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CITRUS FRUIT: DETECTION, CLASSIFICATION, AND SEGMENTATION VIA COMPUTER VISION TECHNIQUE

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ABSTRACT

It's difficult to develop a fruit identification system that is dependable. Orchards exhibit a variety of complicated elements, including shifting light, change in appearance, and occlusion. Citrus fruit orchids are infamous for their difficulty in agriculture. Manual fruit counting has been attempted, however it is time consuming and labor intensive. The main aim of this paper is to minimize human-computer interactions, accelerate identification, and enhance the usability of the graphical user interface over current manual choices. This configuration utilizes a Raspberry Pi and a camera. This approach preprocesses images, extracts features, and classifies fruit using machine learning. This article covers how to count and distinguish tree fruits using computer vision and machine learning.

Keywords: Fruit Detection, Fruit Classification, Computer Vision, Citrus fruit

INTRODUCTION

Agriculture is experiencing a change from a labor-intensive to a technology-intensive paradigm due to rising labor costs and increasing difficulty finding qualified workers. Recently, robotic technology has demonstrated tremendous promise in terms of increasing agricultural productivity and output efficiency. In controlled working conditions for commercial crops like wheat and soybean, such as evidenced by the development of wheat and soybean harvesting equipment, developing a robotic system for automated fruit collection in orchards is substantially more difficult [1]. Without a visual system to detect the working environment and direct the robotic arm, it is difficult to develop a fruit harvesting robot. Due to the complexities of real-world working conditions, fruit harvesting robots must account for obstacles like densely packed branches and fruits in orchards. Using fruit-picking robots requires that they understand their working environment [2].

It is probable that a variety of environmental circumstances, such as changing lighting conditions, changing item appearances, and object occlusion or overlap, will have a detrimental effect on the robotic vision system's effectiveness. The purpose of computer vision is to reduce the number of potential things and, thus, the user's burden. Autonomous fruit detection and counting are required for improved performance. To identify, categorize, and recognize objects, several machine learning and feature extraction approaches are applied. How to classify and forecast? Training the system necessitates a fair pace of learning. Machine learning and computer vision are used in this study to recognize and detect fruits. Computer vision can now categorize fruits as a result of advancements in image processing, computer vision, and object recognition. Computer vision-based fruit recognition has been employed in agriculture and education in recent years.

LITERATURE REVIEW

Visual sensing in orchards has been widely researched. In the industry, machine learning and deep learning algorithms are the most often employed techniques. Classifiers employ feature descriptors to generate information about objects from sensory data. Historically, machine-learning algorithms have relied on feature descriptors to recognize and segment objects in the real world [3]. Agricultural applications using standard machine learning techniques based on visual sensing data are not prevalent [2,4]. Nguyen et al. [5] encoded the look of red apples in their investigation using both color characteristics and geometric components. Following that, the fruits are segmented and recognized from the input shots using a clustering technique based on Euclidean distance in feature space. Numerous studies have established that identical visual sensing segmentation and detection processing approaches apply to orchard scenarios [6-9]. Wang and Lihong [10] used visual features and the LDA model to segregate plants and fruits in a greenhouse unsupervised.

In computer science, deep-learning algorithms are a relatively recent invention. Compared to conventional machine learning techniques, deep learning algorithms have shown superior detection and segmentation accuracy [11]. One deep-learning algorithm employs a two-stage detector, while another deep-learning algorithm uses a single-stage detector [12]. A well-known example of a two-stage detector is the Region Convolution Neural Network (RCNN), which is composed of fast/faster-RCNNs [13, 14] and mask-RCNNs [15]. By combining RPN with RoI pooling, Faster-RCNN combines RoI search and classification into a single network design. As a result, the model is more efficient in terms of computing. For instance, Mask-RCNN augments the detection network with segmentation, allowing the network to recognize and segment the corresponding region in the pictures for each item. Additionally, a one-stage detector, such as You Only Look Once (YOLO) or Single Shot Detection (SSD), can be employed in place of the two-stage detector [16]. The RCNN more precisely and efficiently guesses the item on each grid of feature maps than a one-stage detector. Case segmentation was recently incorporated into the SPRNet network architecture [17]. That is, it, like the mask-RCNN, can do multitask vision sensing. Deep-learning-based algorithms are being applied in many agricultural applications [18]. Two studies, [19, 20], used faster-RCNN for fruit detection, with both groups reporting accurate detection results. Liu et al. [21] discovered an average accuracy of 0.904 while utilizing faster-RCNN to detect kiwifruit in a study employing RGB and NIR pictures. Yu et al. [22] created a mask-RCNN for strawberry harvesting in an unstructured setting. Tian et al. [23] employed YOLO-v3 to monitor the growth of an apple tree at various phases, obtaining an F1 score of 0.817. Kang and Chen [24] combined semantic segmentation and detection to construct a one-stage detector for recognizing fruit and segmenting branches for robotic harvesting in an apple orchard. Numerous more approaches, such as the Fully Convolutional Network (FCN) [25], are being explored and deployed in agricultural visual sensing applications [26, 27].

