Detection and classification of tomatoes by ripeness and size using computer vision

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Abstract. Tomatoes stand out in agribusiness because they are one of the most consumed vegetables in the world. There is a growing demand for healthier foods and tomatoes are an important source of vitamins A, C and B1. Its production, handling and transportation are complex due to its sensitivity to the environment, pest attacks, road conditions, among others. Consumer markets are increasingly demanding, with quality and price being the decisive factors for purchases. The quality of the tomato, which directly affects the price, takes into account the size, color and number of imperfections that the fruit presents, which shows the great importance of classifying the tomato according to these considerations. Nowadays, all this classification is done using archaic and manual processes, causing great subjectivity, errors regarding the quality of the fruit and delays. Given this scenario and taking into account the numerous applications of Computer Vision in agribusiness, this work proposes to create a tomato classifier by color, size and imperfection, using computer vision with artificial intelligence, thus ensuring a standardized, fast and effective classification.

Keywords: Tomato Classification, Computer Vision, Agribusiness

1 Introduction

Tomatoes stand out in agribusiness, as they are one of the most consumed vegetables in the world and an important source of vitamins A, C, B1 and minerals such as potassium and magnesium [1] . According to FAO, Brazil ranks eighth in the ranking of the largest tomato producers in the world [2], the state of Goiás being the largest producer in Brazil [3] whose production value has been growing from 2018 to 2022 according to IBGE data [7]. The Brazilian Program for the Modernization of Horticulture created by the Secretariat of Agriculture of São Paulo in conjunction with the Company of Warehouses and Warehouses of São Paulo (CEAGESP) is the one that determines, through voluntary adhesion, the standardization of tomatoes sold taking into account color, shape, sizes, defects and packaging [4]. The tomato production chain is complex, as it is a highly perishable food. Its cultivation is sensitive at all stages of production, from planting to harvesting, as it is subject to numerous pest attacks, and even transportation and storage. The consumer market is increasingly demanding the quality of vegetables on supermarket shelves and seeking healthy habits [5]. Adopting good practices during harvesting and post-harvest is essential to preserve the quality of vegetables and reduce losses [6]. These factors contribute to the fact that not everything that is produced reaches consumer centers, resulting in a lot of food waste and monetary losses. One of the main difficulties for producers and distributors in quickly and reliably meeting the demand and requirements of consumer markets is the classification of tomatoes according to size, color and defects, since it is a highly perishable food.

The automation of the classification process today is done in a very archaic, subjective and slow way, causing waste and considerable financial loss for producers.

This article proposes a Computer Vision algorithm using Artificial Intelligence for the automatic classification of tomatoes according to their size and color, in a fast, efficient and non-subjective way, making tomatoes available to the consumer market much faster, thus bringing several benefits to the producer, among them the reduction of waste, standardization and profitability.

This article is divided into 5 sections. Section 1 provides an introduction to the work; Section 2 presents the methodology used in this article. Section 3 presents some works related to this area; Section 4 presents a theoretical basis for the techniques used to carry out this article; Section 5 presents the results obtained; and Section 6 presents the conclusions reached during the execution of this work.

2 Methodology

To produce this article, a support for a 25cm high webcam was created as per Fig 1.

Figure 1. Webcam support.

Several images of tomatoes were taken to test and validate the performance of the computer vision algorithm. The steps developed can be seen in Fig. 2.

