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A Novel Method for Identifying Volume Parameters and Monitoring Apple Disease Using Image Processing

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ABSTRACT

The identification and diagnosis of plant diseases have long been considered. This research presents a system for diagnosing the volume and type of apple diseases and the spoilage percentage of rotten apples. To estimate the volume of apples, the method of immersion in water to change the volume of the container was used, ensuring more accurate volume estimation. For disease detection and spoilage analysis, a chamber with constant lighting conditions and a halogen lamp was used. Four images were taken with a camera for better analysis. The volume of apples was calculated through two approximations of the cylinder and incomplete cone. The average error rate in this system was 5%. Also, in the present research, a novel method for feature selection was identified using a combination of the weight feature and the calculated volume of hollow apples. To calculate the percentage of failure of each apple, first, the type of failure was identified. Then, the ratio of loss of each apple relative to the whole apple was calculated and compared with the number obtained from the desired region method, which was accurate. In this study, three major diseases of apples were studied, and an algorithm was written to distinguish these three types of infections from healthy apples. The results showed that the proposed method had the necessary efficiency to calculate the volume and percentage of failure and diagnose the type of apple diseases. In addition, the system's accuracy compared to previous studies increased by up to 95%.

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Introduction

Monitoring health and detecting diseases is critical in fruits and trees for sustainable agriculture. Agriculture has been the base for all people. Nowadays, the growth of plants, crops, and fruits is usually affected by diseases. The disease is a significant problem in an agricultural field [1]. Fruit diseases can cause significant losses in yield and quality appeared in harvesting. Common apple diseases are apple scab, rot, and scar [2]. Apple scabs are grey or brown corky spots. Apple rot infections produce slightly sunken, circular brown or black spots covered by a red halo. Apple blotch is a fungal disease that appears as dark, irregular, or lobed edges [3]. Determining the volume of agricultural products has a significant role in packaging issues and related parameters such as dimensions, boxes, fruit placement, and packaging coefficient [4].

A recognition system is a grand challenge for computer vision to achieve near-human levels of recognition. In the agricultural sciences, images are essential data and information. Photography has been the only method used to reproduce and report such data in recent years. It is not easy to process or quantify the photographic data mathematically. The various diseases on fruits determine yield quality, quantity, and stability. The disorders in fruits reduce the product and deteriorate the variety and its withdrawal from cultivation [5].

Much research has been carried out to automate the visual inspection of the fruits by machine vision concerning size and colour. However, the detection of defects in the fruits using images is still problematic due to the natural skin colour variability in different fruits, high defect types, and the presence of stem and calyx. Therefore, to identify the control factors to consider in the following year to overcome similar losses, it is important to analyse that which is observed.

Three apple diseases including crushed apples, rotten apples, and spotted apples were examined, and segmentation was performed using K-means clustering. Then, the properties of the global colour histogram (GCH), colour coherence vector (CCV), local binary pattern (CLBP) [6] were extracted. In a previous study, the methods used to diagnose apple fruit disease were investigated. This classification examined the damaged and diseased parts of the apple and used image processing to classify diseases. Similarly, a summary of different colour techniques, different texture techniques, different classification techniques, and different classifications was expressed with their destructive benefits and signs [7].

A simple model for determining the volume of bell pepper by selecting the volume of butter was introduced as the basis of calculations to estimate the volume using regular geometric shapes. According to the butter volume, these researchers first obtained the diameter and length of the product, then added a constant coefficient of 1/1 as the product shape coefficient to their computational formula and estimated the volume of pepper. In another study, the volume of watermelon was calculated using a rectangular element and compared with the water transfer method [8]. In a similar survey by neural network and image processing, diseases of fruits from planting to harvest were shown. The accuracy of the diagnoses was 90% [9].

In one system, the growth rate of apples in the garden was calculated automatically using image processing [4]. Intelligent classification of dates was carried out using image processing and machine learning. Dates were divided into specific categories based on their freshness, texture, and colour [10]. A previous study used a thermal camera and neural network (ANN) to detect apple damage. In addition, using image processing and neural network, the volume of the apple and its indentations have been calculated [11].

Johnson et al. present GUI technology that helps medical professionals understand patient bruising [12]. Jawale et al. concluded that average cross-correlation offers a better result for the classification of apple diseases [13]. M. Dhakate et al. used k-means clustering and the GLCM algorithm for classification and detection [3]. Defect segmentation was carried out in two stages in research by Shivaram [13]. Utilising these two-stage systems, computational efficiency can be improved. Likewise, the mentioned method provides a brief overview of the various segmentation methods [13]. Feature extraction was carried out using colour invariant, colour histogram and local binary pattern algorithm by Kartikeyan & Shrivastava. The neural network classifier was used for classification [14]. Jhuria et al. picked three defects of grapes and two apples. From these features, 90% accuracy was achieved [9].

