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Original Article

Computer vision-based device for estimating physical parameters of tomato fruits[1]

Dispositivo baseado em visão computacional para estimar parâmetros físicos de frutos de tomate

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HIGHLIGHTS:

A Raspberry Pi microprocessor was used for image acquisition and as the implementation platform for the algorithm.
The software estimated sphericity, surface area, and volume of tomatoes with R^2 of 0.962, 0.963, and 0.952, respectively.
The developed device shows potential for use in both pre-harvest and post-harvest stages of tomato cultivation.

ABSTRACT: Computer vision systems have been successfully applied to automate processes related to the selection and classification of food based on quality standards. In this context, this research aimed to develop a computer vision system comprising an image acquisition device and software capable of estimating the physical parameters of tomato fruits from digital images. The software was developed in Python and implemented on a Raspberry Pi microprocessor, enabling both image capture and the calculation of fruit physical parameters (volume, sphericity, and surface area). The physical parameters of 45 tomatoes from three classes (Saladette, Italian, and Cherry) were estimated using the proposed system and compared with reference values obtained through traditional methods. The comparison indices revealed a high correlation and agreement between actual and estimated values for all physical parameters when analyzing fruits across all classes. The models generated from the total set of fruits (without class distinction) achieved R^2 values greater than 0.95 for all physical parameter estimates. The computer vision system enabled the measurement of tomato physical parameters, presenting approximate estimates to the reference values obtained by traditional methods. This approach represents a viable alternative for estimating the sphericity, surface area, and volume of tomato fruits.

Key words: digital images, non-destructive methods, Raspberry Pi

RESUMO: Sistemas de visão computacional têm sido utilizados com sucesso na automatização de processos associados à seleção e classificação de alimentos a partir de padrões de qualidade de alimentos. Neste contexto, esta pesquisa teve como objetivo desenvolver um sistema de visão computacional, composto por dispositivo de aquisição e software, capaz de estimar parâmetros físicos de frutos de tomate a partir de imagens digitais. O software foi desenvolvido em Python e implementado em um microprocessador Raspberry Pi, permitindo a captura de imagens e cálculo de parâmetros físicos de frutos (volume, esfericidade e área de superfície). Os parâmetros físicos de 45 tomates de três classes (Saladette, Italiano e Cereja) foram estimados pelo sistema proposto e comparados com valores de referência obtidos por métodos tradicionais. Os índices de comparação apresentaram alta correlação e concordância entre os valores reais e estimados para todos os parâmetros físicos ao analisar frutos de todas as classes. Os modelos gerados a partir do conjunto total de frutos (sem distinção de classes) alcançaram valores de R^2 superiores a 0,95 para a estimativa de todos os parâmetros físicos. O sistema de visão computacional possibilitou a mensuração de parâmetros físicos de tomates, apresentando estimativas aproximadas aos valores de referência obtidos por métodos tradicionais. Essa abordagem representa uma alternativa viável para a estimativa da esfericidade, área de superfície e volume de frutos de tomate.

Palavras-chave: imagens digitais, métodos não-destrutivos, Raspberry Pi

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Introduction

The consumer market increasingly demands higher-quality foods, with visual appearance being a key factor influencing purchasing decisions and perceived product value (Palumbo et al., 2023). Tomatoes (*Lycopersicon esculentum*) play a vital role in the human diet and are among the most widely consumed foods globally. Brazil ranks as one of the world's largest producers, with a national output of approximately 15 million tons in 2023 (IBGE, 2024).

Investment in the development of automated technologies has become crucial in the agricultural sector, aiming to increase productivity, enhance economic returns, and improve product quality (Bhargava & Bansal, 2021). Automation of fruit sorting and classification processes using computer vision has shown promising results, such as in estimating egg volumes (Okinda et al., 2020), 3D modeling of macaúba fruits (Costa et al., 2016), apple detection based on shape features (Liu et al., 2019), and real-time citrus fruit classification (Chakraborty et al., 2023).

