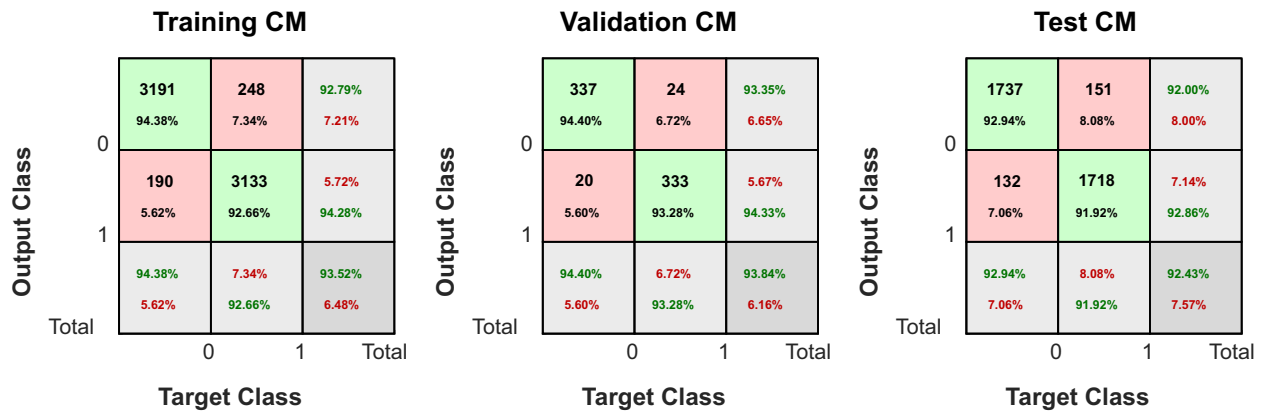
Note: Validation method: Circular-shift cross-validation, $N_i = 636$. NN (AccTest): Avg: 92.53%, Max: 98.42%, Min: 84.29%.

Figure 21
Confusion matrices for the SVM model with the 3-fold validation method



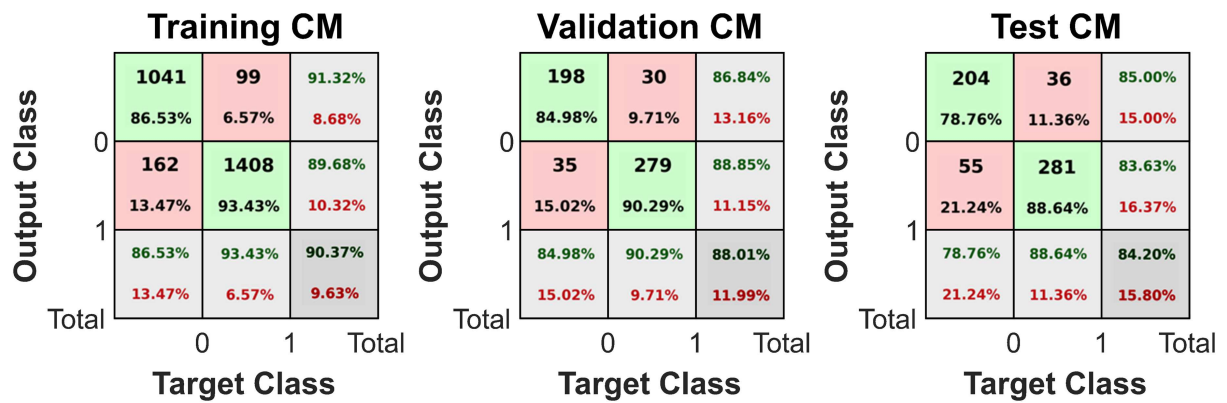
Note: Validation method: 3-Fold, $N_i = 7$. SVM (AccTest): Avg: 92.66%, Max: 96.06%, Min: 89.32%.

