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Leveraging machine learning and image processing computer vision systems to detect defects and improve tomato quality: A review

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ABSTRACT

Computer vision is a technology that integrates image processing and machine learning to evaluate product quality objectively and non-destructively. This study establishes a computer vision system for defect detection and quality assessment of tomatoes by image processing methods and machine learning algorithms, including support vector machine and artificial neural network. The procedure commences with the collection of tomato photos, succeeded by pre-processing, segmentation, and the extraction of features related to colour, texture, and shape. Machine learning models are subsequently utilised to categorise tomatoes according to their ripeness levels and the existence of faults. The results indicate that the system can accurately detect flaws and evaluate the quality of tomatoes, demonstrating superior efficiency compared to manual techniques. This method is anticipated to enhance the uniformity of quality standards and diminish waste in the agriculture sector.

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1. INTRODUCTION

Fruits such as tomatoes undergo various stages of ripeness that change rapidly. The principal factor influencing tomato quality and maturity is hue [1]. Classifying tomatoes based on their colour or ripeness enhances their quality value. Fruit is generally sorted manually by human labour. As technology advances, microcontroller-based automation devices are progressively utilised in the sorting process. These concerns led to the development of a system that employs colour images of tomatoes to distinguish between ripe and unripe specimens [2].

Computer vision systems acquire, process, and analyse images to objectively and securely assess the visual quality of food and agricultural products. picture analysis approaches encompass picture capture, preprocessing, and content interpretation to quantify and categorise relevant elements or sections of the image [3]. The quality variables evaluated and the classification approaches utilised in the development of computer-based systems for assessing fruit quality differ from each other. Non-destructive procedures are quality metrics assessed without inflicting damage to the fruit. This technique often assesses tomato ripeness by spectroscopy and hyperspectral imaging. In contrast to conventional cameras that capture images solely in the three major colours of red, green, and blue (RGB), hyperspectral imaging employs specialised cameras capable of capturing images across hundreds of unique light wavelengths. Utilising high-resolution photographs is costly and necessitates considerable processing time [4].

The objective of this research is to investigate the utilisation of computer vision systems for fault detection and quality assessment of tomatoes via machine learning and image processing methodologies. This technology is expected to expedite and improve the precision of tomato selection and quality inspection, hence enhancing product quality and reducing waste in the agricultural industry.

2. THEORITICAL REVIEW

2.1. Computer Vision

A computer vision system is a discipline that investigates or formulates the theoretical foundations and techniques for the automatic extraction and analysis of valuable information regarding an observed object. The grading and sorting of fruit quality via computer systems employs digital image processing technologies and artificial intelligence (AI) to autonomously evaluate fruit quality.The computer vision system and the fruit sorting system constitute the two subsystems of the computer-mediated fruit quality grading and sorting system.

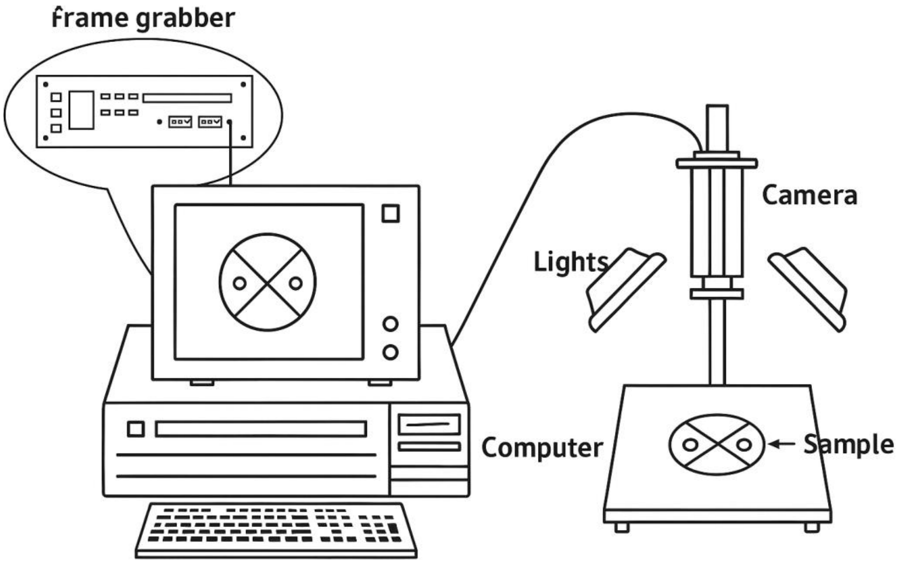

Figure 1. A computer vision system's components.

