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Visual Classification Algorithm for Chonto Tomatoes According to Standard NTC-1103-1 (Color, Size and Shape Parameters)

Algoritmo de Clasificación Visual de Tomates Chonto Según Norma NTC-1103-1 (Parámetros de Color, Tamaño y Forma)

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Abstract: This article introduces the development and implementation a low-cost system for Chonto tomatoes classification, according to their color, shape and size, in accordance with the Colombian technical standard NTC 1103-1. To achieve the aimed objective, a classification algorithm is developed using Python programming language and the OpenCV vision computer library. The results showed that color and maturity classification reached an accuracy of 93%. In the classification by size, the precision was 98%. Regarding the evaluation of eccentricity for determining the shape, an accuracy of 80% was obtained. The aforementioned precision values are comparisons with the result obtained manually by a trained person, which is considered the ideal classification. However, the average response time of the algorithm is 0.48 sec, a lower time than required for human inspection and classification. Based on the precision parameters, it is concluded that the algorithm detects and classifies Chonto type tomatoes according with color, size and shape established in the Colombian technical standard NTC 1103-1.

Keywords: automation, computer vision, tomatoes classification.

Resumen: Este artículo presenta el desarrollo e implementación de un sistema de bajo costo para la clasificación de tomates tipo Chonto de acuerdo con su color, forma y tamaño, conforme a los lineamientos definidos en la norma técnica colombiana NTC 1103-1. Para lograr el objetivo planteado, se realiza el desarrollo de un algoritmo de clasificación utilizando el lenguaje de programación Python y la librería de visión por computador OpenCV. Los resultados obtenidos muestran que en la clasificación para color y madurez se logra una precisión del 93%. En la clasificación por tamaño la precisión alcanzada fue del 98%. En cuanto a la evaluación de la excentricidad para determinar la forma, se obtuvo una precisión del 80%. Los valores antes mencionados de precisión son comparaciones respecto al resultado obtenido de forma manual por una persona entrenada, la cual se considera como la clasificación ideal. Sin embargo, se tiene que el tiempo de respuesta del algoritmo es un promedio de 0,48 seg, tiempo menor al requerido para la inspección y clasificación humana. Con base en los porcentajes de precisión, se concluye que el algoritmo detecta y clasifica los tomates tipo Chonto de acuerdo a su color, tamaño y forma establecidos en la norma técnica colombiana NTC 1103-1.

Palabras clave: automatización, visión por computadora, clasificación de tomates.

1. INTRODUCTION

Agriculture is positioned as one of the most relevant production sectors in the world [1]. Many countries in Latin America have agricultural production as their main economic activity. However, there is no technology available to assist agriculture in places apart from cities, motivating government, academic and private institutions to lead programs in order to increase and maintain the quality of the products using technological tools at low cost and easy to use for farmers [2], [3]. According to Hamdiyah Alhassan [4], improvement in agricultural production is key to the sustainable development of countries, because it reduces poverty by promoting economic growth in general.

Among the different processes of the agricultural production, the product classification plays an important role for marketing and sales. In order to improve inspection times, and improving general production process, manual classification has been the most common selection practice in the food industry [5]. However, product manual classification is considered an intense, not very efficient and precise job due to different factors, such as the difference in the capacity of visual perception of the personnel carrying out the inspection task [6], mainly. To assist in this need, Control and Automation Engineering has been able to integrate computer vision into systems that select and classify products leading to more autonomous, effective and efficient processes [7].

Currently, the tomato is ranked as the eleventh most cultivated vegetable in the world, [8]. In Colombia, tomato is the second most cultivated vegetable, obtaining a production of 851,117 tons in a planted area of 18,996 hectares in 2021 [9]. The greatest sowing areas are located in Boyacá, Antioquia, Norte de Santander and Caldas [10]. Their climatic and soil characteristics allow for good development of tomatoes with high quality [11], good flavor, high nutritional value represented in vitamins (A, B, C, and E) and antioxidants, making it a very attractive food for consumers [12].

Quality plays a very important role in the consumer's decision making when purchasing [13]. Bright colors, freshness, size and defects free surface of tomatoes are the main selection parameters for consumers [14]. Companies that export tomatoes must ensure these parameters within the final selection processes, so that they last during the transport time until they are marketed [15]. Computer vision implemented in tomato factories process lines allows to classify tomatoes efficiently based on their color (state of maturity), size, shape and detecting defects, hence improving quality control, reducing inspection times and therefore reducing operating costs [16], [17].

Regarding the technological advances developed for tomatoes classification, V. Pavithra *et al*. [18], developed a two-phase classification algorithm for Cherry tomatoes, using SVM (Support Vector Machine) to determine the maturity state of the tomatoes by means of color and KNN (K-Nearest Neighbor), to correlate the external and internal characteristics of the tomato, based on texture, color and shape. Similarly, Marcos J. Villaseñor-Aguilar *et al*. [19] designed and implemented a new fuzzy classification architecture based on the RGB color model, in order to optimize the color space parameters (descriptors); achieving greater precision for the identification of the maturity state of tomatoes. On the other hand, Supriya V. Patil *et al*. [20], developed an image processing system for surface defect detection and subsequent classification of type *Rishika-225* tomatoes using OpenCV/Python. Also, S. Dhakshina Kuma *et al.* [21] proposed a three-phase non-destructive inspection and classification system based on image processing: extraction by binarization followed by classification based on coloring, and finally, surface defects identification in tomatoes (black spots, cankers and melanosis in fruit).

