J. of Soil Sciences and Agricultural Engineering, Mansoura Univ., Vol 12 (5):317 - 325, 2021

Journal of Soil Sciences and Agricultural Engineering

Journal homepage: www.jssae.mans.edu.eg
Available online at: www.jssae.journals.ekb.eg

Development of a Real-Time Machine Vision Prototype to Detect External Defects in Some Agricultural Products

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ABSTRACT

The automation of agricultural operations not only improves the quality and productivity of agricultural products but also helps in enhancing the national income. Although human sorting and grading are the traditional methods usually used in the postharvest chains, these methods are inconsistent, time-consuming, subjective, expensive and easily influenced by the environment and human fatigue. Therefore, the main aim of this study was to develop a real-time machine vision prototype for sorting and detecting the quality parameters of different agricultural products. The constructed prototype was used for image acquisition and processing. By using the data of color values of all concerned defects, a simple thresholding (min-max method) was developed and employed using Python software. Three types of defects (greening, black spots and scares) in orange, two defects in potato tubers (greening and black spots) and two defects (broken pods and black spots) in peanut were detected using the developed system based on color differences. The system was also used to detect singular peanut pods (half pods containing one internal seed instead of two or three seeds) based on dimensional features. The results obtained in this study revealed that the developed prototype was used successfully to detect the external defects of tested products with reasonable accuracy.The accuracy of defect detection during real-time operations of orange, potato and peanuts were 96.97, 98.50 and 99.09%, respectively. The developed detection method was also very efficient in the classification of the peanut pods into full-size pods and singular pods and with overall classification accuracy of 100%.

Keywords: Machine vision; real-time; sorting; grading; orange, potato, peanut pods.

INTRODUCTION

All postharvest operations, specially sorting and grading, need to be carefully implemented in order to obtain the maximum quality of products with a minimum level of losses. The sorting and grading systems of agricultural products used by manufacturers, farmers and distributors in Egypt are usually performed by conventional quality assessment and hand grading. Manual sorting and grading are time consuming, slow and inconsistent with the national demands and international markets. To fulfill the more prominent desires of the customers, it is important to possess an automatic quality assessment tool of food products (Brosnan and Sun, 2004). Besides enhancement in the overall quality, the automatic assessment of quality will increase the production rate accompanied with a decrease in the production costs (Sun and Brosnan, 2003). Detection and recognition of peel defects is the primarily expanded application of image analysis to agricultural product inspection. The appearance of surface defects is a direct indication of the lack of quality of farm products (Cubero *et al*., 2011). Thus, external inspection of fruits and vegetables according to color, size, and shape by vision systems is recently implemented and programmed in the industry sorting machines. By the way, sorting of agricultural products depending on the external defects is as yet a difficult task in a view of the high fluctuation of blemish types and presence of stem/calyx ends (Unay and Gosselin, 2007).

Machine vision system as one of most important automatic quality control systems uses the computer to deal with the digital images for making a decision about the identity of the tested objects. Accordingly, machine vision method has been applied intensively in the inspection process of different sorts of agricultural products because it is a very fast, economic and objective assessment tool (Diaz *et al*., 2004; Leemans and Destain, 2004; Li *et al*., 2015). Agricultural products moving at a high speed below the imaging system in the modern inspection lines in packinghouses should be evaluated precisely before being delivered to the packing units. To achieve real-time processing of the images, the algorithms used in this task should be extremely fast. Thus, several researchers have applied specific hardware and software designs to reduce processing time (Lopez *et al*., 2011). In oranges, peaches and apples, there were some important attempts in the identification and distinguishing long stems in order to averts injury to other fruits, or because their absence might imply a quality loss. Thus, Blasco *et al.* (2003) proposed an automated machine vision system for evaluation of the quality of orange, peaches and apples depending on quality factors such as size, color, stem location and presence of external blemishes. The classification accuracy in blemish recognition was 86% and in size estimation was 93%. In another study, Blasco *et al*. (2009) developed image analysis technique for the on-line inspection of the quality of mandarin segments. By extracting morphological attributes from the items, the system robotically detects pieces of peel and other healthy material and separates full segments from broken ones. The accuracy of classification was 93.2% of sound segments. Xiao-bo *et al.* (2010) presented an in-line system using three CCD cameras to detect apple defects and stem-calyxes ends

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DOI: 10.21608/jssae.2021.178987

that cannot appear in the same image. Great separation among healthy and unhealthy apples was obtained and the classification error decreased from 21.8% for a single camera to 4.2% for the three camera method. ElMasry *et al*. (2012) developed a machine vision technique for the detection of irregular potatoes in real time operation. A stepwise linear discriminate analysis was applied to extract the major feature from potato image in addition to shape detection algorithm based on calculating both size-dependent features and Fourier-dependent shape attributes. The accuracy of this on-line sorting unit of moving potatoes was 96.2%. Sofu *et al*. (2016) proposed a programmed apple sorting and quality assessment framework based on real-time processing using decision tree classifier depending on fruits' morphological properties such as color, size and defects. In this study, apples were classified according to external detects such as scab, stain and rot, color, weight and size qualities with an accuracy rate of 73-96%.