The computer vision system comprises two components: the image processing module and the pattern recognition module. Fruits can undergo visual inspection, quality assessment, and sorting via the computer vision system. The system comprises an electromechanical fruit handling device capable of positioning fruit on a conveyor belt and transporting it to the sorting bin through a computer vision system. An image of the underlying fruit is recorded by the computer vision system and transmitted to an image processor. A pattern recogniser perceives the image subsequent to its processing. Upon assessing the quality of the fruit and categorising it based on established criteria, the recogniser directs the sorter to allocate the fruit to the appropriate bin [5].

3. RESEARCH METHODS

3.1. Algorithms for Feature Extraction and Image Processing

This algorithm seeks to establish a tomato rating system predicated on flaws and colour intensity, as illustrated in Figure 2. Initially, a segmentation method is employed on the acquired image to eliminate the. Secondly, the identification of petal and stem markings, as well as defect segmentation, is conducted. Third, extract attributes related to colour, texture, and geometry from all photos. Fourth, classifiers were created utilising support vector machine (SVM), artificial neural network (ANN), and random forest for a comparative examination of the suggested tomato rating technique [6]. The development of a pattern recognition algorithm for sorting tomatoes based on size, shape, colour, and surface defects through digital image analysis is regarded as the most suitable algorithm for tomato grading. It achieves high accuracy and is recommended as the most efficient sorting algorithm, yielding minimal error [7].

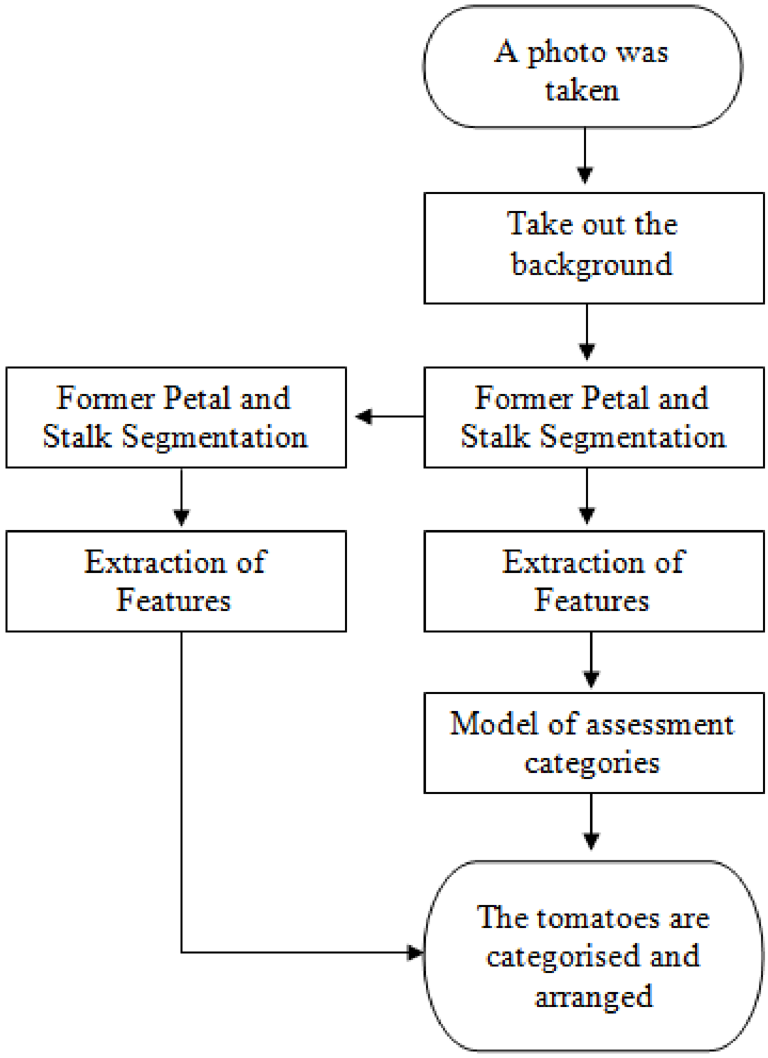

Figure 2. Image processing algorithms.