Manual selection in tomato production remains common. This process is time-consuming, depends heavily on human perception, and lacks adequate precision and uniformity (Kuta et al., 2023). Commercial solutions have used high-speed conveyors with optical sensors to detect fruits that do not meet established standards (Santelices et al., 2025). These fruits are classified instantly based on pre-established criteria, reducing losses due to unnecessary discards (Arjenaki et al., 2013). However, such equipment often requires significant financial investment, making it inaccessible to small and medium-scale producers.

In this context, studies have been conducted to present alternative protocols and accessible technologies for the separation and classification of tomatoes during harvest and post-harvest stages (Bello et al., 2020; Abekoon et al., 2024).

Research efforts include the implementation of computer vision systems to estimate physical characteristics of tomato fruits at harvest (Li et al., 2011), the use of microprocessors to classify types of damage on the tomato epicarp (Kumar et al., 2020), and the application of image processing techniques combined with artificial intelligence to estimate tomato fruit mass (Lee et al., 2020). These areas of investigation aim to automate processes in tomato crop production using image-based technologies.

In this context, this study aimed to develop a computer vision system comprising an image acquisition device and software capable of estimating the physical parameters of tomato fruits from digital images.

Material and Methods

This study was conducted between January and July 2023 at the Department of Engineering of the Federal Rural University of Rio de Janeiro, located in Seropédica, RJ, Brazil (22° 46′ 34″ S, 43° 41′ 13″ W; average altitude of 26 m).

The experiment was conducted using 45 tomato fruits purchased from local markets, divided into three shape-based classes: 15 Saladette-type fruits, 15 Italian-type fruits, and 15 Cherry-type fruits. According to CEAGESP (2003) standards, Saladette tomatoes exhibit a longitudinal-to-equatorial diameter ratio ranging from 0.90 to 1.00; Italian tomatoes have a ratio greater than 1.15; and Cherry tomatoes are classified solely based on equatorial diameter, which must be less than 39 mm.

A Raspberry Pi 3 B+ microprocessor, connected to a camera module, was used for image acquisition. The image-capturing device was mounted on a metal support with adjustable height via a threaded rod. The image acquisition system was enclosed in a wooden chamber with a white interior. The chamber remained open at the top to allow illumination by two 40W LED spotlights. Each fruit was positioned approximately 20 cm from the camera, and the lights were placed at a height of 40 cm above the fruit (Figure 1).

