Image Processing-Based System for Apple Sorting

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***Abstract*—This study sheds light on the evolution of the agricultural industry and highlights advances in production area. The salient recognition of fruit size and shape as critical quality parameters underscores the significance of the research. In response to this challenge, the research introduces specialized image processing techniques designed to streamline the sorting of apples in agricultural settings, specifically emphasizing accurate apple width estimation. A purpose-built machine was designed, featuring an enclosure box housing a cost-effective camera for the vision system and a chain conveyor for classifying Malus domestica Borkh kind apples. These goals were successfully achieved by implementing image preprocessing, segmentation, and measurement techniques to facilitate sorting. The proposed methodology classifies apples into three distinct classes, attaining an impressive accuracy of 94% in Class 1, 92% in Class 2, and 86% in Class 3. This represents an efficient and economical solution for apple classification and size estimation, promising substantial enhancements to sorting processes and pushing the boundaries of automation in the agricultural sector.**

***Keywords*—agriculture, Open Source Computer Vision (OpenCV), apple, sorting, width estimation**

I. Introduction

Agriculture is one of the most critical sectors of the country's economy, and it is directly related to all sectors of society. Quality assessment of fruits and vegetables is an urgent need due to the demands of modern customers in big cities to detect illnesses, failures, and stains [1]. The advent of computational techniques has brought about a significant transformation in the field of agriculture, leading to the emergence of these new technologies [2]. This field has gained immense popularity owing to its ability to optimize crop productivity, minimize resource usage, and reduce environmental impact [3]. Machine Learning and Deep Learning are frequently used computational techniques in this field [4]. These techniques have enabled farmers to make informed decisions based on data-driven insights, thereby enhancing the efficiency of their operations [5]. The integration of computational techniques in agriculture has opened up new horizons and is poised to revolutionize the industry in the years to come [6].

The agricultural industry faces significant challenges in the manual sorting of apples, which is labor-intensive, time-consuming, and prone to human error. Manual sorting methods based on size, shape, and colour are inefficient and costly, particularly for small and medium-sized farms. There is a need for an automated, cost-effective, and accurate solution to classify apples based on their size to meet market demands and improve overall productivity. This work addresses these challenges by developing a system that leverages image processing techniques for efficient and reliable apple sorting. The following state-of-the-art review provides an overview of existing solutions and their limitations, highlighting the need for our proposed method.

A. Literature Review

Various techniques are used in image processing, and exciting proposals have been developed for fruit classification [7] based on image segmentation [8], feature extraction [9], fuzzy logic [10], Artificial Neural Networks (ANNs) [11], adaptive neural fuzzy interference systems [12], and support vector machines [13]. This proposal is based on image segmentation, and different studies on this topic will be checked.

Therefore, Zawbaa *et al.* [14] presents an algorithm for automatically segmenting bananas using a multiple threshold approach, with an average area ratio of over 80% for ten samples. The approach has the potential for quality monitoring in banana ripening rooms. Furthermore, Mustafa *et al.* [15] have developed an automatic fruit recognition system that can identify the names of fruits with a high degree of accuracy. The system used shape and colour features and has been tested on various types of fruits. Parallelly, Luo *et al.* [16] proposed method achieved high accuracy in detecting concave points and the number of grape berries, with a reasonable error in measuring berry size.

Iqbal *et al.* [17] outlined specific techniques for grading citrus fruits by estimating size and shape. The results

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agreed with human assessment, focusing on sweet-lime and orange fruits. Likewise, Baptista *et al.* [18] presents a methodology used in the study involving edge-based and colour-based detection methods to segment images of orange fruits, also using MATLAB image processing toolbox for results computation and comparison.

Apples are a widely consumed fruit, renowned for their flavor, texture, and nutritional value [19]. The apple industry's complexity is evident in the diverse cultivars and quality standards required to meet varying market demands [20]. From the sweet and tangy taste of Gala apples to the crisp texture of Granny Smiths, apples offer many options [21]. Their cultivation and distribution require meticulous attention, making apples a critical agricultural product [22]. Their universal appeal and health benefits make them a staple worldwide [23]. In 2023, global production of pears and apples total in 95,835,964 tons, with China leading in apple production at 47,571,800 tons and Ecuador producing 7,210 tons [24]. Product sorting is crucial in the food industry, requiring specialized machinery like robots to handle high production rates [25]. On large farms, advancements in teleoperation and robot autonomy aid farmers [26, 27]. Defective or damaged fruits are sorted out based on size, shape, color, and quality, enhancing production efficiency, inventory management, food safety, and market-specific product tailoring [28]. Early research in agricultural computer vision introduced image segmentation techniques for fruit quality analysis, using Emboss Filter and Hough Transform [29]. This technology has driven the automation of apple grading, reduced post-harvest costs and improved efficiency, precision, and uniformity compared to manual grading methods [30, 31].