COMPUTER VISION

Computer vision emerged in the late 1960s alongside the rise of artificial intelligence. Its primary purpose was to increase the artificial mechanism's intelligence by installing cameras and explaining what they witnessed. Thus, computer vision should be capable of recognizing three-dimensional objects in two-dimensional pictures. Each image conveys information about the current or the past.

Open Computer Vision (OpenCV) was launched by Intel in 1999. It has subsequently been upgraded to focus on real-time computer vision. This library was built in the C and C+ programming languages. It is compatible with both Windows and Linux. This library is compatible with Python, MATLAB, Ruby, and a variety of other programming languages. Image processing (shape and color detection) is straightforward using Numpy and Python. Fruit sorting and grading using computer vision is a trustworthy process. The evolution of computer vision in horticulture is discussed in this article. Computer vision-based counting and sorting would be less expensive, quicker, and more precise.

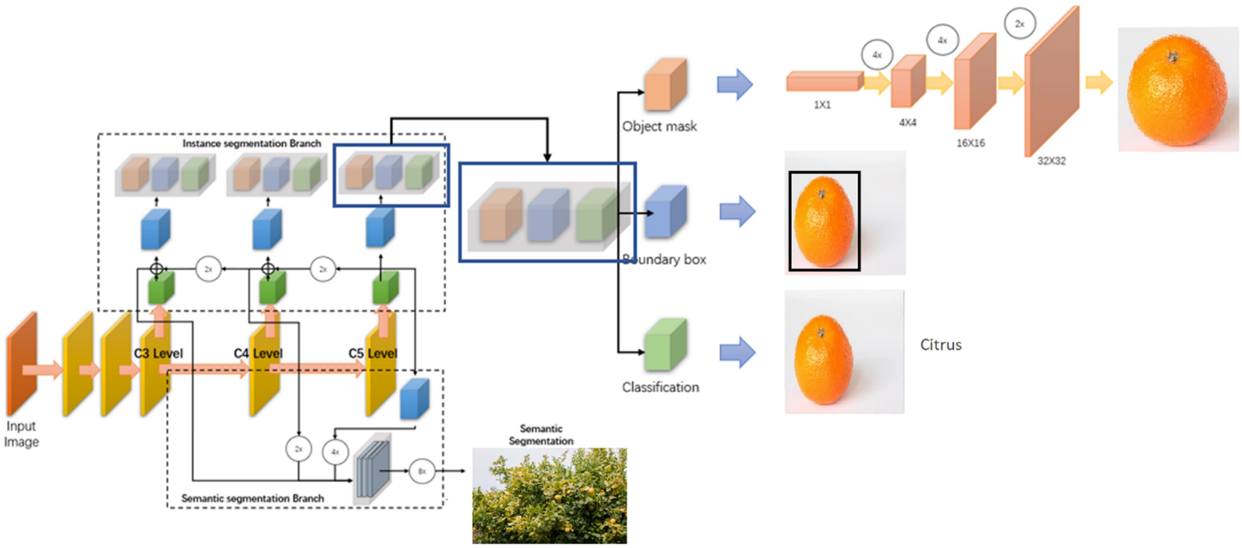

Figure 1: Computer Vision of Fruit Detection classification and Segmentation

METHODOLOGY

Numerous methods for fruit identification have been developed. Fruits are identified and differentiated using color and shape analysis methods. The authors propose a revolutionary fruit recognition and sorting method that integrates color and shape analysis. To categorize and sort fruit images, the proposed approach makes use of nearest neighbor's classification. As a result, our graphical user interface displays the fruit's name and count.

