Estimation of Fruit Number in Coffee Trees by Maturity Level, based on Color Space Weighting, using a New Segmentation Algorithm

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***Abstract*—Computer vision systems are essential for automating agricultural tasks such as disease detection and fruit defect identification. However, their application in coffee farming faces significant challenges due to environmental variability and the complex structure of coffee trees, which complicate image acquisition. Thus, this study addresses two key questions: 1) Can low-cost, user-friendly equipment adapt to crop conditions while ensuring image quality? 2) Can a computer vision algorithm accurately count and classify coffee beans with over 80% accuracy using data from low-cost cameras? To answer these questions, an image acquisition system was developed based on the phenological characteristics of coffee plants, ensuring focused and consistent image capture. Additionally, a novel algorithm was created, utilizing statistical analysis of color spaces to effectively separate fruits from the background, segment images, and count fruits. The algorithm achieved accuracy rates, when compared with a traditional approach, within the desired range for each coffee fruit class: green (83%), green-olive (79%), cherry (86%), and raisin (80%). These results demonstrate the potential of this approach for accurate and efficient fruit processing in coffee farming, particularly when images are captured directly from tree branches.**

Link to graphical and video abstracts, and to code: https://latamt.ieeer9.org/index.php/transactions/article/view/9330

***Index Terms*—Coffee fruit estimating, Computer Vision, Image Processing.**

I. Introduction

BRAZIL'S agricultural sector is highly diversified, with coffee standing out as a cornerstone commodity; the country is the world's largest coffee producer, followed by Colombia and Vietnam, cultivating two primary varieties: Robusta/Conilon (Coffea canephora) and Arabica (Coffea arabica L.). This work focuses on Arabica coffee, the predominant variety in Brazil, highlighting its importance in the country's agricultural landscape.

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From a computational perspective, the morphological characteristics of the coffee tree—such as its branches, leaves, flowers, and fruit—are essential for generating parameters used in image processing algorithms. Estimating crop productivity is essential for farmers to effectively plan material, financial, and human resources, offering insights into expected expenses and profits. In coffee production, two primary approaches are commonly used. **The first approach** focuses on water availability, analyzing how water deficits impact plant development across different crops. Mathematical models are employed to link specific plant parameters to climatic conditions, providing an approximate estimation of coffee production [1]–[4]. The **second approach** to estimating productivity focuses on individual coffee trees, analyzing the quantity of fruit on selected branches to develop a statistical model for total fruit yield estimation. This method is less invasive than destructive sampling, which involves stripping fruit from branches for counting. A key study by [5] highlights that the branches selected for analysis are typically from the upper part of the tree. This choice is deliberate, as the upper branches, located in the apical meristem region, are younger and tend to produce more fruit.

Numerous studies employ computer vision methods to monitor cultivated areas of specific crops, enabling the estimation of total cultivated area and the spatial distribution of trees, which helps determine the number of trees in a given planting area [6]–[8]. However, knowing the cultivated area and tree count alone is insufficient for accurate productivity estimation. To achieve this, it is necessary to establish relationships between image-derived parameters and meteorological and phenological variables of the trees.

Counting fruit directly on the tree is an attractive alternative, as it provides a method to estimate tree productivity and, by extension, the productivity of the entire cultivated area. However, computer vision systems face a significant challenge: occlusion. Many researchers focus on improving methods for recognizing occluded structures in agricultural imagery. For instance, studies by [9]–[13] highlight efforts to enhance algorithms for fruit identification and counting under uncontrolled conditions.

Despite advancements in sensor technology, data processing systems, and mathematical techniques for image analysis, errors in most studies related to fruit identification and counting under uncontrolled conditions are primarily caused by processing algorithms in areas where occlusion occurs. Researchers have explored various methods to address challenges like occlusion and uncontrolled lighting in computer vision systems for agricultural applications. One approach involves fusing images with data from other sensors, as discussed in studies like [14]. [15] developed a non-destructive method for counting fruits on coffee tree branches using digital images to estimate yield per tree and, consequently, per cultivated area. In another study [17], the YCrCb color space was employed to isolate coffee bean pixels from other tree structures.