The classical approach for detecting and identifying fruit diseases is based on naked-eye observation by experts. In some developing countries, consulting experts are expensive and time-consuming due to the distant locations of their availability. Automatic detection of fruit diseases is essential to detect diseases as early as they appear on the growing fruits [5]. Detection of disease and health monitoring of plants are significant challenges for sustainable agriculture. Hence, there is a need to automatically detect plant disease using image processing techniques at an early stage with greater accuracy [15]. Sharma et al. present a novel hybrid model, combining Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, for multi-class classification of apple diseases [16]. The model was trained and evaluated on a dataset of images of apple leaves exhibiting different severity degrees of black rot disease. The results of the experiments showed that the hybrid model outperformed traditional single-model approaches, achieving an accuracy of 99.02% in the initial severity degree classification of the disease. This demonstrates the potential of combining CNNs and LSTMs to achieve high accuracy in complex image classification tasks, particularly in the field of plant disease diagnosis. The proposed model provides a valuable tool for apple farmers, researchers, and extension workers in the early detection and management of apple diseases [16].

Apple Scab and Apple Rust are major apple leaf diseases that significantly reduce yield. Acharya et al. used an enhanced Capsule Neural Network (CapsNet) to classify apple diseases, achieving a 91.37% accuracy on the Kaggle Plant Pathology 2020 - FGVC7 dataset, surpassing previous methods by 3.67%. The proposed method is efficient and outperforms existing techniques [17].

LALNet, a high-speed machine vision algorithm for detecting apple leaf diseases, was introduced [18]. An efficient stacking module (EALD) and a Squeeze-and-Excitation (SE) module were utilized to enhance feature attention. A detection accuracy of 96.07% was achieved, with a model size of 6.61 MB and a detection speed of 6.68 ms per image.

A recent study proposed a novel approach for detecting apple leaf diseases using image processing and machine learning techniques [19]. This method involved segmenting the disease-affected areas, enhancing images, selecting features, and other essential steps. To enhance visibility and pinpoint disease locations in the images, the researchers utilized a combination of 3D-Box filter, de-correlation, 3D-Gaussian, and 3D-median filters [20].

The quality of an apple fruit largely depends on the techniques used for processing it. Post-harvest inspection of apple fruit is needed for grading and sorting them. When it is carried out manually, it is difficult to provide in-line quality for process control. Machine vision helps in this inspection task. Identification of defects is performed using colour and other morphological information about an apple using a machine-vision system. Product inspection in the food industry is a common need that involves quality verification, defect removal, process control, and sorting, or grading the food products.

According to the mentioned methods for calculating the volume and detecting failure and calculating the percentage of apple loss, the element method with appropriate accuracy for estimating the volume was observed. According to the characteristics of the failure, the failure of apples was diagnosed. A Raspberry Pi board was used as the processor and its camera as the system camera to build an efficient, cost-effective and portable system.

Methodology

This research utilized digital image processing to prepare images for calculating the volume and damage of apples. Initially, pre-processing operations were conducted, followed by feature extraction to assess spoilage. Two methods were employed: one for apples that appeared healthy, using volume and weight to determine density and hollowness, and another to measure damage as a percentage. This study also examined three common apple diseases (scab, blotch, and rot) and distinguished them from healthy apples. All processes were executed using the OpenCV library and a Raspberry Pi 3 with its camera, which proved to be an effective and affordable alternative to a Canon 550D camera for these calculations. All processing commands were written in Qt 5.4.2 software and the Open CV library, a library for image processing was written in C++. For taking the images, the apples were placed in a space with black walls, and two lamps were placed around the apples for better images. 120 images of 30 healthy apples were taken at all angles, and many images of spoiled apples were taken under the same conditions.

Image processing algorithm

As shown in Figure 1, the operation of detection and pre-processing of healthy apples involved the images stored in the Raspberry memory being recalled, then corrupted using the colour recognition technique and bubble technique in Open CV software. The presence or absence of apples was determined by appearance. Initially, using the bubble actuators and commands, the image was checked for bubbles which are the minor defects of apples. Otherwise, it passed through the following filter, which used the colour recognition technique; and if no damage was detected in this part, it entered the volume estimation stage as a healthy apple.

