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DETERMINATION OF THE VOLUME OF UNBOILED ARECANUT KERNELS USING IMAGE PROCESSING

Ajit SALUNKE^{*1, 2, 3}, Sunilkumar HONNUNGAR^{2, 3}, Arunachalam VADIVEL⁴

¹Goa University, Don Bosco College of Engineering, Department of Mechanical Engineering, Fatorda, Goa, India

²Visvesvaraya Technological University, Faculty of Engineering, Belagavi, Karnataka, India

³Visvesvaraya Technological University, SDM College of Engineering and Technology, Department of Mechanical Engineering, Dhavalagiri, Dharwad, Karnataka, India, sunilhonnunar@sdmcet.ac.in

⁴ICAR – Central Coastal Agricultural Research Institute, Horticultural Science Section, Goa, India, arun.ceo.innovations@gmail.com

*correspondence: ajs62014@gmail.com

Areca nut cultivation, though widespread in India, accounting for 50% of the global output, relies on visual attributes such as colour, texture, size, shape, and tactile traits like softness for quality assessment. The paradigm shift towards alternate industrial and medical applications emphasises the need for grading based on physical and mechanical properties. Real-time measurement of crucial physical parameters, particularly the volume of kernels, poses a considerable challenge that is not yet effectively addressed. The study focused on estimating the volume of unboiled areca nut kernels cultivated in Goa, India, utilising real-time image processing with segmentation. The devised system employed two cameras positioned at right angles to determine the diameters and thickness of the kernels. The research findings disclosed an average difference of 2.67% between volume estimations by image processing and the water displacement method. The paired *t*-test results revealed no significant difference ($P > 0.05$) between the volumes obtained from the two methods. Additionally, Spearman's rank correlation coefficient demonstrated a very strong correlation between the two measurement techniques. The proposed method overcoming the limitations of the ellipsoidal method achieved 97.33% accuracy with the potential for real-time measurement of the kernel volumes, providing a basis for automated quality grading based on density and porosity.

Keywords: segmentation; python; quality grading; regression

The evaluation of physical characteristics plays a crucial role in establishing standards for the design of grading, conveying, processing, and packaging systems for agricultural products. It is essential to thoroughly understand how food materials respond to physical and chemical treatments to ensure optimal food quality. Changes in the physical properties of food can occur during processing operations, and overlooking these alterations can lead to potential processing failures. Therefore, it is imperative to consider these physical properties to maintain high food quality and safety standards (Wilhelm et al., 2004). Among these, product volume is essential in the quality grading process that relies on true density or porosity as a critical factor. Although agricultural products are commonly gauged by weight due to their simplicity in measurement, volume-based sorting and growth monitoring present a potentially more efficient alternative to weight sorting. In addition, weight estimation becomes feasible through volume if the density of the produce is known, especially when dealing with minor density variations (Koc, 2007; Rashidi and Gholami, 2008; Khojastehnazhand et al., 2010). Areca nuts exhibit significant physical properties such as shape, size, true density, bulk density, porosity, sphericity, volume, mass, and mechanical properties like plasticity, bio yield point fracture, and compressive stress (Kaleemullah and Gunasekar, 2002; Aware et al., 2013; Bulan et al., 2020; Sridhar, 2015). The research studies have revealed correlations between

properties like true density, porosity, and bio yield point with moisture content in areca nut kernels. The assessment of crucial properties like true density and porosity plays a vital role in effectively characterising the quality of nuts and seeds by estimating volume and mass. The correlation among these physical properties facilitates automated grading equipment development, integrating mechanical and optical techniques (Salunke and Honnunar, 2022). Moreover, colour-based classification has limitations due to sorting inaccuracies and complexity of algorithms (Salunke and Honnunar, 2020). Commonly employed methods for volume measurement involve gas displacement and water displacement. However, these techniques come with limitations, particularly regarding real-time applications. Systems designed for grading based on size and mass have proven ineffective, as they often overlook the inherent physical properties that signify the quality of agricultural products. Kaleemullah and Gunasekar (2002) and Bulan et al. (2020) used the water displacement method for volume measurement to obtain the true density of the areca nut kernels. The imperative for density and porosity-based grading underscores the need for real-time measurement of volume and mass to gauge agricultural products' quality accurately. The image processing technique is employed in indirect volume estimation of fruits and vegetables (Jana et al., 2020), sweet potato (Huynh et al., 2022), leaf vegetables (Yeh et al., 2014), and tomato (Nyalala et al., 2019). Saadati

et al. (2024) identified armyworm-infected leaves in corn by image processing and deep learning with an accuracy of more than 98%. Meyer et al. (2018) used the radial projection technique of image processing for the volume measurement of strawberries and found the technique comparatively accurate for research and commercial applications for irregularly shaped products. Siswanto et al. (2014) used a volume measurement algorithm for food products with irregular shapes using computer vision based on Monte Carlo method and observed a reduction in computation time. Huynh et al. (2020) used image processing for real-time size and mass estimation of slender axisymmetric fruit/vegetables using a single top-view image and obtained an accuracy of 96.5% and 96.8% for carrots and cucumbers respectively. Fazel et al. (2020) used an adaptive neuro-fuzzy inference system to predict the bruise volume caused by the impact on apples and found the technique better than regression models. Sabliov et al. (2002) developed an image processing-based method to measure the volume and surface area of eggs, peaches, and lemons with MATLAB. Lee et al. (2017) developed a technique for the estimation of the volume of strawberries using changes in the regularity of seeds on the fruit surface with smartphone and image processing in MATLAB.