From a computer vision perspective, proper image acquisition enhances processing capabilities and technique effectiveness. However, the lack of dedicated acquisition instruments in agriculture complicates this process. To address these challenges, this article presents an edge detection algorithm for estimating fruit counts from images captured on coffee tree branches. The proposed algorithm was compared to another traditional approach and achieved accuracies of 83% for green fruits, 79% for green-olive fruits, 86% for cherry fruits, and 80% for raisin fruits. These results are significant as the images were taken directly in the field, introducing a novel approach to fruit image processing in coffee cultivation.

II. Methodology

The distribution of coffee fruits and other structures within the tree canopy makes capturing clear images particularly difficult, especially for deep structures inside the tree and high foliage, which are hard to access. Accurately estimating the quantity of fruit at various maturity stages (green, olive green, cherry, and raisin) allows harvest forecasts to be extrapolated across entire planting regions through statistical analysis, without requiring fruit drop. This approach saves significant time and enhances the accuracy of large-scale harvest projections. In this context, the goal of this study was to automate coffee harvest estimation by maturity stage using low-cost, user-friendly equipment tailored to coffee tree conditions, ensuring high image quality and consistency. The system must also include a segmentation algorithm capable of counting and classifying coffee beans with over 80% accuracy. This threshold was empirically determined based on manual fruit counting statistics used by producers, which often involve total fruit drop. Manual counting is then generalized as the average production per tree within a plot, typically leading to an accuracy below 70%. Achieving 80% accuracy with an automated system represents a significant improvement in harvest prediction for entire plantations. Additionally, this accuracy allows better utilization of each fruit variety, as different maturity stages define distinct harvest classes. The methodology consisted of two stages: first, implementing a mechatronic device to capture images directly from coffee tree branches, and second, developing a fruit estimation algorithm. The first stage, involving the image collection system, will be briefly described without extensive detail, as it falls outside the scope of this article. The second stage, the coffee fruit estimation algorithm, segments the fruits in the acquired image, classifies the beans by color—indicating their maturity level—and subsequently counts the fruits in each identified class, as shown in Fig. 1. This framework will be discussed in detail in the following sections.

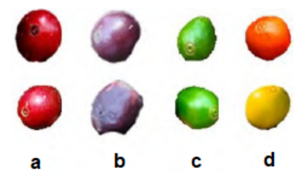

Fig. 1. Samples and their classes, (a) Cherry, (b) Raisin, (c) Green and (d) Olive green.

A. Mechatronic Device for Collecting Images Directly from Coffee Tree Branches

The mechatronic device developed by the authors to automate the collection of coffee fruit images from tree branches is schematically shown in Fig. 2. This patented device consists of a ring equipped with USB cameras that slides along the coffee tree branch, enabling image capture of the fruits. It includes hardware to control the ring's movement and software for image processing and result export via Wi-Fi. With this system, users can capture images from specific branches, process them to count the fruits, and export the results to any Wi-Fi-enabled device, such as a smartphone, personal computer, or laptop. Using this device, the authors collected images from coffee trees in Brazil and Colombia, creating a dataset that represents various stages of fruit maturity. These images were later used in the fruit counting algorithm, which will be discussed in the following sections.

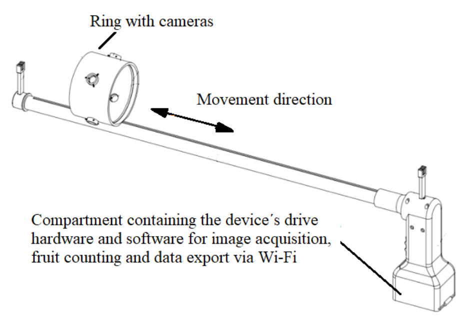

Fig. 2. Mechatronic Device for Collecting Images Directly from Coffee Tree Branches.

B. Algorithm for Processing Images Collected by the Image Acquisition Device

To accomplish the image processing task, particularly in the classification and counting of fruit, the authors developed the methodology illustrated in Fig. 3. The first stage of the methodology involved creating a coffee plant image dataset using the device described above. Two experiments were conducted to build this dataset: the first at a farm in Monte Sião, Minas Gerais, Brazil (Latitude: 22°27'18.44"S, Longitude: 46°30'42.82"W), and the second in Tapartó, Andes, Antioquia, Colombia (Latitude: 5°42'4"N, Longitude: 75°58'2"W). Both were carried out in the morning and afternoon. These experiments resulted in two datasets: one with 1,500 images at a resolution of 300×300 pixels and another with 600 images for each of the four coffee classes (green, olive green, cherry, and raisin) at 50×50 pixels per image. As described in the following sections, these images were used to define segmentation masks applied in each color space.