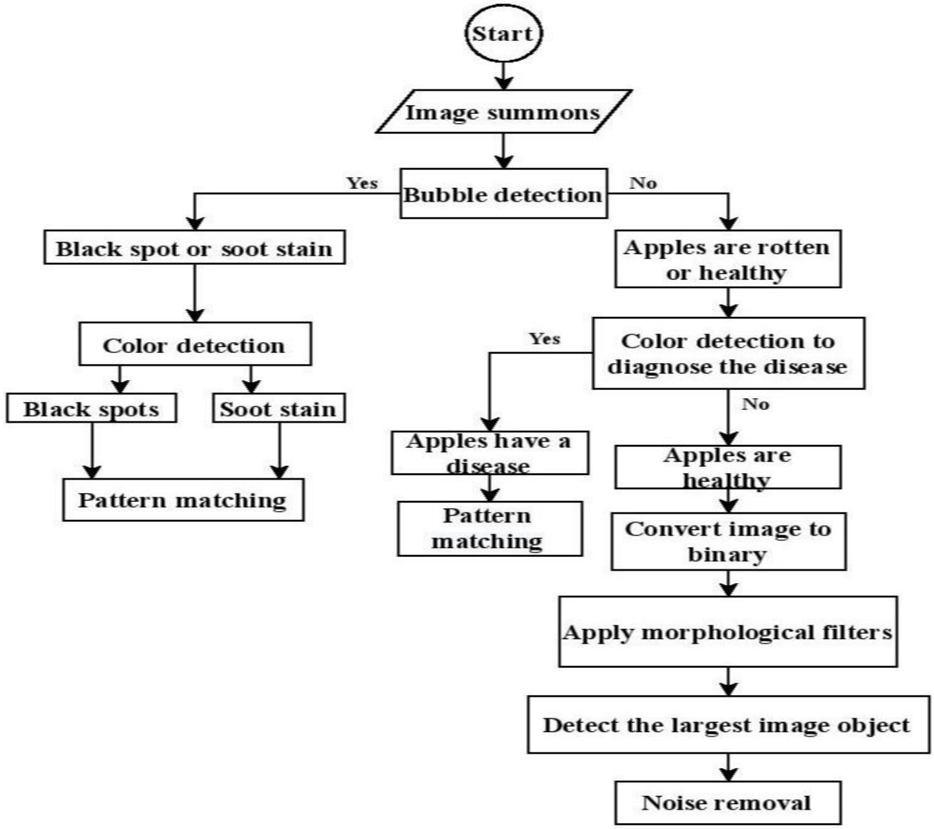


Figure 1. Operation of detection and pre-processing of healthy apples.

According to the studies performed on the three types of damages mentioned, differences were extracted in terms of the color of the damage and the dimensions and shape of the spots. For example, apples with a black spot or soot spot damage had minor damage with different colours and shapes, and rotten apples had more damage than the other two types.

Pre-processing on healthy apples

According to Figure 1, after determining whether the apple had an apparent malfunction or not, the program continued. If the apple was visually healthy, the above program continued. First, the image was changed from color to grey and then to binary, using morphology filters. The binary image has discontinuities in some parts due to differences in light. Furthermore, it is better to eliminate these discontinuities before separating the apple from other objects in the image. After executing the commands, a complete image of the apple was created without any noise. Figure. 2 shows examples of pre-processing.

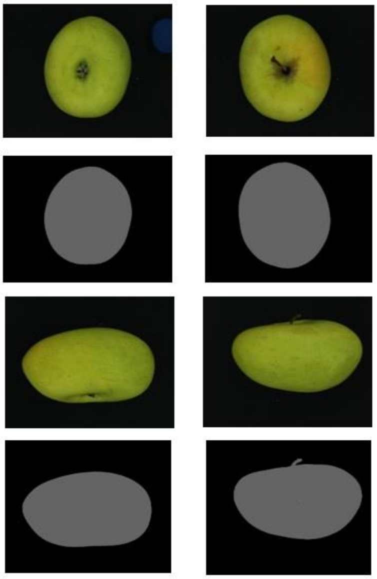


Figure 2. Samples of pre-processing on healthy apples.

Pre-processing on spoiled apples

If the received image had a visual defect, the processing of the damaged apples would start. First, the damaged part of the apple was determined by color or bubble detection. In this stage, the pattern-matching technique was used to ensure the diagnosis of the type of disease to improve the system's accuracy. In this method, an image of each type of disease with the desired characteristics is taken and adapted to the diagnosed area. If the images matched, the type of disease is correctly diagnosed. Then, according to the defined features, the type of failure is determined, and finally, the image of the failure part is extracted without noise. Figure 3. shows some of these processes.

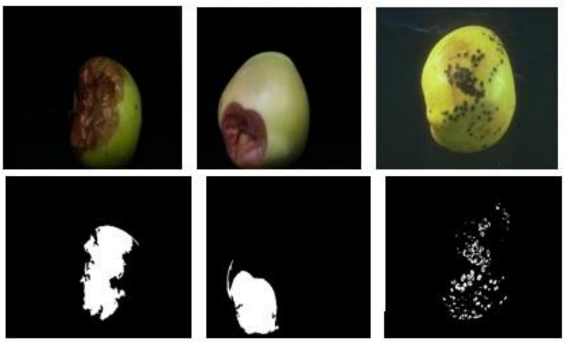


Figure 3. The output of processes on unhealthy apples.