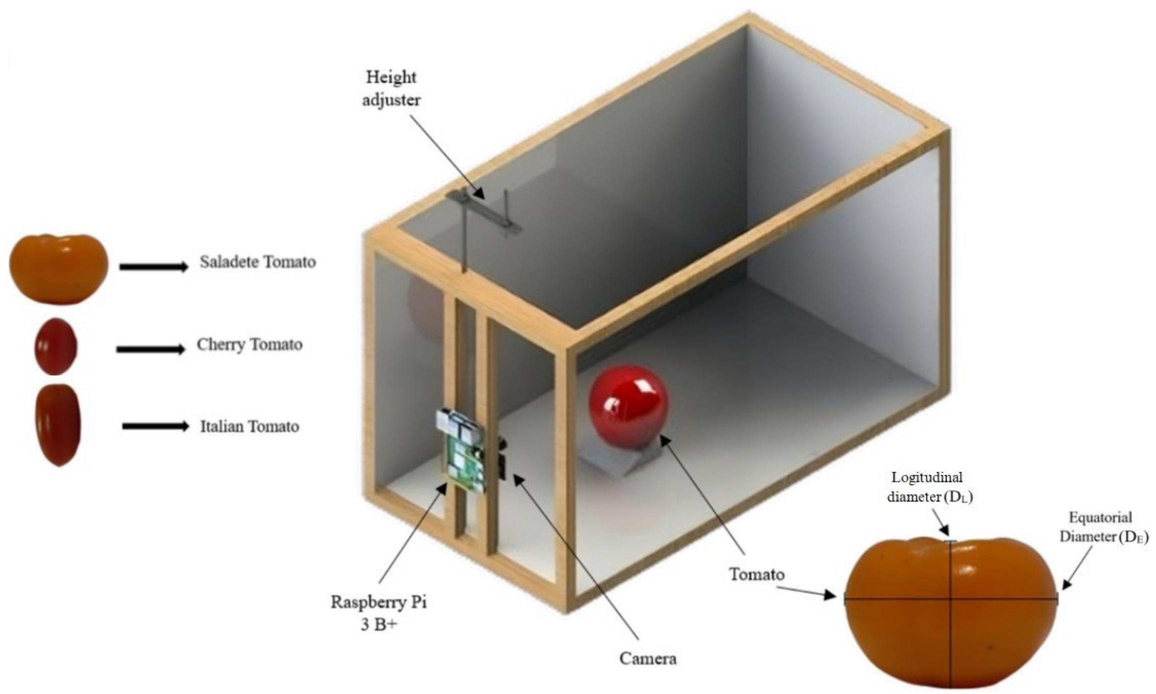

Figure 1. Tomato classes used in the experiment and the layout of the experimental setup for image acquisition

The physical parameters, including equatorial diameter (D_E), height (D_L), and volume (V), were determined after image capture using traditional methods and served as reference values for comparison.

The reference values for D_E and D_L represented the largest horizontal and vertical dimensions of each fruit, respectively (Figure 1), and were measured using a digital caliper (Western Pro) with a resolution and accuracy of 0.1 mm.

The reference values for the volume of Saladette and Italian tomatoes were obtained using the water displacement method, as described by Costa et al. (2016). The volume of Cherry tomatoes was estimated using Eq. 1 due to their small size and the difficulty in detecting water displacement. Sphericity (SP) and surface area (SA) were calculated based on the reference values of D_E and D_L using Eqs. 2 and 3, respectively, following the approach by Li et al. (2011).

$$V = \frac{\pi\left(D_E D_L^2\right)}{6} \tag{1}$$

$$SP = \frac{\left(D_E D_L^2\right)^{\frac{1}{2}}}{D_E} \tag{2}$$

$$SA = \pi\left(D_E D_L^2\right)^{\frac{2}{3}} \tag{3}$$

where:

V - is the cherry tomato fruit volume (cm^3);
SP - is the tomato fruit sphericity (dimensionless);
SA - is the tomato fruit surface area (cm^2);
D_E - is the tomato fruit equatorial diameter (cm); and,
D_L - is the tomato fruit height (cm).

The equation-based method was not used for Saladette and Italian tomatoes, as they have more irregular and less uniform shapes. These characteristics could lead to distorted results, making the water displacement method more appropriate for obtaining reference values.

The software named Tomato Image Metrics – TIM (Instituto Nacional da Propriedade Industrial, registration number: BR512024000055-0) was developed to process images and estimate physical parameters. The TIM software was written in Python, using the OpenCV2 and NumPy libraries, and implemented on a Raspberry Pi 3 B+ microprocessor.

TIM enabled image capture and resizing, as well as fruit edge detection using the Canny detection method on grayscale images. Differentiation between fruit, shadow, and background was adjusted by setting the Canny edge detector's tolerance values. Subsequently, the algorithm calculated the distance between the start and end of the edge in each vertical band of the digital image (in pixels), enabling the measurement of the equatorial diameter and height of the fruit.

The physical parameters SP and SA were calculated using Eqs. 2 and 3, respectively, implemented within the computational routine. The volume (V) was estimated by summing the areas of ellipses formed on each line of the fruit's edge image. A scaling factor, used to convert pixel values to centimeters, was calculated based on the ratio between the experimentally obtained diameter and the actual diameter. This proportion was then used to convert other parameters and shape factors. Figure 2 shows a flowchart of the computational routine executed by the TIM software, from obtaining the images to generating the estimated physical parameter values.