Several researchers utilised the ellipsoid approximation method to determine the volume of fruits like watermelon, kiwifruit, and tangerine (Koc, 2007; Rashidi and Gholami, 2008; Khojastehnazhand et al., 2010). However, they deemed this method unsuitable, citing significant statistical differences compared to the water displacement method. On the contrary, employing image processing with disk and segmentation methods proved effective for volume estimation, demonstrating high accuracy of up to 98% and yielding statistically insignificant results. Koc (2007) introduced an image processing (IP) technique utilising disk approximation to sort watermelons by volume using a single camera. The method involved estimating volume from surface images of each watermelon by treating each two-dimensional boundary image as the sum of individual disk elements and revolving half of the height of each rectangular element around the X-axis, producing a cylindrical disk. No statistically significant differences were observed compared with the water displacement method through the paired *t*-test and Bland-Altman approach. The percentage difference between the two methods was 7.7%. However, Bland-Altman analysis revealed that the image processing method tended to overestimate volume as watermelon size increased. Addressing this limitation, Khojastehnazhand et al. (2010) applied two charged-coupled device (CCD) cameras for tangerine volume estimation, eliminating the need for camera rotation. This improved method proved accurate and precise with an average percentage difference of 2.6%, notably being rotationally invariant and not requiring fruit alignment on the conveyor. The background segmentation method employed was not reliant on threshold values, making it adaptable for use with various fruits. The authors have extended these algorithms for estimating the mass and surface areas of oranges and other citrus fruits. Omid et al. (2010) developed a two-camera machine vision system for accurately measuring the volume of citrus fruits, achieving a 96% accuracy compared to the water

displacement method. The method involved using Visual Basic to divide the fruit image into elementary elliptical frustums and calculate the volume as the sum of individual frustum volumes. Computed volumes strongly agreed with actual volumes determined by the water displacement method, with a high coefficient of determination (R^2) value of up to 0.985 for lemon, lime, orange, and tangerine. Bland-Altman approach indicated that the accuracy of computed volume remained unaffected by the size of citrus fruits. Correlation equations establishing a relationship between mass and volume resulted in a grading accuracy of 94% and demonstrated a high correlation between volume and mass. The results conformed with the study by Khojastehnazhand et al. (2009) and Huynh et al. (2022), which estimated the volume of oranges and sweet potatoes respectively using a similar segmentation approach. The differences between the computed volumes obtained through the image processing method and those measured by the water displacement method were not statistically significant at the 5% level. Bland-Altman results further demonstrated that the size of the orange had no impact on the accuracy of the estimated volume determined by the image processing technique. The computed volume and the measured mass of oranges were highly correlated with $R^2 = 0.93$. Rashidi and Gholami (2008) employed image processing with the disk technique to calculate the volume of kiwifruit. They assumed each 2D image to be comprised of rectangular elements. The volume determined by this method was not statistically different from that obtained from the water displacement method, with an average percentage difference of 7.8%. However, Bland-Altman plot indicated that this method was unsuitable for flattened or misshaped fruits, a finding consistent with similar observations in cantaloupe as reported by Rashidi et al. (2009), with average percentage differences of 7.6%. In a study by Keshavarzpour et al. (2013) using the disk image processing method, the volume of cantaloupes did not significantly differ from the volume measured by the water displacement method, with an average percentage difference of 7.6% between the two methods. Bland-Altman approach further confirmed that the image processing method satisfactorily estimated the volume for all sizes of cantaloupes. These elaborate studies have found the segmentation method effective in determining the volume of various agricultural products with potential real-time applications in various post-processing operations.

This research aims to validate a method based on mechanical and visual techniques using Python and OpenCV to measure the volume of unboiled type (Chali) arecanut kernels using the segmentation method of image processing. The technique was validated with the water displacement method and its suitability for potential application in the quality grading of kernels based on density and porosity is statistically analysed. The correlation between volume and mass is established, and the potential for mass prediction based on volume measurements is explored.

Material and Methods

Water displacement method

The kernel volume was determined by a 250 mL graduated cylinder displacing water maintained at 25 °C, as performed by Kaleemullah and Gunasekar (2002) (Fig. 1).