The present study arises from the question: How to implement a low-cost computer vision system to classify chonto type tomatoes following the parameters of the Colombian technical standard NTC-1103-1 [22], in terms of color, size and shape?

2. METHODOLOGY

For this project, the Chonto type tomato was chosen as the study object. 40 tomatoes were randomly selected with different states of ripeness (color), sizes and shapes. The places of purchase were chain distributors and local markets in the city of Barranquilla (Colombia). A first group of 25 tomatoes was used for extraction and analysis of characteristics. A second 15 tomatoes group was used for the validation of the developed algorithm. Figures 1 and 2 depict tomato selections with different varieties in color, size and shape.

2.1 Computer vision system

Figure 3.a) depicts the computer vision system hardware for image taking and processing. It includes a webcam-type camera (Asisttics brand model WCFHD01 with 1080p resolution), a 12W light bulb Smart-Bulb dual color with 1200 lumens with light intensity capability through WiFi connection, a 5W commercial LED bulb, an HP® Brand computer with 8 Gb of RAM and Ryzen 3-3500U processor and Windows® 10 (64-bit) operating system. Python 3.7 is the programming language, with Open Computer Vision 4.0.1 (Open CV) as the base library for image processing. The tool for Graphical User Interface-GUI is Spyder. Figure 3.b) depicts the hardware set up.

Fig. 1. *Chonto tomatoes sample*
Source: *Own elaboration*

Fig. 2. *Stages of ripening, shape and selected sizes*
Source: *Own elaboration*

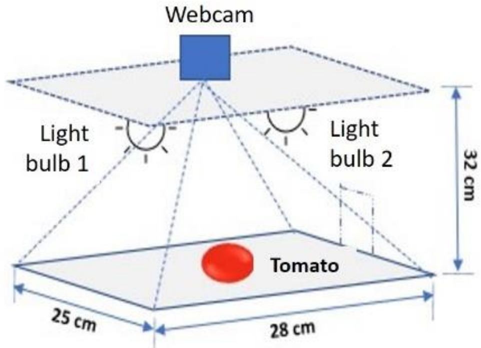
2.2 Detection and classification algorithm

The tomato detection and classification algorithm is comprised of four stages: Image acquisition, image processing, feature extraction, and results visualization. A good camera and a proper calibration is a must for image acquisition. The image processing is to be based on segmentation and morphological transformations. At the feature extraction stage, the color, size, shape and defects of the tomato are determined. Results are to be summarized in the GUI created. The camera calibration process is explained next.

2.2.1. Calibration

The camera was calibrated to eliminate any possible distortion introduced during image acquisition stage. The process was carried out by following the Zhang [23] method, of using patterns similar to those of a chess board. A total of 27 images of the chess board pattern with 5x4 size scale were taken at different angles, see Fig. 5. Zhang's calibration algorithm used only 26 images for analysis; it returned the values of the camera matrix and distortion coefficient parameters. Figures 5.a) y 5.b) depicts the distorted chess board image and the distortion free calibrated image, respectively.

a)



b)

Fig. 3. *a) Vision control system summary for tomato detection. b) Internal area for feature detection and extraction*
Source: *Own elaboration*

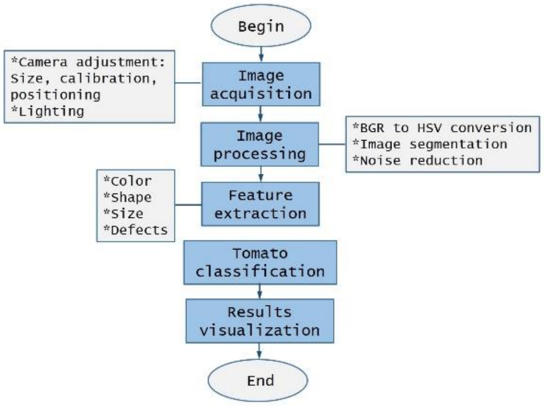
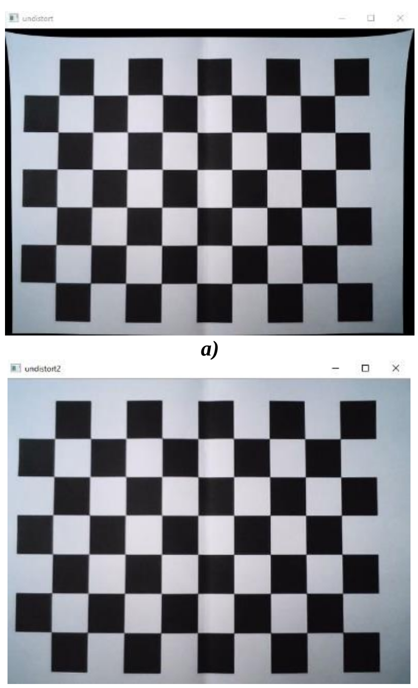


***Fig. 4**. Chonto type tomatoes classification algorithm*
***Source:** Own elaboration*

2.2.2. Color space conversion

The camera uses a sensor based on the three channels Red-Green-Blue, or RGB space, which is not a suitable color space for color recognition; therefore, the Hue-Saturation-Value HSV color space is used. In the latter domain, the color range is expanded, including tones and light saturation, thus increasing the precision and accuracy in the recognition and correct assignment of colors of all the pixels that contain the tomatoes [24]. Figure 6 illustrates an image in HSV space.



a)

b)

***Fig. 5**. a) Pattern image prior to camera calibration process (distorted image)*
b) Post-calibration pattern image of the camera (undistorted image)
***Source:** Own elaboration*