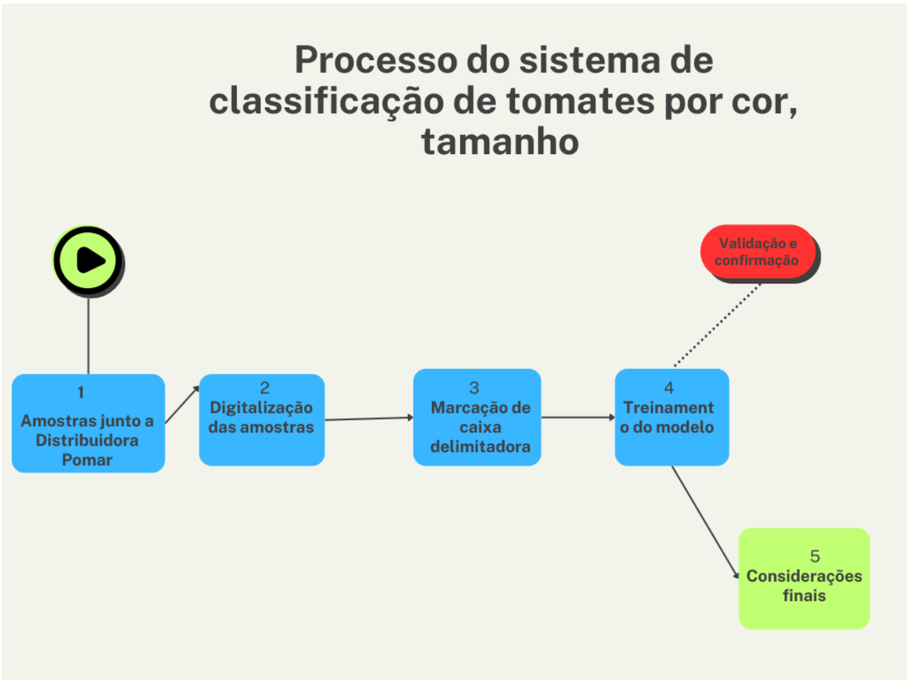

Figure 2. Representation of the process.

where:

1. Acquisition of images of tomatoes from the saladette group [4] for forming the dataset Fig. 3 was carried out in partnership with the company Distribuidora Pomar located in Viana/ES. Initially, 173 tomatoes were photographed at different stages of ripeness, enabling the network to differentiate ripe tomatoes from green ones.

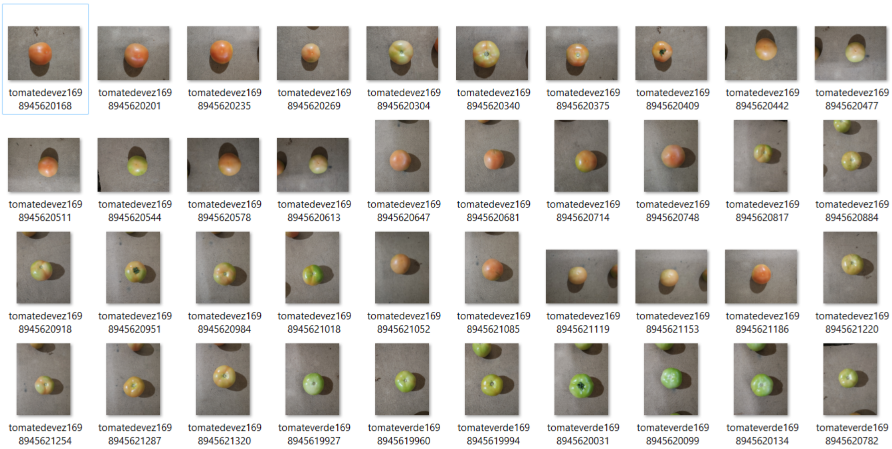

Figure 3. Sample of tomatoes at different stages of ripening.

2. Choosing the best photos to prepare the dataset so that you can separate the different stages of tomato ripening into classes.
3. Bounding box marking using the roboflow tool that makes it easier to load images and annotate objects and generate a dataset as shown in Fig. 4.