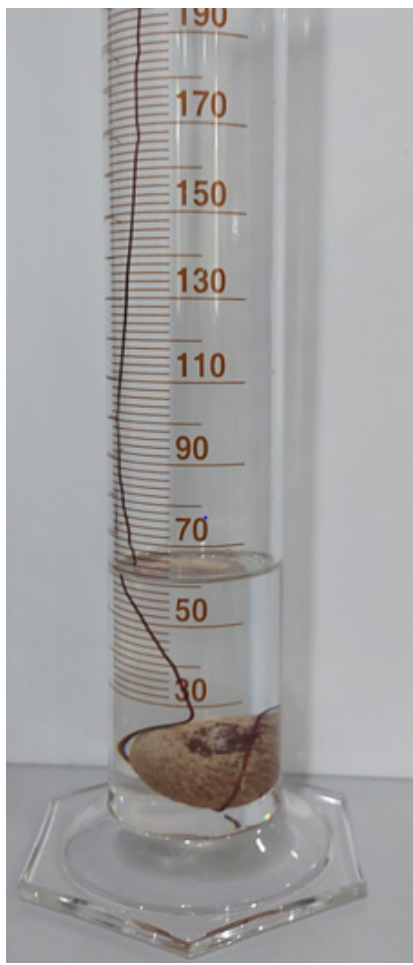


Fig. 1 Water displacement method

Volume measurement system

The machine vision system employed in this research featured two Logitech webcams, each with a maximum resolution of 720 p at 30 frames per second and equipped with standard objective lenses (Fig. 2). A 3W white LED linear light source was provided in the image acquisition chamber, and the system was equipped with a laptop running Python 4 and OpenCV. A uniform background was achieved with black paper. The cameras were strategically positioned at right angles to each other to capture the top and

side images of kernels. The top camera was mounted on a frame attached to device's top panel, while the side camera was fixed at the bottom. An OpenCV program was developed to record RGB colour images from both cameras (Fig. 3a), and these images were then converted into an eight-bit grayscale representation with 256 shades from black (0) to white (255). Using a thresholding method, a binary image was generated from the selected region of interest in the grayscale image (Fig. 3b). Based on experimental findings, the threshold levels of 90% and 80% were established for the top

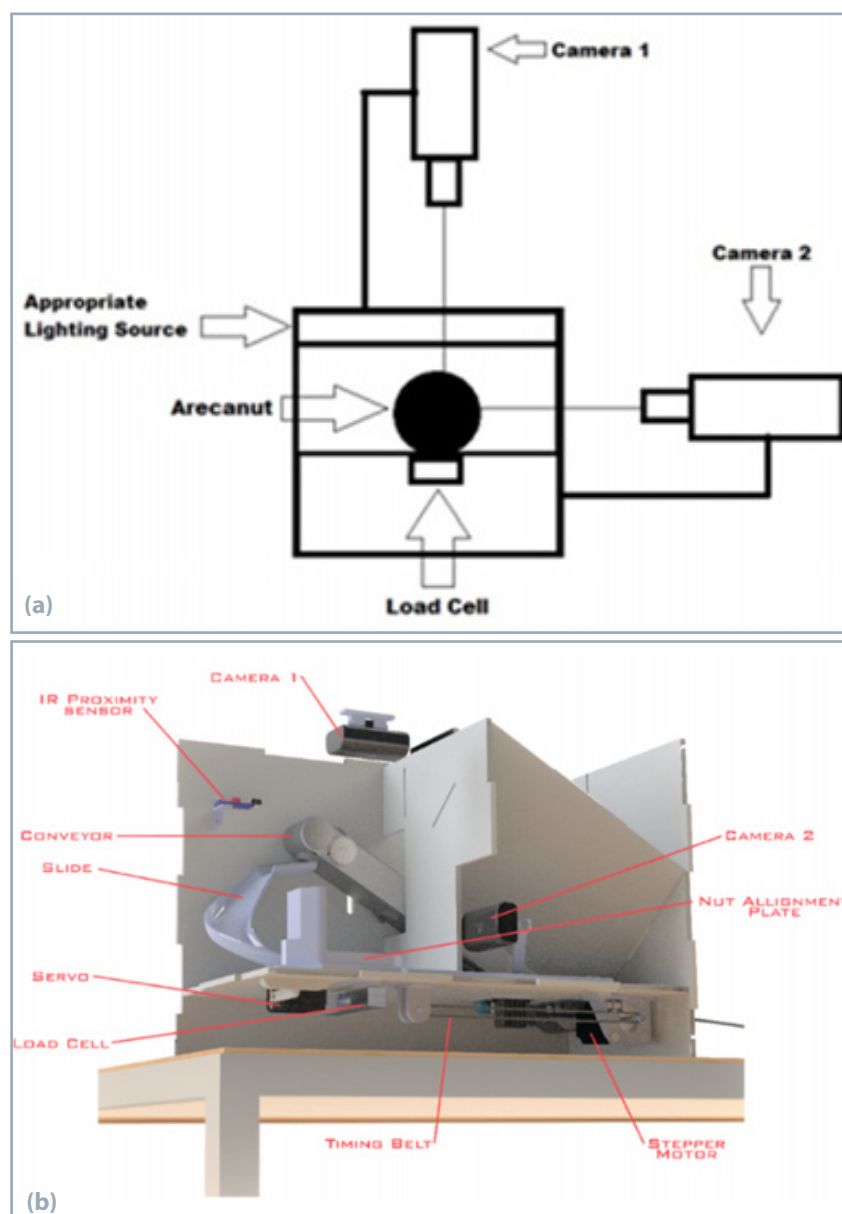


Fig. 2 (a) Schematic view of the machine vision system; (b) Volume measurement system