Although various researchers used computer vision system supported with different algorithms for sorting and grading tasks, these efforts are not yet applied in a wide scale in the Egyptian production market. Due to the disadvantages of the traditional inspection methods and the advantages of the automated inspection methods and the increasing concerns of the Egyptian consumers to obtain high quality products, the present work mainly aimed to establish a smart system based on the imaging technology for a real-time sorting and detecting the quality parameters of different agricultural products. The challenge of the developed system was not only to identify the type of the defect but also to locate such defects on the fruits during their passage over the conveyor belt directly without stopping the movement during image acquisition. The developed system could be used in General Organization for Export and Import Control.

MATERIALS AND METHODS

Sample preparation

Freshly harvested samples of the examined agricultural products (orange fruits, potato tubers and peanut pods) were collected from different production farms in Ismailia Governorate, Egypt. The healthy units of these products were carefully selected to be free from any diseases, bruises, blemishes or any other visible damages. Figure 1 shows some representative images of the normal (healthy) and defected samples of orange fruits, potato tubers and peanut pods.

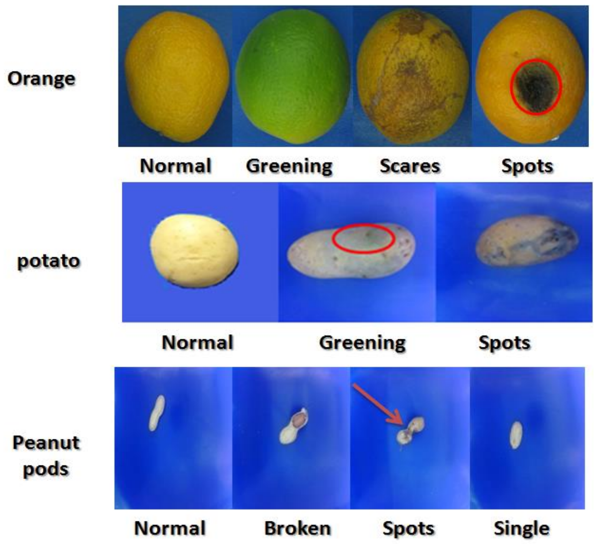

Figure 1. Photographs for the normal (healthy) and defected samples of orange fruits, potato tubers and peanut pods used in this study.

Construction of the Machine Vision Prototype

The machine vision prototype used in this study was designed and fabricated at the Agricultural Engineering Department, Suez Canal University, Ismailia, Egypt. As shown in Figure 2, the developed system composed of a conveyor belt, an inspection chamber, a digital camera, a polarized filter and an image acquisition and processing unit. The inspection chamber was built and mounted over the conveyor belt to transport fruits in the on-line fruit inspection machines. The camera and the lighting system were placed inside this inspection chamber. The image acquisition system consists of a machine vision camera (Elp-Usb500w02m-L21, Ailipuglobal, CHINA) to capture real-time images for any objects located on the conveyor within the camera's field of view. The machine vision camera usually used for capturing images when the conveyor is fully operated (the motor is switched on) for real-time inspection process it was located vertically over the surface of the conveyor belt. The illumination system consisted of nine led tube with a power of 10 W each and four fluorescent tubes (18 W each). Polarized filters and sheets were placed in front of the lamps and the camera lens to reduce the bright spots in the scene by means of cross polarization.

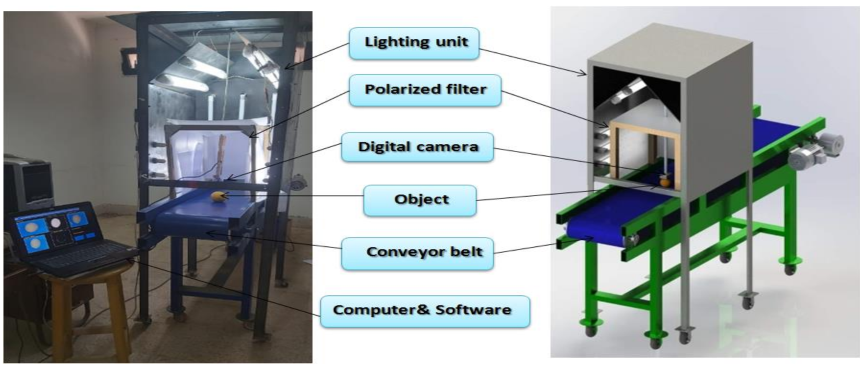

Figure 2. The designed machine vision prototype for quality inspection of agricultural products.

Detection of Product Defects

The on-line applications depend basically on the speed of image processing routines; where the fastest algorithm was implemented to overcome speed limitations. In this study, the min-max method was used to detect external defects in real-time operations when the conveying belt is on the movement mode. The color features of the sound and defected portions were extracted from defects of different severity and then saved in color matrices in the training step to be used for the classification of every single pixel in the image frames during fruits' movement on the conveying belt. The classification based on min-max method is a process by which the defect can be segmented according to its minimum and maximum color values. In this way, a pixel containing the minimum and maximum color values (Red, Green and Blue) were marked. During classification, if the color values of a pixel fall between the two ranges (minimum and maximum) of a certain defect, this pixel is considered defective, otherwise this pixel is considered normal.

Figure 3 shows how different processes were carried out along this sequence of detection. First of all, the illumination unit was turned on and a fruit (either normal or defected) was introduced on the moving conveying belt with the defect facing the camera. The camera instantly acquires live images of the fruit and the program developed in Python starts to process the image frames sequentially and instantaneously. The program developed in Python simultaneously acquires and extracts all fruit features in terms of dimensions and color and then processes this information by min-max method to detect and segment the defect from the normal surface and from the background.