Figure 22
Confusion matrices for the NN-MLP-BP model with the 3-fold validation method



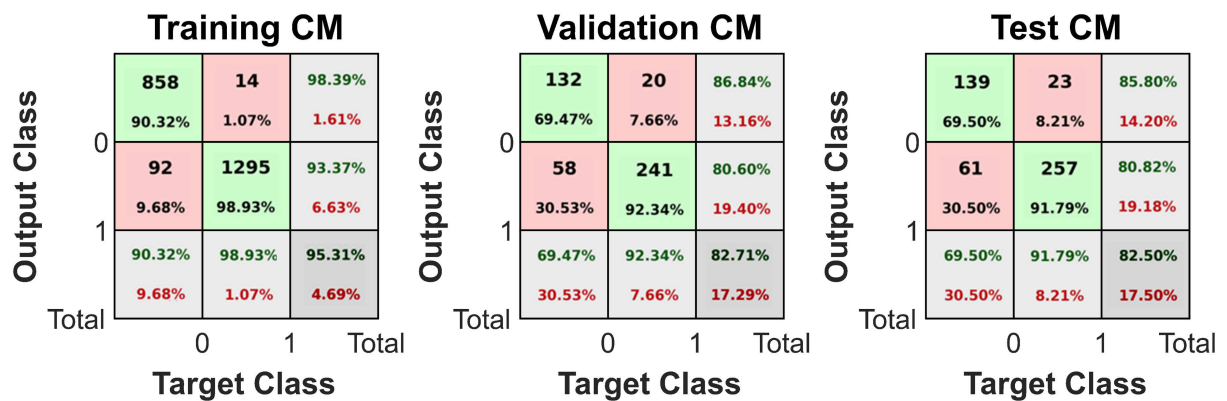
Note: Validation method: 3-Fold, Ni = 7. NN (AccTest): Avg: 92.42%, Max: 96.06%, Min: 88.76%.

Figure 23
Confusion matrices for the YOLOv11 deep learning model with the 6-fold hold-out validation method



Note: Validation method: 6-Fold hold out YOLOv11 (AccTest): Avg: 84.20%, Max: 87.50%, Min: 82.29%.

Figure 24
Confusion matrices for the ResNet50 deep learning model with the 6-fold hold-out validation method



Note: Validation method: 6-Fold hold out ResNet50 (AccTest): Avg: 82.50%, Max: 85.42%, Min: 78.12%.

the system automatically adopts the best characteristics for each case. In addition, the work will focus on collecting a larger and more varied database under different environmental conditions to improve the robustness of the presented models.

5. Conclusions

The results demonstrate an accurate performance of the classification method based on descriptors derived from fruit sectorization, outperforming deep learning networks such as YOLOv11 and ResNet50, which require higher computational load than machine learning algorithms such as SVM and MLP NNs. From this perspective, the proposed algorithm becomes especially attractive for scenarios with limited computational resources.

The exclusion of highly green sections had a favorable impact on the performance of the proposed algorithm since these regions generally do not exhibit defects because they are in the maturation stage. Likewise, the removal of the pedicel sector and the shadows generated at the edges by the chamber lighting contributed positively to the classification results. In addition, retraining the classifiers with a new supervised database may enable the algorithm to adapt to different classification criteria, given the inherent subjectivity and tolerance applied when selecting a tangerine. Moreover, throughout the study, several descriptors and color models were evaluated. Many of them were discarded because they did not achieve satisfactory classification performance. This was mainly because the information provided did not clearly reflect what humans perceive when selecting a tangerine, which is based primarily on peel color uniformity, stain size, and total affected area.

Finally, future work may consider evaluating alternative classifiers and new descriptors obtained through sectorization, adapted to similar citrus fruits such as orange, lime, lemon, and grapefruit, among others.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in Mendeley Data at <https://doi.org/10.17632/9tfbpxpyjz.1>

Author Contribution Statement

Guillermo Kemper: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Santiago Huamani:** Conceptualization, Resources, Writing – original draft. **Sebastián Rojas:** Conceptualization, Resources, Writing – original draft. **Enrique Tabory:** Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Enori Cardenas:** Formal analysis, Investigation, Writing – original draft. **Kevin Guerra:** Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft.