Images of the 45 tomato fruits used in the experiment were captured and processed employing the algorithm and the optical device designed for image acquisition, allowing

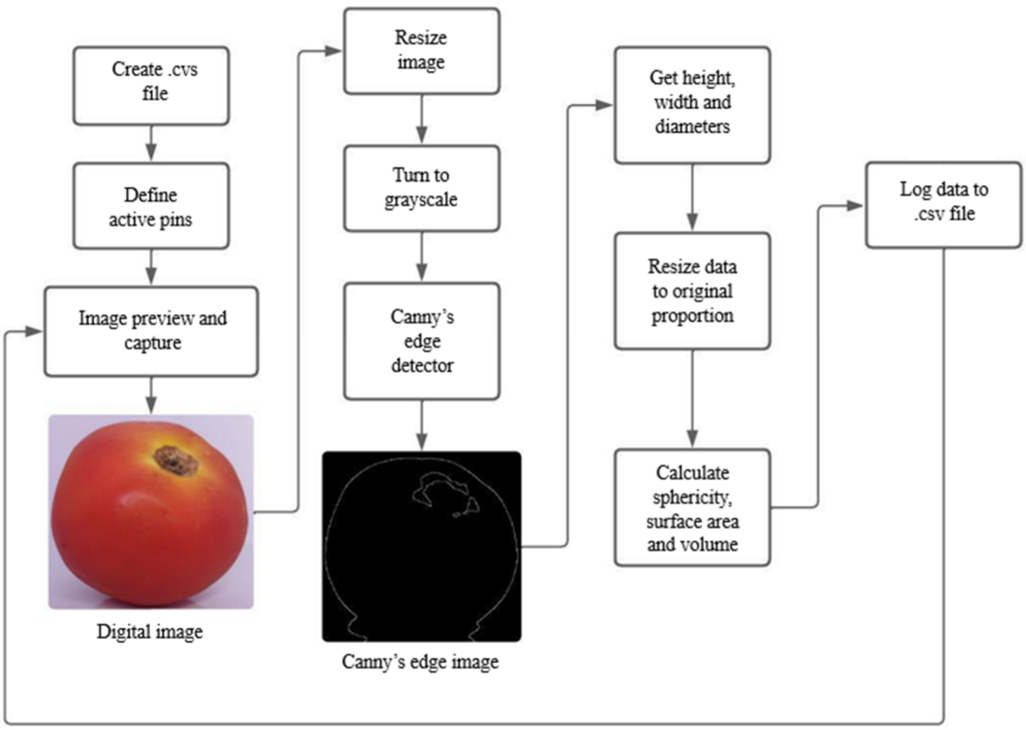

Figure 2. Flowchart of the computational routine implemented in the Tomato Image Metrics (TIM) software for estimating tomato physical parameters

the estimation of the physical parameters SP, SA, and V for each fruit.

Boxplot analyses were used to assess dispersion and identify outliers in the physical parameters estimated for each tomato class. Additionally, a boxplot analysis was performed considering all the fruits collectively (without class distinction). Outliers may indicate possible measurement errors in the TIM software, as fruits of the same class tend to be more uniform.

Comparisons between the values estimated by the TIM software and the reference values were assessed using Pearson's correlation coefficient (r) (Eq. 4), classified according to Hopkins (2000) (Table 1), the concordance index (CI) (Eq. 5), proposed by Willmott et al. (1985), and the performance index (PI) (Eq. 6), proposed and classified by Camargo & Sentelhas (1997) (Table 1).

