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DEVELOPMENT OF A TRUE DENSITY-BASED AUTOMATED QUALITY GRADING DEVICE FOR UNBOILED ARECANUT KERNELS

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ABSTRACT

The automated sorting of arecanut kernels is a significant challenge that has not been effectively addressed thus far. Scientific grading techniques are necessary given the paradigm change toward investigating alternative uses for arecanuts in industry and the medical field. This research work emphasizes the relatively unexplored aspect of the post-harvest process; quality grading of kernels based on physical properties. It aimed to develop a novel approach for classifying unboiled (Chali) arecanut kernels cultivated in Goa, India based on their true density, using a combination of mechanical and visual techniques. The study explored the potential of true density as a quality indicator for real-time grading of the kernels. To achieve this, automated grading equipment was devised, utilizing a load cell to measure the kernel's mass and the ellipsoid approximation method to estimate its volume. A machine vision system captured the top and side images of the kernels to measure their volume. Python programs were created to enable image acquisition, processing, object detection, measurement and kernel segregation. Real-time kernel classification was accomplished by establishing serial data communication between the Python code and the Arduino board. The kernel segregation process was facilitated by servomechanism and a stepper motor. The kernels were classified into acceptable and non-acceptable categories based on a threshold value of true density. The research successfully established a method that utilizes the physical attributes of arecanut kernels as parameters for quality grading. However, the study encountered challenges with the density measurements, as the paired t-test results revealed significant differences between the kernel true density measured by the device and the true density estimated using the weighing scale-water displacement method, indicating a percentage error of 13.2%. Addressing these challenges would lead to more accurate density calculations, thereby enhancing the overall effectiveness of the kernel classification process. Furthermore, the technique allowed for the offline estimation of the kernels' porosity, which was found to be 45.3%. In future research, the integration of density and porosity measurement systems could be explored for real-time quality evaluation based on porosity, offering potential opportunities for further enhancement and optimization of the grading process. The technology could be further applied to other types of nuts and agricultural products, thereby overcoming the limitations of color-based sorting using image processing.

Key words: Quality grading, True density, Machine vision, Arecanut kernel, Python

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INTRODUCTION

Factors like density and porosity, which are notably influenced by moisture content, play a critical role in evaluating the characteristics and overall quality of food products [1]. The mechanical properties of dried agricultural products vary with porosity [1]. Variations in density during the maturation process of agricultural products can significantly impact product quality [2]. True density evaluation is a valuable tool in characterizing and predicting the quality of dried and processed products. Researchers have proposed various non-linear regression models to effectively predict the density based on moisture content [3].

Several authors have reported the use of flotation in liquid solutions for density sorting, peanuts [2], grapes [4], mulberries [5], and mangoes [6,7]. Rolle *et al.* [4] classified Muscat Hamburg grapes by density using flotation in various salt solutions and identified the potential of using densimetric sorting to grade grape berries based on quality attributes like skin hardness and berry cohesiveness. Wang *et al.* [5] used a densimetric flotation method to classify mulberries into five ripening stages and reported that ripeness significantly impacted their volatile composition, color, texture and sensory attributes. Kapse and Katrodia [6] investigated the ripening behavior of mangoes in a solution of sodium chloride and found that the specific gravity of most mature mangoes fell within a range of 1.0 to 1.02. Hor *et al.* [7] used the Archimedes principle to predict mango sensory quality during ripening by developing models that included density and maturation time. They found that higher mango density correlated decreased firmness. A logistic regression model confirmed the relevance of density in predicting mango sensory quality. However, the flotation methods were found to be impractical due to concerns regarding contamination of the fruits and kernels, which could negatively impact their quality. Additionally, the specific gravity of the liquid medium used in the sorting process could vary during operation, further complicating the method. Zaltzman *et al.* [2] introduced the fluidized bed medium method for density separation of agricultural products with small density differences with magnesium sulfate as the medium, overcoming the limitations of liquid solutions.

Image processing has been used by researchers to estimate the physical properties like volume and density of dry beans [8], tomatoes, mushrooms, strawberries [9], mangosteen [10], mangoes [11], dates [12] and barley grains [13]. Kumar *et al*. [8] used image processing to determine the density and porosity of dry beans, comparing results with digital vernier caliper measurements. The study identified a linear relationship between bean dimensions and pixel values, establishing that bean density indicates their soundness. Concha-Meyer *et al.* [9] developed a computer vision system to measure the density of tomatoes, mushrooms and strawberries based on mass and volume. This method showed a

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strong correlation with the traditional water displacement method, with less than a 2.3% difference, surpassing other techniques. Alturki *et al.* [12] devised computer vision algorithms to grade dates based on their density, calculated by summing pixel intensities for shape description, achieving 99% accuracy. Walker and Ponozzo [13] estimated barley grain density by ellipsoid approximation, achieving the highest correlation of 0.63 when compared to the gas displacement method. These studies highlight the effectiveness of computer vision and image analysis techniques in assessing the quality of irregularly shaped agricultural products by density.

However, few commercial prototypes are available for real-time density-based sorting of agricultural goods. To date, there have been no documented studies or research on the utilization of density as a quality grading parameter for arecanuts. Kaleemullah and Gunasekar [14] observed a relationship between the density and porosity of unboiled arecanut kernels with moisture content. The water displacement method, as employed by them and Bulan *et al*. [15] allows for the estimation of the true density of arecanut kernels and fruits. The physical properties of arecanuts and the correlation among them can facilitate the development of automated grading equipment, integrating both mechanical and optical techniques as highlighted by Salunke and Honnungar [16].