References

- [1] United States Department of Agriculture Foreign Agricultural Service. (2026). *Citrus: World markets and trade*. <https://www.fas.usda.gov/data/citrus-world-markets-and-trade>
- [2] Instituto Nacional de Defensa de la Competencia y de la Protección de la Propiedad Intelectual. (2014). *Cítricos. Mandarinas, tangelos, naranjas y toronjas. Requisitos [CITRUS. Mandarines, tangelos, oranges, grapefruits. requirements]* (NTP Standard No. 011.023:2014). Retrieved from: <https://www.procitrus.org/img-apps/info-notas/infonotas-1600203821.pdf>
- [3] TOMRA. (n.d). *Fruit sorting, grading, packing, and filling solutions*. <https://www.tomra.com/food/machines/fruit>
- [4] Nuño-Maganda, M. A., Dávila-Rodríguez, I. A., Hernández-Mier, Y., Barrón-Zambrano, J. H., Elizondo-Leal, J. C., Díaz-Manríquez, A., & Polanco-Martagón, S. (2023). Real-time embedded vision system for online monitoring and sorting of citrus fruits. *Electronics*, 12(18), 3891. <https://doi.org/10.3390/electronics12183891>
- [5] Li, P., Jiang, X., Wu, Y., Fu, Q., & Qin, S. (2025). External defect detection of Orah mandarin based on a non-brightness correction algorithm. *Frontiers in Plant Science*, 16, 1654143. <https://doi.org/10.3389/fpls.2025.1654143>
- [6] Huang, F., Xie, J., Jie, S., & Suwannata, N. (2025). Classification of Guanxi mandarin orange grades using machine vision algorithms. *Journal of Applied Informatics and Technology*, 7(2), 305–324. <https://doi.org/10.14456/jait.2025.19>
- [7] Hadimani, L., & Garg, N. M. (2021). Automatic surface defects classification of Kinnow mandarins using combination of multi-feature fusion techniques. *Journal of Food Process Engineering*, 44(1), e13589. <https://doi.org/10.1111/jfpe.13589>
- [8] Li, H., Wang, X., Bu, Y., David, C. C., & Chen, X. (2025). YOLOv8-Orah: An improved model for postharvest orah mandarin (*Citrus reticulata* cv. Orah) surface defect detection. *Agronomy*, 15(4), 891. <https://doi.org/10.3390/agronomy15040891>
- [9] Lu, J., Chen, W., Lan, Y., Qiu, X., Huang, J., & Luo, H. (2024). Design of citrus peel defect and fruit morphology detection method based on machine vision. *Computers and Electronics in Agriculture*, 219, 108721. <https://doi.org/10.1016/j.compag.2024.108721>
- [10] Duraisamy, M., Govindaraj, R., Mohan, N., Kamalakannan, A., Bindal, S., & Titus, A. (2022). Performance evaluation of deep learning based mandarin fruit sorting system with industrial camera. In *2022 3rd International Conference on Smart Electronics and Communication*, 1238–1243. <https://doi.org/10.1109/ICOSEC54921.2022.9951937>