2.2. Image Processing

The image processing module was acquired by the subsequent steps:

a. Image pre-processing: Tomato images captured by the camera contain noise and specular reflections. These impacts diminish image quality and fail to deliver accurate information for future processing. A median filter is utilised on the image to mitigate reflections and noise [8]. This phase commences with the acquisition of the tomato image entered into the system, followed by the conversion of the RGB image into its respective R, G, and B channels. Subsequently, it identifies the channel most appropriate for use in the segmentation phase [9].
b. Segmentation: this phase is executed to isolate the tomato region from the image. The image is initially transformed to binary with the Otsu method. This results in the image being segmented into two regions: backdrop and tomato. If the faults in the tomato match the intensity of the background, the tomato region appears to contain holes. To delineate the entire tomato region, the gaps are populated with pixels assigned a value of 1 [8].
c. Feature Extraction and Selection: To ascertain the defectiveness of a tomato, the statistical features pertaining to colour and colour texture for each of the red (R), green (G), and blue (B) components are retrieved as follows:

- Colour Statistical Features: Statistical features are derived from each colour channel, resulting in 9 distinct colour statistical characteristics [8]. Colour identification is intricate, as factors like brightness and clarity influence the perception of fundamental colours (red, blue, yellow) and their combinations (orange, green, purple, etc.) [10].
- Colour Texture Features: Four texture features are derived from each colour channel utilising the gray-level co-occurrence matrix (GLCM) of the image. The GLCM elements denote the values of the probability density function Pij, which quantifies the frequency of pixel pairings with intensity values (i,j) that are separated by a distance d in a specified direction. The ripeness of a tomato is closely associated with its colour. Consequently, colour attributes are derived from tomato photos to categorise them as either ripe or unripe [8].

2.3. Defect Identification

This study employs the benefits of LAB colour space for the detection of tomato defects. Five hundred tomato photos exhibiting varying levels of defects are randomly picked and transformed from RGB to LAB colour space. The intensity values of L, A, and B spaces are retrieved from each pixel in each image and classified as faulty or healthy pixels. The extracted colour space features are represented by LM, a matrix of dimensions Is by 4, corresponding to 500 photos and 3 colour spaces. The pixels are labelled as 1 for healthy and -1 for defective, where Is denotes the total number of pixels across all images (1280 * 720 * 500). The efficacy of the fault detection model is assessed based on the subsequent equation:

$$\frac{num(Xse==Pe)}{num(Xse)} k \in [1, (0.3 * I_S)] \tag{1}$$

where, (Xse == Pe) indicates that the quantity of Pe is equivalent to the magnitude of Xse.

2.4. Feature Extraction of Colour Attribute

The LAB colour space is utilised for its capacity to minimise variance caused by sensor sensitivity. The LAB colour space is a three-dimensional colour system characterised by absolute and variable colours represented along the L, A, and B axes. L denotes brightness, with the darkest black at L = 0 and the brightest white at L = 100, whereas A and B signify colour channels. Three colour features were retrieved from each space: mean, standard deviation, and range. Consequently, nine colour features are recovered from each image. These colour attributes rely solely on individual pixel values and do not consider the relative relationships of grey values. Figure 3 illustrates the transformation of the original RGB image into the LAB colour space.