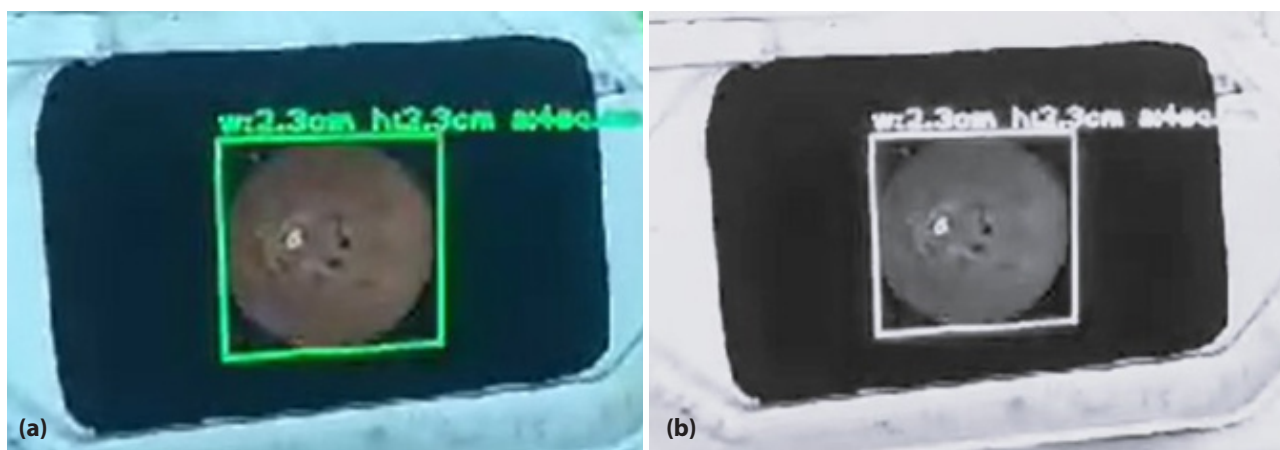


Fig. 3 (a) RGB image of kernel; (b) 2-bit image of kernel

and side cameras, respectively. Pixels below the threshold were converted to black (0), while those above were transformed to white (255), resulting in a binary image representing the kernel. Edge detection was applied to identify the kernel's edge in the image.

Volume evaluation using the segmentation method

The background is removed for the segmentation of the areca nut, and the kernel image is divided into several distinct sectors or frustums (Fig. 4), as illustrated for tangerine, cantaloupe, and citrus fruits (Khojastehnazhand et al., 2010; Keshavarzpour and Achakzai, 2013; Omid et al., 2010). The surface area of each sector is found using Eq. (1).

$$A_i = \pi \frac{d_{i1}}{2} \cdot \frac{d_{i2}}{2} \quad (1)$$

where: d_{i1} and d_{i2} – the two perpendicular diameters of the lateral surface determined by the two cameras

The volume of each sector ($V_{i,i} = 1, 2, \dots, n$) is calculated using Eq. (2).

$$V_i = \left(\frac{A_i + A_{i+1}}{2} \right) \cdot \delta \quad (2)$$

where: A_i and A_{i+1} – the surface areas of i and $i+1$ segments, respectively; δ – the thickness of a segment (assuming all segments are of equal thicknesses), the number of segments is set to 100

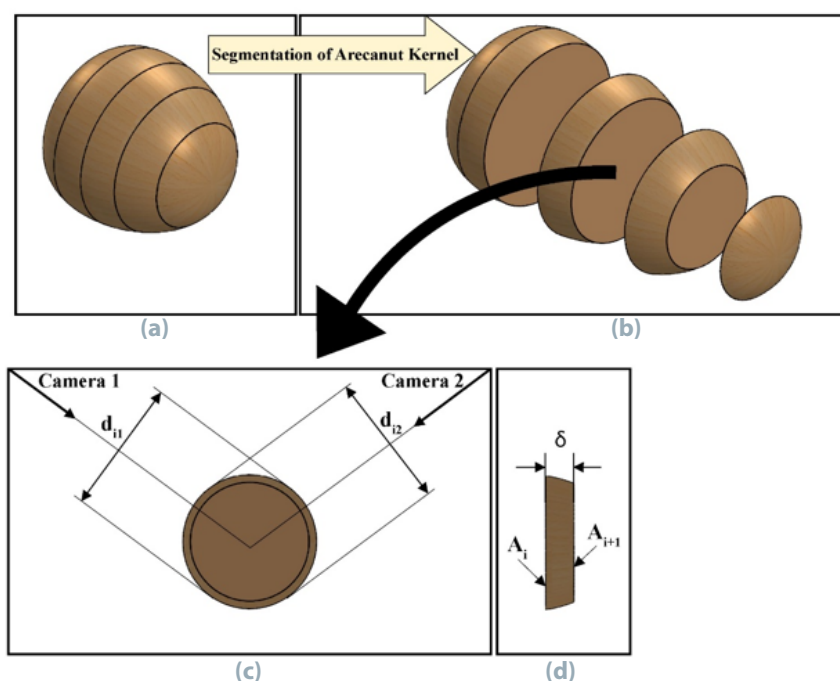


Fig. 4 (a) Arecanut kernel; (b) Segmentation of kernel; (c) Extraction of two diameters of one surface of one sector; (d) Thickness of sector and its surface areas

The program calculates the segment thickness based on the measured thickness of the kernel. Once the volume of all sectors was obtained, the total volume of the kernel was calculated by adding them up. The top camera calculates the diameter d_{i1} . The side camera measures the diameter d_{i2} and the thickness δ .