Volume calculation methods

Different algorithms have been proposed to calculate volume through images. Each of these has different characteristics and also depends on various variables. Methods for estimating the volume of apples are presented below:

Approximate method (approximate cylinder): In this method, the volume of the apple is obtained by dividing the apple into two cylinders. The top of the apple, which is similar to a circle, is calculated and multiplied by half the length of the apple. The bottom area of the apple is also calculated and multiplied by half the length of the apple. In this way, the volume of two cylinders with different values is calculated and finally added, and the total volume of the apple is calculated.

Disk method (rectangular alignment): If a rectangle of length d/2 and height h revolves around a vertical axis, the resulting shape will be a disk whose thickness is (h) and its diameter (d). Figure 4 shows the volume obtained from the rectangular period according to Equation 1 [3].

$$V = \frac{\pi \times h \times d^2}{4} \tag{1}$$

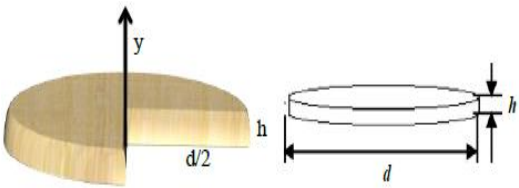


Figure 4. Disk resulting from rectangle rotation.

Incomplete cone method (trapezoidal model): If a trapezoidal trapezoid with height (h), small base (r_1), and large base (r_2) is given around the vertical axis of that period, the resulting shape will be an incomplete cone with height (h) and radius of the bases (r_1, r_2). Figure 5 shows the volume obtained from the trapezoidal period using Equation 2.

$$V_i = \frac{\pi h}{3}(r_1^2 + r_2^2 \times r_2) \tag{2}$$

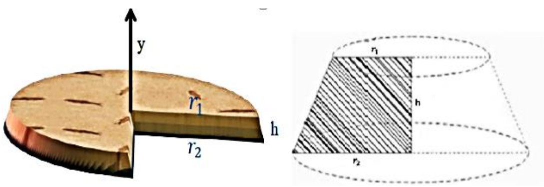


Figure 5. Disk resulting from Trapezius rotation.

It is possible to observe from the pictures that the incomplete cone method is similar to the disc method, but it has greater accuracy because in this elementation, the smaller volumes ignored by the rectangular elementation were compensated (Figure. 6).

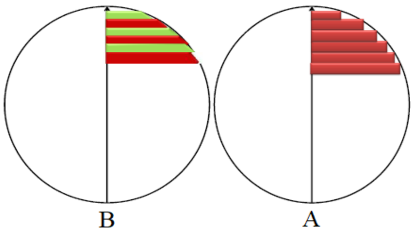


Figure 6. Rectangle separation and cone separation.

Extracted features

After the object in the image was obtained without noise, the necessary properties were extracted from the image. The characteristics required for each apple such as their detection steps were different. It is required to count the broken pixels and the total pixels of apples to calculate the percentage of apparent damage to apples. According to the selected method, the information extracted from the image would also be different from calculating the volume. According to the volume formula, in the incomplete cone method, first, the image is divided and then in each step, r_1, r_2 and h are calculated. In the cylindrical approximation method, it is necessary to calculate the radius of the apple from the top and the radius of the apple from the bottom and the length of the apple (Figures 7 and 8).

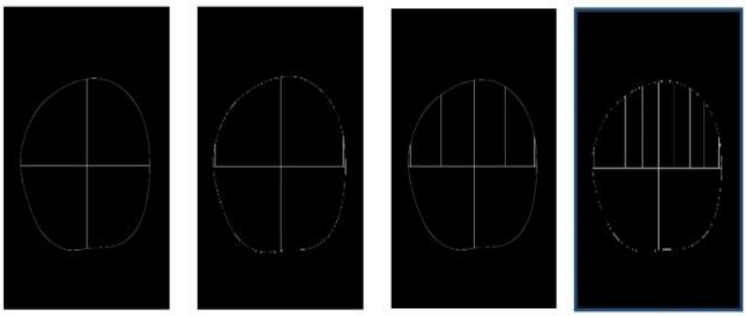


Figure 7. Features extracted in incomplete cone method.