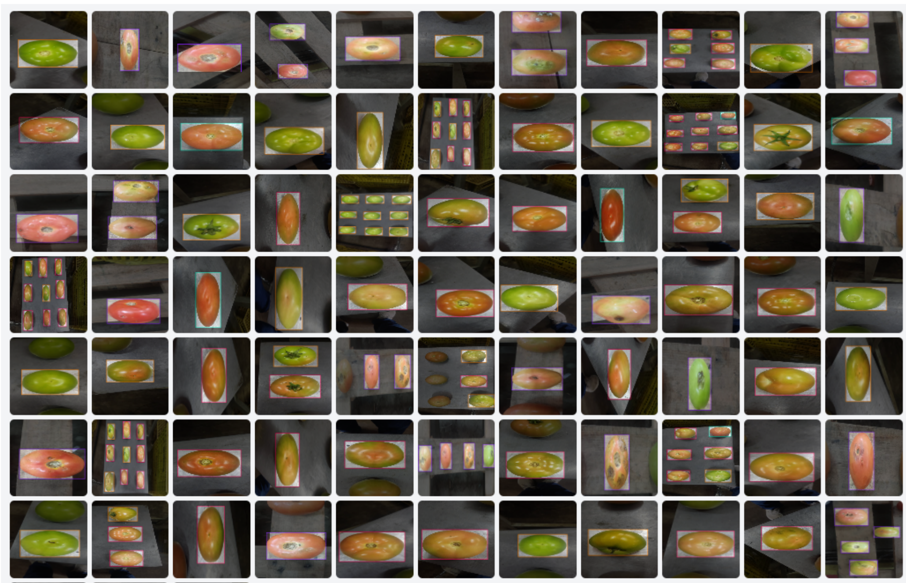

Figure 4. Appointments made with the roboflow platform.

4. Model training using YOLOv8 [8] for detecting and classifying tomatoes according to color and size.
5. Validation of the model for detection and classification of tomatoes according to color and size.

3 Related Works

The reduction in the cost of electronic devices has allowed the introduction of computer vision into a large part of industrial processes, especially those that require repetitive or high-precision work. Processes of this type are inherent to agriculture, and in it we can find a wide variety of computer vision applications, such as those reviewed in Tillett [9]; Brosnan e Sun [10], Patel et al. [11]; Saldaña et al.[12]; Seema, Kumar e Gill [13]; Tripathi e Maktedar [14].

However, there are not many academic works on the use of Computer Vision for the specific classification of tomatoes. In the work of LOURO et.al. [15], the MLP neural network is used to classify tomatoes, a network that does not have the same performance as deep neural networks, but in Cyrrilo [16] computer vision was applied only to detect the shape of the tomato, which shows the great potential of this work.

4 Theoretical foundation

The YOLO (You Only Look Once) family is a series of object detection models that revolutionized computer vision because they have a broad capacity to perform real-time detection with high precision and efficiency. Their applications range from security and surveillance, with the detection of objects and behaviors in video, to autonomous vehicles, which use YOLO to identify pedestrians and other obstacles. In industries, YOLO is used for automated quality inspection, while in precision agriculture, it helps monitor and classify agricultural products, such as tomato detection and grading. YOLOv8, used in this paper, combines high accuracy with speed, making it ideal for real-time applications. It offers an efficient model that not only identifies objects of interest in a scene, but also provides bounding boxes, class labels, and confidence scores very quickly, providing a user-friendly real-time view. Furthermore, YOLOv8 goes further, allowing the detection of objects without the need to detail their exact shape, which is the case with tomatoes, since they do not have a perfect shape, which makes it particularly useful in scenarios where identifying the presence and approximate location of objects is sufficient. The YOLOv8 model, used in this article, was trained to detect tomatoes and classify them by ripeness. However, for size classification, an auxiliary algorithm was created that calculates the size of the tomato given the distance between the object (tomato) and the webcam, the standard size of the image, and the space occupied by the bounding box in the image. Therefore, if the distance between the webcam and the photographed tomato changes, you just need to tell the algorithm how many pixels can be considered small or large.

5 Results

After the markings were made in Roboflow, the dataset with the images and markings made and organized into: train, valid and test was downloaded together with the file. Fig. 5 shows the performance of the algorithm developed in this work.

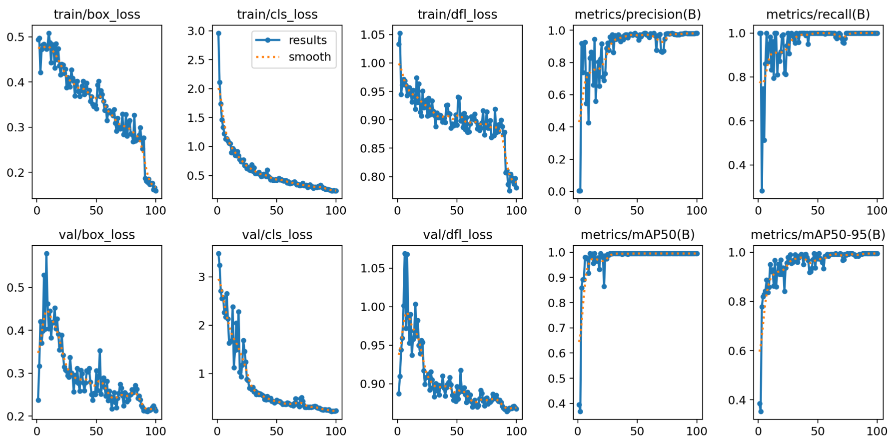

Figure 5. Result of training yolov8n network on graphs: results.png.