Programming

The algorithm (Fig. 5) uses Python script for capturing and processing video frames from the cameras. The application is designed to perform

specific actions based on the detected markers and contours in images. An OpenCV program is utilised for image processing and toggles between the camera's top and side views, continuously capturing frames and detecting objects. It further applies colour thresholding to identify objects in the frame using Canny filters, computes the pixel-to-cm ratio based on the detected marker, and displays the image with annotations such as the dimensions of detected objects. Aruco markers are used for scaling, enabling the conversion of pixel distances to physical distances.

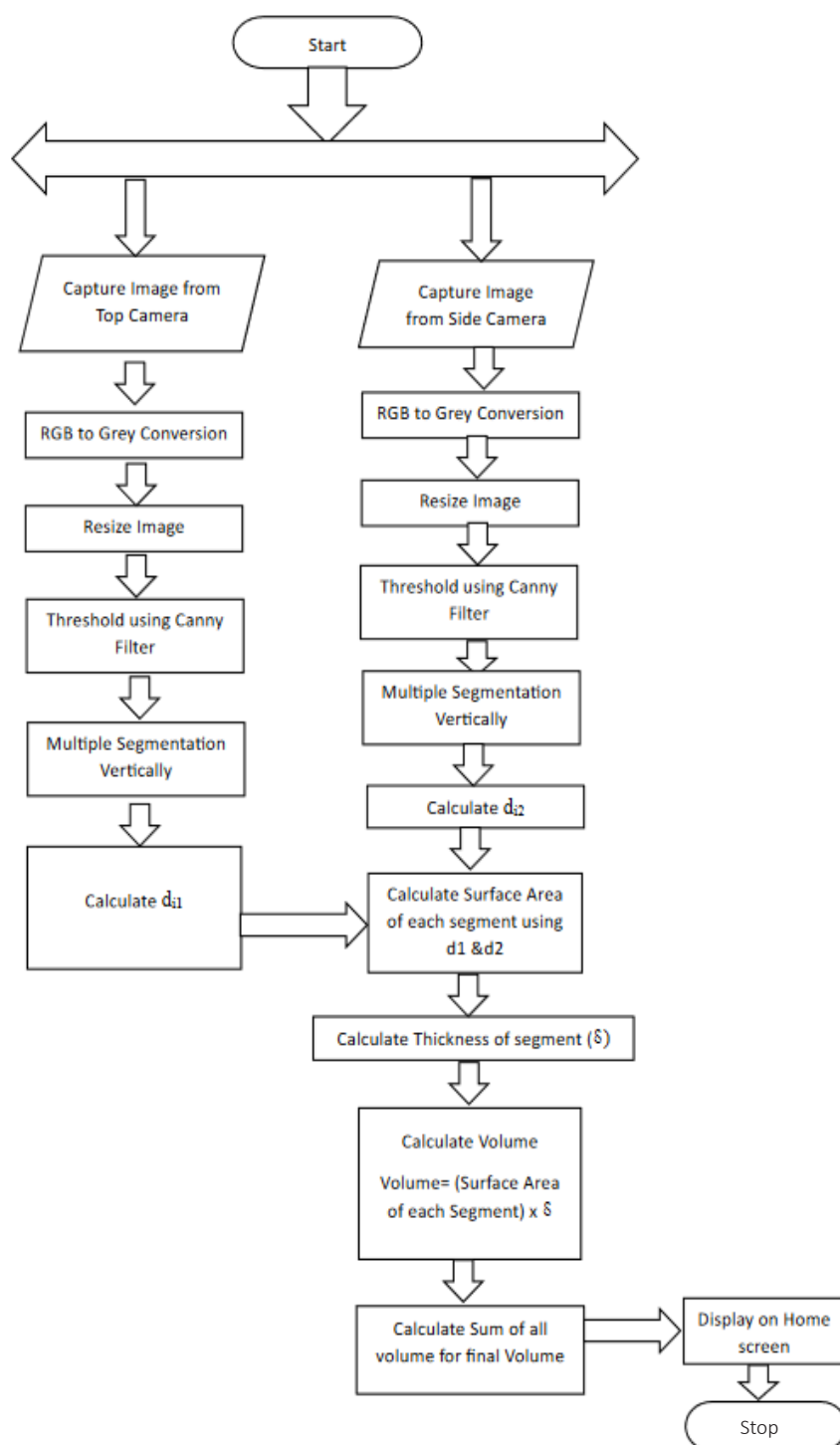


Fig. 5 Flow chart of the image processing process for volume estimation

The Aruco markers are detected within the image, indicated visually by polygons drawn around them. The program measures the perimeter of the Aruco marker to determine the pixel-to-cm ratio. The kernel image is divided into multiple segments and the surface area of each segment is calculated from its two perpendicular diameters. The program further computes the volume based on the previously determined area.

Statistical analysis

Statistical analyses were performed using MS Excel and Minitab. A paired *t*-test and the mean difference confidence interval approach were employed to compare kernel volume measurements obtained from image processing and the water displacement method (WDM). Spearman's rank correlation coefficient was used to determine the association between these two measurement techniques. Regression analyses were performed for both methods, yielding the coefficient of determination (R^2). Bland-Altman method was applied to plot the agreement between kernel volume measurements from the water displacement method and image processing. Additionally, the regression analysis was conducted to identify the statistical relationship between mass, measured by a digital weighing scale (DWS), and volume obtained from image processing, with the corresponding R^2 value determined. Spearman's rank correlation coefficient was also calculated.