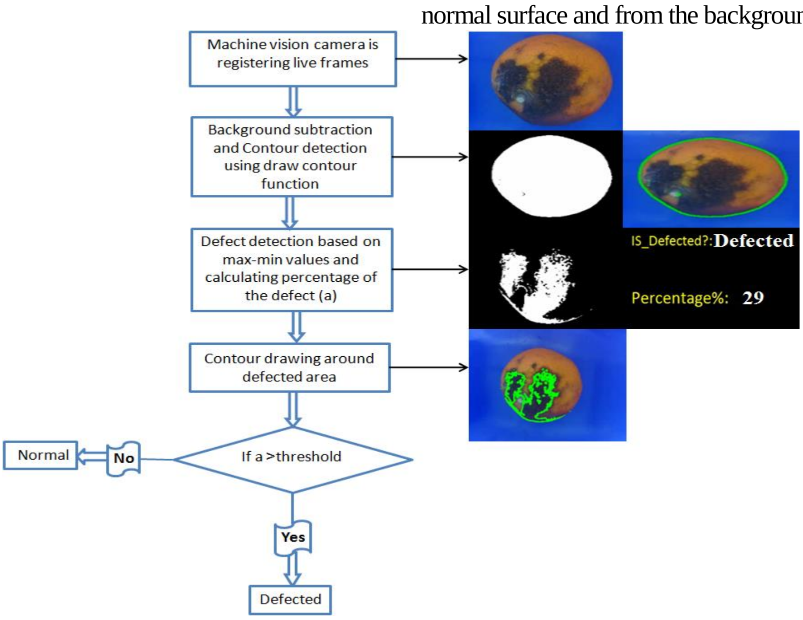

Figure 3. Flowchart of proposed algorithm used in fruit recognition and defect detection in real-time operation.

As clearly shown in Figure 3, when the image is acquired by a machine vision camera, it is automatically segmented to separate the fruit from the background (the blue conveyor). Since this machine vision configuration produced a high contrast image, it was possible to accurately perform segmentation by using a range between upper and lower value in the blue channel. This resulted in a binary image in which the whole fruit looks white (ones) and the background looks dark (zeros). Contours can also be highlighted as a curve joining all the continuous pixels along the boundary with the same color intensity. The contour of either the fruit or the defect is an important step to locate the exact location of the fruit over the conveyor belt and to locate the defects on the fruit. The contours are also important when shape analysis of fruits or detected defects is required. The contour line was drawn by using the ready-to-use function in Python called *cv2.drawContours*.

To detect a defect in the image, the segmentation was performed by using the image intensity ranged between the lower (Min) and the upper (Max) intensity values in every color channel saved in colour matrices as explained earlier in the Min-Max method. In brief, when a pixel lies within the range between the minimum and maximum intensity values it is considered as a defect; otherwise it is considered as a normal pixel. Finally, another python function was used to show the segmented defect appeared in binary image in a colored form. Moreover, the area of the detected defect and its percentage from the whole area of the recognized fruit were also calculated. In some cases the algorithm was able to detect very small defect but the fruit itself cannot be considered defected fruit unless the size of defect is higher than a certain limit (threshold). The calculated size of the defect was then compared with such threshold (based on the standard requirements of the fruit under investigation) and the fruit is considered defected fruit only when the calculated defect size exceeds this threshold. All image processing steps involved in the fruit recognition and defect detection in real-time operations were entirely programmed in python and showed in Figure 3.

Controlling software

In this study, a graphical user interface (GUI) with an icon-direct manipulation-based style was programmed in Python to control the whole real-time process over the conveyor belt, to save the recognition and detection results and to monitor the progress of all operations as shown in Figure 4. The simplicity and usability of the designed interface enables it to be simply used for non-technical operators. The GUI shows (1) the original input image or the frame coming from camera stream, (2) the binary fruit produced from segmentation process with global thresholding, (3) the contour fruit produced by drawing the contour line using the python built-in function *cv2.drawContours*, (4) the colored defect detected in the fruit using the min-max method, (5) the detected defect isolated alone in a separate binary image and (6) a message to inform the user whether a defect is detected or not as well as the percentage of the detected defect in relation to the whole area of the fruit.

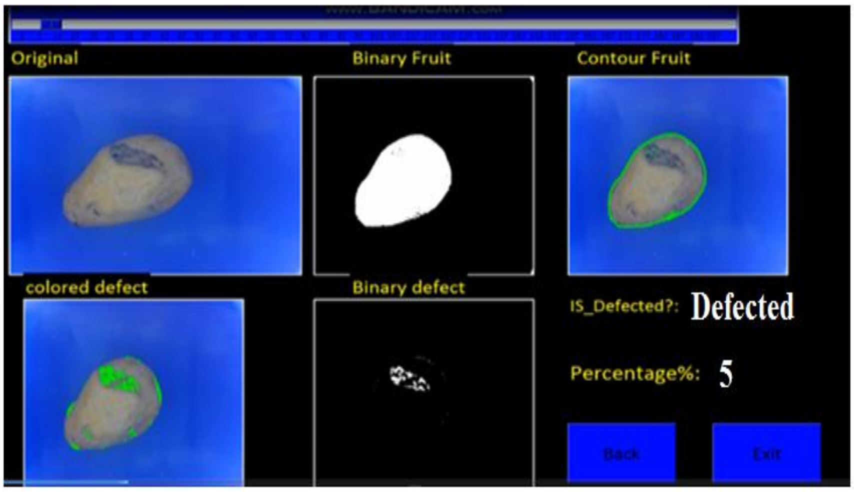

Figure 4. The graphical user interface (GUI) designed for fruit recognition and defect detection for real-time operation.