Image Acquisition

It all begins with image acquisition. Following capture, the image may be processed in a variety of ways to achieve today's vision goals. However, even with image enhancement, if the image is not caught properly, the expected results may not be reached.

Background Subtraction

It is extensively employed in a wide variety of vision-based applications. Consider a static camera that records how many people enter or depart a room, or a traffic camera that collects vehicle information. In such situations, it is necessary to first separate the individual or vehicle. To distinguish the dynamic foreground from the static backdrop, all you need is a single image of the background, such as a room devoid of people or a road devoid of vehicles. Therefore, just remove it. You just obtain the foreground. However, because the majority of individuals lack such a picture, we must eliminate the backdrop from the images we do possess. It becomes more difficult when the automobiles cast shadows. Due of the shifting nature of shadows, simple subtraction classifies them as focus [28].

RGB to HSV Conversion

RGB or HSV color vision processing. Red, green, and blue are the primary colors. The HSV color system is used to define colors. It is frequently preferred to the RGB color model [29]. The HSV model generates visible colors. HSV specifies hue in terms of color, vibrancy, and brightness, whereas RGB defines color in terms of fundamental colors. The color vision of the basketball robot is based on the HSV color space.

1. A hue is a color. Above is a slanted circle. The hue value is between 0 and 255, with 0 representing red.
2. The degree to which a color is saturated. Its value ranges from 0 to 255. Vibrancy diminishes the saturation of colors and gives them a fading appearance.
3. The value of a color indicates its brightness. 255 is wonderful in this scenario.
4. The HSV value for White is 0-255, 0-255, 255. Black has HSV values of 0-255, 0-255, and 0. In black and white, this is referred to as "value." When a value hits its extremes, its color and saturation become irrelevant.

Thresholding

Picture thresholding is a simple and effective technique for separating the foreground and background of an image. By converting grayscale photographs to binary pictures, this image analysis technique isolates objects. Image thresholding works best with photographs that include a lot of contrast. These include histogram and thresholding on many levels.

Detection of color

To open a photograph, save it using OpenCV as a three-dimensional array or matrix that contains the pixel location and RGB color channel information. Each RGB pixel has eight bits of red, green, and blue information. When they are merged, they give us the color of the pixel. The most intense value is an 8-bit value with an RGB value of (255, 255, 255). The RGB value of white is (255,255,255). If all RGB components were disabled, the screen would display a black pixel (0, 0, 0).

Detection of Shapes

Shape is critical for purchasing, identifying, and assessing fruit. If the numbers are substantially comparable inside a certain form class or category but notably different between them, the shape description succeeds. The state of being unique. Any method to form description should be unambiguous or exhaustive. For example, compactness and elongation are size-dependent shape measures, but region-based (pixel spatial information) and boundary-based shape metrics are size-independent.

Elimination of Noise and Threshold

Noise is a problem with digital photographs. Noise is introduced during the image capturing process, resulting in pixel values that do not accurately reflect the scene's intensities. Noise may be introduced into a picture in a variety of ways, depending on how it is generated. If the image is taken digitally, noise may be introduced by the data gathering technique (such as a CCD detector). Linear filtering is capable of removing some noise. This can be accomplished through the use of averaging or Gaussian filters. Averaging filters can be used to reduce grain noise from images. Due to the fact that each pixel is adjusted to its neighbors' average, grain-induced local variations are minimized. Noise reduction is a two-step procedure that begins with disguising the noise and ends with its elimination. The noise masking algorithm classifies via thresholding and segmentation. To extract noise from the masked region, an amplitude threshold is utilized. The masked area is then segmented and filtered using a segmentation size.