- [11] Singh, R., Nickhil, C., Upendar, K., Mishra, P., & Deka, S. C. (2025). Deep learning-based approach for classifying mandarin orange maturity. *Sustainable Food Technology*, 3(6), 2215–2225. <https://doi.org/10.1039/D5FB00408J>
- [12] Bautista, K., Delgado, J. T., Urrea, S., Arguello, H., & Garcia, H. (2025). Estimation of a color uniformity index in mandarins using an artificial intelligence-based system. In *2025 XXV Symposium of Image, Signal Processing, and Artificial Vision*, 1–5. <https://doi.org/10.1109/STSIVA66383.2025.11156458>
- [13] Kurdthongmee, W., & Sukkuea, A. (2025). Non-destructive volume estimation of oranges for factory quality control using computer vision and ensemble machine learning. *Journal of Imaging*, 11(10), 352. <https://doi.org/10.3390/jimaging11100352>
- [14] Frederick, Q., Burks, T., Watson, A., Yadav, P. K., Qin, J., Kim, M., & Ritenour, M. A. (2023). Selecting hyperspectral bands and extracting features with a custom shallow convolutional neural network to classify citrus peel defects. *Smart Agricultural Technology*, 6, 100365. <https://doi.org/10.1016/j.atech.2023.100365>
- [15] Jiang, T., Zuo, W., Ding, J., Yuan, S., Qian, H., Cheng, Y., . . . , & Yao, W. (2025). Machine learning driven benchtop Vis/NIR spectroscopy for online detection of hybrid citrus quality. *Food Research International*, 201, 115617. <https://doi.org/10.1016/j.foodres.2024.115617>
- [16] Zhang, H., Zhang, S., Dong, W., Luo, W., Huang, Y., Zhan, B., & Liu, X. (2020). Detection of common defects on mandarins by using visible and near infrared hyperspectral imaging. *Infrared Physics & Technology*, 108, 103341. <https://doi.org/10.1016/j.infrared.2020.103341>
- [17] Zhang, J., Zhang, H., Zhang, Y., Yin, J., Zhan, B., Liu, X., & Luo, W. (2025). Qualitative and quantitative analysis of Nan-feng mandarin quality based on hyperspectral imaging and deep learning. *Food Control*, 167, 110831. <https://doi.org/10.1016/j.foodcont.2024.110831>
- [18] Lee, A., Baek, I., Kim, J., Hong, S.-J., & Kim, M. S. (2025). Deep learning approaches for bruised mandarin orange classification by fluorescence hyperspectral imaging. *Postharvest Biology and Technology*, 230, 113724. <https://doi.org/10.1016/j.postharvbio.2025.113724>
- [19] Wu, Y., Zhu, X., Huang, Q., Zhang, Y., Evans, J., & He, S. (2023). Predicting the quality of tangerines using the GCNN-LSTM-AT network based on Vis–NIR spectroscopy. *Applied Sciences*, 13(14), 8221. <https://doi.org/10.3390/app13148221>
- [20] Luengo, J. M., Femenia, J. L., Terol, M., & Fraile, F. (2025). Citrus sorting dynamic control using multispectral computer vision. In *2025 IEEE International Conference on Engineering, Technology, and Innovation*, 1–8. <https://doi.org/10.1109/ICE/ITMC65658.2025.11106566>
- [21] Singh, R., Nickhil, C., Upendar, K., Deka, S. C., & Nisha, R. (2025). Non-destructive estimation of mandarin orange fruit quality during the ripening stage using machine-learning-based spectroscopic techniques. *Journal of Food Measurement and Characterization*, 19(2), 862–875. <https://doi.org/10.1007/s11694-024-02999-5>
- [22] Hua, Y., Wu, S., Liang, L., Jiang, M., Fan, Y., & Xie, W. (2024). Citrus objects recognition in orchard scene using HSV methods. In *International Conference on Image Processing and Artificial Intelligence*, (p. 132132 L). <https://doi.org/10.1117/12.3035257>
- [23] Burger, W., & Burge, M. J. (2022). *Digital image processing: An algorithmic introduction*. Switzerland: Springer. <https://doi.org/10.1007/978-3-031-05744-1>
- [24] Soltani Firouz, M., & Sardari, H. (2022). Defect detection in fruit and vegetables by using machine vision systems and image processing. *Food Engineering Reviews*, 14(3), 353–379. <https://doi.org/10.1007/s12393-022-09307-1>
- [25] Bhagwat, R., & Dandawate, Y. (2021). A framework for crop disease detection using feature fusion method. *International Journal of Engineering and Technology Innovation*, 11(3), 216–228. <https://doi.org/10.46604/ijeti.2021.7346>
- [26] Rezer, E. T., Lairan, N., & Jingga, K. (2025). Enhancing fruit freshness detection through hybrid CNN-random forest architecture. In *2025 6th International Conference on Artificial Intelligence and Data Sciences*, 565–570. <https://doi.org/10.1109/AiDAS67696.2025.11213754>
- [27] Bradshaw, T. J., Huemann, Z., Hu, J., & Rahmim, A. (2023). A guide to cross-validation for artificial intelligence in medical imaging. *Radiology: Artificial Intelligence*, 5(4), e220232. <https://doi.org/10.1148/ryai.220232>
- [28] Wan, H., Wan, Y., Yang, Z., Han, Y., Wu, W., & Yao, M. (2026). Lemon defect detection based on seagull algorithm optimization–support vector machine model. *Applied Fruit Science*, 68(1), 40. <https://doi.org/10.1007/s10341-025-01744-6>

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