In fact, the message that shows whether a defect was detected in the fruit or not depends basically on the calculated area of the defect in relation to the whole calculated area of the fruit. In case of surface defects detected in orange fruits, potato tubers and peanut pods, the defect and the whole object (the fruit, tuber or pod) were segmented by the methods explained earlier and total number of pixels for each was estimated. The percentage of the defect in relation to the whole object surface was calculated from the following equation and declared as a message for orange, potato and peanut as shown in Figure 5:

$$\textbf{Percentage of defect} = \frac{\textbf{No. of pixels of the defected area}}{\textbf{No. of pixels of the whole fruit}} \times 100$$

The percentage of defect was determined at the minimum levels of all international specifications to obtain the highest quality (excellent grade); so that the product is free from any external defects even if its area is very small and to ensure the efficiency of the proposed system. For instance, a tuber of potato is considered defected when the percentage of greening and black spots exceeds 3.125% (Noordam *et al*., 2000).

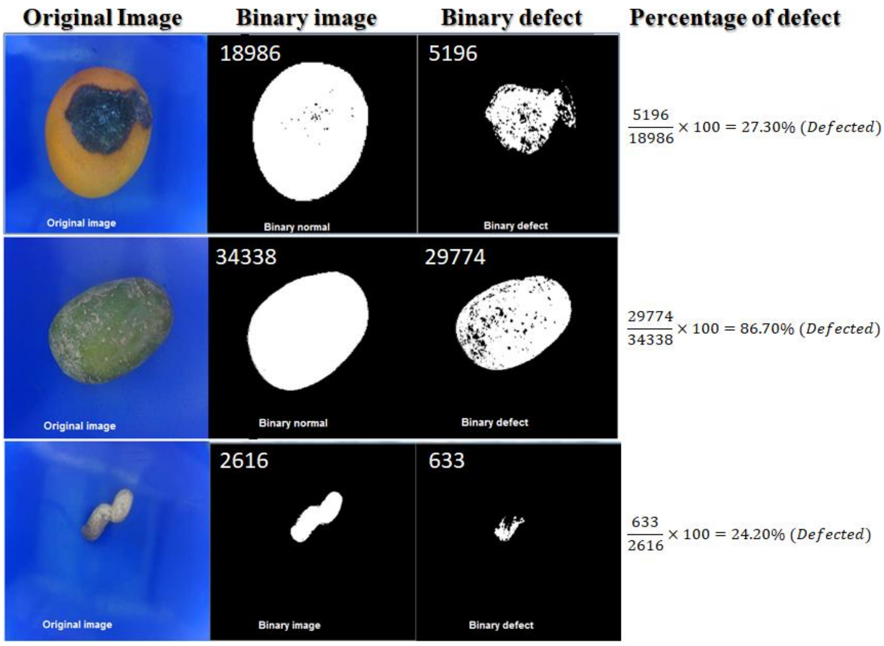

Figure 5. Identification whether a fruit is defected or not based on the calculated percentage of the defect (the area of the defect in relation to the whole calculated area of the fruit).

In case of detecting peanut pods that are evidently free from any surface defects but having a single seed instead of two seeds inside the pod, the detection depends on the whole size of the pods in the image. As the size of peanut pods is a very important attribute for sorting and grading, the bigger size is usually preferable and considered of a high quality. Because the normal pod should contain two or three seeds, the pods that contain only a single seed in the pod are considered defected pods as well. For a certain variety, pods with two seeds are obviously larger in size and length than the singular ones. Thus, when the size and the length of a healthy pod is less than a certain limit, it was considered as a single pod. This limit for discrimination was practically identified after analyzing all images of the tested variety of peanut pods saved in the image database that contains images of pods having two seeds (normal pods). The image was routinely segmented and the total number of pixels belonging to the pod was estimated. When the calculated number of pixels (size) was less than 5000 pixels, the pod was considered as a single defected pod. In addition, when the calculated length was less than 110 pixels, the pod was considered as a single defected pod.

Practically speaking, this process could be efficiently used for size grading not only for peanut pods but also for different agro-food products when the size is the limiting factor in identifying the grade of these products. Therefore, in real-time applications, the same defined limit (5000 pixels for size and 110 pixels for length) was used for detecting single seeds instantly during their movement over the conveyor belt by machine vision camera (Figure 6) and a message was shown on the GUI to declare the pod is a defected single pod for the user who wants to take an action for excluding this pod from the production line. As the real-time operations utilize python in processing and analyzing the image, all high-speed python functions were used in this process. For example, the image was routinely segmented, a boundary box was drawn around the pod to calculate its major and minor dimensions, and number of pixels (area) of the binarized pod in the image. The peanut pods were considered as single when their area was less than a threshold of 5000 pixels and their length was less than a threshold of 110 pixels. The full procedure of detecting single pods in real-time application is shown in Figure 7.