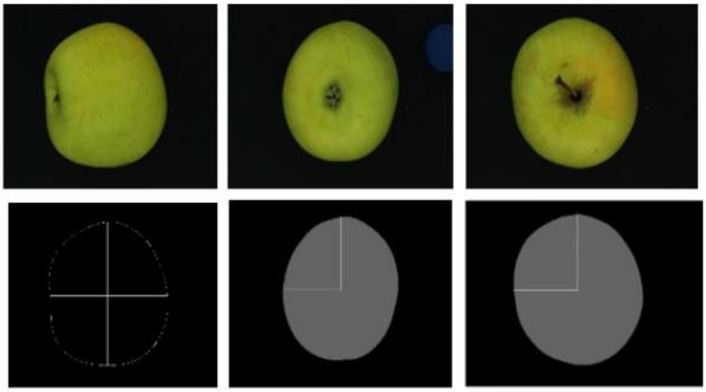


Figure 8. Extracted features for cylinder approximation.

Calculation of apple indentations

The point noteworthy in this section is that apples also have a recess (at the top and bottom), which is adequate when calculating the volume with the water displacement method. To calculate them by image processing in the said methods was not considered. Therefore, the following method was used to calculate this recess. At first, the apples were cut in half, and a picture was taken of them. Then indented parts were extracted using the optimal region technique (Figure 9). Then, their volume was calculated by Equation (4). Finally, the total volume of apples was reduced. The average percentage of error calculated after considering the indentation in the incomplete cone method was reduced to 5%, and the cylindrical approximation method was reduced to 11%. The error percentage was calculated from Equation (3).

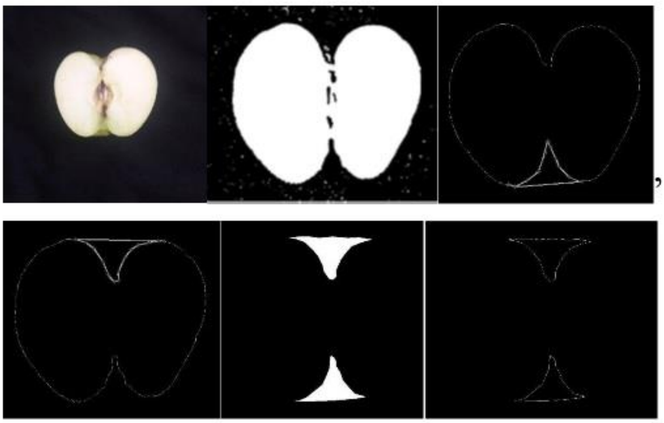


Figure 9. Extraction holes of apple.

$$Error\% = \left|\frac{Actualsize - Calculatedsize}{Actualsize}\right| \times 100 \quad (3)$$

$$V_{final} = V_{total} - V_2 \quad (4)$$

In this equation, V_{final} is the final volume calculated and V_{total} is the volume calculated through an incomplete cone or a cylindrical approximation.

Calibration

The critical point in calibration is that the software shows all the outputs in pixels, so to check the correctness of the obtained numbers, it was necessary to convert these numbers into centimetres. A square with specific dimensions was placed equal to the distance from the apple to the camera. Its dimensions were calculated in pixels, and finally, using a simple linear equation, the value of each pixel in centimetres was calculated. After calculating the error percentage relation, the conversion error percentage was estimated, showing the number 1% error, a low and usable error percentage.

Identification of hollow apples

Many of the apples looked healthy, but they weighed less than other apples. Using the program and calculating the volume and specificity of the weight, their density was calculated. This made it possible to identify empty apples. This algorithm will be efficient for apples of the same genus because apples of the same type have the same density and can therefore be examined. Given the density of each type of apple, this algorithm will be efficient for calculating their hollowness.

Calculating the percentage of apparent damage to apples

First, the damaged part of the apple was detected, and processing operations were performed to obtain a noise-free image. Then the broken pixels and the pixels of the whole apple were counted and calculated using Equation (5). The amount of damage to each apple was obtained by four numbers. Each of these four numbers indicates the extent of damage to a particular part of the apple. These four images were extracted from 4 images that completely cover an apple. As a result, the final number indicated the failure of a whole apple, not just one side of the apple. Finally, a category was written to separate the apples and categorise them. This category could be altered entirely and adjusted.

$$\text{dp}=\frac{\text{Numberofproblematic}}{\text{Totalnumberofpixels}} \quad (5)$$

Results and discussion

As previously mentioned, the volume of the apple was measured by immersion in water and all calculations were undertaken using accurate measurements by digital calipers. Then, after the image processing steps, the dimensions of length and width were calculated in pixel number. Based on the photographs taken from four directions, the volume of the apples was estimated according to their weight and the obtained density using trapezoidal and cylindrical methods. Next, apple disease was diagnosed with the aid of image processing and the percentage of failures was obtained. Table 1 shows some of the data obtained from the laboratory and image processing. Finally, pixel dimensions in the program were converted to millimeters. The average error of 2% in this transformation shows the accuracy of the performance. The results were then compared with previous research in this field.