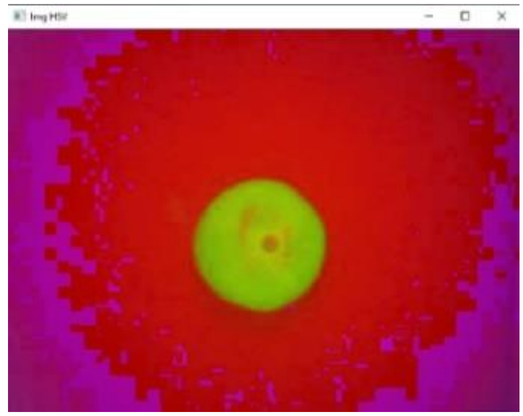


***Fig. 6**. RGB to HSV color space transformation*
***Source:** Own elaboration*

2.2.3. Segmentation

The segmentation technique is a method for defining contours. It is used to detect the limits of the tomato and the background of the image, so that the dimensions, shape, and state of the tomatoes are calculated. To differentiate the tomato from its background, the tomato HSV values that represent its color range according to its maturity state were determined, leading to the transformation in Fig. 7.

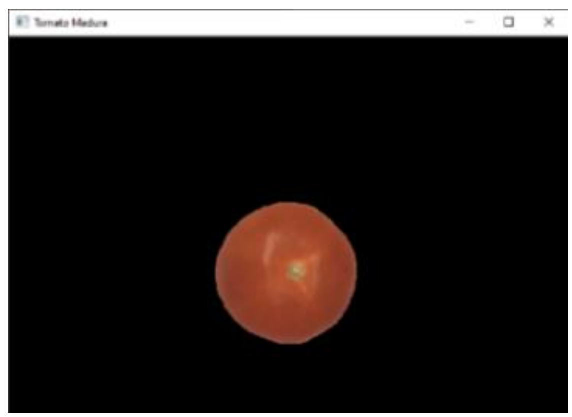
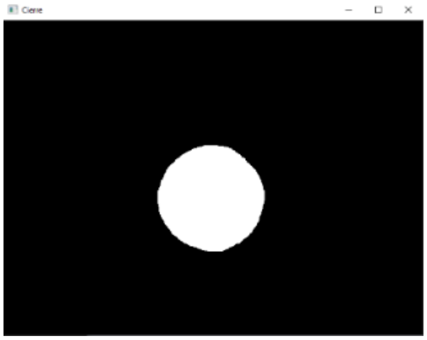


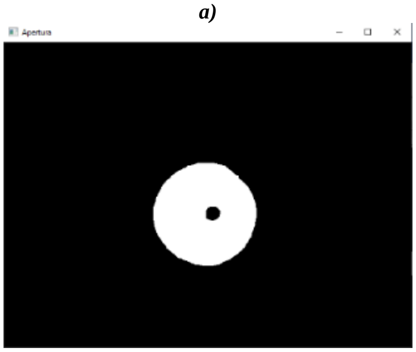
***Fig. 7**. Tomato image segmentation with thresholding*
***Source:** Own elaboration*

2.2.3. Morphological transformations

The segmentation process is followed by morphological transformations, in order to reduce the noise introduced by the digital acquisition of the image. The processes used were “Opening” and “Closing” [25]. Figure 8.a) shows the tomato picture after the “Opening” process, while Fig. 8.b) present the final result after the “Closing” process.



a)



b) Closing

Fig. 8. *Application of morphological transformations*
Source: *Own elaboration.*

2.3. Feature extraction

2.3.1. Color extraction

The Colombian technical standard NTC-1103-1 [22] establishes degrees of tomato ripening according to its color, summarized in Table 1.

Table 1: *Ripening states NTC-1103-1 [22]*

Grade	Description
Green	The surface is completely green. The fruit has reached its maximum size. The tone can vary from light to dark.
Incipient coloration (1/4 pintón)	It shows a definite change in color, from green to opaque yellow, pink or light red but not more than 30% of the tomato surface.
Medium coloring (Half pintón)	It shows between 30 and 60% of the surface in pink or red.
Advanced coloring (3/4 pintón)	More than 60% of the surface shows a pinkish-reddish or red color, but the fruit is not yet completely red.
Red	It has developed an intense red color over the entire surface.

Source: *Own elaboration adapted from [22]*

A graphic illustration of ripening state is in Fig. 9, where grades 5 and 6 are variations of the "Red" state in Table 1. The color extraction phase consists in determining experimentally the HSV values that correspond to the color grades given by the NTC 1103-1 standard [22].

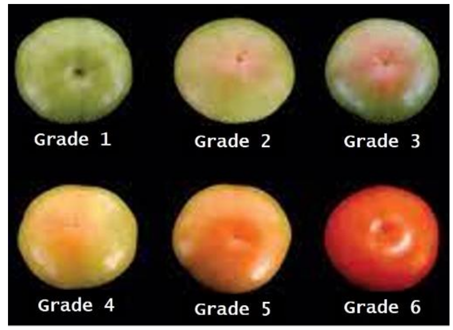


Fig. 9. *Degrees of maturity based on the color of tomatoes*
Source: *Adapted from [26] for illustrative purposes.*

A sample of size 25 was used to stablish relation between the color grades of the standard and the HSV values. The objective is to define the lower and upper limits for each color grade, named maturity (ripening) state of the tomato. Table 2 summarizes the results obtained after analyzing the 25 tomatoes. There were stablished the states: ripe tomato, *pintón* tomato, green tomato, and tomato defects (that is, damaged areas).