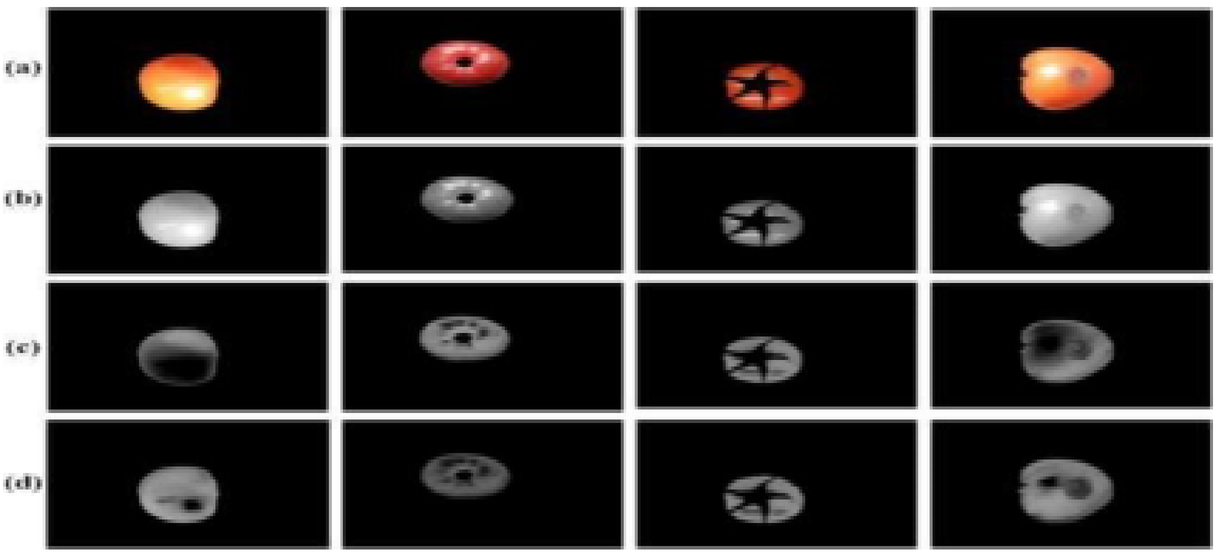

Figure 3. Transformation of colour photographs to LAB colour space: (a) RGB image, (b) LAB L-space, (c) room-A LAB, and (d) room-B LAB [6].

4. RESULTS AND DISCUSSIONS

The results reveal that the created defect model can identify defective pixels with an accuracy of 0.989 on the validation dataset. Figure 3 depicts the identification of faulty pixel portions using the methods applied.

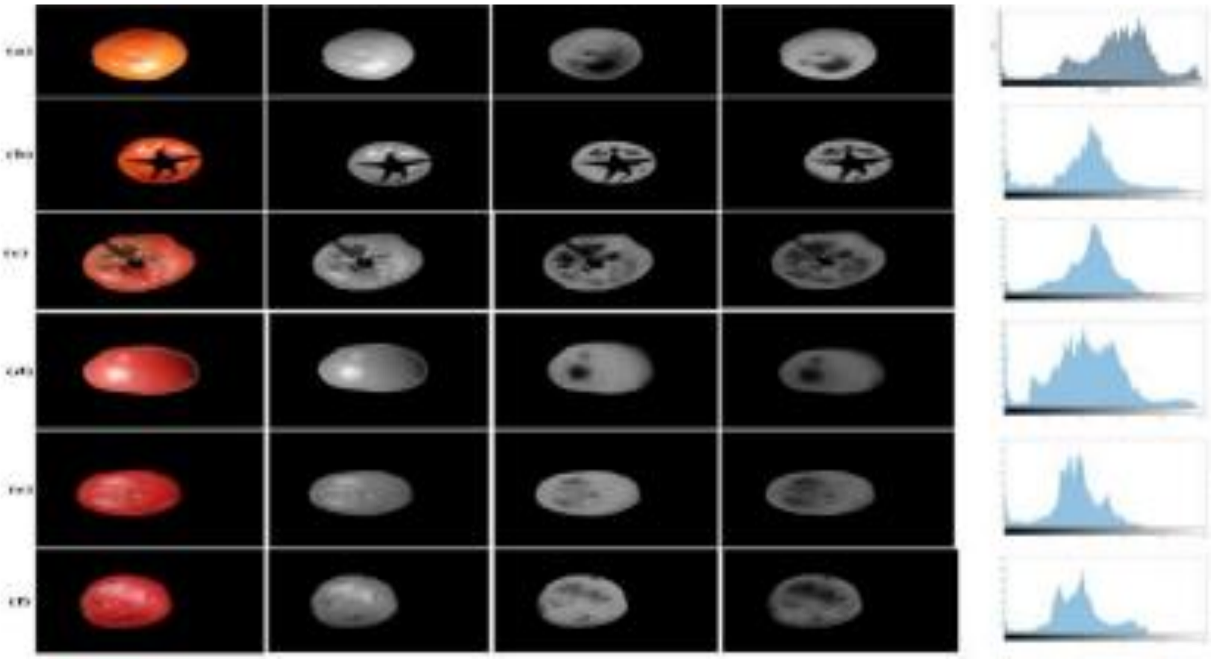

Figure 3. Tomato characteristics utilising LAB colour space and their corresponding histograms: (a) healthy pink; (b) healthy with petals; (c) rejected; (d) healthy dark red; (e) second-grade scarlet; and (f) rejected [6].

5. CONCLUSION

The utilisation of computer vision systems for defect detection and quality assessment of tomatoes using image processing and machine learning has been demonstrated to enhance accuracy and efficiency in the inspection process. Physical techniques include surface texture analysis, light intensity-based image processing, and colour change detection can efficiently identify flaws in tomatoes. Furthermore, computer learning technologies like SVM (Support Vector computer) and ANN (Artificial Neural Network) facilitate the classification of tomato quality based on recognised visual attributes. These procedures yield faster and more uniform checks than manual methods and may also adapt to varying illumination conditions. This substantially enhances production efficiency and minimises waste in the agricultural sector.

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