Table 1. Some of the data obtained from the laboratory and image processing.

The dimensions of the apple using image processing in terms of millimeters		The dimensions of the apple using image processing in terms of pixels		The dimensions of the apple using a digital caliper in millimeters	
Length	Width	Length	Width	Length	Width
80.43	77.12	671	622	80.58	79.02
79.93	73.39	636	584	78.22	73
80.81	71.76	643	571	79.53	70.92
78.42	80.68	624	642	77.58	79.78

Because there was no significant difference between the length and width calculated using image processing and the length and width measured by calipers, it was possible to equate the numbers obtained from image processing with the actual values calculated by caliper. The percentage of average error in this method was calculated as 2%. For example, for the length and width in Tables 2 and 3, the actual and calculated averages were compared, and considering that the differences were minute in the experiments, the lengths and widths resulting from image processing could be used instead of the calculated lengths and widths used with digital calipers.

Table 2. Comparison of the exact and calculated average length.

	Number	Average
Exact length (mm)	30	77.36
Image processing length (mm)	30	76.97
Length difference (mm)	0	0.38

Table 3. Comparison of the exact and calculated average width.

	Number	Average
Exact width (mm)	30	72.94
Image processing width (mm)	30	73.35
width difference (mm)	0	0.41

Table 4 shows the number of volumes calculated from the cylinder approximation and their actual values. In Table 5, some volumes are calculated through incomplete cones, and their actual values are shown.

According to the diagram in Figure 10, which compares the proposed method with other methods using the volumes calculated from the two incomplete cone and cylinder approximation methods, the incomplete cone method is closer to the actual value. As a result, it has a lower error rate.

Table 4. Some output number of calculation of volume using cylinder approximation.

Actual volume (cm^3)	Calculated volume (cm^3)	Volume of apple indentations	Lower cylindrical volume (cm^3)	Upper cylindrical volume (cm^3)	Error (%)
263	295.11	8.89	149	155	12.16
249	275.08	6.92	135	147	10.44
200	221.77	5.23	110	115	10.5
231	258.84	16.7	125	141	12.12

Table 5. Some output number of calculation of volume using incomplete cones.

Actual volume (cm^3)	Calculated volume (cm^3)	Volume of apple indentations	Error (%)
283	274.11	8.89	4.22
270	263.08	6.92	5.6
216	210.77	5.23	5.38
263	244.84	16.7	5.99

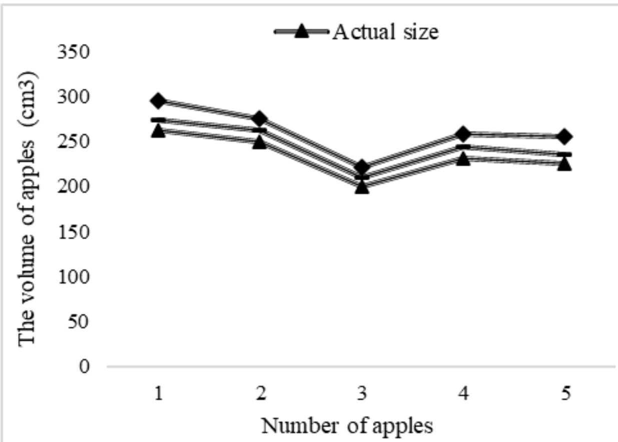
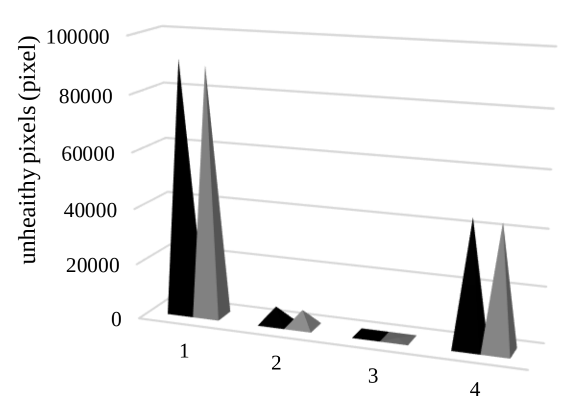


Figure 10. Some calculated volumes and real volumes.

According to the diagram in Figure 11, the number of calculated pixels differs from the number of selected and exact pixels. This difference occurs for various reasons; in some samples, after processing the apple tail, the end of the apple was identified as defective, which causes a difference in number. Occasionally there is a correlation between the broken pixels close to each other, eventually causing the number to differ from the actual value. As mentioned earlier, sometimes the faults were detected with differences in size and colour, so it is impossible to detect the same colour range and some pixels are not considered in the calculations. Nevertheless, there is little difference between the actual and calculated graphs and so they can be used.