$$r = \frac{\sum_{i=1}^{n}\left(X_i - \bar{X}\right)\times\left(Y - \bar{Y}\right)}{\sqrt{\sum_{i=1}^{n}\left(X_i - \bar{X}\right)^2 \times \sqrt{\sum_{i=1}^{n}\left(Y_i - \bar{Y}\right)^2}}} \qquad (4)$$

$$CI = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - X_i\right)^2}{\sum_{i=1}^{n}\left(\left|Y_i - \bar{X}\right| + \left|X_i - \bar{X}\right|\right)^2} \qquad (5)$$

$$PI = r \times CI \qquad (6)$$

where:

r - is the Pearson correlation coefficient (dimensionless);

CI - is the concordance index (dimensionless);

PI - is the performance index (dimensionless);

Xi - is the i-th referenced term (cm, cm^2, or cm^3);

Yi - is the i-th estimated value (cm, cm^2, or cm^3);

X - is the mean of the referenced values (cm, cm^2, or cm^3);

Y - is the mean of the estimated values (cm, cm^2, or cm^3); and,

n - is the total number of observations.

The relationship between estimated and reference values for each physical parameter of the tomatoes was also assessed using simple linear regression models, based on the analysis of the coefficient of determination (R^2), coefficient of variation (CV), standard error (SE), and maximum absolute error (MAXE). Model significance was evaluated in RStudio software using p-value, with $p \leq 0.01$ (*) considered statistically significant. Higher p-values were considered non-significant (ns). The analyses were conducted for each fruit class (Saladette, Italian, and Cherry), as well as for the entire dataset without class distinction (overall).

Results and Discussion

The Cherry tomato class exhibited the smallest variation when analyzing the variation in physical parameters estimated using boxplot diagrams (Figure 3). This suggests that the smaller size and higher uniformity of these fruits allowed for minimal variation in the estimated physical parameters. Such uniformity may also have contributed to more consistent fruit positioning during image acquisition, resulting in more consistent estimated values.

Greater variation was observed in the estimated SA and V values for Italian tomatoes compared to other tomato types.

Table 1. Classification of Pearson's correlation coefficient (r) and the performance index (PI) used to compare the values estimated by the TIM software and reference values

Pearson's correlation coefficient (r) - Hopkins (2000)		Performance index (PI) - Camargo & Sentelhas (1997)	
Value	**Classification**	**Value**	**Classification**
$\lvert r \rvert < 0.1$	Very low	PI < 0.40	Terrible
$0.1 < \lvert r \rvert < 0.3$	Low	0.41 < PI < 0.50	Bad
$0.3 < \lvert r \rvert < 0.5$	Moderate	0.51 < PI < 0.60	Sufferable
$0.5 < \lvert r \rvert < 0.7$	High	0.61 < PI < 0.65	Median
$0.7 < \lvert r \rvert < 0.9$	Very high	0.66 < PI < 0.75	Good
$\lvert r \rvert > 0.9$	Almost perfect	0.76 < PI < 0.85	Very good
		PI > 0.85	Great