In Ref. [32], digital parameterization has been explored to evaluate apples for quality sorting accurately. This was achieved through the use of pattern recognition methods and image analysis techniques. Later, the work of [33] developed apple fruit recognition algorithms based on colour features for yield estimation, bridging computer science with agricultural engineering. Their work encountered challenges in detecting deeper fruits and leaves in tree canopies, indicating the need for algorithm refinement.

Some research had required refinement over time, like the case of Ref. [34], where they developed a cost-effective machine vision system for infield apple sorting and grading, achieving high accuracy in orientation estimation and size grading through image processing techniques, and later improved their techniques in [35], obtaining better accuracy for the same task. Their system utilized a low-cost Charge-Coupled Device (CCD) colour camera and Light-Emitting Diode (LED) lighting, demonstrating the potential for affordable solutions in agricultural applications.

There has also been research on apple classification using neural networks, as presented in [28], where an automatic apple grading system that utilizes back propagation neural network and machine vision technology was developed. The system aims to classify apples in real time based on physical parameters such as size, colour, and external defects.

Further studies focused on the outdoor identification of fruits, like [35], which proposed a fast segmentation method for colour apple images under natural conditions, combining adaptive mean-shift and Ncut techniques for improved precision in apple image extraction. Later, Gonga *et al.* [36] developed a machine vision system for estimating apple size in tree canopies using a 3D machine vision system. The primary goal was to accurately estimate the significant axis of apples for selective, robotic harvesting and crop-load estimation. Image processing techniques such as colour and shape features, histogram equalization, and Otsu's thresholding were used to segment and detect apples in colour images. The accuracy of estimating the central axis was 69.1% for the 3D coordinates-based method and increased to 84.8% for the pixel size-based method.

More recent research has used advanced pre-processing methods and innovative approaches to apple classification techniques. Chithra and Henila [37] introduced a novel thresholding algorithm for apple sorting, achieving high accuracy rates through image analysis techniques. The Global Thresholding Algorithm and Machine Learning (ML) classifiers demonstrated promising results for automating fruit classification. Henila and Chithra [38] developed a fuzzy cluster-based thresholding method for apple fruit segmentation, achieving a high testing accuracy rate. The study emphasized the importance of accurate region segmentation in apple images for post-harvest processes.

Similarly, the study by Baneh *et al.* [39] introduced a small-scale apple sorting machine integrated with a smart vision system, emphasizing precision and computational efficiency in fruit sorting. The incorporation of image processing techniques such as local thresholding and machine learning led to accurate calyx recognition and promising results for practical fruit sorting processes. Another work presented in [25] implemented a sorting machine using image processing techniques, including the K-means algorithm, to process captured images from two industrial colour cameras set on roller and transporter conveyors. The sorting method proposed obtained an accuracy rate in ranges from 73% to 96%.

Other studies have focused on advanced methods to detect and classify apples before harvest, such as [40] which devised a method for accurately positioning apple fruits in orchards using image processing and information fusion techniques, enabling precise yield forecasting and fruit harvesting. Their approach involved RGB (Red, Green, and Blue) image processing and depth image processing, achieving remarkable accuracy in calculating the world coordinates of apples. In contrast, the study presented in [41] proposed a different solution to this problem, by using an apple image segmentation method based on colour-texture fusion features and machine learning, focusing on pixel classification for precise fruit identification. While their study demonstrated high accuracy with machine learning algorithms, future work aims to enhance texture feature performance and reduce the computational resource burden for mobile platforms. Table I shows several works that have been focused on the development of classification techniques for apples based on image processing. For each study, we have included the proposed technique and the results achieved and compared to our work. This review reveals several common disadvantages, such as high costs, complexity, and the need for advanced technical expertise. Many systems are either too expensive to implement on small farms or require sophisticated hardware and software that are difficult to operate and maintain. These limitations hinder widespread adoption and prevent small-scale farmers from benefiting from technological advancements in apple sorting. This work proposes an affordable, easy-to-operate solution that upholds accuracy and efficiency. This system aims to provide a practical alternative for small farms by addressing these issues, enhancing their productivity and market competitiveness.