Results and Discussion

Comparison of volume measurement with segmentation and water displacement methods

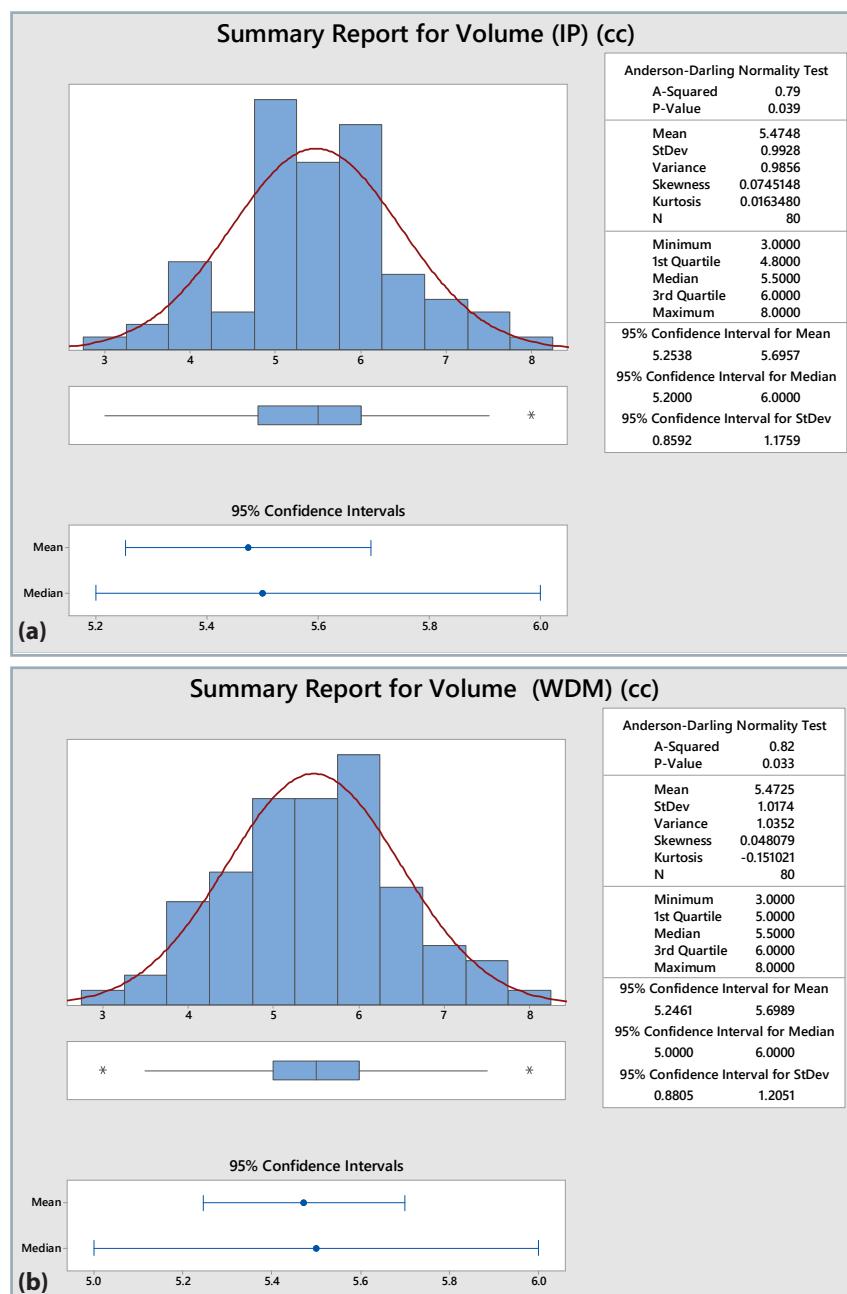
The volume values of arecanuts determined by the segmentation and water displacement methods (Table 1) were compared. The descriptive statistics for both methods are presented in Fig. 6. The mean volume obtained using the segmentation method was 4.57 cm^3 , with a minimum volume of 3 cm^3 and a maximum of 8 cm^3 . The average percentage difference between volume estimates from segmentation and water displacement