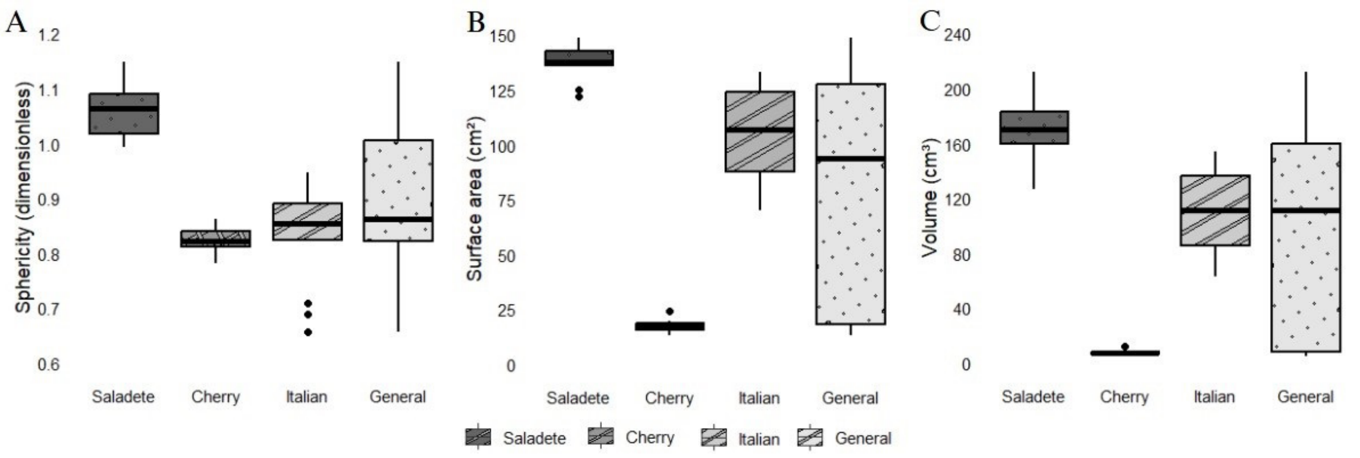

Figure 3. Boxplot diagrams of physical parameters of tomato fruits: sphericity (A), surface area (B), and volume (C)

These values were more dispersed, asymmetrically distributed, and positively correlated, with some data approaching the upper limit. The SP parameter also showed a dispersed, asymmetrical distribution, with values close to the lower limit. The presence of outliers may be attributed to imprecision in SP estimation, potentially caused by fruit positioning or errors during image acquisition. These outliers were removed from further analyses.

A uniform and concentrated distribution was observed for SA and V in Saladette tomatoes. The estimated SP values showed a more uniform distribution relative to the analyzed physical parameters, although asymmetrically positive. Overall, Saladette tomatoes often exhibit variation in the upper region (near the stem), which can cause distortions in height estimation and, consequently, in SA and SP. Height also influences V estimation, as this parameter is calculated by summing elliptical layers.

The comparison between estimated and reference values of physical parameters (Table 2) for the complete set of fruits (without class distinction) showed that the correlation coefficient (r) was classified as almost perfect, the performance index (PI) was rated as excellent, and the concordance index (CI) exceeded 96%. The performance of these parameters indicates proximity between estimated and reference values. Under suitable image acquisition conditions, the TIM software provides physical parameter estimates that closely match those obtained through traditional methods, regardless of tomato shape class.

The comparison between estimated and reference values for each class showed that Cherry tomatoes had estimates closest to the reference values for the SA and V parameters, while Italian tomatoes had estimates closest to the reference values for the SP parameter (Table 2). The r correlation for Saladette tomatoes was classified as very high for SA and SP. All physical parameters of Cherry tomatoes had r correlations classified as very high. Italian tomatoes showed a correlation classified as almost perfect for SP and high for SA and V.

The analysis of CI for each class showed that V was the best-fitting parameter for Saladette (CI = 0.762) and Cherry (CI = 0.859) tomatoes, while SP was the best-fitting parameter for Italian tomatoes (CI = 0.973). Finally, PI, which was obtained from the ratio between r and CI, was used as a global index for comparing estimated and reference values. Among the classes, the best performances were observed for SP (PI = 0.936) and SA (PI = 0.741) in Italian tomatoes, both classified as excellent, and for V (PI = 0.723) in Cherry tomatoes, classified as good.

Table 2. Comparison indices between estimated and reference values for physical parameters (sphericity, surface area, and volume) of tomato fruits