TABLE I. APPLE CLASSIFICATION TECHNIQUES AND PROCESSES

Author	Year	Main Contribution	Image Processing Techniques	Machine implemented	Accuracy and Metrics
Baneh *et al.* [39]	2023	Development of a small-scale apple sorting machine with a smart vision system.	Local thresholding, machine learning.	Small-scale apple sorting machine.	Calyx recognition up to 97%, stem end region recognition 100%.
Henila *et al.* [38]	2021	Fuzzy cluster-based thresholding for apple sorting.	Fuzzy clustering, Thresholding.	NA	Accuracy rate: 98.33%.
Gongal *et al.* [36]	2018	Estimation of apple size using a 3D machine vision system.	Colour and shape features, Histogram equalization, Otsu’s thresholding	3D coordinates-based method: 69.1%, pixel size-based	Method: 84.8%.
Ji *et al.* [35]	2016	Fast segmentation of colour apple image for recognition	Adaptive mean-shift, Normalized Cut (Ncut).	NA	Segmentation error: 121 out of 150 images (<1%). Maximum error: 3.001%.
Sofu *et al.* [25]	2016	Design of an automatic apple sorting system using machine vision.	Image processing, K-means algorithm	Roller conveyor, transporter conveyor.	Sorting accuracy: 73–96%.
Mizushima *et al.* [31]	2013	Developing low-cost color vision system for apple orientation estimation.	Linear Support Vector Machine, Otsu’s Thresholding Method.	NA	Orientation estimation: D apples - 87.6% success rate, GD apples - 86.2% success rate.
Bhatt *et al.* [28]	2013	Developing automatic apple grading model with neural network and vision.	Image segmentation, colour analysis, defect detection.	Web camera mounted onto the conveyor belt.	Overall accuracy: 96%.
Mizushima *et al.* [34]	2011	Creating low-cost machine vision for apple sorting and grading.	Image distortion correction, real-time estimation of apple orientation, shape, and size.	Low-cost CCD colour camera, LED lightings, bi-con roller conveyor.	Orientation estimation: 87.6% and 86.2% accuracies for specific apple varieties. Size estimation: RMSE of 1.79 mm; Two-size grading error: 4.3%.
Juneja *et al.* [29]	2009	Introduced image segmentation for fruit quality analysis in agriculture using Emboss Filter and Hough Transform.	Edge Detection, Histogram Analysis, Emboss Filter, Hough Transform.	NA	High accuracy in colour and size analysis.
Proposal	2024	Algorithm designed to accurately estimate apple diameters.	Dimension reduction, normalization, colour segmentation using Gaussian filter.	Semi-Automatic sorting machine.	Accuracy Class 1: 94%. Accuracy Class 2: 92%. Accuracy Class 3: 86%.

B. Main Contribution

The article details the design and implementation of an apple sorting system, including hardware and software components. The software component uses an image pre-processing algorithm based on dimension reduction and normalization. The image acquisition uses a low-cost colour camera, and once the picture is pre-processed, an algorithm for colour detection, segmentation, and size measurement based on width is implemented.

The main contributions of this work are as follows:

1. An algorithm was developed that combines image resizing, normalization, and computer vision techniques for colour identification, masking, and segmentation to classify apples based on their width.
2. Affordable sorting machine was designed to incorporate affordable and easy-to-operate hardware and software components, making it accessible to small farms.
3. High Accuracy and Efficiency in sorting tasks with 94% accuracy for Class 1, 92% for Class 2, and 86% for Class 3.
4. Controlled environment for consistency using an enclosure box to minimize the impact of external lighting conditions and enhance measurement consistency.

These contributions collectively highlight the strengths of our proposed method, offering a reliable, efficient, and scalable solution for apple sorting in the agricultural industry. Notably, the design of an Affordable Sorting Machine, incorporating useful and easy-to-operate hardware and software components, underscores its accessibility to small farms, a key aspect of its appeal.

C. *Outline*

This paper is structured as follows: Section II provides an overview of the system and introduces the materials used in the study. In Section III, the proposed methodology for apple sorting is presented. The experimental results, including segmentation, apple measurement, and sorting, are detailed in Section IV. Section V delves into the discussion, highlighting the distinctive aspects of the proposed approach. Finally, Section VI offers concluding remarks and insights derived from the research.

II. System Overview

The machine constructed is depicted in Fig. 1, showcasing its hardware, which shows electronic and mechanical elements. The detection and sorting area measures 200 × 350 × 170 mm and is constructed from Alucobond. The machine consists of an enclosure box, where the apple is placed. A chain-type conveyor system is attached to the worktable, along with guides that direct the apple through the work area. The worktable includes three gates, which open as needed for the corresponding classification as shown in the Fig. 2. The chain-type conveyor system, operates at a speed of 5 m/s.

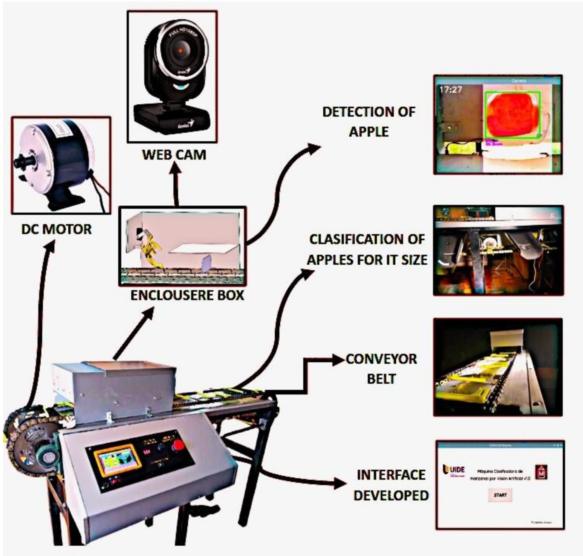


Fig. 1. The hardware used in apple's sorting system.