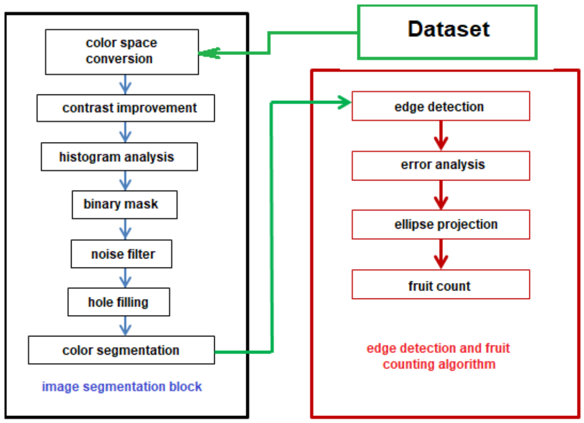

Fig. 3. Proposed methodology for processing coffee bean images collected with the device developed by the authors.

Color Space Weighting Method

Segmenting objects of interest in images captured under varying lighting conditions is a significant challenge in image processing, as human perception and recognition rely on experience and feature analysis. To address this, the candidate color channel method proposed by [16] was improved by automating the channel analysis system and refining the weighting method for selecting each color channel. A total of 200 images per fruit class and 200 background images from the dataset (coffee plant images from Brazil and Colombia) were used. Histogram statistical analysis was conducted in four color spaces: RGB, Hue, Saturation, and Value (HSV), CIELab, and YCbCr, as shown in Fig. 4.

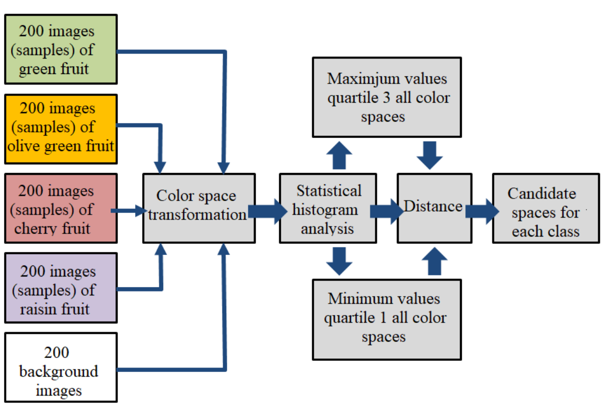

Fig. 4. Diagram of the steps for preprocessing the candidate color spaces.

As a result, a dataset was generated with comparative information on each color component of the four color spaces for each fruit class and the background, to be analyzed statistically. Based on this information, it is possible to determine the value ranges representing each class and background in each color channel, as well as the distance between the data distributions of the fruits and the background. The proposed method aims to identify the channels with the greatest distance between the maximum and minimum values of the fruits and the background. This distance determines the most suitable color spaces for segmentation. Table I presents the first and third quartiles, along with the median values obtained after analyzing each color space channel. The distance calculation rules were defined to ensure a positive value whenever there is a clear separation between the pixel distributions of the fruits and the background. Channels with the greatest positive distance between these groups are selected as candidates for segmentation. In the first stage, selected candidates receive a higher weight in the selection process for new candidate channels, increasing their probability of being chosen for new images. However, some may still be discarded during the process.