Group	Physical parameters	r	CI	PI
Saladette	Sphericity	0.887	0.640	0.567
	Surface area (cm²)	0.721	0.665	0.479
	Volume (cm³)	0.652	0.762	0.501
Cherry	Sphericity	0.730	0.690	0.503
	Surface area (cm²)	0.866	0.835	0.723
	Volume (cm³)	0.862	0.859	0.741
Italian	Sphericity	0.962	0.973	0.936
	Surface area (cm²)	0.682	0.784	0.535
	Volume (cm³)	0.694	0.756	0.525
General	Sphericity	0.981	0.968	0.950
	Surface area (cm²)	0.982	0.988	0.970
	Volume (cm³)	0.976	0.986	0.961

r – Correlation coefficient; CI – Concordance index; PI – Performance index

The better fits observed between estimated and reference values for Cherry tomatoes may be attributed to the symmetry between fruit diameter and height, which facilitated the calibration of these parameters through image-based measurements. Importantly, the reference volume for the Cherry tomato class was calculated using an ellipsoid (Koc, 2007), whereas the water displacement method was used for the other classes. This difference in measurement method may have contributed to the closer match between estimated and reference values.

Additionally, Saladette and Italian tomatoes were positioned horizontally in the image acquisition chamber, which may have caused shaded regions and influenced the estimation of physical parameters and, consequently, their indices based on RGB values. Image processing techniques can be applied to minimize the effect of shading. Ponce et al. (2018) estimated the mass and size of olives using digital images and employed a salt-and-pepper filter, as well as conversion to the HSV color model, to reduce shading effects and improve background segmentation.

The best performance metrics were obtained when analyzing the entire fruit dataset without class distinction. This demonstrates that acquiring images from a larger number of samples tends to reduce the influence of estimates with high deviation from reference values. These deviations may result from image acquisition issues (e.g., shading or noise) or from fruits with deformations and irregular shapes.

The use of algorithms that allow image rotation or 3D reconstruction may reduce errors related to fruit positioning during acquisition. Zhang et al. (2020) compared methods for estimating apple volume using 3D reconstruction versus the water displacement method, achieving a Pearson correlation coefficient of 90.32% using the LS-SVM algorithm. Another possibility is the application of convolutional neural networks (CNNs), which have enabled fruit classification and identification regardless of their orientation relative to the camera (Chakraborty et al., 2023).

The fit of the linear relationship between estimated and reference values, with an R^2 above 95% (Table 3), without distinguishing between fruit classes, reaffirmed the potential of the algorithm developed to estimate physical parameters in a manner similar to traditional methods, regardless of fruit shape. The lowest standard error (SE) observed was 0.019 for the SP parameter, with a maximum error (MAXE) of 0.110.

The intra-class linear adjustments showed that Cherry tomatoes had the best linear relationships for estimating SA (R^2 = 0.750) and volume V (R^2 = 0.744), with the lowest standard error values for the analyzed physical parameters: 0.723 and 0.741 cm^3, respectively (Table 3). Italian tomatoes showed the best linear relationship for estimating SP (R^2 = 0.925), with the highest standard error (SE = 0.022 cm) and the lowest maximum error (MAXE = 0.050 cm) among the tomato classes.

Omid et al. (2010) compared volume estimation using image processing and the sum of elliptical layers with the water displacement method for citrus fruits and obtained R^2

Table 3. Analysis of the models obtained for the physical parameters: sphericity, surface area, and volume

Group	Physical parameters	Equation	R^2	CV	SE	MAXE
Saladette	Sphericity	y = 0.123 + 0.829*x	0.786	0.046	0.013	0.110
	Surface area (cm^2)	y = -2.259 + 1.086*x	0.519	0.088	3.295	26.180
	Volume (cm^3)	y = 34.186 + 0.828*x	0.426	0.129	5.675	30.840
Cherry	Sphericity	y = 0.496 + 0.414*x	0.533	0.024	0.005	0.060
	Surface area (cm^2)	y = 8.045 + 0.498*x	0.750	0.113	0.723	6.140
	Volume (cm^3)	y = 3.523 + 0.504*X	0.744	0.167	0.741	3.490
Italian	Sphericity	y = 0.046 + 0.962*x	0.925	0.101	0.022	0.050
	Surface area (cm^2)	y = -3.278 + 1.032*x	0.466	0.197	5.299	22.710
	Volume (cm^3)	y = -2.758 + 1.103*x	0.482	0.263	7.527	35.350
General	Sphericity	y = 0.232 + 0.736*x	0.962	0.135	0.019	0.110
	Surface area (cm^2)	y = -3.021 + 1.068*x	0.963	0.611	8.312	26.180
	Volume (cm^3)	y = 1.245 + 1.036*x	0.952	0.726	10.676	35.350