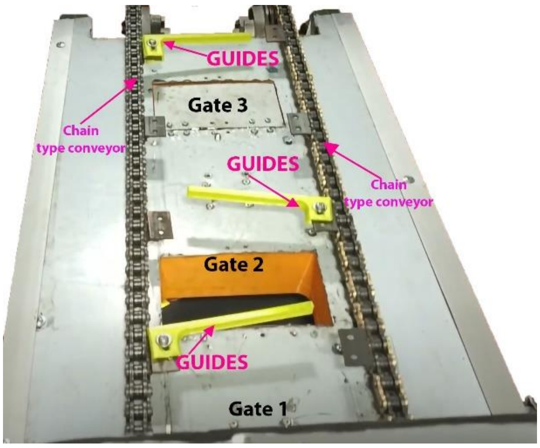


Fig. 2. Working table with chain conveyor belt and three gates.

The machine has a Raspberry Pi 4 Model featuring 8 GB of RAM, allowing for real-time object detection and precise measurements. This enhances efficiency and precision in the sorting process. The Raspberry Pi 4 is the central controller, overseeing all machine operations, managing peripheral devices, and executing the crucial width detection process for subsequent sorting. This setup is depicted in the project scheme, as shown in Fig. 3.

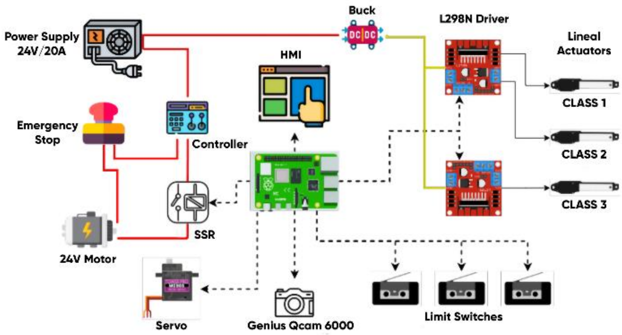


Fig. 3. The hardware used in apple's sorting system.

III. Proposed Apple Sorting

Apples were sorted based on width using image processing techniques implemented through a programmed algorithm using Python and OpenCV libraries.

Segmenting an image into its constituent environment has posed a significant challenge in image processing. For image processing, a prior dataset is not required. The machine is specifically designed for Malus domestica Borkh apples, and it processes the apples images directly without the need for a pre-existing dataset.

The primary goal of this phase was to identify or segment the apples from the background, enabling subsequent sorting based on their size. This research employed image processing techniques to classify apples into three distinct categories based on their width measurements. The size of the apple was determined by its width, representing the longest distance across the apple's cross-section. A conversion from pixel measurements to millimeters was implemented to ensure precise size determination using an ArUco marker.

The diagram of the proposed apple sorting is illustrated in Fig. 4. This sorting is achieved through the following steps:

A. *Image Acquisition*

The image was acquired using an image-capturing system, with the Genius Qcam 6000 camera employed for this purpose. The camera and Raspberry Pi 4 easily communicate via a USB connector suitable for the Raspberry board. The camera specifications are shown in Table II.

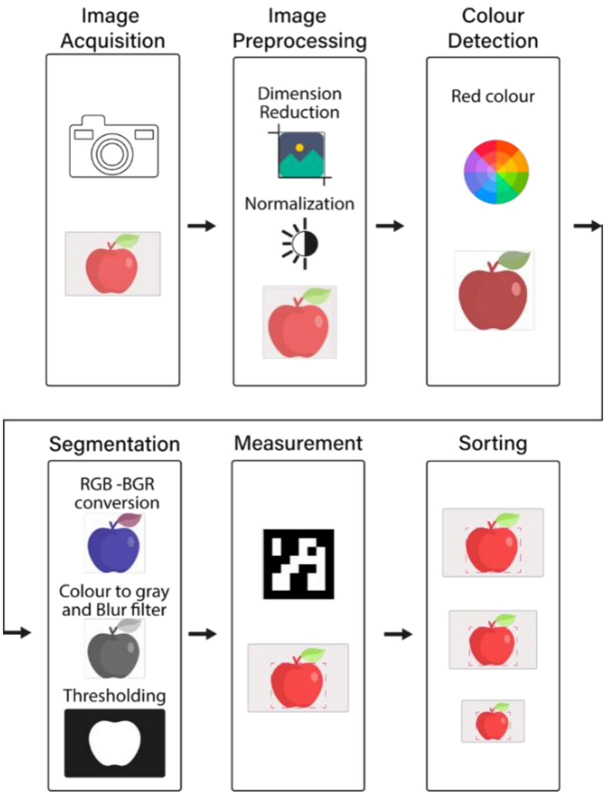


Fig. 4. Diagram of the apple sorting method.