The calculated distances are then normalized and expressed as percentages for input into the binarization algorithm. Table II presents the quartile values and median obtained from the analysis of each color space component for each class. After selecting the candidate channels, they are binarized using the first (Q1) and third (Q3) quartile values from the histogram analysis to ensure proper isolation of the fruits in each class. Once binarization is complete, masks are generated (Fig. 5) and used in the weighting process to create a final mask applied to the original image. For weighting the color channels analyzed in the first stage, which correspond to the isolated samples of each fruit class, Equation 1 is used. Channels with a greater positive distance receive a bonus in the weighting process.

$$SampleAnalysis = \begin{cases} ChannelA_{Candidate_1} * 0.15 \\ ChannelA_{Candidate_2} * 0.10 \\ ChannelA_{Candidate_3} * 0.05 \end{cases} \tag{1}$$

$$ImageAnalysis = \begin{cases} Channel_{Candidate_1} * 0.15 \\ Channel_{Candidate_2} * 0.10 \\ Channel_{Candidate_3} * 0.05 \end{cases} \tag{2}$$

$$RemainingChannels = Channel_n * (0.4/N) \tag{3}$$

where:

$ChannelA_{Candidate_n}$ = channels analyzed with samples of fruits from each class that present the greatest separation distance between the bottom and the fruits, n = 1, 2, 3;

$Channel_{Candidate_n}$ = channels analyzed with the input image that has the largest separation distance between the background and the fruits, n=1,2,3;

$Channel_n$ = channels analyzed with the input image that present positive separation distances between the background and the fruits, n=1,2,3....n;

N = Total number of channels with positive distance not classified with highest probability.

TABLE I
QUARTILE AND MEDIAN VALUES OBTAINED AFTER ANALYZING EACH OF THE COLOR SPACE COMPONENTS, FOR EACH OF THE CLASSES (GREEN, OLIVE GREEN, CHERRY AND RAISIN)

Color Channels	R	G	B	H	S	V	L	a	B	y	Cb	Cr
Green 3rd quartile	136	157	116	0.31	0.43	160	6117	-404	2238	124.50	-5.49	0.58
Green Median	104	124	85	0.24	0.30	126	5072	-995	1411	97.77	-11.79	-3.39
Green 1st quartile	80	94	62	0.19	0.20	96	4064	-1631	753	74.89	-18.91	-8.69
Green Olive 3rd quartile	163	123	177	0.95	0.54	169	5518	2432	1337	112.51	1.45	26.98
Green Olive Median	124	83	84	0.83	0.41	129	4348	1389	537	83.34	-3.80	15.37
Green Olive 1st quartile	89	54	58	0.18	0.26	94	3297	155	-98	58.70	-10.81	4.09
Cherry 3rd quartile	170	75	92	0.95	1.00	171	4633	3862	2807	84.45	-0.54	54.08
Cherry Median	130	36	47	0.58	0.67	131	3654	2897	1266	51.87	-7.52	35.51
Cherry 1st quartile	96	0	0	0.00	0.46	96	2814	2031	196	33.70	-16.69	22.49
Raisin 3rd quartile	79	56	73	0.92	0.43	83	3061	1399	1	55.27	6.50	10.00
Raisin Median	60	41	54	0.86	0.33	62	2436	897	-290	41.84	2.52	6.81
Raisin 1st quartile	46	31	39	0.76	0.23	47	1962	565	-794	31.84	0.45	4.32

TABLE II
DISTANCES OBTAINED FOR EACH OF THE CHANNELS

Color Channels	R	G	B	H	S	V	L	a	B	y	Cb	Cr
Green	-9	-55	-7	**0.06**	-0.04	-26	-1334	**18**	**533**	-219.69	**4.09**	-5.28
Olive Green	-31	**12**	-47	-0.62	**0.07**	-24	**67**	-45	-374	**1.87**	-3.06	**3.54**
Cherry	-48	-75	-92	-0.95	-0.54	-43	-894	-4279	-2903	-39.71	-21.48	-58.7
Raisin	**39**	**49**	**24**	**0.15**	-0.04	**48**	**1620**	**552**	-193	35.67	-9.62	**3.69**

To remove potential noise from the resulting binary image, morphological operations were applied to filter out isolated pixels. This was followed by a hole-filling step to close any gaps and ensure that the segmented regions are uniform.