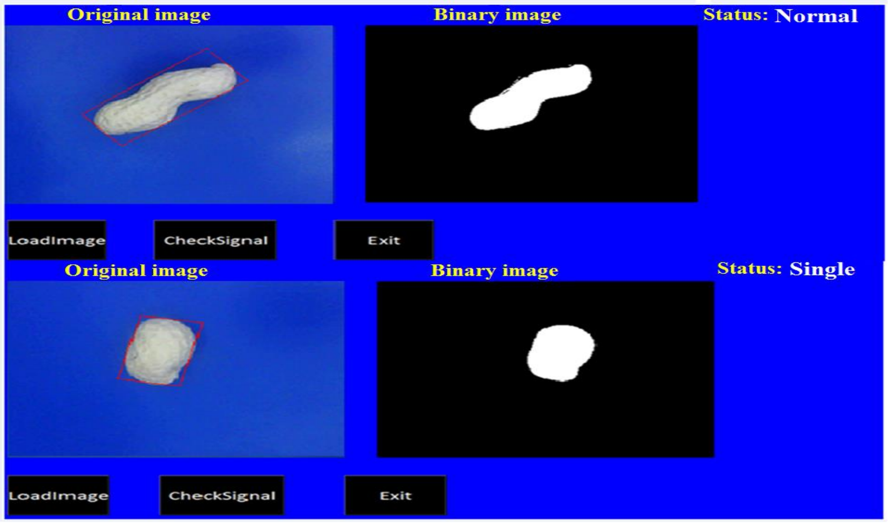

Figure 6. Detection of singular peanut pod based on the calculation of the size and the length of the segmented pod in the binary image.

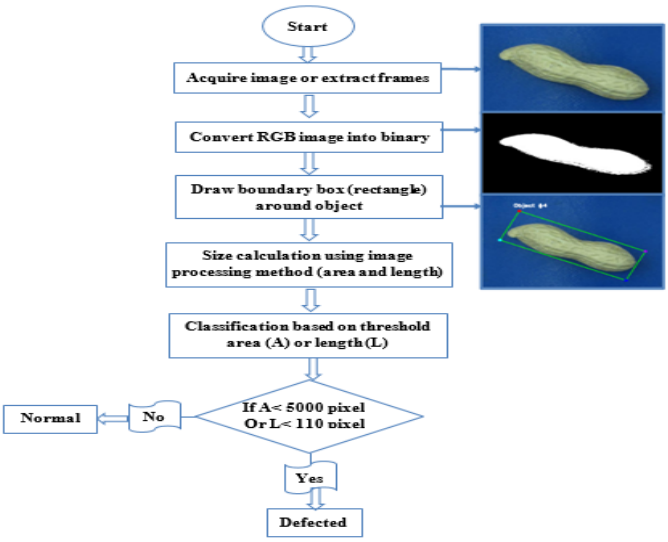

Figure 7. Flowchart of the whole procedure used in detecting single pods using the proposed machine vision in real-time applications.

RESULTS AND DISCUSSION

Color Calibration

Before using the machine vision camera, it was extremely important to ensure that the color values (R, G and B) extracted from the images represent the real color values of the imaged objects. Therefore, the RGB values of 24 standard colors of the color checker card were related with those values recorded in the image under different lightening conditions and camera settings. The measured RGB values under each setup were compared with their real values provided by the card manufacturer and the best setup that gives the highest correlation coefficient was selected to be used in all subsequent experiments of this study. Figure 8 presents the calibration results for the selected setup, in which it is quite clear to figure out that the correlation coefficient was higher than 95% for the three-color channels (red, green and blue). This confirms that the colors that will be measured or extracted by this system are close to the real colors of the tested fruit units.

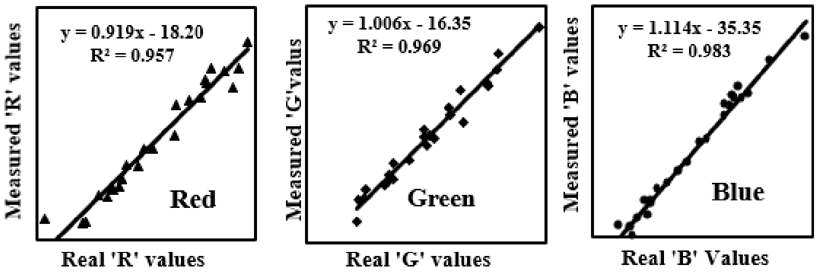

Figure 8. The results of color calibration of the cameras used in the study.

Detection of defects based on color

Different external defects in orange (greening, black spots and scares), potato (greening and black spots) and peanut (broken pod and black spots) were targeted to be detected using the min-max method in real time operation by using the developed machine vision prototype shown in Figure 2. Most external defects were identified through their colors, making the classification of pixels into homogeneous regions an important part of the algorithm. The challenge of the system was not only to identify the type of the defect but also to locate such defects on the fruits during their passage over the conveyor belt directly without stopping the movement during image acquisition.