TABLE II. SPECIFICATION OF THE MACHINE VISION SYSTEM

Description	Camera
Lens Type	Fixed Focus Lens
Resolution	1920 × 1080 colour image
Optical zoom	2MP
Frame rate	Up to 30 fps
View angle	Up and down 90° / Rotation 360°

To enhance the effectiveness of the detection process, each apple was positioned in the basket mechanism as shown in the Fig. 5, and subsequently, the camera captured an image of the apple. A single image suffices for the entire process, specifically for classifying the apple based on its width. The input image was in RGB format with dimensions of 1920 × 1080 pixels.

Fig. 5. Apple positioned in the basket mechanism.

The camera enclosure box was designed to allow light to enter mostly from above the apple, resulting in clear and well-defined contours. The presence of shadows was observed in the bottom area of the apple due to this configuration; however, they did not significantly impact the task. Since the standard was solely concerned with the apple's width and did not emphasize its height, the shadows above were deemed inconsequential.

B. Image Preprocessing

Image pre-processing is a crucial aspect of digital image analysis, and a two-image processing methodology is presented here. The proposed pipeline included dimension reduction and normalization. These steps collectively contribute to the effective preparation of apple images for subsequent analysis tasks.

The dimension reduction of the image was carried out because after implementing the camera enclosure box with the designed apple stand, it became apparent that the captured image included a substantial extra background area. Consequently, the idea of cropping the sides of the image emerges as a means to narrow the focus exclusively on the center, which represents the Region of Interest (ROI). By reducing the image size through this cropping process, the algorithm's response time was effectively decreased, resulting in a faster classification process. This optimization allows for more efficient utilization of computational resources, facilitating timely and effective object classification. The output image of this step was 300 × 400 pixels.

The normalization process was employed to adjust the contrast and brightness of the image, especially in the region of interest. The normalization formula was used to ensure that each dimension of the data ranges from zero to one. Data normalization was calculated using the Eq. (1) [41].

$$Y = \frac{X - X_{min}}{Xmin_{max}} \tag{1}$$

where, Y is the normalized value, X is the original value, X_{min} is the minimum value and X_{max} is the maximum value.

C. Colour Detection

Studies conducted on the surface colour shades of apples demonstrated that sorting could be achieved by analyzing the red colour density in red apples [41].

The goal was to extract the region of interest from the captured image. An image of the mentioned apples was captured to establish the colour range, and the RGB values of the lightest and darkest pixels within that image were determined. Defining these colour limits enabled the isolation and extraction of the regions of interest corresponding to the red apples for subsequent analysis. The colour limits utilized for filtering can be found in Table III.

TABLE III. COLOUR LIMITS FOR FILTERING

Colour	BGR Values
Dark Limit	100,500
Upper Light Limit	25,510,020

D. Segmentation

The subsequent stage in the pipeline involved converting the image from the RGB (Red, Green, Blue) to the BGR (Blue, Green, Red) colour space.

This conversion enhanced the ease of handling and ensured compatibility with specific image processing algorithms. Moreover, the segmentation process utilized the blue channel to distinguish the apple from the background, facilitating the recognition of the apple's components within each image channel.

Size measurement heavily relied on segmentation. Optimized image processing, the apple image underwent grayscale conversion. Ensuring detection accuracy and mitigating noise interference necessitated denoising the apple image. A Gaussian blur operation with a (15, 15) kernel size was preferred for its superior visual outcomes. Gaussian blur is the best method for reducing noise in an image because it gives more importance to the central pixels rather than the peripheral ones. This smoothing process enhances the detection and analysis of significant features by minimizing the impact of minor, irrelevant details or noise. Consequently, it improves the accuracy of apple segmentation by yielding a more uniform and cleaner image [42].

The apple segmentation was evaluated through thresholding, a straightforward image segmentation method. Its primary objective was to distinguish an object of interest from the background in an image.

The thresholding operation can be described using Eq. (2) as provided by [43].

$$dst(x,y) = \begin{Bmatrix} maxVal & \text{if } scr(x,y) > thresh \\ 0 & otherwise \end{Bmatrix} \tag{2}$$

where $dst(x, y)$ is the output pixel value at position (x, y) in the thresholded image, $scr(x, y)$ is the pixel value at position (x, y) in the input image, $\max Val$ is the maximum value assigned to pixels that are above the threshold, and *tresh* is the threshold value used to determine the segmentation of the image. Pixels with values above this threshold will be set to $\max Val$, and pixels below or equal to the threshold will be set to 0.

E. Measurement

To achieve millimeter measurements of the apple, it was crucial to isolate the apple from the background in the image. This segmentation process was referred to as thresholding in the preceding step. Next, contour detection was executed on a binary image, ensuring the retrieval of only the external contours and disregarding any nested ones. Subsequently, bounding rectangles were calculated for the contour, defining the smallest rectangular regions encompassing the contours. The function provided four essential values: the top-left corner's x and y coordinates, along with the rectangle's width (w) and height (h). This process enabled the precise measurement of the apple's size based on the bounding rectangles of its detected contours in the image.

ArUco markers were used for accurate pixel-to-millimeter conversion in this study. The ArUco marker dimensions used in the experiment were 50 × 50 mm.