This research aimed to combine mechanical and visual techniques using Python and Arduino for the real-time classification of unboiled arecanut kernels based on true density. Programs were developed for image processing, object detection and measurement, kernel segregation, and Arduino interfacing. The method's suitability for potential application in automated quality grading of the kernels based on density was explored.

MATERIALS AND METHODS

Twenty-five pieces of unboiled arecanut kernels of different sizes, obtained from a local farmer and chosen at random, were used for the study. The kernel's true density was estimated from mass and volume measurements. A digital weight balance of accuracy ± 0.01 gm was used to estimate the mass. The kernel volume was determined by a 250 mL graduated cylinder displacing water maintained at 25 °C, as performed by Kaleemullah and Gunasekar [13]. The bulk density was measured by filling a one-liter glass measuring cylinder with the kernels and then weighing the nuts as performed by Bulan *et al*. [14]. Porosity was measured from the bulk and true densities using Equation 1 as reported by Kaleemullah and Gunasekar [13].

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$$\varepsilon = (1 - \rho_b / \rho_{t)}) \times 100 \quad (1)$$

where ρ_b = bulk density in g/cm^3 and ρ_t = true density in g/cm^3.

Density-based quality grading system for arecanut kernels

The block diagram of the proposed system for the quality characterization of unboiled arecanut kernels is shown in Figure 1. The automated quality grading device shown in Figure 2 consisted of a density measurement system designed to measure the mass and volume of arecanut kernels. The hopper transports the nuts onto the 3D-printed conveyor made of thermoplastic polyurethane material, which is activated by an analog signal from a sensor. The conveyor is driven by a DC-geared motor of 60 rpm, and an L298 motor driver is used to drive the motor. The grading device has gears made of laser-cut acrylic material, and pulleys made by 3D printing using polylactic acid. A GT 2 standard was used for the pulley, belt and idler. An optical proximity sensor was used to detect the kernel on the conveyor. The load cell, with an accuracy of ± 0.01 g and a 0 to 1kg range, was used to measure the mass of the kernels as they were transferred over it, and an HX711 amplifier was used to convert the analog signal to digital output. To measure the volume of the kernels, a machine vision system with two cameras placed at right angles to each other captured perpendicular images from the top and side of the kernels. The image acquisition program was developed in Open CV in Python 4 using the ellipsoid approximation method. The AT mega 328 IC controller interfaced to the laptop took inputs from the load cell, and a buck converter stepped down the voltage from 12 V to 5 V for the controller. A Python program segregated kernels into acceptable and non-acceptable categories based on the threshold value of the true density. The Arduino microcontroller relayed output to the stepper motor and servo mechanism. The stepper motor pushed the nut forward, and the servo mechanism actuated once the program detected a kernel of acceptable quality, pushing it into a storage bin. Inferior kernels were allowed to move forward and were deposited in a separate box outside the grading equipment. A NEMA 17 4.2 kg-cm stepper motor with 1.8-degree resolution was used, and an A4988 stepper driver stepped down the power from 24 W to 3 W, controlling the steps. A limit switch was used for stepper homing, and an SG 90 servo (1.6 kg-cm, 4.8 to 6 V) facilitated the kernel segregation.

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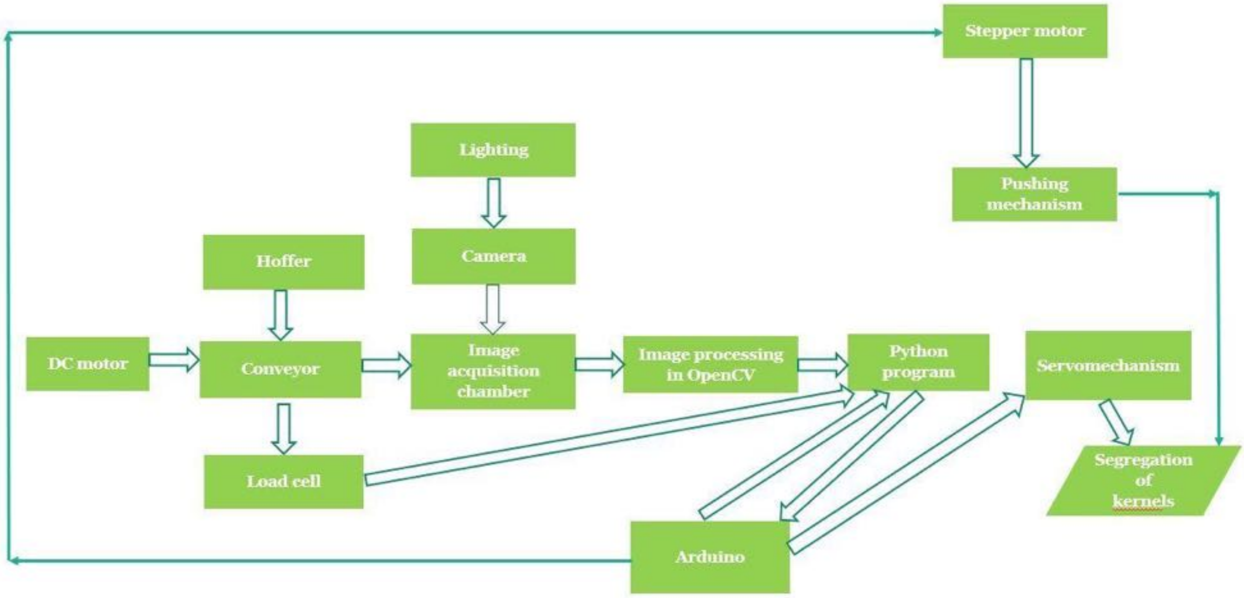