Table 1 Measured mass and volume of arecanuts used in the study

No	Volume (cm ³)		Mass (g)	No	Volume (cm ³)		Mass (g)
	IP	WDM	DWS		IP	WDM	DWS
1	6	6	5.06	41	6	6	8.2
2	5.2	5	5.96	42	6	6	7.98
3	4	4	4.51	43	5.5	5.5	7.4
4	4.8	5	5.65	44	6.5	6	8.26
5	4.8	5	5.82	45	5	5	7.3
6	4.8	4.5	5.75	46	4.8	5	8.13
7	4.8	5	6.14	47	6	6	7.88
8	4.8	5	5.53	48	6	6.5	8.33
9	4.4	4.5	5.57	49	7	7	8.89
10	6	6	6.67	50	5.5	5.5	5.79
11	4.5	4.5	4.93	51	6.5	6.5	8.47
12	5.5	5.5	6.68	52	5.5	6	7.37
13	6	6	6.35	53	7.5	7.5	9.49
14	4.8	4.5	5.1	53	6.5	6.5	8.13
15	4	4	4.07	54	7	7	9.23
16	4.8	4.5	5.2	55	4.8	5	7.65
17	3	3	3.8	56	5	5.5	6.81
18	3.6	3.5	4.1	57	6	6.5	7.68
19	4	4	5.05	58	4.8	4.5	6.81
20	5.5	5.5	6.14	59	6	6	7.34
21	4.8	4.5	5.71	60	5.6	5	8.47
22	4.08	4	4.76	61	6.5	6.5	8.94
23	4	4	4.65	62	5.4	5.5	7.41
24	3.9	4	4.13	63	6.5	6.5	7.61
25	3.6	3.5	4.37	64	6	5.8	8.78
26	5.6	5.5	8.23	65	8	8	9.7
27	4.4	4.5	6.61	66	4.8	5	7.38
28	5.2	5.5	8.33	67	6	6	8.3
29	5.5	5.5	7.21	68	6	6	8.02
30	5.2	5	9.03	69	4	4	6.73
31	6.5	6.5	8.73	71	5.6	5.5	8.43
32	5.5	5	8.5	72	7.5	7.5	8.73
33	6	6	7.43	73	7	7	9.52
34	5	4.5	8.12	74	6	6	8.29
35	5.6	6	8.11	75	6	6	8.82
36	5	5.5	7.27	76	6	6.5	8.54
37	6	6	7.98	77	7	7	9.57
38	5.5	5.5	7.94	78	7.5	7.5	10.45
39	5.5	5.5	6.93	79	5.5	5	6.68
40	5	5	6.94	80	6	5.5	6.67

Table 2 T-test analyses on comparing volume measurement methods

No.	Parameter	Volume (WD and IP) (cm ³)
1	P-value	0.931 (>0.05). not significant
2	mean difference	0.0022
3	standard deviation	0.2332
4	95% confidence interval for mean difference	(-0.0496, 0.0541)

**Fig. 6** Graphical summary of descriptive statistics for (a) Image processing; (b) Water displacement method

methods was 2.67%. Anderson-Darling normality test indicated that the data from both the segmentation and water displacement methods did not follow a normal distribution (Fig. 6). Spearman's correlation coefficient, which was used to evaluate the relationship between the two methods, was 0.961 ($P < 0.05$), indicating a very strong association. Similarly, the coefficient of determination ($R^2 = 94.7\%$) obtained from the regression model (Fig. 7) also reflects a strong correlation between the methods. The paired samples t-test indicated that the kernel volume measured with water displacement was not significantly different from the volume estimated with image processing ($P > 0.05$) (Table 2). The mean volume difference between the two methods was 0.0022 cm^3 (95% confidence interval: $-0.0496, 0.0541 \text{ cm}^3$), with a standard deviation of 0.2332 cm^3 .

The 95% of the volume differences were expected to lie between $d_2 - 1.96 \text{ sd}_2$ and $d_2 + 1.96 \text{ sd}_2$, known as 95% limits of agreement (Koc, 2007). The 95% limits of agreement for comparing the volumes measured with the water displacement and segmentation method were calculated at -0.4548 cm^3 and 0.4593 cm^3 . The outer (broken) lines indicate the 95% limits of agreement, and the centre line shows the average difference. Bland-Altman plot (Fig. 8) indicates that the kernel size does not significantly affect the volume estimation, as reported by Koc (2007) for watermelon. The improved accuracy can be attributed to using two cameras for image acquisition. The results indicate the effectiveness of the segmentation method for unboiled arecanut kernels and are consistent with the study for tangerine (Khojastehnazhand et al., 2010).

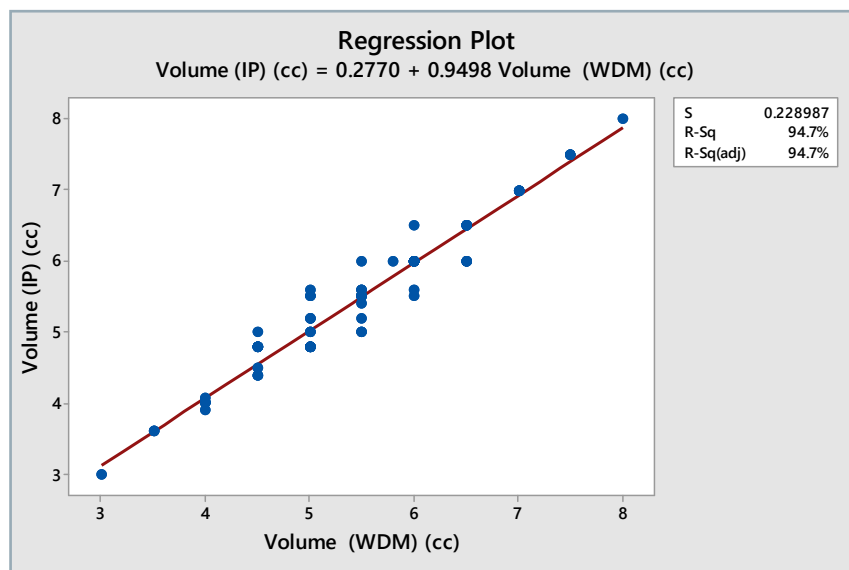


Fig. 7 Kernel volume measured by the image processing (IP) and water displacement method (WDM) with the line of equality

The regression equation is shown below (Eq. 3).

$$\text{volume (IP) (cc)} = 0.2770 + 0.9498 \text{ volume (WDM) (cc)} \quad (3)$$

Correlation of mass and volume

The mass of kernels was measured using a digital weighing scale. The measurement readings are shown in Table 1. The regression plot of kernel mass and volume (Fig. 9) shows a weak correlation between the two measurements ($R^2 = 68.3\%$). Spearman's rank correlation coefficient was 0.773. These findings suggest that modelling mass based on volume is not suitable for arecanut kernels.