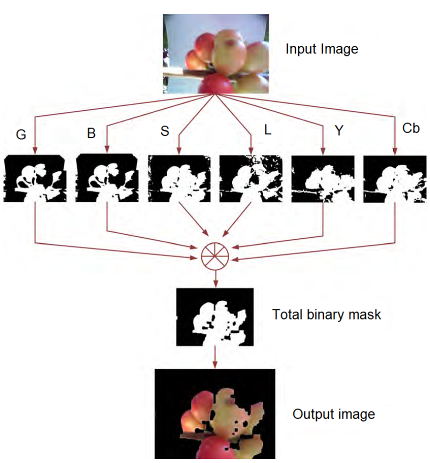

Fig. 5. Masks obtained for each of the candidate color spaces chosen in the previous step.

C. Edge Detection Algorithm and Fruit Counting

The edge detection methodology follows the approach proposed by [15], which adapts the chain method to identify arcs in the image, interpreted as potential fruits. This method can lead to errors in fruit counting. To mitigate these errors, we propose a method that leverages the geometry of ellipses, which closely approximate the shape of coffee tree fruits. In this approach, the ellipse equation is parameterized using metrics derived from the image data. As shown in Fig. 6, each detected arc consists of two points marking the beginning and end of the curvature, namely (x1, y1) and (x2, y2).

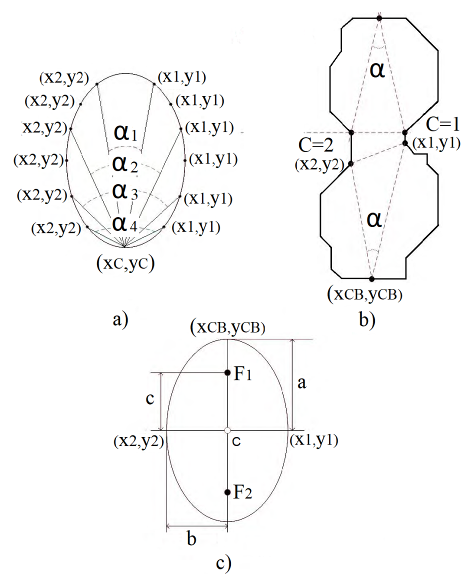

Fig. 6. Method for projecting ellipses.

Along the path between these points, the most extreme point is identified as (xc, yc). This point is determined by measuring the distance between coordinates (xi, yi) and (xi-1, yi-1) whenever there is a change in the direction of the edge. This parameter is recorded in the Position vector. Once the coordinates of points (xc, yc), (x1, y1), and (x2, y2) are known, a line is projected connecting these points to the center of the ellipse, as illustrated in Fig. 6b. Trigonometric ratios are then used to calculate the angle α. For each set of coordinates (x1, y1) and (x2, y2), potential values for the angle α and parameter a are projected. Using these parameters and the ellipse equation, it is then possible to project the ellipse corresponding to the analyzed arc. Angle values exceeding 160 degrees are disregarded as fruit segments. The sequential steps for implementing the proposed algorithm are outlined below.

Input: Image with edges
Output: Image with projected ellipses
Define starting point for analysis (X_i, Y_i)
Create mask to analyze edge
Initialize the process for traversing the edge (counter-clockwise)
Store the code corresponding to the pixel and its position (Position)
Detect change of direction at the $(1, -2)$*,* $(2, -2)$*,* $(-2, -1)$ *and* $(-1, 1)$ *edges*
Define the coordinate where the change in direction occurred (X_f, Y_f)
Search the matrix (Position) for the coordinate where the change in direction of rotation on the edge occurs (X_c, Y_c)
Calculate the angular coefficients m *of the lines formed by* $[(X_i, Y_i)$ *and* $(X_c, Y_c)]$ *and* $[(X_f, Y_f)$ *and* $(X_c, Y_c)]$
Calculate the angle α
$\alpha = \arctan\left(\frac{m(X_i,Y_i)(X_c,Y_c) - m(X_f,Y_f)(X_c,Y_c)}{1 + m(X_i,Y_i)}\right)$
Analyze the value of α *to determine the parameters* b *and* a *of the ellipse*
Project the ellipse under the candidate arc

The angle α determines the opening of the arc detected at the edge. Using this angle, parametrization is performed as depicted below. These parameters have been established through experimental validation. Using this parameters, the coordinates forming the ellipse are generated in the orientation illustrated in Figure 7c. Subsequently, the coordinate system is rotated so that its edges align with those visible in the image. Each iteration involves rotating the ellipse by 20° until the projected ellipse overlaps at least 70% with the edge pixels.