During the ArUco marker detection process, accurate locations and identifications of the corners of these markers were achieved, along with retrieval of their unique IDs. To perform the pixel-to-millimeter conversion, the ArUco marker size was 50 mm, and the width of the ArUco marker 157 pixels, was utilized. By applying the Eq. (3).

$$Size(mm) = \frac{w \times 50mm}{157px} \tag{3}$$

where, w is the width of the rectangle formed in the image in pixels.

F. Sorting

The machine adeptly classifies apples into three distinct categories based on their width measurements, as can be seen in Table IV.

TABLE IV. MEASUREMENT FOR EACH APPLE SORTING CLASS

Class	Dimensions
Class 1	$w \geq 65$mm
Class 2	$60 \leq w < 65$mm
Class 3	$50 < w < 60$ mm

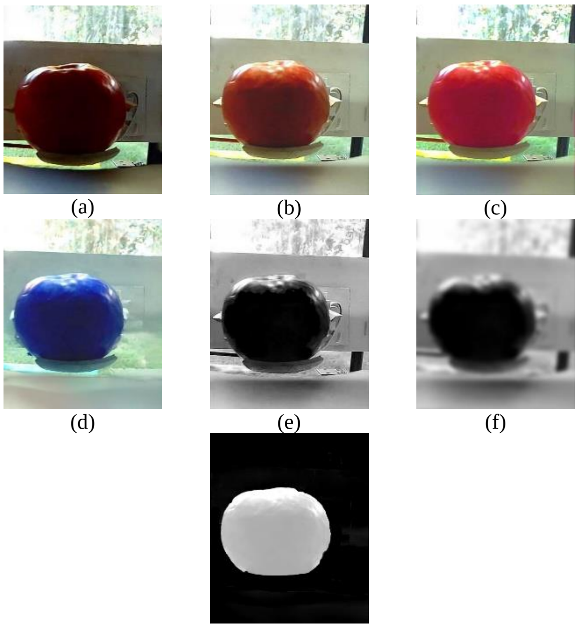
Specifically, Class 1 encompasses apples with a width greater than or equal to 65 mm, Class 2 comprises apples with a width less than 65 mm but greater than 60 mm, and Class 3 consists of apples with a minimum width of 50 mm. Once the apple's measurement in millimeters is obtained, its class is defined according to the diameter measurement. The apple is then transferred from the basket mechanism to the worktable. It is transported across the worktable by the chain conveyor belt mechanism, where the gates corresponding to each class are located. When the corresponding gate opens, the apple falls into the appropriate repository.

IV. EXPERIMENTS AND RESULTS

This section presents the results of essential tasks, including the segmentation, measurement, and classification of apples. The proposed apple sorting process begins when the apple is placed in the basket mechanism. The experiments were conducted with a batch of 50 apples of the species Malus domestica Borkh. By standard, there are typically only two classifications based on width which defines the Codex Alimentarius STAN 299–2010 standard [44]. However, through this experimentation, the range has been expanded to verify the effectiveness of this proposal by incorporating the classification of three width-based classes.

A. Segmentation

The entire process, from the source image to segmentation, is illustrated in Fig. 6. A photograph was taken after placing the apple in the enclosure box, as depicted in Fig. 6(a). This marked the initiation of various pre-processing steps, as highlighted in Fig 6(b). Subsequently, colour detection, as shown in Fig. 6(c), and segmentation were carried out. The segmentation process encompassed initial stages, including the conversion from RGB to BGR, as depicted in Fig. 6(d). Fig. 6(e) and Fig. 6(f) illustrate the process of transforming the image to grayscale and applying a Gaussian filter, respectively. Fig. 6(g) demonstrates the implementation of binary thresholding.



(a) (b) (c) (d) (e) (f) (g)

Fig. 6. Acquisition, preprocessing, and segmentation of apple image. (a)Source Image; (b) Image Preparing; (c) Colour Detection; (d) Convert from RGB; (e) Colour to gray; (f) Gaussian Filter; (g) Thresholding

A small threshold may not adequately display the apple area, whereas an overly large threshold could result in an incomplete representation of the apple region, leading to image distortion. This study established the threshold within the [90, 160] range. Fig. 6(g) illustrated the segmentation effect of an apple using a threshold of 130, revealing a comprehensive representation of the apple area. Table V compared apple extractions using eight different thresholds. The segmentation of apples using thresholds within the range of [120, 130] was straightforward and closely matched the actual scenario. However, when the threshold values of [90, 100, 140, 150, 160] were employed, the obtained segmentations needed refinement, failing to capture the region of interest accurately.