The decision-making procedure to classify the tomato in the categories in Table 2 requires counting the number of pixels for each color range [26]. The total number or pixels is compared using a conditional programing function. The tomato is classified as Ripe if at least 90% of the total pixels corresponds to the color red. The tomato is classified as Unripe if at least 90% of the total pixels corresponds to the color green. The *pintón* maturity state of the tomato corresponds to a range (60, 90)% of total pixels with orange color. For tomato defects, pixels counting should be classified as colors different to green, yellow, red or orange.

Table 2: *HSV values for recognition of ripeness states of tomatoes*

Tomato characteristic	HSV Lower limits	HSV Upper limits
Ripe tomato (Red)	(0,117,0)	(11,255,255)
Pintón tomato (Yellow)	(10,95,108)	(18,255,255)
Green tomate	(16,78,0)	(35,255,255)
Defective areas of tomato	(0,0,0)	(179,255,93)

Source: *Own elaboration*

2.3.2. Tomato size estimation

Used tomato size estimation procedure is similar to Chanchal Gupta [27] method. It begins with the detection of the occupied area by the tomato segmented image ("contourArea" function in OpenCV). Next, the perimeter of the recognized area is calculated ("arcLengh" function in

RCTA
Revista Colombiana de Tecnologías de Avanzada
UNIPAMPLONA

OpenCV). Now, determine the closed rectangular contour that bounds the tomato area ("minAreaRect" function in OpenCV). It follows the detection of the characteristic points of the rectangle ("boxPoints" function in OpenCV). Finally, the rectangle that encircles the area is drawn and calculated by using the "boundingRect" OpenCV function. It is considered that the sides of the rectangle are the diameters of the main axes of the tomato, according to its oval (ellipse) shape.

Since the size of the sides that were obtained has image units, or pixels, it is necessary to transform these units into length units using a conversion factor, calculated in 27.2727 pixels/centimeter. This is a constant value because the camera was set at a fixed position and inclination with respect to the detection area of the tomatoes. In case of change in the image capture conditions, the GUI created allows recalculating the conversion factor.

According with NTC-1103-1 standard [22], the tomato is considered as an ellipse with definitions of largest diameter and smallest diameter. Depending on the diameter, tomatoes are classified as: small-sized from 3 cm to 5.4 cm in diameter, medium-sized with a diameter between 5.4 cm and 7.7 cm, and and large-sized tomatoes have diameters greater than 7.7 cm, usually up to 12 cm. Figure 10 shows the calculated measurements for size classification purposes, for this particular case the tomato was classified as medium-sized tomato with both axes (diameters) between 5.4cm and 7.7cm.

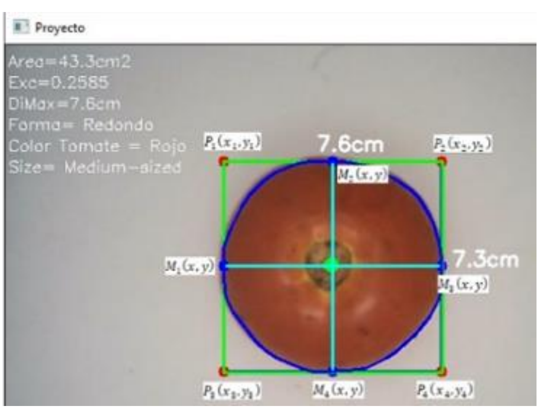


Fig. 10. *Tomato area detection for size estimation*
Source: *Own elaboration*

2.3.2. Tomato shape estimation

According to Arjenaki's [28], the tomato shape can be identified by its curvature, leading to a binary classification: round or oblong (oval). The tomato shape index was associated to its eccentricity as a way of determining how much is the tomato deviated from being circular. The eccentricity, ε, of a circle is ε = 0. The eccentricity of the ellipse lies in the range 0 < ε < 1. The Equation (1) is used to calculate the eccentricity:

$$\epsilon = 2\frac{\sqrt{\left(\frac{L_{max}}{2}\right)^2-\left(\frac{L_{min}}{2}\right)^2}}{L_{max}}, \qquad (1)$$

where L_{max} and L_{min} are the lengths of the maximum and minimum axes, respectively, according to [29]. For this research, the eccentricity was defined based on the results of the first 25 tomatoes, yielding eccentricities $\varepsilon < 0.4$ for round tomatoes, and $\varepsilon > 0.4$ for oblong tomatoes.

2.3.2. Detection of tomato defects

The damaged areas detection analysis, or defects, was performed on some tomatoes intentionally chosen in poor conditions with surface damages, mainly apparent black spots on the exterior. The color intensity for that surface in poor condition was compared. If the percentage of damaged (dark) color exceeded 5% of the total pixels, then the tomato surface was classified as defective, for a poor quality –unhealthy- fruit. Figure 11 depicts a poor condition tomato under test.