Figure 1: Block diagram of the automated quality grading device for unboiled arecanut kernel

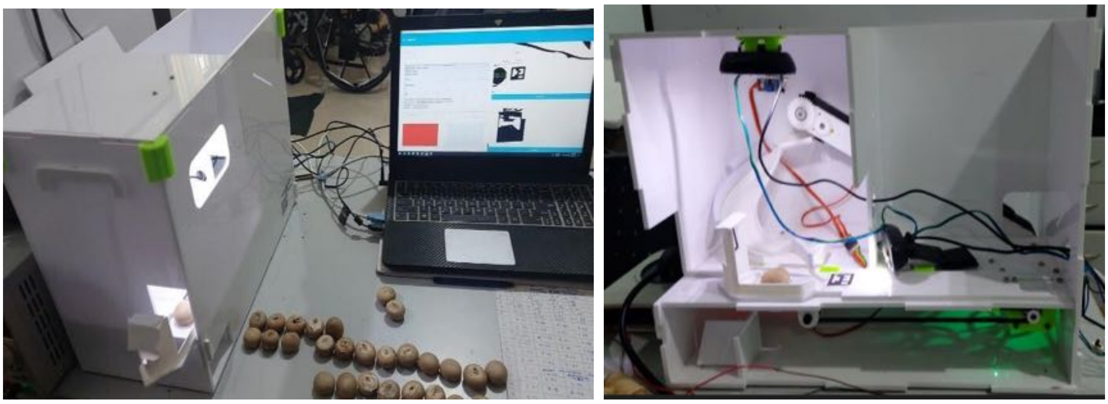

Figure 2: Automated quality grading device for unboiled arecanut kernels

Real-time estimation of true density of arecanut kernels

The device was tested for real-time monitoring of the true density of the unboiled arecanut kernels. The process involved placing the kernels sequentially on a hopper, allowing them to fall on a load cell, and capturing top and side images using cameras. The OpenCV program displayed the mass, volume and true density of the kernels in real time on the front panel. Green and red indicators displayed the acceptable and rejected kernels, respectively. Table 5 shows the measurement readings of true density obtained from the device and DWS-WD method, respectively. The experimental threshold density was set at 1.3 g/cm^3 with a standard deviation of 0.24 g/cm^3. The kernels were categorized as acceptable or rejected as illustrated in Table 5. The graded kernels were collected in their respective bins.

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Programming and interfacing of hardware and software

The contents of the main program directory and Python packages used in the programming of the system are shown in Table 1 and Table 2, respectively.

Algorithm for the quality grading process

The algorithm for the automated quality grading process for arecanut kernels is illustrated in Figure 3. The application is built using the KivyMD framework. The MainApp class in app.py serves as the core component of the kernel sorting system, enabling communication between the user and the system for both manual and continuous processing modes. The program establishes a connection with the Arduino board through serial communication, obtaining data from the cameras and load cell. In the event of an Arduino connection failure, the user is prompted to verify the connection and port settings, and the program can be restarted. The application offers a load cell calibration feature, to ensure accurate weight measurements. The conveyor belt moves until a kernel is detected on the load cell. At this point, the kernel is properly positioned within the cameras' fields of view, and images are captured. OpenCV is utilized for image processing, determining the major and minor diameters as well as the length of the kernel to calculate its volume. Combining the volume with the measured mass from the load cell allows the program to calculate the kernel's true density. For sorting the kernels into acceptable and non-acceptable categories, the Arduino code activates the servomechanism based on the threshold value. The application provides a user-friendly interface with a toolbar, navigation drawer and buttons. Users can configure various settings, such as serial communication parameters, camera sources, thresholds and refresh periods. The interface consists of the main home and settings screens, accessible through the navigation panel. Output is displayed on the home screen, while the settings screen allows users to adjust necessary parameters. To ensure system stability, the application includes a reset function that allows reverting to the last saved settings and restarting processing.