$\alpha \geq 160^\circ$	$a = 0$
$140^\circ < \alpha \leq 160^\circ$	$a = 6b$
$120^\circ < \alpha \leq 140^\circ$	$a = 5,5b$
$100^\circ < \alpha \leq 120^\circ$	$a = 3b$
$80^\circ < \alpha \leq 100^\circ$	$a = 2,5b$
$60^\circ < \alpha \leq 80^\circ$	$a = 2b$
$40^\circ < \alpha \leq 60^\circ$	$a = 1,75b$
$20^\circ < \alpha \leq 40^\circ$	$a = 2b$
$10^\circ < \alpha \leq 20^\circ$	$a = 3,75b$
$\alpha \leq 10^\circ$	$a = 9b$

The ellipse is projected only if it fits entirely within the original image coordinates, with the origin positioned at (1,1) in the image. Ellipses extending into the negative quadrant or exceeding the image boundaries are discarded. This ensures that the algorithm counts only those fruits that are fully visible within the image. For the fruit count, the algorithm considers the number of centroids of the ellipses projected in the previous step. For each cluster (glomerulus), the algorithm determines the number of fruits in each class by executing image processing procedures specific to each fruit class. To ensure that the ellipses generated by the algorithm accurately correspond to fruits in the image, a watershed transform is applied. The binary mask used for growing these regions is the image containing the ellipses. This method effectively identifies which ellipses correspond to actual fruits in the image, thereby improving the accuracy of fruit detection and classification. Ground truth data was obtained through direct visual counting in the field, followed by image-based validation. During data collection, a set of reference cards with predefined color shades from the literature was used. A harvesting specialist matched each shade to a specific maturity class based on previously harvested fruits. Classification was carried out without detaching the fruits from the plants. Afterwards, the images were analyzed individually to count the total number of fruits in each maturity class.

III. Results

The dataset used to validate the proposed technique was divided into two parts. The first part consisted of 1500 images of coffee fruits from the Coffea Arabica and Coffea Canephora varieties, standardized to a size of 300x300 pixels for ease of use. The second part contained samples of coffee beans categorized into four classes: Cherry, Olive Green, Green, and Raisin. For each coffee class, 600 images of size 50x50 pixels were stored.

Edge Detection and Ellipse Projection

Fig. 7 shows examples of the results of implementing the edge detection and ellipse projection algorithm.

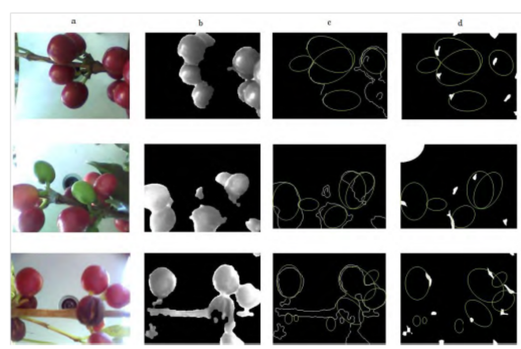

Fig. 7. Examples using the edge detection and ellipse projection.

A. Fruit Counting

The image processing method was evaluated using all 1500 samples obtained with the data acquisition device. In the initial validation stage, the algorithm's fruit counting were compared to manual counts for each class. Table III presents the total counts for each class. Based on these values, a confusion matrix was constructed for each class, following the approach proposed by [17]. True Positives (TP) represent fruits correctly identified by both manual inspection and the algorithm. False Positives (FP) denote fruits identified by the algorithm but not confirmed by manual inspection. Each fruit class and background were evaluated separately using the color channels. For fruit counting, the number of centroids of the ellipses projected in the previous step was considered. For each cluster, the number of fruits from each class is determined after processing the images for each class. The results of this processing step are shown in Fig. 8.

Fig. 8. Examples using the proposed algorithm.

TABLE III
TOTAL FRUIT FOR EACH CLASS, MANUAL COUNT VS. ALGORITHM COUNT

	Total Manual	Total Algorithm
Green	2892	2985
Olive Green	2172	1878
Cherry	6053	5278
Raisin	2295	1882
Total	13412	12023

Table IV shows the confusion matrices for each class.