	1	2	3	4
Actual decay	91035	6011	324	45110
Calculated decay	89424	5953	332	44467

Figure 11. Some unhealthy pixels and their real number.

The volume calculated by image processing in apples without indentations is more accurate than in apples with indentations because these indentations are taken into account during the calculation through the displacement of water, but in image processing, only indentations are taken into account. The top and bottom of the apple are considered and because these indentations are not reduced from the original volume number, they cause errors.

Also, the number of errors in some apples that had larger dimensions than others is higher and they are less accurate than normal-sized apples. One of the main reasons for this lower accuracy is that larger-sized apples have a greater distance when they are placed under the camera. They will have less contact with the camera due to their larger dimensions, and this issue causes the calibration of length and width and other measured lines to not be done correctly; when the apple is closer to the camera, it includes more pixels, leading to errors.

Table 6. Comparing the calculated failure percentage and the actual failure percentage.

Photo name	Total number of pixels	The number of damaged pixels after image processing	Calculated failure percentage	Actual number of bad pixels	Actual failure percentage (%)
1	213918	89424	0.41	91035	42.68
2	301133	5953	1.9	6011	1.99
3	233553	332	0.14	324	0.13
4	265497	33367	16.74	45110	16.99
Total			59.78		61.76

According to Table 6, the average number of actual and calculated pixels of the percentage of apple failures have very little difference, and for this reason, it is possible to use the presented algorithm to calculate the percentage of failure.

Conclusion

In this study, three practical elements in quality including apple volume, type of apple failure, and percentage of apple failure (yellow apple), were investigated using different parameters and methods. This is because the cylindrical approximation method was unsuitable due to the strong dependence on one parameter and the need for different images, and finally, the low error percentage. The incomplete cone method was selected as a highly suitable method for performing volume calculations of apples due to its high accuracy and non-dependence on only one parameter. Furthermore, to evaluate the hollow apples, which were suitable in terms of volume, a density number was obtained from the combination of the volume calculated in the program and the weight of the apples, and the number of hollow apples was determined in proportion to the volume and weight. To diagnose the type of failure of apples, first, only the element of failure dimensions was used, the output of which was not appropriate and misdiagnosed a large number of diseases. Then, diseases were diagnosed by colour recognition technique. In this method, there was less error than the previous method. However, because the disease colour ranges sometimes overlapped, it still had a significant error rate. As a result, the bubble selection technique was used which had the capability of examining many features of each disease including dimensions, colour, degree of resemblance to the circle, and colour level, and significantly increased the accuracy of the system. Finally, using the combination of colour recognition and bubble separation techniques, the best possible result was achieved. The separation of three diseases and the diagnosis of healthy apples was the output of this algorithm. The failure percentage of apples was selected accurately using the desired region technique, and the exact failure number was obtained. It had good accuracy in performing the failure percentage. According to a selection table regarding failure percentage, apples were graded in quality.

The speed and practicality of the proposed methods were extremely simple compared to other studies that carry the heavy computational burden of image processing or a complex multi-camera system. The definition of an accurate and efficient algorithm that can distinguish healthy apples from spoiled ones and distinguish three types of spoilage from each other, calculate the volume and percentage of spoilage, detect the number of empty apples, and finally classify based on the amount of spoilage is remarkable. Additionally, this system can be used in grading and packaging apples for export due to its ability to calculate the dimensions of the apple and its apparent volume. Implementing the system on a small and inexpensive Raspberry Pi 3 board that is also portable will significantly increase the building of this system. In the present research, a portable and inexpensive system was designed with the mentioned functions based on image processing.

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References

[1] Ramya, R., Kumar, P., Sivanandam, K., & Babykala, M. (2020, January 22-24). *Detection and Classification of Fruit Diseases Using Image Processing & Cloud Computing* [Conference session]. 2020 International Conference on Computer Communication and Informatics, Coimbatore, India. https://doi.org/10.1109/ICCCI48352.2020.9104139

[2] Hartman, J. (2010). *Apple fruit diseases appearing at harvest*. University of Kentucky.