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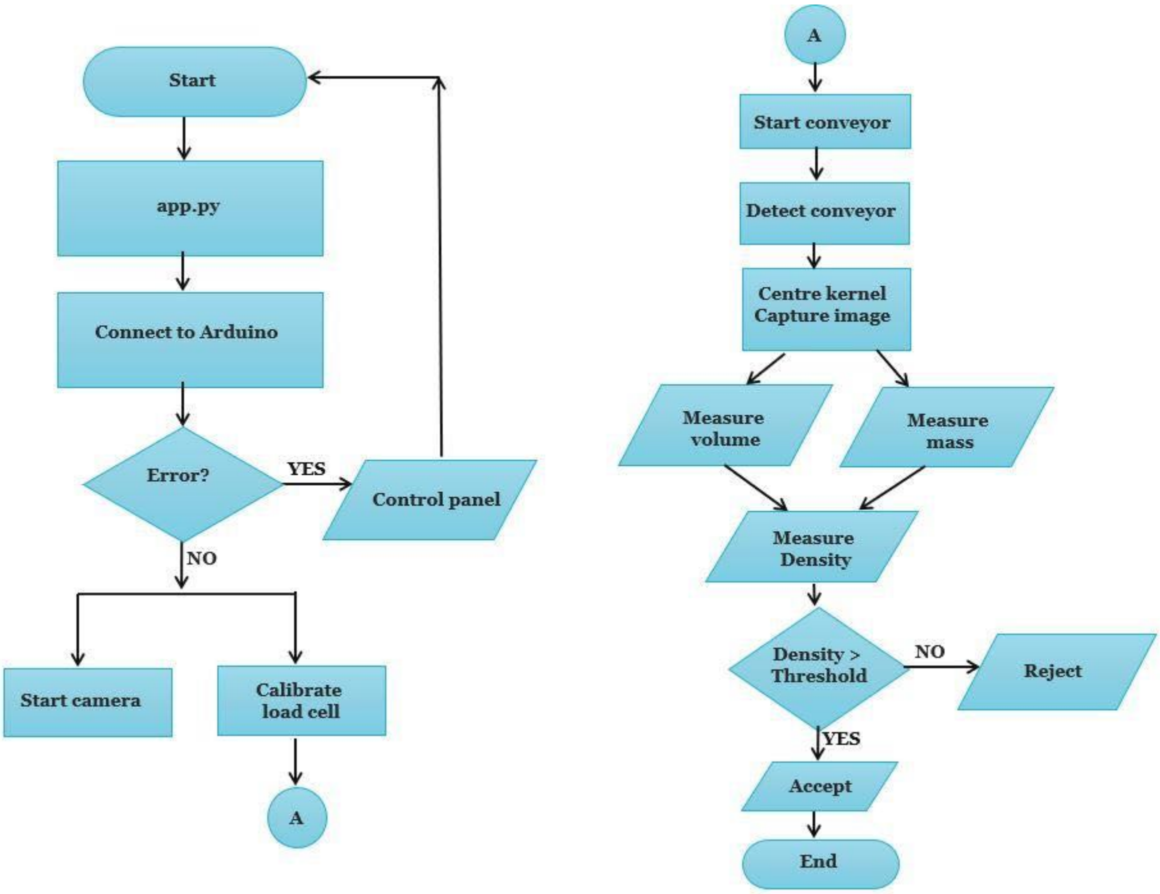

Figure 3: Quality grading process algorithm

Machine vision algorithm

The algorithm presented in Figure 4 demonstrates the process of image processing and the measurement of the width and height of the arecanut kernels in centimeters using a pixel-to-cm ratio obtained from an Aruco marker. The initial step involves setting up the necessary variables, such as the video source, pixel-to-cm ratio, threshold value, and distance. The frame dimensions are configured to 1280x720, and an Aruco dictionary is loaded along with parameters for marker detection. The code continuously reads and processes frames from the video feed, converts them into a grayscale image, and computes the intensity values. The next step involves applying a binary threshold to the grayscale image using the specified threshold value. This operation enables the separation of foreground and background, simplifying the subsequent object detection process. The program detects the Aruco marker within the binary image, calculating the Aruco perimeter and the pixel-to-cm ratio based on the marker's size. Once the Aruco marker has been identified, it iterates over the detected object contours. For each contour representing a kernel, the code calculates its width and height in centimeters using the pixel-to-cm ratio and the dimensions of the kernel's bounding box.

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Furthermore, it draws the boundary of each detected kernel and displays the calculated dimensions on the frame for visual reference.