The predictive equation obtained from the regression analysis is shown in Eq. (4).

$$\text{volume (cc)} = 1.716 + 0.5246 \text{ mass (g)} \quad (4)$$

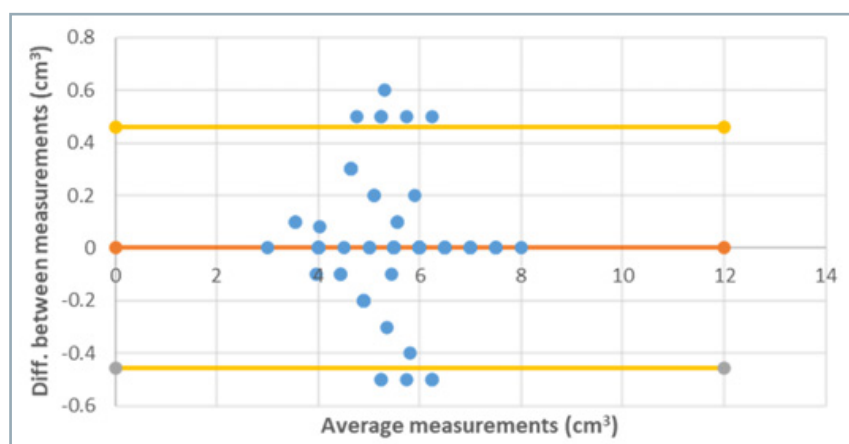


Fig. 8 Bland-Altman plot

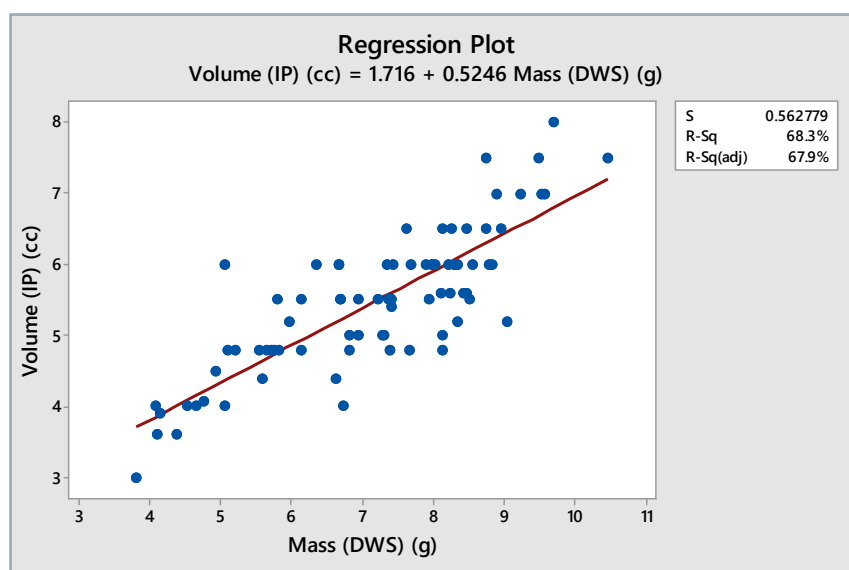


Fig. 9 Comparison of mass and volume measurements

Conclusion

The segmentation method of image processing was found to be effective for the volume measurement of arecanut kernels, as suggested by various researchers for other agricultural products (Koc, 2007; Khojastehnazhand et al., 2010; Rashidi and Gholami, 2008; Rashidi et al., 2009; Keshavarzpour and Achakzai, 2013; Omid et al., 2010; Khojastehnazhand et al., 2009), overcoming the limitations of the ellipsoidal method. The real-time volume measurement technique for kernels achieved an accuracy of 97.33%, with no statistically significant differences with the water displacement values. The increased accuracy can be attributed to the enhanced algorithm used to generate segment thickness from kernel's actual thickness. Bland-Altman approach indicated that kernel size did not impact volume estimation, which is consistent with findings for tangerine (Khojastehnazhand et al., 2010). The finding can be ascribed to adopting two cameras and considering the lateral surface areas of elliptical frustums, in contrast to the conventional use of simple circular disks for volume estimation. These results align with those reported by Omid et al. (2010)

and Khojastehnazhand et al. (2010) for citrus fruits and tangerines, respectively. It is noteworthy that the existing studies primarily focus on fruits, and this particular method has not been explored extensively for arecanut volume estimation. The current study lays the groundwork for automated quality grading device based on density and porosity and optimisation studies for processing parameters. Additionally, this work may extend to similar agricultural products such as cashew nuts, walnuts, hazelnuts, etc.

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