Segmentation

Photographs are split in a variety of ways. Segmenting a picture enhances its representation and analytical capabilities. Natural materials or surfaces are employed in these zones. This technique locates objects and lines in photographs (e.g., lines or curves). A technique for endowing each pixel in a picture with its own unique visual personality. Optimal segmentation frequently makes use of local image information such as color to construct histograms, edges, borders, and texture. It is predicated on the assumption that the image's homogeneous hues correspond to distinct clusters and hence to meaningful objects. It assigns pixels to a certain color class. Due to the fact that segmentation results vary according to color space, no one color space is appropriate for all images. As a result, researchers sought to determine the optimal color space for segmenting color images. In this study, color photographs are partitioned using color spaces, and the optimum color space for each image kind is determined [30].

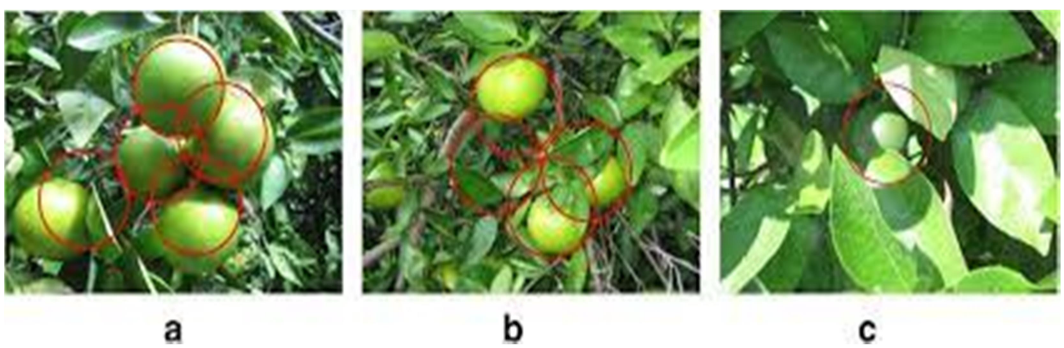

Figure 2: a) Detection of Shapes, b) Detection of Color c) Background Subtraction

Sorting by Color and Shape

Manually sorting large quantities of fruit takes time. Sorting is not an exact technique due to the fact that skill differs across individuals. Manual sorting is more error-prone and expensive. These agricultural industries must operate more precisely, consistently, and efficiently to fulfill the demands of the worldwide fruit market. As a result, post-harvest automation for sorting and grading is necessary. To grade and sort, both external and internal quality factors are employed. Color is an aspect of externality. Additionally, techniques for identifying skin abnormalities and color are used. The critical need is for non-destructive grading and sorting [29, 31].

Fruits Counting

The fruit counting technique proposed here recognizes monolithic fruit portions, often known as blobs or objects. Following erosion, we employ 8-connectivity to deduce the binary picture's connected components. Each connection is a representation of an orange. The number of connected components in a tree image indicates the number of fruits. This is the graphical user interface for recognizing the fruits of photographs. This division makes it easier to count the number of unique fruits. The next section illustrates the phases of the algorithm on the test picture [32].

RESULTS

Additionally, photos from publicly available online fruit databases, movies, and digital camera photographs may be utilized as input. Photographed throughout the day under cloudy conditions. The images are pre-processed in Python using Open CV tools to determine if the fruit is ripe or unripe using the Kmeans clustering algorithm. The following are the findings:

a) b)

Figure 3: a) Image Segmentation of Close up detection of Fruit b) Image Segmentation of Counting of Fruit

CONCLUSION

This study studies the identification, counting, and sorting of on-tree fruit. This method might be used to automate fruit counting, hence reducing costs associated with human counting and losses associated with inaccurate estimations. This area has significant future potential and, when developed, will result in a very successful agricultural system. On-tree fruit detection employs image augmentation, feature extraction, and classification, followed by color-space segmentation, RGB color identification, and the HSI approach for detection. Fruit counting has received very little attention. Fruits have been counted using morphological techniques. The following are some potential features that may be beneficial to researchers in the same field:

- Multiple strategies may be used to separate overlapping fruits and form identification.
- Fruit grading is another important area of research, with the goal of determining the quality of fruits and setting their market price.
- A smartphone application that utilizes automatic on-tree fruit detection and counting may be developed to deliver a timely and accurate response.

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