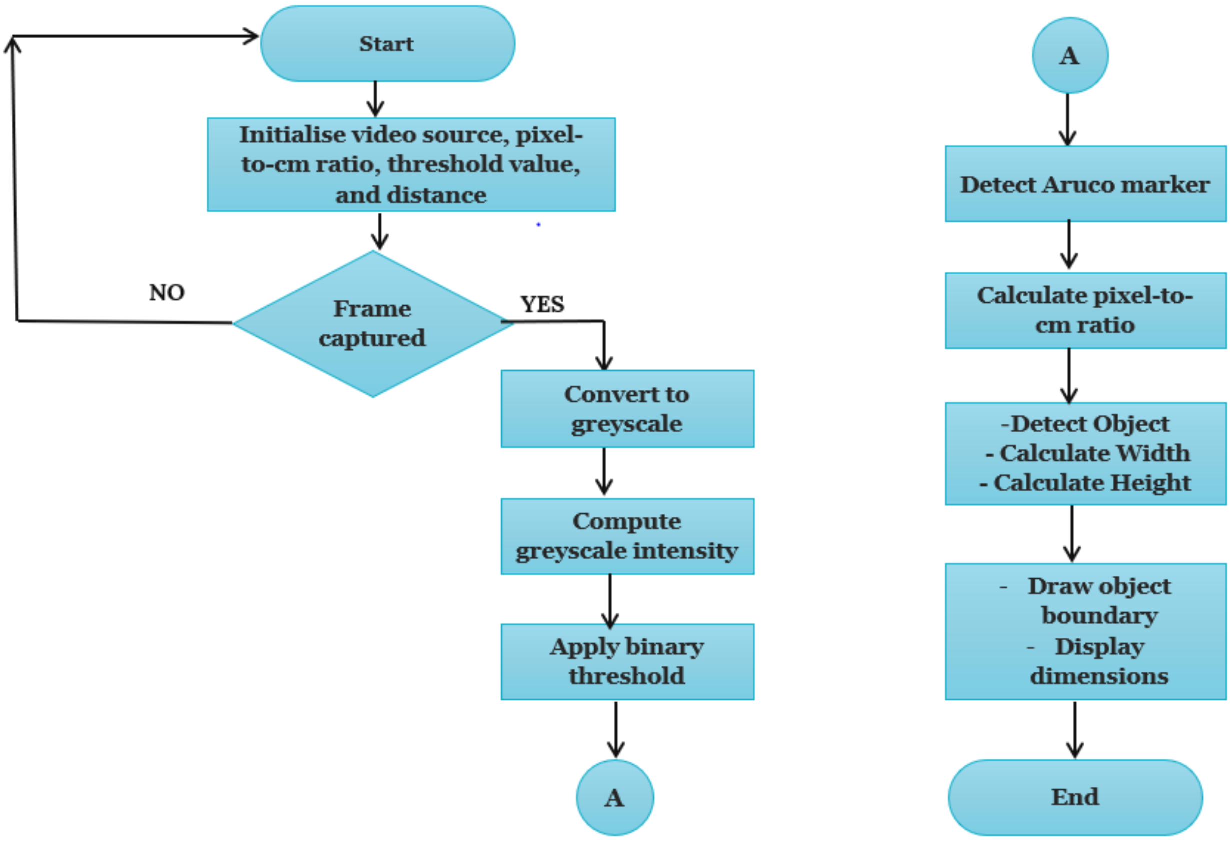

Figure 4: Machine vision algorithm

Object detection algorithm

Figure 5 illustrates the algorithm to perform object detection for the kernel within a given frame based on a homogeneous background. The first step involves converting the image to grayscale. Then, an adaptive thresholding technique that automatically determines thresholds for different regions of the image based on the local pixel intensity variations is applied to it. This generates a binary mask that segments the image into the foreground (kernel) and background. The program locates contours in the mask and iterates over each of them, calculating their area. If the area exceeds a predefined threshold of 2000 pixels, the contour represents the kernel and is added to a list for storage.

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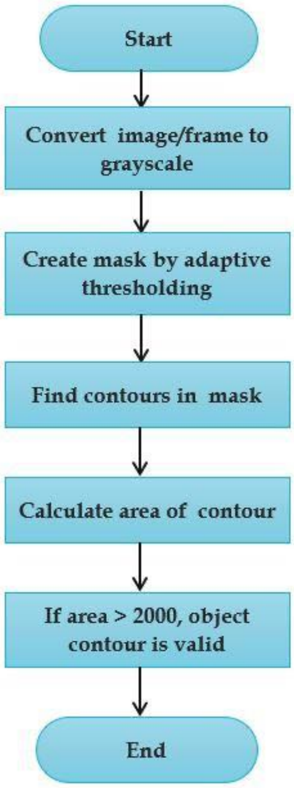

Figure 5: Object detection Algorithm

Measure Objects algorithm

The algorithm depicted in Figure 6 focuses on Aruco marker detection and the calculation of the pixel-to-cm ratio of the kernel. The program loads the necessary Aruco detector parameters and the Aruco dictionary. Further, the Aruco markers are detected within the image, indicated visually by polygons drawn around them. The program measures the perimeter of the Aruco marker, which is further divided by 20 to determine the pixel-to-cm ratio.

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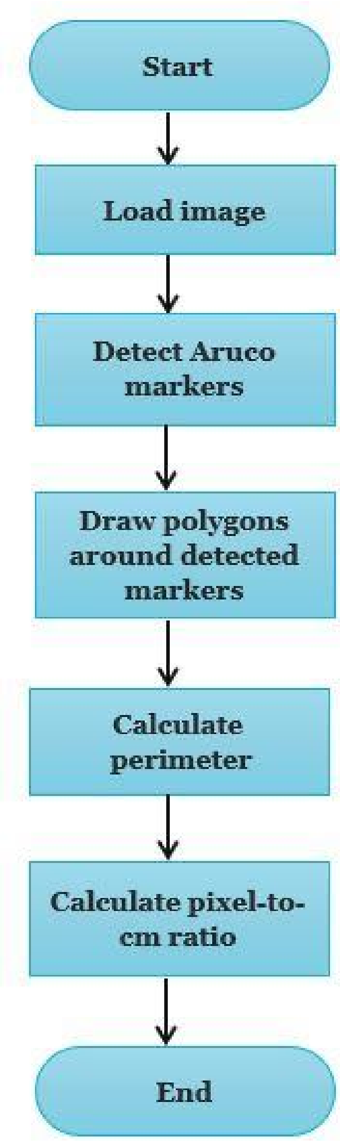

Figure: 6 Measure object algorithms

Kernel Segregation Algorithm

The kernel segregation mechanism is based on the logic depicted in Figure 7. Upon powering the Arduino board, the code initializes the serial communication, sets pin modes, attaches the servo motor, and establishes the initial position of the servo. It then moves the servo motor to this position and calls a function to move the stepper motor to a designated home position. Additionally, the code initializes a variable and invokes a function responsible for controlling the stepper motor. Another function is called to initialize and calibrate a load cell. In the main loop, the code continuously checks for incoming serial data and calls corresponding functions to perform specific actions based on the received commands. These functions facilitate moving the stepper motor to specific positions, bringing the

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system to a cantered position, executing actions for different states (accept or reject), setting the system to standby mode, controlling the conveyor belt based on sensor input, and measuring the mass of the kernel using the load cell. The commands are outlined in Table 3. Automatic mode runs them as states and moves to the next state upon communication from Arduino.