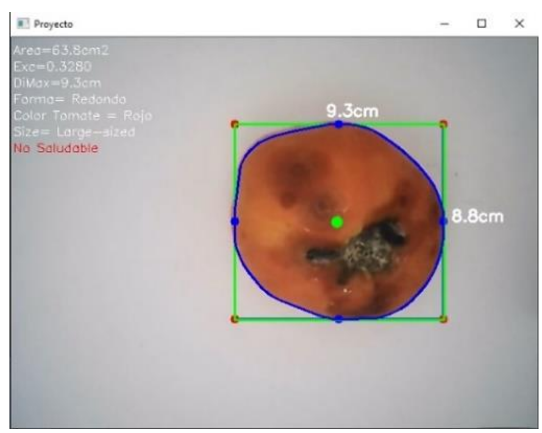


Fig. 11. *Detection of tomatoes in poor condition*
Source: *Own elaboration*

3. RESULTS

Initially, 25 tomatoes were used to characterize color, size and shape. A second group of 15 tomatoes was used to evaluate the created software results within the evaluation limits. The images taken of the second group of 15 tomatoes are in Annex 1 for reference. The results obtained from the comparison between manual sorting and software sorting for the second group of 15 tomatoes are grouped in Tables 3, 4 and 5. The objective of this

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test is to validate the degree of accuracy of the tomato classification. Table 3 contains the comparison between color and condition, both manual and software resulting values. Table 4 shows the comparison of the dimensions between the two main axes of the tomatoes, comparing the values given by the software versus the actual values measured with a caliper. Table 5 presents the classification by shape, both manually and by software.

The results of the classification by color and condition, Table 3, show a single discrepancy between the manual classification and the value returned by the software. This discrepancy occurs in tomato No 12, which is reproduced in Fig. 12. The discrepancy is due to the location of the tomato surface defect in the inferior part of the tomato; the camera only can inspect the superior layout of the tomato. However, the accuracy rate was 14/15, or 93.33%, in terms of color classification. Regarding the condition, the software was able to identify defects with 100% accuracy.

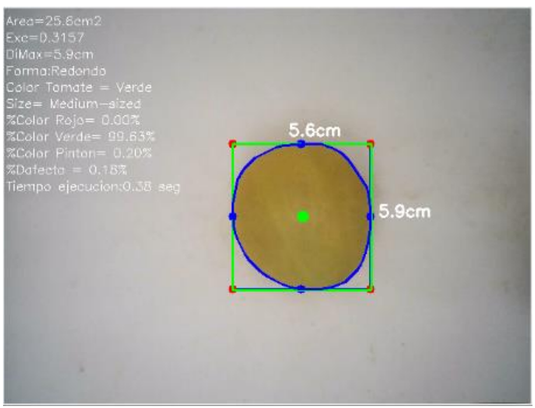

***Fig. 12**. Tomato with discrepancy in color classification*
***Source:** Own elaboration*

***Table 3:** Color and defect recognition in tomatoes, manually vs software results*

No	Color (Real)	Color (Software)	Condition (Real)	Color (Software)
1	Red	Red	Optimum	Optimum
2	Red	Red	Optimum	Optimum
3	Green	Green	Optimum	Optimum
4	Advanced Pintón	Advanced Pintón	Unhealhty	Unhealthy
5	Half Pintón	Half Pintón	No saludable	No saludable
6	Green	Green	Optimum	Optimum
7	Half Pintón	Half Pintón	Optimum	Optimum
8	Advanced Pintón	Advanced Pintón	Optimum	Optimum
9	Red	Red	Optimum	Optimum
10	Advanced Pintón	Advanced Pintón	Optimum	Optimum
11	Half Pintón	Half Pintón	Optimum	Optimum
12*	Incipient Pintón	Green	Optimum	Optimum
13	Green	Green	Optimum	Optimum
14	Half Pintón	Half Pintón	Optimum	Optimum
15	Red	Red	Optimum	Optimum

***:** Color classification difference
***Source:** Own elaboration*

The results for the visual measurement of tomatoes, grouped in Table 4, show that there is a maximum error of 9.84% (or 6.9mm), between the actual dimension of a tomato and the value obtained by the software. For the calculation error, the dimension measured by caliper was taken as the real. This value is acceptable for measurement by visual methods without resorting to stereo vision. Therefore, it is considered that the measurement serves as an indication to determine the size and shape of the tomato following the guidelines of the NTC-1103-1 [22] standard.

***Table 4:** Tomato dimensions recognition*

No	Mayor/ Minor axis + [cm]	Mayor /Minor axis + + [cm]	% Error Mayor/Minor [%]	Size result +	Size result ++
1	5.4/5.3	5.38/5.3	0.37/0.00	Small	Small
2*	6.8/6.7	6.79/6.1	0.15/9.84*	Medium	Medium
3	5.7/5.2	5.73/5.3	0.52/1.89	Medium	Medium
4	6.4/6	6.28/6.1	1.91/1.64	Medium	Medium
5	6.1/5.4	5.71/5.47	6.83/1.28	Medium	Medium
6	5.8/5.6	5.79/5.62	0.17/0.36	Medium	Medium
7	7.1/5.9	7.28/5.67	2.47/4.06	Medium	Medium
8	5.8/5.1	6.025/5.2	3.73/1.92	Medium	Medium
9	9.7/8.2	9.54/8.04	1,68/1.99	Big	Big
10	6.2/6	6.12/5.89	1.31/1.87	Medium	Medium
11	8.8/8.3	8.58/8.33	2.56/0.36	Big	Big
12	5.9/5.6	5.785/5.59	1.99/0.18	Medium	Medium
13	4.6/4.3	4.7/4.32	2.13/0.46	Small	Small
14	4.5/4.3	4.525/4.4	0.55/2.27	Small	Small
15	4.1/3.9	4.09/3.94	0.24/1.02	Small	Small

+: Manually; ++: By software; *: Greatest error % in size.
***Source:** Own elaboration*

Finally, with respect to the classification of tomatoes by shape, the results are grouped in Table 5. Eccentricities were calculated for both the dimensions measured by caliper and dimensions calculated by the software. In this case, the calculated eccentricities lead to different shapes in three: cases No. 2, 3, 5 in Table 5. This discrepancy is explained by the angle that the tomato is disposed for the picture; while performing manual measurements it is possible to accommodate the fruit in different ways.