With the trained network, tests were carried out with another group of tomatoes. Using the same support shown in Fig. 1.

Several units were tested, in 100% of the tests carried out to classify the tomatoes according to ripeness and size, the algorithm got them all right, which can be seen in some samples in Fig. 6. It was defined that tomatoes that have a total circumference of up to 24cm will be considered small and tomatoes with a circumference greater than 24cm will be considered large.

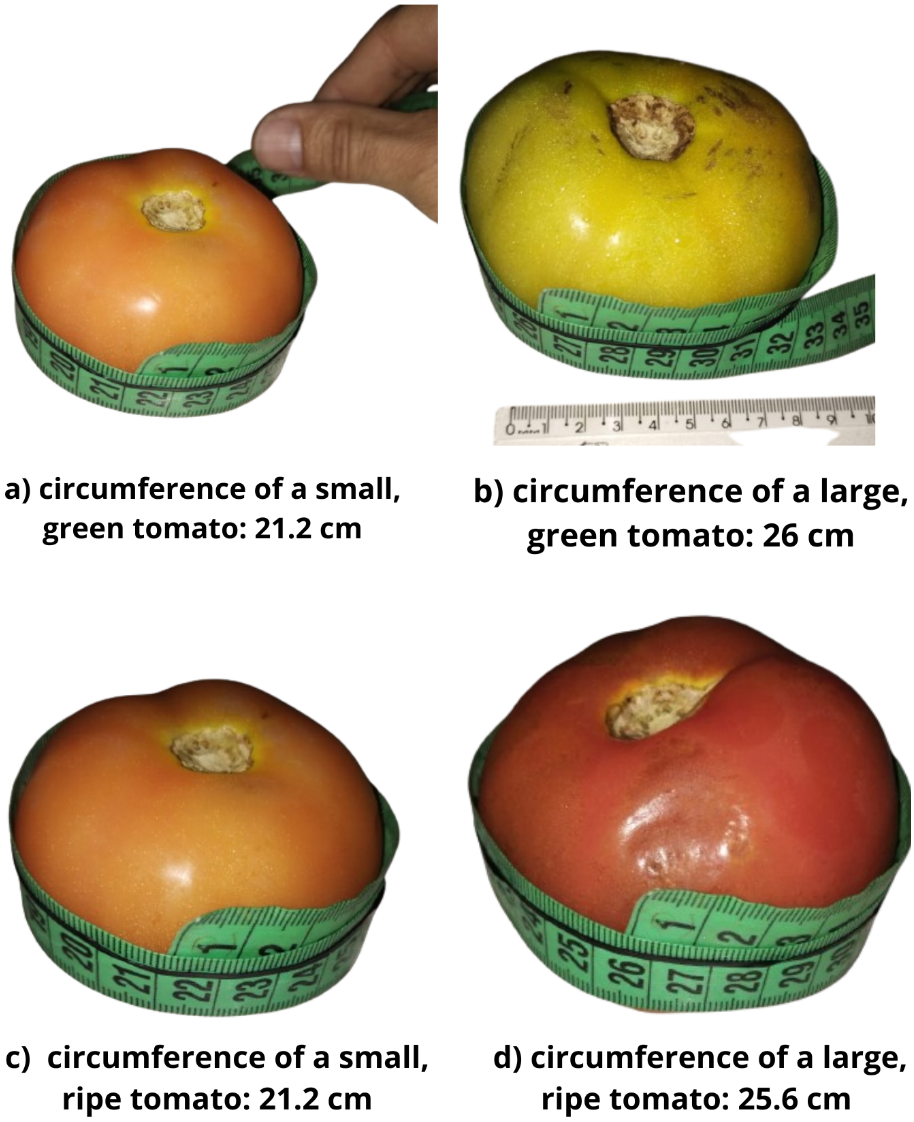

Figure 6. Classification according to maturity and size

Fig. 7 shows the algorithm's return as well as its bounding boxes with the prediction confidence. It can be seen that it reached 98% for detection and classification by maturity and 100% for size.