Figure 9 shows an example of the detection progress of the defects in orange via the designed GUI in real time by using the min-max method. Before running the detection algorithms, the orange samples were initially classified into three groups: normal fruits (healthy fruits without any noticeable defects), fruits with greening symptoms, fruits with black spots and scared fruits. In Figure (9a), the GUI displayed a message to inform the user the fruit is normal as the passing fruit was a health fruit without any symptoms of defects. Thus, the second message that declares the percentage of defect was '0' indicating this particular fruit was free from any defects. In case of passing a fruit with greening symptoms as shown in Figure (9b), the GUI instantly declared that the fruit is defected and the percentage of the present defect was 49%. Similarly, the GUI of the system announced that the fruit was defected with a black spot with a percentage of 26% (Figure 9c) and the fruit was defected with scares with a defect percentage of 16% (Figure 9d).

The designed machine vision prototype was tested also for detecting different defects in potato tubers and peanut pods. In case of passing a potato tuber with greening symptoms, the GUI instantly declared the tuber as defected and the percentage of greening defect was higher than the acceptable level (1%). Similarly, when the tuber contains a black spot defect with a percentage more than 3.25%, the GUI of the system declared the tuber is defected with a black spot. In case of peanut pods, the GUI displayed two messages to the user: one message to show the class of the pod (normal or defected) and another message to show the percentage of the defect in relation to the whole surface of the pod. Any classification image of a pod having any percentage (≥ 0%) of red color was considered as a symptom of broken pods and should be declared as a defected pod. When the pod contains a black spot defect with a percentage greater than 0%, the GUI of the system declared this pod as defected with a black spot.

The performance of the developed system is shown in Table (1), which presents the number of samples tested by the system and the results of detection (whether sound and defected). The overall correct classification (OCC%) of the system was then calculated as the number of fruits detected correctly over the total number of the tested fruits. In general, the developed system was able to detect the defects in tested fruits with accuracy more than 96%. Higher detection accuracy of 99% reported for peanut pods while lower accuracy of 96.97 reported for orange.

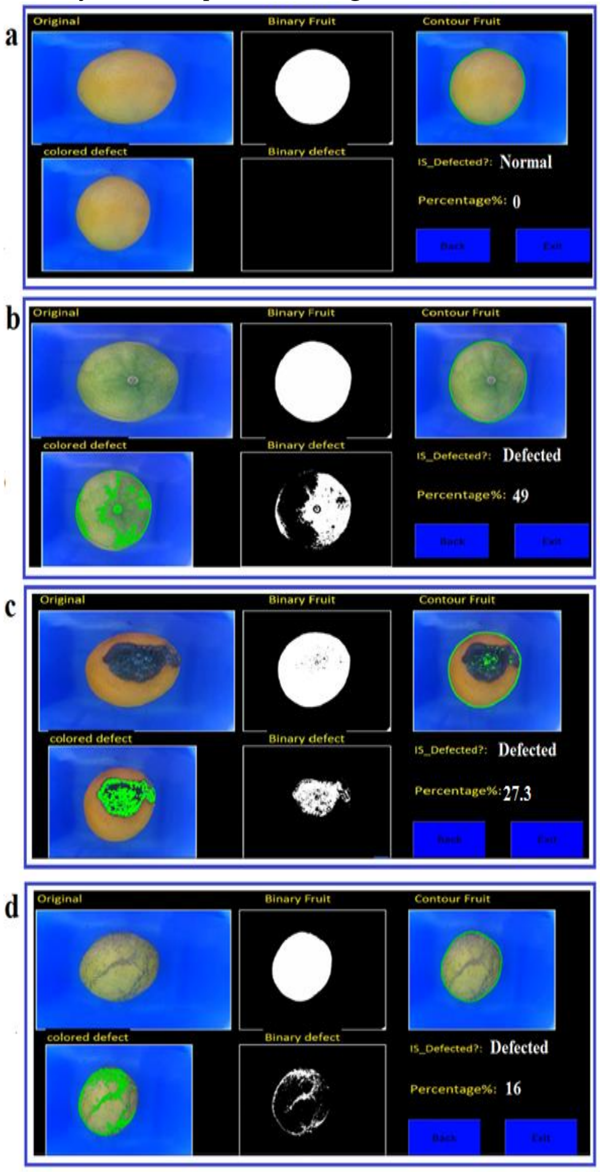

Figure 9. The designed GUI of the machine vision prototype showing how the different defects were detected in orange fruits in real time by using min-max method: (a) normal fruit, (b) greening detection, (c) black spots detection and (d) scares detection.

Table 1. Performance of the developed machine vision prototype in detecting the external defects in orange, potato and peanut based on color.

Product	Run	No. of input samples	Output		Total	No. of correctly detected	OCC (%)
			Normal	Defect			
Orange	Run 1	Normal (60)	60	0	120	120	100
		Greening (60)	0	60			
	Run 2	Normal (60)	60	0	105	105	100
		Black spots (45)	0	45			
	Run 3	Normal (60)	50	10	105	95	90.47
		Scares (45)	0	45			
		Total			330	320	96.97
Potato	Run 1	Normal (30)	29	1	70	69	98.57
		Greening (40)	0	40			
	Run 2	Normal (30)	30	0	63	62	98.41
		Black spots (33)	1	32			
		Total			133	131	98.50
Peanut pods	Run 1	Normal (60)	58	2	110	108	98.18
		Broken (50)	0	50			
	Run 2	Normal (60)	60	0	110	110	100
		Black spots (50)	0	50			
		Total			220	218	99.09