TABLE V. MEASUREMENT FOR EACH APPLE SORTING CLASS

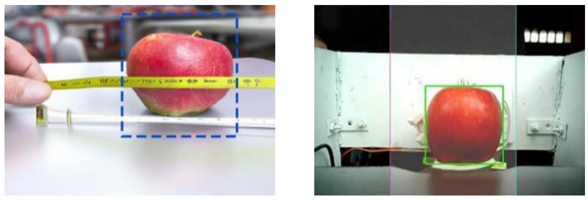
Threshold	Region of interest
90	Incomplete
100	Incomplete
110	Incomplete
120	Basically complete
130	Complete
140	Incomplete
150	Incomplete
160	Incomplete

B. Apple Measurement

Unlike traditional methods for apple measurement, using manual tools and human observation, the enhanced method using machine learning, provides more precise data and helps to make a more informed decision on how to treat the fruit.

Fig. 7(a) depicts the manual width measurement, representing the width measurement done by hand. Additionally, Fig. 7(b) illustrates the width measurement using our purpose-built method.

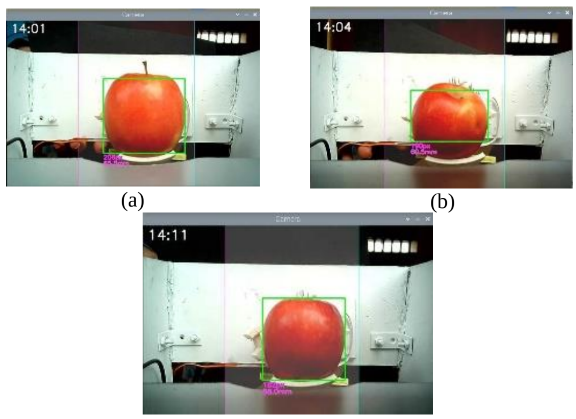
Fig. 8 provides an overview of the three distinct apple classes. In Fig. 8(a), representing the first class, an aligned rectangle along the apple contour spans a total of 206 pixels on a single axis. Applying Eq. (3), this precise approach yields an accurate apple width measurement of 65.60 mm. For Fig. 8(b), corresponding to Class 2, a 190 pixels rectangle results in a width of 60.51 mm. Finally, Fig. 8(c) displays the rectangle obtained from Class 3, which measures 180 pixels along a single axis, resulting in a width of 58.00 mm.



(a) (b)

Fig. 7. Comparison of human measurement and computer vision measurement. (a) Human Measurement; (b) Machine Measurement.

Fifty measurements of Malus domestica Borkh apples were conducted along a single axis, utilizing both manual techniques and our recommended measurement methodology. Table VI below presents the actual size of real apples alongside their corresponding estimated values, across with calculations of the absolute error between the measured values. The average error in estimating the width of apples using pixel size was found to be 1.253%.



(a) (b) (c)

Fig. 8. Acquisition, preprocessing, and segmentation of apple image. (a) An apple from class 1; (b) An apple from class 2; (c) An apple from class 3.

C. Apple Sorting

When measuring apples, they were categorized by size based on their width. The first apple was measured and found to have a width of 65.60 mm, placing it into Class 1. Similarly, the second apple had a width of 60.5 mm, categorizing it as Class 2. The third apple measured 58.00 mm in width, classifying it as Class 3. After successfully detecting the classes within the camera enclosure box, a signal was transmitted to the controller, prompting it to activate the corresponding gate for their respective classifications. Subsequently, the apple proceeded along the conveyor belt until it reached the point of classification.

TABLE VI. MEASUREMENTS OF THE REAL AND EXPERIMENTAL WIDTH

No.	Actual Size (cm)	Estimated size (cm)	Error %
1	64.00	63.22	1.21
2	58.45	58.13	0.54
3	60.81	59.72	1.79
4	64.8	65.22	0.64
5	67.87	68.13	0.38
-	-	-	-
46	67.50	67.70	0.29
47	60.20	59.90	0.49
48	56.20	56.70	0.89
49	69.05	68.09	1.39
50	61.15	59.00	3.15

All detection outcomes were grouped into four types: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN), depending on the relationship between the real class and the predicted class. The classification efficiency was evaluated using performance metrics such as accuracy, precision, and recall. The experimental studies produced classification results, which are presented in Table VII.

TABLE VII. PROPOSAL CLASSIFICATION RESULTS

Class	TP	TN	FP	FN
1	16	31	3	0
2	15	31	3	1
3	13	17	0	5

The procedures for computing accuracy, precision, recall, and F1–Score were elaborated in Eqs. (4)–(7), as provided by [35].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

$$Precision = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

$$F1 - Score = \frac{2(Precosion \times Recall)}{Precosion \times Recall} \tag{7}$$

Table VIII presents the sorting outcomes based on colour extraction and apple width measurement. Class 1 achieved the highest accuracy rate of 0.94, followed by Class 2 with 0.92, and Class 3 with 0.857. Additionally, Class 1 and Class 3 exhibit the most favorable precision or specificity values, scoring 0.848 and 1.00, respectively. In terms of recall and sensitivity, Class 1 outperforms the others with a perfect score of 1.00. Class 1 demonstrated the highest accuracy and excellent precision, making it a reliable choice for the sorting task. Class 3 also exhibited outstanding precision, ensuring accurate identification.