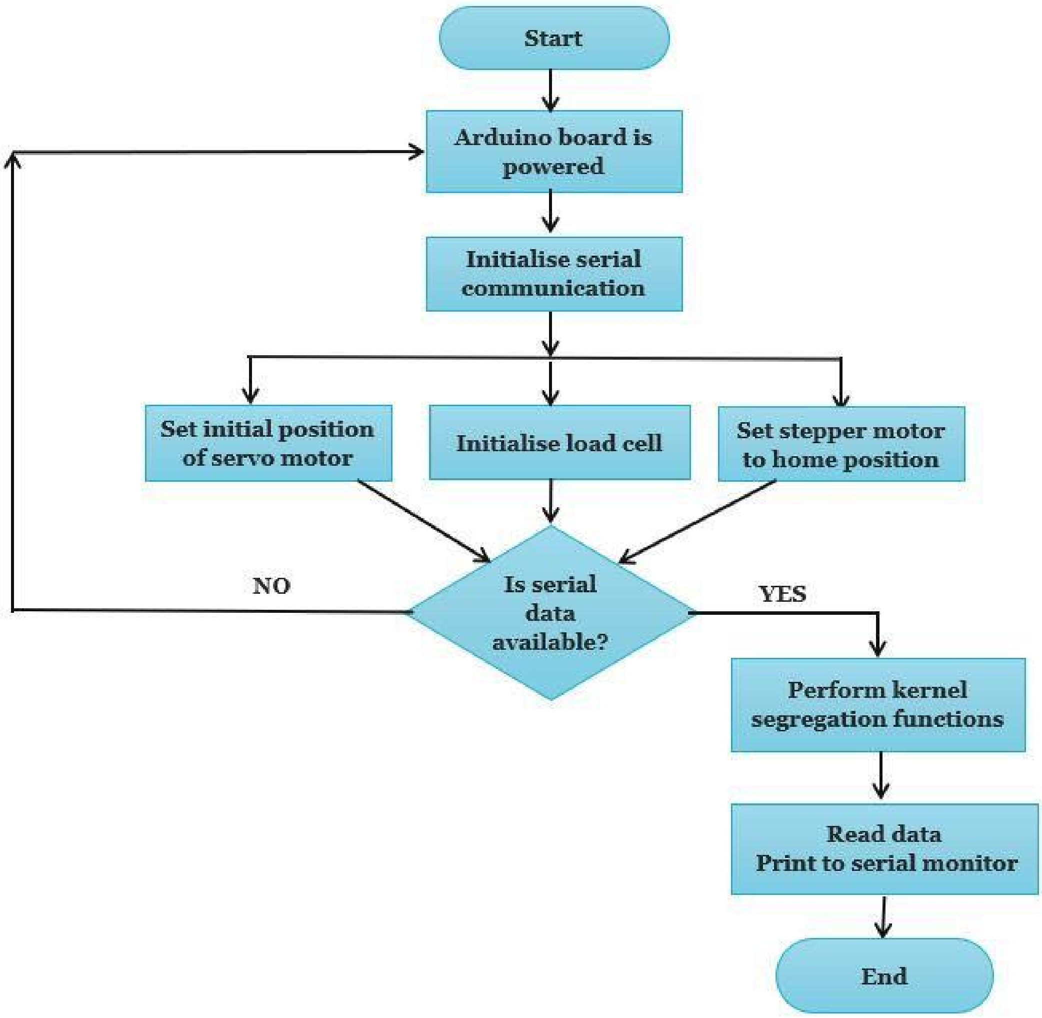

Figure 7: Kernel segregation algorithm

Arduino Interfacing algorithm

The algorithm allows for establishing a serial connection between Python and an Arduino board. It enables communication, data read/write, and setting configurations like port, baud rate, and timeout. The Arduino IDE is used to upload a simple sketch to the board, enabling serial communication with the laptop. Python code, utilizing the serial module, interacts with Arduino. The user navigates to the Python script's directory to execute the code. Table 4 outlines the library functions for Arduino interfacing.

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Statistical analysis

The statistical analyses were performed using Minitab, and the mean, standard deviation, and variance of the true density of the arecanuts by load cell-ellipsoid approximation (LC-EA) and digital weighing scale-water displacement (DWS-WD) methods were found, respectively. The difference in measurements and percentage error was found. A line of equality plot of density measurements using both methods was established.

RESULTS AND DISCUSSION

The device's density measurements were compared with measurements obtained using the DWS-WD displacement method as outlined in Table 6. The data revealed that the maximum true density was 1.55 g/cm^3, and the minimum true density was 0.68 g/cm^3. The mean true density difference between the machine measurements and the DWS-WD method was 0.1360 g/cm^3, with a standard deviation of 0.1145 g/cm^3 (95% confidence interval: 0.0888, 0.1832). The mean percentage error for true density measurements by the quality grading device was found to be 13.18%. The device's true density estimation by the LC-EA method was plotted against the results of the DWS-WD method in Figure 8. The paired t-test results in Table 7 indicated that the kernel true density measured by the device significantly differed from the density estimated with conventional methods ($P < 0.05$). The bulk density of the kernels was estimated to be 0.63 g/cm^3 and porosity was obtained using Equation 1. Table 8 shows the measurement readings of porosity for the samples and the mean porosity of the kernels was found to be 45.34 %. Equation 2 reveals the correlation between the densities measured by both these methods. The coefficient of determination R^2 was found to be 78.76%.

$$\text{Density}_{\text{LC-EA}}\ (\text{g/cm}^3) = -\ 0.045 + 1.159\ \text{Density}_{\text{DWS-WD}}\ (\text{g/cm}^3) \qquad (2)$$