The results also revealed that the method employed in this study was very effective in detecting defected orange fruits with OCC up to 96.97% in average as shown in Table 1. This overall accuracy is greater than that obtained by Blasco *et al.* (2007) who proposed an algorithm able to correctly distinguish 95% of the external defects in citrus fruit (orange and mandarin). In case of the scares, the system was unable to differentiate between some healthy and defected fruits resulted in low efficiency of 90.47% (Table 1). The system considered some areas of healthy peel as scares and this may due to the convergence of the colors at the borders of the fruits. This problem is usually occurred at border pixels due to the similarity in color values between scares portions and the sound skin in many cases as shown in Figure (10a). This overlapping of the color values between the pixels of the scares with those of the sound peel led to a difficulty to distinguish them from each other. Also, the peripheral areas of round objects like orange fruits look usually darker than those in the central part due to the fruit's spherical geometry that reflect greater amount of radiation at the zenith towards the camera than in the equatorial area (Gómez-Sanchis *et al.*, 2008). There are some morphological image processing operations that could be applied to alleviate this problem, but this will be on the expenses of the time required for this operations. For instance, Blasco *et al.* (2003) applied a smoothing procedure based on a mode filter to the segmented image in order to smooth the boundary between adjacent regions and to eliminate isolated bad classified pixels during the automatic, non-destructive inspection and handling of spherical-shape fruits such as orange, apple and peaches. Another problem in this method when detecting scares is the inability of the system to detect all parts of the scares, although the result shows that the fruit was already defected, but the failure to identify all the affected areas is an obstacle in this system as shown in Figure (10b). Applying some sophisticated machine learning algorithm can help in obviating these kinds of problems.

The results outlined in Table (1) also proved that the applied method was very effective in detecting the greening and black spots in potato tubers with overall accuracy of 98.50%. However, there were some problems encountered during the real-time operations in classifying the pixels in the image to take the detection decision. These problems led to lower performance in detecting normal tubers as defected ones. It was noticed that the boundary pixels of the normal tubers may appear darker and then classified as either greening or black spot defects leading to classifying those tubers as defected tubers. The classification accuracy in this study was comparable with that obtained by Noordam *et al.* (2000) who built a high-speed, color vision unit for real-time inspection and grading of potato tubers. For five cultivars of potato, the pixel classification experiment with six color groups showed classification above 90 %. Compared to the machine vision system built in this study, Razmjooy *et al.* (2012) built a system for the identification of surface defects on potato with accuracy of around 95%.

a
b

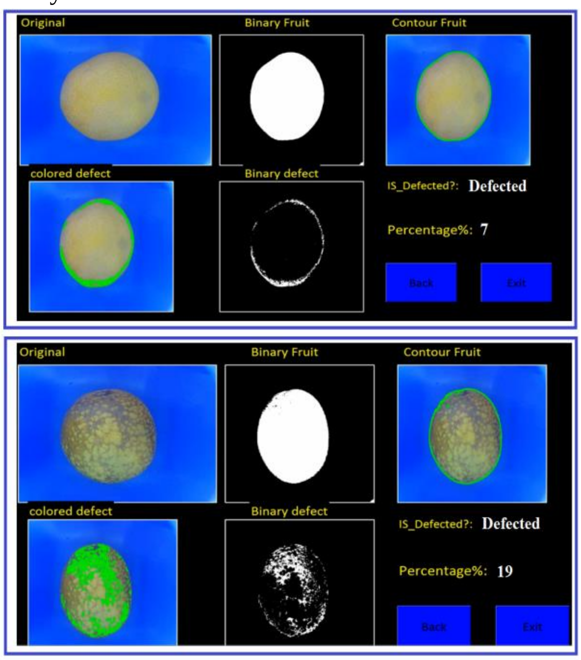

Figure 10. Some problems encountered during the detection of defects in orange fruits tested during real-time operations. (a) normal detection problems and (b) scares detection problem.

Table 1 show also that the applied classification method was efficient in detecting the defected pods accurately with high classification accuracy. However, some sound pods were classified as broken pods with overall classification accuracy of 98.18% due to misclassification of boundary pixels. In general, the overall accuracy of this system in detection of defects in peanut pods was 99.09%.

Detection of defects based on size

The developed machine vision system along with the image processing algorithm was also used for size grading of peanut pods by detecting singular pods during their movement on the conveyor belt in real-time operation. The main goal of this assignment was to detect singular peanut pods (half pods containing only one internal seed instead of two or three seeds) in real time according to dimensional features. The GUI used in size detection is shown in Figure 11. The results revealed that the developed detection method was very efficient in the classification of the peanut pods into full-size pods and singular pods and with overall classification accuracy of 100% as shown in Figure 11 and Table 2. The accuracy of developed system is higher than that obtained by Jarimopas and Jaisin (2008) who designed a machine vision sorting system for sweet tamarind pods with average accuracy of 89.8%.