***Table 5:** Tomato shape recognition*

No	ε (Software)	ε (Real)	Shape (Software)	Shape (Real)
1	0,1796	0,1718	Round	Round
2*	0,1778	0,4392	Round	Oblong
3*	0,4158	0,3801	Oblong	Round
4	0,3538	0,2377	Round	Round
5*	0,4728	0,2869	Oblong	Round
6	0,2119	0,2405	Round	Round
7	0,5576	0,6272	Oblong	Oblong
8	0,5008	0,5051	Oblong	Oblong
9	0,5342	0,5383	Oblong	Oblong
10	0,2751	0,2716	Round	Round
11	0,3378	0,2396	Round	Round
12	0,3157	0,2574	Round	Round
13	0,3264	0,3939	Round	Round
14	0,2462	0,2334	Round	Round
15	0,254	0,2683	Round	Round

***:** Shape classification differences
Source: *Own elaboration*

4. CONCLUSIONS

This research establishes an automatic way to classify color, size, shape and surface defects of Chonto type tomatoes under the Colombian technical standard NTC 1103-1 guidelines using image processing software. A routine for analyzing tomato photographs was programmed by integrating Python language and Open Computer Vision (OpenCV) library for image processing.

The results obtained show that the classification algorithm achieved accuracies of 80% in shape, 93.33% in color, and 100% in size and defects. These values are considered satisfactory, considering that only one photo was analyzed in each case. However, the low percentage of shape classification suggests that more than one photo should be taken to improve this percentage.

It is suggested as future work, the integration of a mechanical system for tomato rotation that allows the capture and subsequent analysis of more than one photo from different angles. In this way the height of the tomato can be obtained and possible side effects can be evaluated, in addition to color and shape. Considering that the maximum execution time of the evaluation routine for each photo is 0.48 seconds, evaluations of 3 photographs, for example, do not anticipate a very long time for the complete evaluation of the product. In addition, the use of a stereo vision system would raise the effectiveness of the algorithm by improving the image quality.

As for the use of the algorithm, it might be programmed in the controller of an academic Delta robot owned by the Universidad del Atlántico. In this way, the classification and selection of tomatoes can be carried out in real time following the guidelines established in the Colombian technical standard NTC 1103-1.