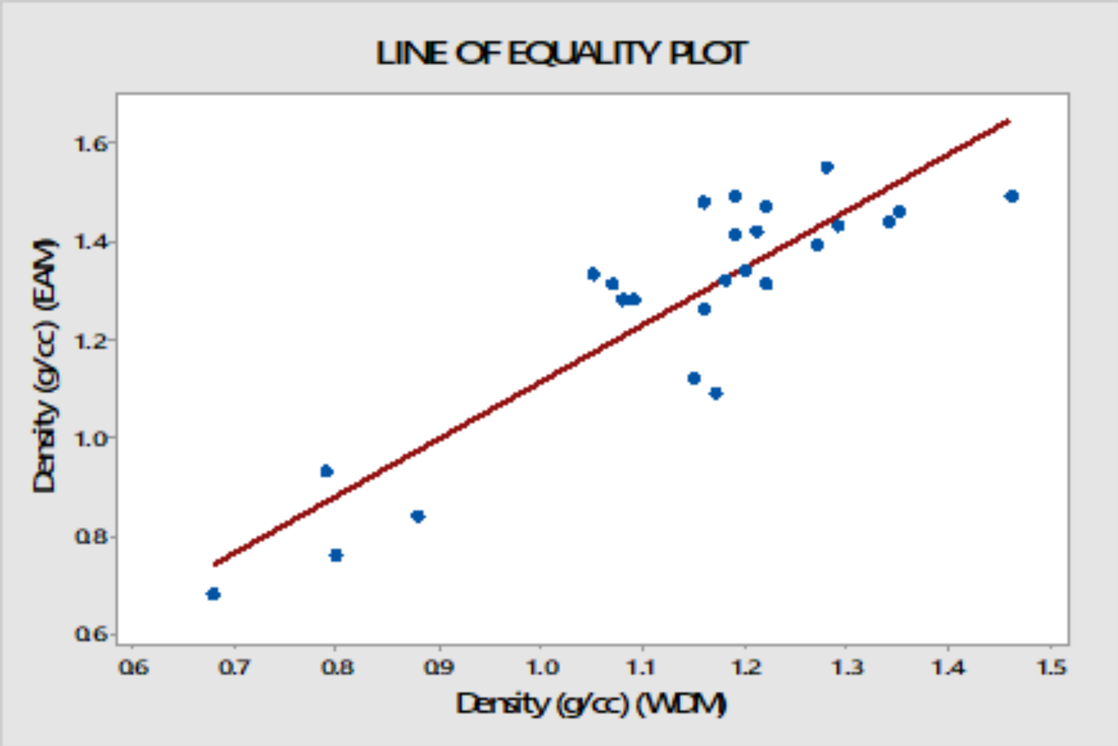

Figure 8: Line of equality plot for kernel true density measurements

CONCLUSION AND RECOMMENDATIONS FOR DEVELOPMENT

The automated quality grading device successfully segregated the unboiled arecanut kernels into acceptable and non-acceptable categories based on the true density. The technology can immensely benefit farmers and traders by eliminating the tedious task of sorting and quality characterization of arecanut kernels. Nevertheless, overcoming the system's limitations is essential to render it viable for real-time applications. The technique for mass determination exhibited considerable accuracy. The discrepancies observed in the real-time true density measurement technique of kernels were attributed to errors in volume measurements resulting from the asymmetrical shape of the kernels, leading to deviations from the ellipsoid approximation. To enhance the system's accuracy and commercial viability, it is necessary to explore alternative techniques in image processing. By adopting more suitable volume measurement methods like the segmentation approach, the device can be refined to provide more precise true density estimations, thereby reducing discrepancies with the current approach. Furthermore, by estimating the bulk density, there is an opportunity for real-time measurement of the porosity of the kernels. Investigating the impact of bulk density on product quality and its correlation with drying parameters could provide valuable insights for optimizing the drying process. This entails integrating the density and porosity measurement systems to enable porosity-based quality characterization of the arecanut kernels, offering possibilities for enhanced grading and commercial viability.

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Table 1: Main program directory used in the study

Library	Source files for image processing and serial communication
NutSegrigationV1	Arduino code for nut segregator
Resources	Widgets for various custom app objects like panel screens and widgets
screen	app screens, i.e., home and settings screen
app.py	Main Python script to be run. Combines libraries, widgets, and screens
requirements.txt	Python packages used for the project
settings.json	Contains the app settings to save and use even after it is closed and open
temp.py	Testing purpose

Table 2: Python packages used in the study

Package	Function
Kivy and KivyMD	For interface
OpenCV	Image processing and display
Serial	Serial communication with Arduino
NumPy	Basic image array processing
JSON	Read/write settings

Table 3: Commands for kernel segregation

Key	Function
t	Calibrates the load cell to 0
z	Starts the conveyor, stops on detecting a nut, sends "s" for success
c	Centers the nut to stage for image processing
m	Measures the weight of the nut
v	Measures the dimensions, volume, and density of nut
g	Passed nut in acceptance slot
b	Failed nut in rejection slot

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Table 4: Library functions for Arduino interfacing

Function	Description
refresh ()	Closes the port and tries to connect it again
write ()	Writes to Arduino serial bus
read ()	Reads from Arduino serial bus
set_port ()	Sets com port
set_baud ()	Sets the serial baud rate

Table 5: Measured true density of arecanut kernels used in the study*

Sample No.	Density (LC- EA) [a] g/ cm^3	Accept/ Reject	Density (DWS-WD) [b] g/ cm^3
1	1.28	Reject	1.08
2	1.42	Accept	1.21
3	1.28	Reject	1.09
4	0.93	Reject	0.79
5	1.47	Accept	1.22
6	1.55	Accept	1.28
7	1.48	Accept	1.16
8	0.68	Reject	0.68
9	1.49	Accept	1.19
10	1.39	Accept	1.27
11	1.49	Accept	1.46
12	1.26	Reject	1.16
13	1.31	Accept	1.22
14	1.46	Accept	1.35
15	1.34	Accept	1.2
16	1.32	Accept	1.18
17	1.44	Accept	1.34
18	1.43	Accept	1.29
19	1.09	Reject	1.17
20	0.84	Reject	0.88
21	0.76	Reject	0.80
22	1.33	Accept	1.05
23	1.31	Accept	1.07
24	1.41	Accept	1.19
25	1.12	Reject	1.15