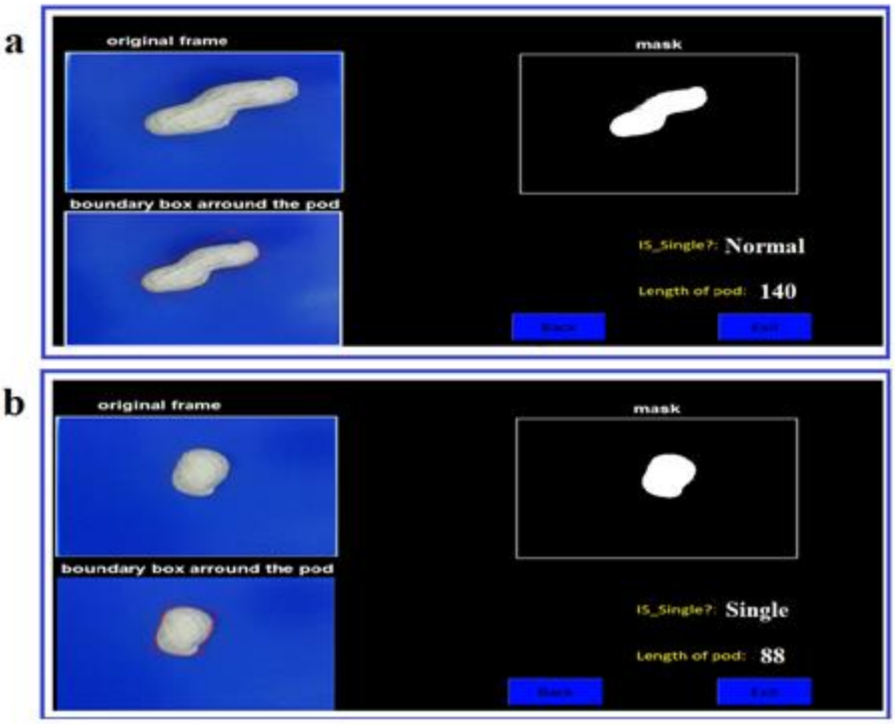

Figure 11. Classification of peanut pods to single and full-sized pods (normal pods) based on its size and length in real time. (a) normal pod detection and (b) singular pod detection.

Table 2. Performance of the developed detection system for single peanut pods based on size and length in real time

The product	No of input samples	Output		Total	No. of correctly detected	OCC (%)
		Normal	Singular			
Peanut	Normal 90	90	0	90	90	100
	Singular 90	0	90	90	90	100
	Total			180	180	100

CONCLUSIONS

A machine vision prototype was developed in this study to detect some external defects in orange fruits, potato tubers and peanut pods during on-line operation. The min-max algorism was developed in python software and employed in all real-time testing. It can be concluded from the results obtained from this study that the developed system was able to detect the defects in tested fruits with accuracy more than 96%. Higher detection accuracy of 99.09% reported for peanut pods while lower accuracy of 96.97 reported for orange. The method was very effective in detecting the greening and black spots in potato tubers with accuracy of 98.50%. The results also revealed that the developed detection method was very efficient in the classification of the peanut pods into full-size pods and singular pods and with overall classification accuracy of 100%.

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تطوير نموذج أولي للرؤية الآليه لكشف العيوب الخارجية في بعض المنتجات الزراعية خلال عملية التشغيل

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إن ميكنة العمليات الزراعية لا يؤدي إلى تحسين جودة وإنتاجية المنتجات الزراعية فحسب، بل يساعد أيضًا في تعزيز الدخل القومي. على الرغم من أن طرق الفرز والتصنيف اليدويه هي الطرق التقليدية المستخدمة عادة في عمليات ما بعد الحصاد، إلا أن هذه الأساليب غير ثابته وتستغرق وقتًا طويلاً وقد تكون متحيزه ومكلفة وتتأثر بسهولة بالبيئة ومدى إرهاق العماله. لذلك، كان الهدف الرئيسي من هذه الدراسة هو تطوير نموذج تجريبى للرؤية الآلية يستخدم فى هيئة الرقابه على الواردات والصادرات لإكتشاف صفات الجوده والفرز لبعض المنتجات الزراعية مثل البرتقال والبطاطس وقرون الفول السوداني خلال عملية التشغيل. تم إستخدام النموذج الذي تم إنشاؤه للحصول على الصور ومعالجتها. ثم بإستخدام بيانات قيم الألوان لجميع العيوب المعنية، تم تطوير كود بطريقة min-max وتطبيقه بإستخدام برنامج Python. تم الكشف عن ثلاثة أنواع من العيوب بالبرتقال (الإخضرار، البقع السوداء والندوب) وعيبان في درنات البطاطس (بقع خضراء وسوداء) وعيبان في الفول السوداني (قرون مكسورة وبقع سوداء) بإستخدام النظام المطور على أساس الفروق اللونية. تم إستخدام النظام أيضًا للكشف عن قرون الفول السوداني الفردية (تحتوي نصف القرون على بذرة داخلية واحدة بدلاً من بذرتين أو ثلاث بذور) بناءً على إختلاف الأبعاد. أظهرت النتائج التي تم الحصول عليها في هذه الدراسة أن النموذج الأولي المطور تم إستخدامه بنجاح لإكتشاف العيوب الخارجية للمنتجات المختبرة بدقة معقولة. وكانت دقة الكشف عن العيوب فى البرتقال والبطاطس والفول السوداني 96,97 و 98,50 و 99,09٪ على التوالي. وكانت طريقة الكشف المطورة أيضًا فعالة للغاية في تصنيف قرون الفول السوداني إلى قرون كاملة الحجم وقرون مفردة وبدقة تصنيف شاملة بنسبة 100٪.