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ANNEXES

Annex 1: Tomato recognition pictures

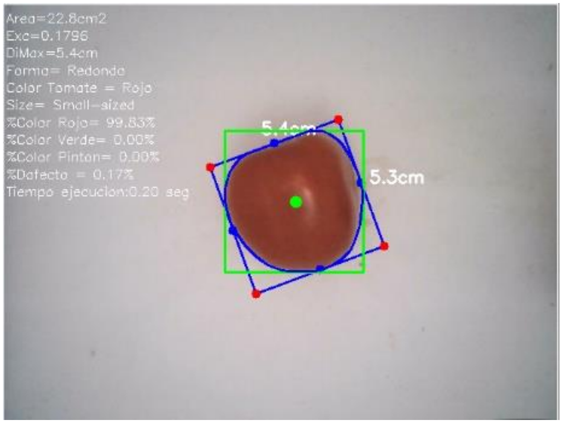

Fig. A-1. *Algorithm results for tomato No 1*
Source: *Own elaboration*

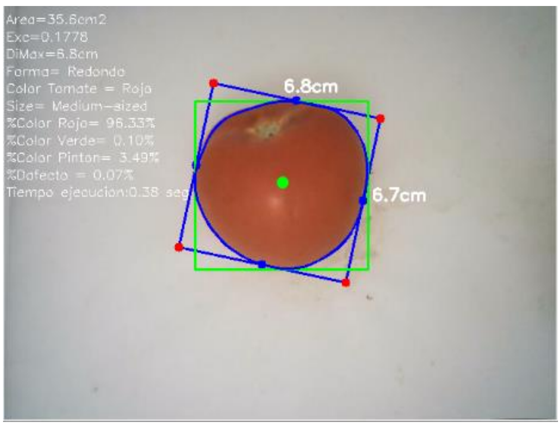

Fig. A-2. *Algorithm results for tomato No 2*
Source: *Own elaboration*

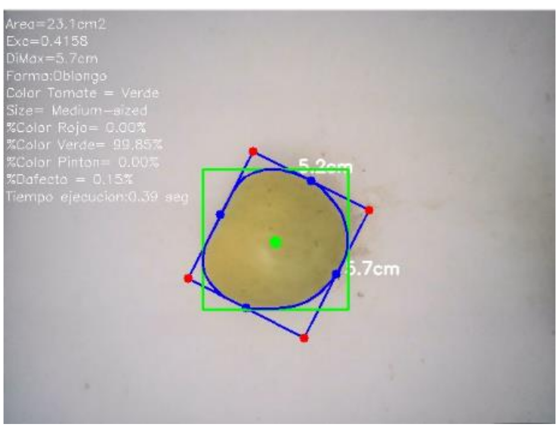

Fig. A-3 *Algorithm results for tomato No 3*
Source: *Own elaboration*

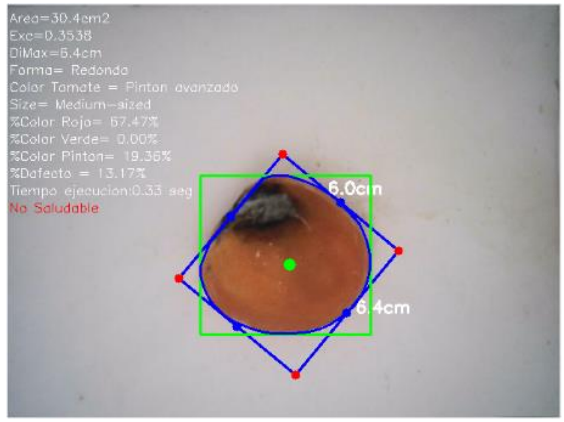

Fig. A-4. *Algorithm results for tomato No 4*
Source: *Own elaboration*

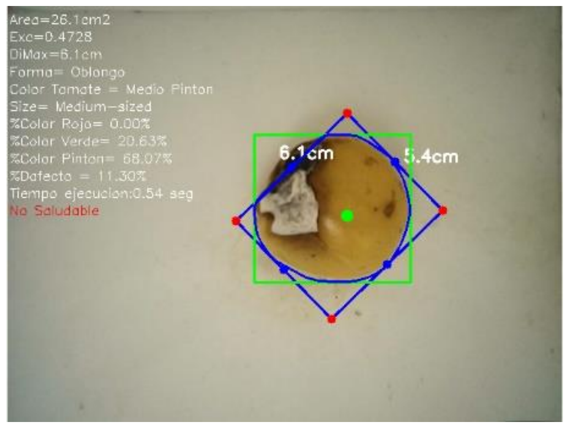

Fig. A-5. *Algorithm results for tomato No 5*
Source: *Own elaboration*

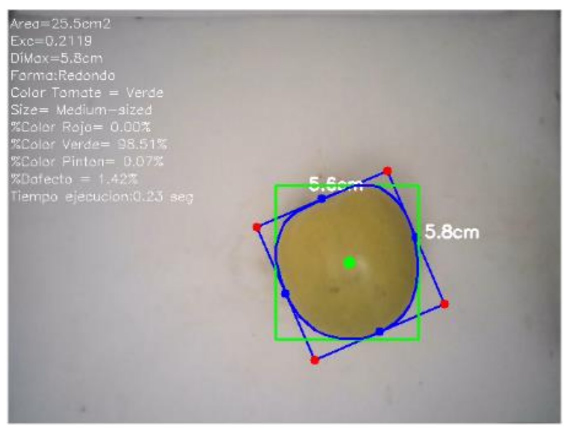

Fig. A-6. *Algorithm results for tomato No 6*
Source: *Own elaboration*

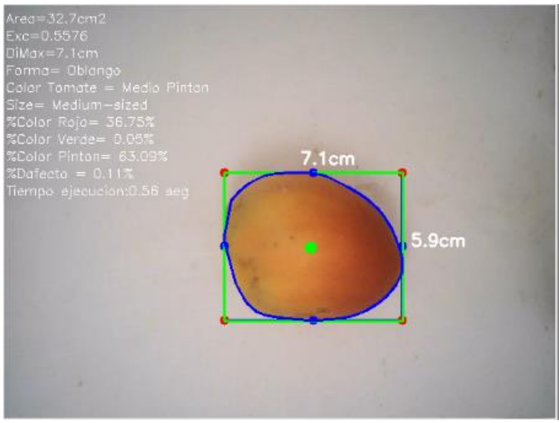

Fig. A-7. *Algorithm results for tomato No 7*
Source: *Own elaboration*