TABLE IV
CONFUSION MATRIX FOR EACH CLASS

(a) Green Class			(b) Olive Green Class		
	Fruits	Not Fruits		Fruits	Not Fruits
Fruits	2492	493	Fruits	1476	402
Not Fruits	400	0	Not Fruits	696	0
(c) Cherry Class			(d) Raisin Class		
	Fruits	Not Fruits		Fruits	Not Fruits
Fruits	4555	723	Fruits	1512	370
Not Fruits	1498	0	Not Fruits	783	0

Confusion matrices are constructed based on the fruits counted manually compared to those counted by the algorithm. For each class, accuracy (Equation 4), sensitivity (Equation 5), and F1 Score (Equation 6) are calculated:

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Sensibility = \frac{TP}{TP + FN} \tag{5}$$

$$F_1 = 2 * (\frac{Precision * Sensibility}{Precision + Sensibility}) \tag{6}$$

Table V presents this parameters for each fruit class as well as for the total number of fruits detected. Table VI shows that the proposed algorithm achieved an F1-score of 0.79, a value comparable to those btained by 2D methods (ranging from 0.80 to 0.83), and slightly lower than those achieved by 3D reconstruction systems ($\geq$ 0.85). However, the latter require additional sensors and volumetric processing, which increase both the cost and operational complexity in field applications. In contrast, the proposed solution relies solely on 300 × 300 px RGB images and a portable device, simplifying deployment and reducing overall costs. Three main limitations were identified: (i) performance degradation under extreme lighting conditions, such as deep shadows or overexposed areas; (ii) difficulty in distinguishing individual fruits in cases of severe occlusion by leaves or branches; and (iii) the need for precise device positioning to ensure proper focus and branch coverage. Future work will explore the use of controlled lighting and multispectral sensors to enhance robustness under these challenging conditions.

TABLE V
PRECISION, SENSITIVITY AND F1-SCORE VALUES FOR EACH CLASS

	Precision	Sensitivity	F1-Score
Green	0.83	0.86	0.85
Olive Green	0.79	0.68	0.73
Cherry	0.86	0.75	0.80
Raisin	0.80	0.66	0.72
Total	0.83	0.75	0.79

IV. CONCLUSIONS

This article introduces a novel 2D image processing algorithm designed for segmenting and counting fruits on coffee tree branches. The algorithm employs a color space weighting system and was validated using a database of 1500 images of fruit-laden branches divided into clusters (glomeruli), achieving an accuracy of 83% for the samples. The proposed system offers a non-invasive alternative that preserves tree integrity while automating the fruit counting task. It proves to be an effective solution for accurately segmenting occluded fruit, a common challenge in crops like coffee. Accurate classification of fruit into green, green-olive, cherry, and raisin is crucial for decision-making in coffee harvesting. Among these classes, the cherry class is particularly significant as it indicates fruit readiness for picking, allowing producers to plan and manage logistics efficiently. With an accuracy rate of 86%, the proposed algorithm is a reliable tool for this task, ensuring precise identification and quantification of cherries to facilitate timely harvest operations. Based on the data obtained from the algorithm, future work involves developing a mathematical model that correlates the automated fruit counting results with those obtained manually over a specified period. This correlation aims to create a yield estimation model that accurately predicts coffee production based on automated image processing techniques. This approach will help validate the algorithm's accuracy and reliability in real-world applications, enhancing its utility in agricultural decision-making processes.

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TABLE VI
COMPARISON OF PRECISION, SENSITIVITY AND F1-SCORE PARAMETERS

	Precision				Sensibility	F1-Score
	Green	Cherry	Raisin	Total		
Proposed Method	83%	86%	80%	75%	79%	79%
Bazame et al., 2021 [18]	86%	85%	80%	83%	82%	82%
Ramos et al., 2017 [15]	83.57%	83.09%	88.02%	83%	-	-
Ramos et al., 2018 [19]	90%	96%	-	-	-	-
Rodrigues at al., 2020 [17]	-	-	-	59.40%	66.90%	-

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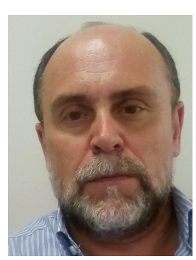

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