[3] Dubey, S. R., Dixit, P., Singh, N., & Gupta, J. P. (2013). Infected fruit part detection using K-means clustering segmentation technique. *International Journal of Artificial Intelligence and Interactive Multimedia*, *2*(2), 65-72. https://doi.org/10.9781/ijimai.2013.229

[4] Genno, H., & Kobayashi, K. (2019). Apple growth evaluated automatically with high-definition field monitoring images. *Computers and Electronics in Agriculture*, *164*, 104895. https://doi.org/10.1016/j.compag.2019.104895

[5] Dubey, S. R., & Jalal, A. S. (2012, November 23-25). *Detection and Classification of Apple Fruit Diseases Using Complete Local Binary Patterns* [Conference session]. Third International Conference on Computer and Communication Technology, Allahabad, India. https://doi.org/10.1109/ICCCT.2012.76

[6] Ngouajio, M., Kirk, W., & Goldy, R. (2003). A simple model for rapid and nondestructive estimation of bell pepper fruit volume. *HortScience*, *38*(4), 509-511. https://doi.org/10.21273/HORTSCI.38.4.509

[7] Dubey, S. R., & Jalal, A. S. (2012). Adapted approach for fruit disease identification using images. *International Journal of computer vision and image processing*, *2*(3), 44-58. https://doi.org/10.4018/ijcvip.2012070104

[8] Koc, A. B. (2007). Determination of watermelon volume using ellipsoid approximation and image processing. *Postharvest Biology and Technology*, *45*(3), 366-371. https://doi.org/10.1016/j.postharvbio.2007.03.010

[9] Jhuria, M., Kumar, A., & Borse, R. (2013, December 9-11). *Image processing for smart farming: Detection of disease and fruit grading* [Conference session]. 2013 Institute of Electrical and Electronics Engineers Second International Conference on Image Information Processing, Shimla, India. https://doi.org/10.1109/ICIIP.2013.6707647

[10] Nasiri, A., Taheri-Garavand, A., & Zhang, Y-D. (2019). Image-based deep learning automated sorting of date fruit. *Postharvest Biology and Technology*, *153*, 133-141. https://doi.org/10.1016/j.postharvbio.2019.04.003

[11] Jawale, D., & Deshmukh, M. (2017, April 6-8). *Real time automatic bruise detection in (Apple) fruits using thermal camera* [Conference session]. 2017 International Conference on Communication and Signal Processing, Chennai, India. https://doi.org/10.1109/ICCSP.2017.8286542

[12] Johnson, B., & Fazel-Rezai, R. (2016, May 19-21). *Contusion (bruise) segmentation & diagnosis: A graphical user interphase approach* [Conference session]. 2016 Institute of Electrical and Electronics Engineers International Conference on Electro Information Technology Grand Forks, North Dakota, USA. https://doi.org/10.1109/EIT.2016.7535332

[13] Samajpati, B. J., & Degadwala, S. D. (2016, April 6-8). *Hybrid approach for apple fruit diseases detection and classification using random forest classifier* [Conference session]. 2016 International Conference on Communication and Signal Processing, Melmaruvathur, India. https://doi.org/10.1109/ICCSP.2016.7754302

[14] Kartikeyan, P., & Shrivastava, G. (2021). Review on emerging trends in detection of plant diseases using image processing with machine learning. *International Journal of Computer Applications*, *975*(8887), 39-48. https://doi.org/10.5120/ijca2021920990

[15] Henila, M., & Chithra, P. (2020). Segmentation using fuzzy cluster-based thresholding method for apple fruit sorting. *Institution of Engineering and Technology Image Processing*, *14*(16), 4178-4187. https://doi.org/10.1049/iet-ipr.2020.0705

[16] Sharma, R., Kukreja, V., Sood, P., & Bhattacharjee, A. (2023, May 18-20). *Classifying the Severity of Apple Black Rot Disease with Deep Learning: A Dual CNN and LSTM Approach* [Conference session]. 3rd International Conference on Advances in Computing, Communication, Embedded and Secure Systems, Kalady, Ernakulam, India. https://doi.org/10.1109/ACCESS57397.2023.10199549

[17] S, S., S, S., Acharya, V., & Ravi, V. (2024). Apple foliar leaf disease detection through improved capsule neural network architecture. *Multimedia Tools and Applications*, *83*(16), 48585-48605. https://doi.org/10.1007/s11042-023-17463-7

[18] Ang, G., Han, R., Yuepeng, S., Longlong, R., Yue, Z., & Xiang, H. (2023). Construction and verification of machine vision algorithm model based on apple leaf disease

images. *Frontiers in Plant Science*, *14*, 1246065. https://doi.org/10.3389/fpls.2023.1246065

[19] Mohapatra, S. K., Sarangi, P. K., Sarangi, P. K., Sahu, P., & Sahoo, B. K. (2022). Text classification using NLP based machine learning approach. *American Institute of Physics Conference Proceedings*, *2463*(1), 020006. https://doi.org/10.1063/5.0080301

[20] Hasan, S., Jahan, S., & Islam, M. I. (2022). Disease detection of apple leaf with combination of color segmentation and modified DWT. *Journal of King Saud University - Computer and Information Sciences*, *34*(9), 7212-7224. https://doi.org/10.1016/j.jksuci.2022.07.004