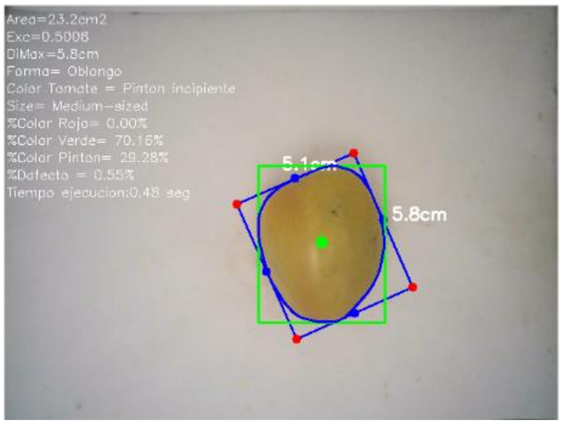

Fig. A-8. *Algorithm results for tomato No 8*
Source: *Own elaboration*

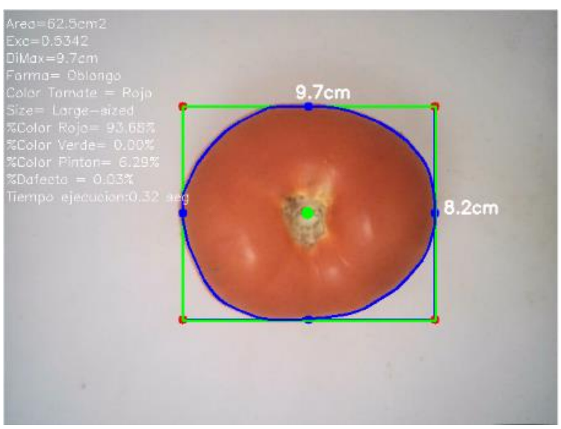

Fig. A-9. *Algorithm results for tomato No 9*
Source: *Own elaboration*

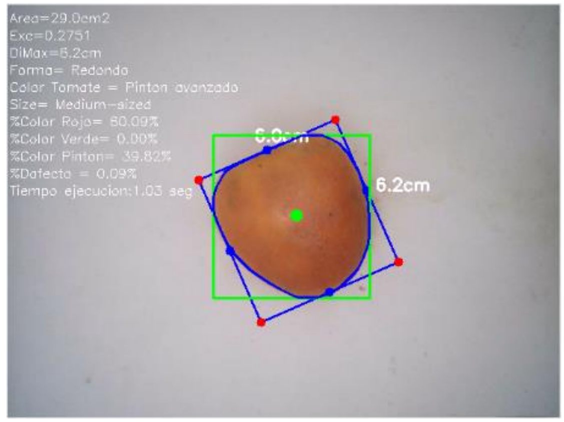

Fig. A-10. *Algorithm results for tomato No 10*
Source: *Own elaboration*

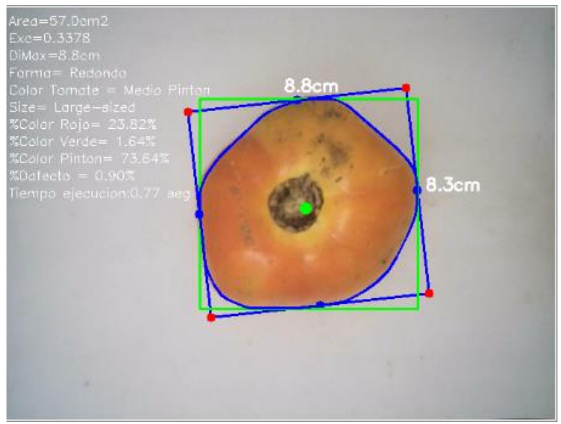

Fig. A-11. *Algorithm results for tomato No 11*
Source: *Own elaboration*

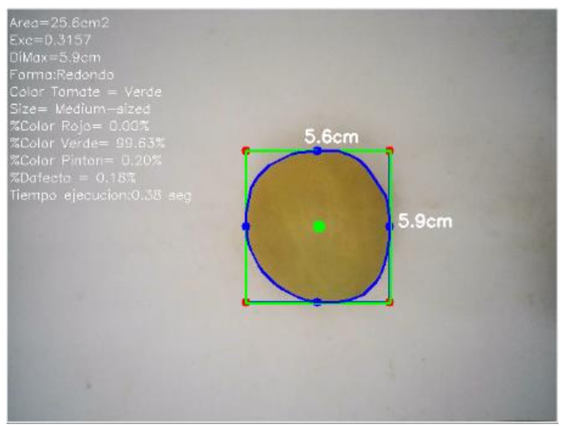

Fig. A-12. *Algorithm results for tomato No 12*
Source: *Own elaboration*

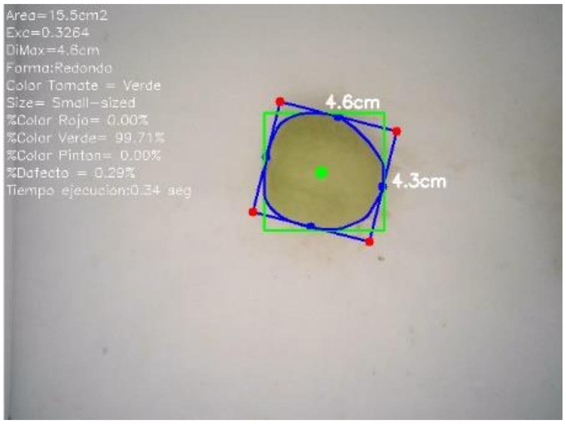

Fig. A-13. *Algorithm results for tomato No 13*
Source: *Own elaboration*

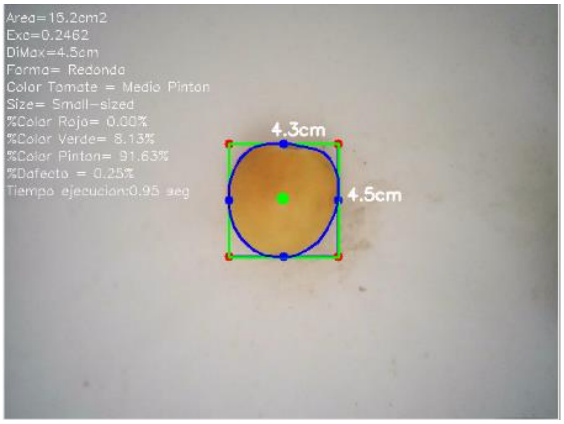

Fig. A-14. *Algorithm results for tomato No 14*
Source: *Own elaboration*

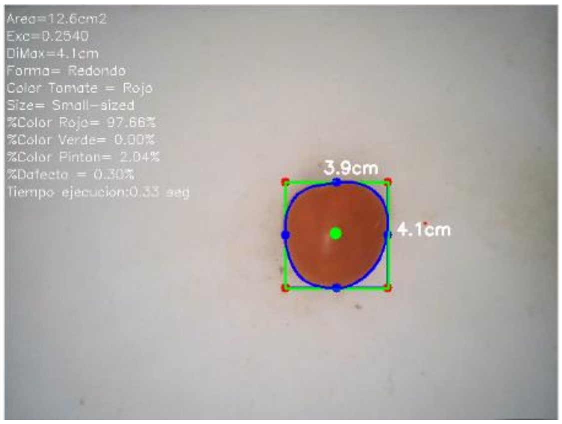

Fig. A-15. *Algorithm results for tomato No 15*
Source: *Own elaboration*