* Threshold density for acceptance of kernels: 1.3 g/cm^3
[a] Load Cell - Ellipsoidal approximation method
[b] Digital weighing scale - Water displacement method

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Table 6: Descriptive Statistics for density measurement N=25

Variable	Mean	Standard Deviation	Variance
$Density_{LC\text{-}EA}$ [a] (g/cm^3)	1.275	0.24	0.577
$Density_{DWS\text{-}WD}$ [b] (g/cm^3)	1.1392	0.1839	0.0338
Density Difference (g/cm^3)	0.1360	0.1145	0.0131
Error (g/cm^3)	0.1512	0.0925	0.0086
% Error (g/cm^3)	13.18	8.10	65.64

[a] Load Cell - Ellipsoidal approximation method
[b] Digital weighing scale - Water displacement method

Table 7: Estimation for Paired Difference

μ_difference	St. Dev.	95% CI for μ_difference	T- Value	P- Value
0.1360	0.1145	(0.0888, 0.1832)	5.94	0.000

μ_difference: Difference of Mean of ($Density_{LC\text{-}EA}$ – $Density_{DWS\ \&\ WD}$)

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Table 8: Measured porosity of arecanut kernels

Sample No.	Density (LC- EA) g/ cm^3	Porosity (%)
1	1.28	50.78
2	1.42	55.63
3	1.28	50.78
4	0.93	32.26
5	1.47	57.14
6	1.55	59.35
7	1.48	57.43
8	0.68	7.35
9	1.49	57.72
10	1.39	54.68
11	1.49	57.72
12	1.26	50
13	1.31	51.9
14	1.46	56.85
15	1.34	52.99
16	1.32	52.27
17	1.44	56.25
18	1.43	55.94
19	1.09	42.2
20	0.84	25
21	0.76	17.1
22	1.33	2.3
23	1.31	51.9
24	1.41	55.31
25	1.12	43.75

REFERENCES

1. **Rao MA, Rizvi SSH and AK Datta** Engineering properties of foods (3rd ed.). CRC Press, 1995.

2. **Zaltzman A, Verma BP and Z Schmilovitch** Potential of quality sorting of fruits and vegetables using fluidized bed medium. *Transactions of the ASAE*. 1987; **30(3)**: 0823–0831.

3. **Rodríguez-Ramírez J, Méndez-Lagunas L, López-Ortiz A and SS Torres** True density and density during the drying process for vegetables and fruits: a review. *Journal of Food Science*. 2012; **77(12):** 146–154.

4. **Rolle L, Torchio F, Giacosa S and SR Segade** Berry density and size as factors related to the physicochemical characteristics of Muscat Hamburg table grapes (Vitis vinifera L.). *Food Chemistry*. 2015; **173**: 105-13.

5. **Wang K, Li Q, He P, Jia X, Ren W, Wang J and H Xu** Grading by fruit density: An effective way to control the drying characteristics and qualities of mulberry (*Morus nigra* L.). *Food and Bioprocess Technology*. 2023; **17**: 1814–1830.

6. **Kapse BM and JS Katrodia** Ripening behavior of kesar mangoes in relation to specific gravity *Acta Horticulturae.* 1997; **455**: 669–678.

7. **Hor S, Léchaudel M, Mith H and C Bugaud** Fruit density: A reliable indicator of sensory quality for mango. *Scientia Horticulturae*. 2020; **272**:109548.

8. **Kumar M, Bora G and D Lin** Image processing technique to estimate geometric parameters and volume of selected dry beans. *Journal of Food Measurement and Characterization*. 2013; **7:** 81-89.

9. **Concha-Meyer A, Eifert J, Wang H and G Sanglay** Volume estimation of strawberries, mushrooms, and tomatoes with a machine vision system. *International Journal of Food Properties*. 2018; **21(1)**: 1867–1874.

10. **Teerachaichayut S, Yokswad W, Terdwongworakul A, Jannok P and SV Fernandes** Application of image analysis for determination of mangosteen density. Journal of Advanced Agricultural Technologies. 2015; **2(2)**: 92-97.

11. **Khalid NS, Abdullah AH, Shukor SAS, Syahir AS, Mansor H and N Dalila** Non-Destructive Technique based on Specific Gravity for Post-harvest Mangifera Indica L. Cultivar Maturity. 2017. *Asia Modelling Symposium (AMS).*

12. **Alturki AS, Islam M, Alsharekh MF, Almanee MS and AH Ibrahim** Date fruits grading and sorting classification algorithm using colors and shape features. *International Journal of Engineering Research and Technology*. 2020; **13(8):** 1917-1920.

13. **Walker CK and JF Panozzo** Measuring volume and density of a barley grain using ellipsoid approximation from a 2-D digital image. *Journal of Cereal Science*. 2012; **55(1)**: 61-68.

14. **Kaleemullah S and JJ Gunasekar** Moisture dependent physical properties of arecanut kernels. *Biosystems Engineering*. 2002; **2(3)**: 331-338.

15. **Bulan R, Devianti, Ayu ES and A Sitorus** Effects of moisture content on some engineering properties of arecanut fruit, which are relevant to the design of processing equipment. *INMATEH- Agricultural Engineering*. 2020; **60(1**): 61-70.

16. **Salunke A and S Honnungar** A review of unboiled arecanut drying process and its correlation with mechanical properties, 3rd International Conference (Online) on Contemporary Advances in Mechanical Engineering, Mohali, Punjab, India: Materials Today Proceedings. 2021.