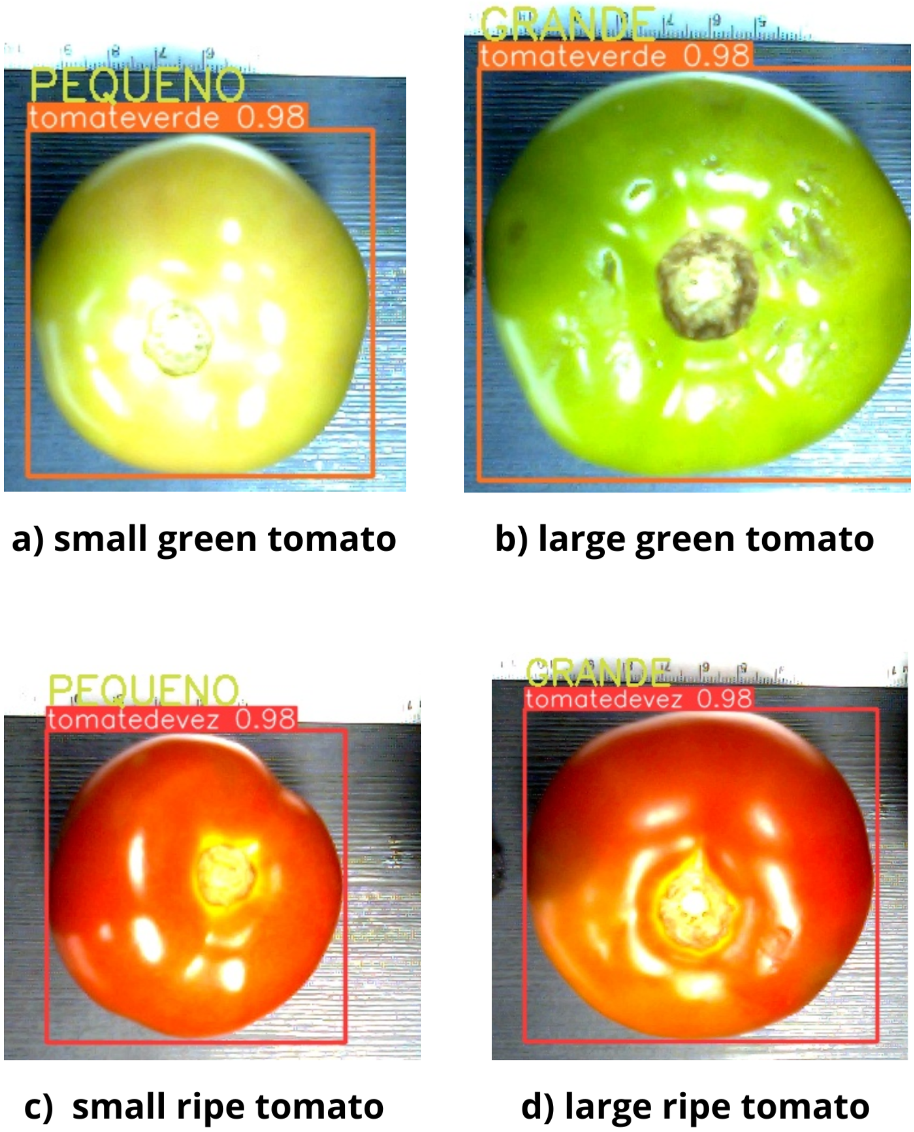

Figure 7. Prediction Confidence

The results shown in Table 1 indicate that the average accuracy of the method is 98% for detection, maturation and size.

Table 1. Tomato Measurement Results

Tomato	Measured Size (cm)	Error (%)	Result
1	21.2	0.0	small and green
2	21.2	0.0	small and mature
3	26.0	0.0	big and green
4	25.6	0.0	big and mature

6 Conclusions

In this work, a computer vision algorithm was presented using artificial intelligence for the detection and classification of tomatoes by ripeness and size.

The results presented indicate that the measurement method used is effective in determining the size and ripeness of tomatoes with excellent accuracy. However, there are some variations that may impact the results, such as ambient light, image quality, among others. However, all of this is being addressed in the continuation of this work. The use of the Roboflow tool to mark the bounding boxes of the images was important for the process of creating the dataset.

As future work, the authors plan to increase the dataset to improve the classification capacity and install the tomato sorter at Distribuidora Pomar and also perform weight estimation.

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