R^2 – Coefficient of determination of simple linear regression; CV – Coefficient of variation; SE – Standard error; MAXE – Maximum absolute error. * - Coefficient significant at $p \leq 0.01$; ns - Coefficient not significant

values between 96 and 99%, similar to the results obtained by the proposed algorithm.

However, the volume estimation method used in this study tends to perform better when the fruit has symmetry along its axes. According to Araujo et al. (2020), axis uniformity was also an important factor in estimating height, diameter, and thickness of passion fruit seeds, enabling linear models with R^2 values above 97%.

Khojastehnazhand et al. (2008) estimated the volume of mandarin fruits and obtained a linear fit with an R^2 of 95.91% when comparing the water displacement method and the volume calculated from elliptical layers in images. In addition to axis symmetry, the use of two cameras positioned at 90° within the image acquisition device improved the estimation of physical parameters, an approach that could be considered for updating the TIM software and image acquisition protocol.

Currently, computer vision is widely used in precision agriculture through automated equipment for harvesting (by selecting ripe fruit), pest control, yield mapping, and post-harvest classification based on physical characteristics (Mavridou et al., 2019; Wang et al., 2019; Tripathi & Maktedar, 2020). This study demonstrates the feasibility of applying a computer vision system capable of estimating physical attributes of interest, whether at harvest or postharvest stages.

Li et al. (2011) pointed out that sphericity and surface area are strongly correlated with tomato fruit mass, which facilitates the development of harvesting machines by allowing the calculation of the ideal force to apply to each fruit, helping to avoid physical damage.

Thus, identifying fruit volume, sphericity, and surface area in tomato production and processing can be useful in harvesting, selecting fruits of commercial interest, or sorting them according to established categories.

Conclusions

1. The image acquisition system proposed using the Raspberry Pi microprocessor and the developed software enabled the measurement of physical parameters of tomatoes, providing estimates that closely approximated the reference values obtained through traditional methods.

2. When analyzed by class, Italian tomatoes showed the best performance for sphericity, while cherry tomatoes provided the most accurate estimates for surface area and volume. In contrast, the comparison indices demonstrated a high correlation and agreement between the actual and estimated values for the evaluated physical parameters when analyzing the fruits without class distinction.

3. The developed software, named Tomato Image Metrics (TIM), registered under number BR512024000055-0, enabled image processing and estimation of physical parameters such as sphericity, surface area, and volume of tomatoes with different shapes. In general, Cherry tomatoes showed greater accuracy, which can be attributed to the uniformity and regularity of their shape. However, the models generated without class distinction achieved R^2 values greater than 0.95 for all estimated physical parameters. This result indicates that using a larger sample size for generating estimation models contributes to increased accuracy, minimizing distortions caused by irregular fruit shapes.

4. Sphericity showed the lowest maximum errors and the best linear fit, regardless of fruit shape, and was considered the best physical parameter estimated by the software when compared to traditional methods.

Authors' contributions: Conceptualization: Anderson G. Costa and João Célio L. de Carvalho; data curation: João Célio L. de Carvalho; project administration: Anderson G. Costa and João Célio L. de Carvalho; methodology and investigation: João Célio L. de Carvalho; formal analysis and visualization: João Célio L. de Carvalho, João Paulo B. Cunha, and Vânia R. G. Nascimento; writing (original draft preparation): Anderson G. Costa, João Célio L. de Carvalho, and Vânia R. G. Nascimento; writing (review and editing): Anderson G. Costa and João Célio L. de Carvalho; funding acquisition and resources: Anderson G. Costa; supervision: Anderson G. Costa.

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