TABLE VIII. SORTING METRICS RESULTS

Class	Accuracy	Precision	Recall	F1 score
Class 1	0.94	0.848	1.00	0.913
Class 2	0.92	0.833	0.937	0.881
Class 3	0.857	1.00	0.722	0.838

D. Comparative Analysis

Table IX provides a detailed comparison between the proposed method and the main works highlighted in the Introduction section. It not only summarizes each work's main contribution, results, and disadvantages, but also provides a direct comparison with the proposal. This comparison, guided by your expertise, highlights the unique advantages of our approach in terms of accuracy, cost, and practicality, demonstrating its effectiveness against current benchmarks in the field.

TABLE IX. COMPARISON WITH OTHER WORKS

Author	Main Contribution	Results	Cons	Proposal
Baneh *et al.* [39]	Small-scale apple sorting machine with smart vision system	Calyx recognition up to 97%, stem end region recognition 100%	Focuses on specific features, not overall size	Broader application scope
Gongal *et al.* [36]	3D machine vision system for apple size estimation	69.1% accuracy for 3D coordinates-based, 84.8% for pixel size-based	Complex and expensive	Higher accuracy (up to 94%). More cost-effective and accessible.
Sofu *et al.* [25]	Automatic apple sorting system using machine vision	Sorting accuracy ranges from 73% to 96%	Non consistent handling of diverse apple shapes	Competitive accuracy with better consistency through controlled environment.
Mizushima *et al.* [31]	Low-cost colour vision system for apple orientation estimation	Orientation estimation: D apples-87.6%, GD apples-86.2%	Focuses on orientation rather than size	Higher accuracy in size classification,
Bhatt *et al.* [28]	Automatic apple grading model using neural networks	Overall accuracy of 96%	Requires complex neural networks and hardware resources	Combines traditional image processing with cost-effective hardware, achieving high accuracy without complexity.

By comparing these works, it becomes evident that the proposed method excels in critical areas such as accuracy, cost-effectiveness, and simplicity. These advantages make it a practical and scalable solution for small and medium-sized farms, addressing common limitations in existing apple sorting systems. The controlled environment used in the system enhances measurement consistency, further contributing to its effectiveness.

V. Discussion

Table IX highlights the potential advantages of our proposed system compared to similar models found in the state of the art. The proposed system achieves an accuracy of up to 94%, making it both cost-effective and accessible. It emphasizes the use of traditional image processing techniques and operates in real-time.

Since this implementation operates in real-time, it is important to verify the total time consumed in the entire process. The total time required for the process, from image pre-processing to classifying the apple into its corresponding repository, must be considered. Image processing begins when the photograph is taken, taking approximately 33 ms due to the camera's frame rate of 33 fps. Following this, as shown in Table X, the total time for image pre-processing is 2.4 ms. For the classification stage, where the apple is moved from the enclosure box to the corresponding gate, the process takes about 3 s. Therefore, the total time from image acquisition to classification is 3.0024 s. This indicates that the classification process takes 3 s per apple. The longest time is taken to move the apple from the enclosure box to the repository. This proposed system has significant implications for enhancing automated agricultural sorting processes, potentially leading to improved quality control and increased productivity.

TABLE X. Timetable for Image Pre-Processing

Class	Time (ms)
Image acquisition	0.3
Image pre-processing	0.5
Colour detection	0.6
Segmentation	0.5
Measurement	0.5
Total Time	2.4

VI. Conclussions

Implementing the apple sorting machine into three classes according to the measuring width, adhering to national standards, relies heavily on image processing, specifically the segmentation of apples from images. The error in measuring the apple's transversal area is found to be 1.253%, which corresponds to the error between the manual and the proposed methods.

The proposed system is designed for Malus domestica Borkh kind apples, precisely the red variety. As there is a red colour detection step, the system is tailored exclusively for red apples of any type. Moreover, using a vision system such as a camera is susceptible to the influence of lighting conditions. The apple is isolated in an enclosure box where conditions are controlled. The entire process, including pre-processing, colour detection, segmentation, measurement, and sorting, is automated, taking approximately 3 seconds per apple.

While the proposed apple sorting machine demonstrates promising capabilities in enhancing fruit classification processes through image pre-processing techniques, several limitations and disadvantages need to be addressed. These include the system's specificity to red apples, sensitivity to lighting conditions, dependency on accurate threshold selection, and processing time. Addressing these challenges is essential for broader applicability and improved efficiency in agricultural practices.

In conclusion, the findings presented in this paper underscore the promising capabilities of image pre-processing techniques in elevating fruit classification processes. Within the agricultural industry, these results unveil prospects for heightened productivity and enhanced quality control.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Andrea Pilco and Viviana Moya conceptualization and conducted the research; Angélica Quito, Juan P. Vásconez, and Matías Limaico analyzed the data; Andrea Pilco, Viviana Moya and Angélica Quito wrote the paper; all authors had approved the final version.

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