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Application of Computer Vision and Image Processing Technologies in Agro-Product Quality Control

Tarımsal Ürün Kalite Kontrolünde Bilgisayarlı Görme ve Görüntü İşleme Teknolojisinin Uygulanması

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ABSTRACT

Post harvest quality evaluation processes are very critical operations and play an important role in determining the product's acceptability and marketability. Computer vision and image processing technologies have been applied widely in food industries in order to evaluate the quality of agricultural products such as; sorting, grading, and classification processes due to the performance, low cost, and effectiveness of the technologies. In this article, we aim to review the application of computer vision and image processing technologies in evaluating the quality of agricultural products such as fruits, vegetables, and nut products with more attention to hazelnuts.

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ÖZET

Hasat sonrası kalite değerlendirme süreçleri çok önemli işlemler olup, ürünün kabul edilebilirliği ve pazarlanabilirliğinin belirlenmesinde önemli rol oynamaktadır. Bilgisayarla görme ve görüntü işleme teknolojisi, ayırma, derecelendirme ve sınıflandırma işlemleri gibi tarımsal ürünlerin kalitesini değerlendirmek için teknolojik performansı, düşük maliyeti ve etkin olması nedeniyle gıda endüstrilerinde yaygın bir şekilde uygulanmaktadır. Bu makalede, tarımsal ürünlerin kalitesinin değerlendirilmesinde bilgisayar görme ve görüntü işleme uygulamaları kullanılarak; fındık ürününe daha fazla değinilerek, meyve, sebze ve kuruyemiş ürünlerinin kalitesinin değerlendirilmesi yapılmıştır.

1. INTRODUCTION

A computer vision system is a technology that was created by combining a camera and a computer. Sandoval et al. (2018) characterized computer vision systems as states that encompass the capture, processing, and analysis of two-dimensional pictures. Machine vision systems (MVS) and computer vision systems (CVS) attempt to mimic human vision in order to obtain information from an object without requiring physical involvement (Timmermans, 1998). Image processing techniques are used by computers and machine vision to interpret the image or object being inspected. In general, image processing algorithms take a picture as an input and generate a transformed image as an output. Filters, smoothing, sharpening, and even grayscale conversion can be applied to images. Image processing is used by both computer vision and machine vision to analyze images, but interpretation is used to reach to a decision or logical conclusion as a result. This choice or logical conclusion in machine vision is frequently followed by an autonomous action in industry (Anand and Priya, 2019). The main issue in machine vision systems is to create a machine human-like vision skills. These systems, like the human brain, should be trained not only to process images but also to analyze and interpret them. In comparison, image processing is mainly about the use and application of mathematical functions and transformations of images. In computer vision, both the quantitative and qualitative information from visual data are important. Similar to human vision, it is about distinguishing between objects, classifying them, sorting them according to their size, color, texture, and so on (Pinto et al., 2008). Image processing methods are used to accomplish computer vision tasks. Beyond a single image, information in computer vision can be extracted from static images or moving images such as video clips (Naik and Patel, 2017). Machine learning and artificial intelligence methods are widely used to understand and use images for inspection purposes. These techniques aim to mimic the unique nature of human thought.

1.1. Computer Vision System for Inspection

An image sensor, a frame grabber, and a computer with appropriate software and algorithms form a conventional image processing system. The analog signal from the sensor is digitized into a series of integers and saved in the computer as an image. The object is then displayed using various image processing algorithms that extract a pattern from the image. The extracted pattern is classified by classification algorithms, which in turn can generate a signal to animate a trigger that directs the object to the desired route. Figure 1 shows a block diagram of the software and hardware components of a typical inspection (classification) vision system.

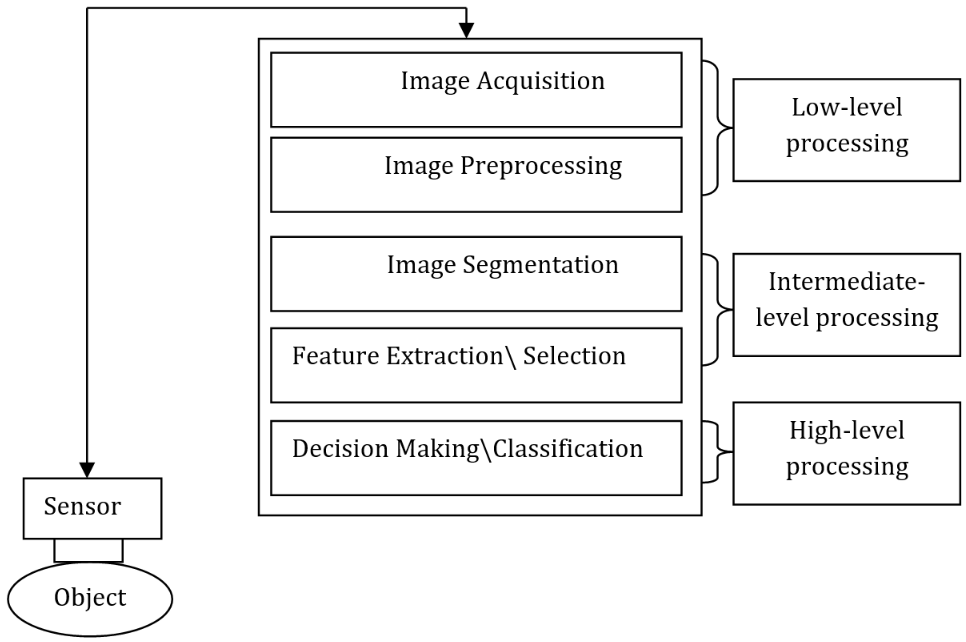

Figure 1. A schematic representation for classification process by machine vision system

In the food industry, where machine vision technology has been widely used over the past two decades as a means to automatically determine and manage food quality, computer vision technology is becoming increasingly important. Since most food products have a heterogeneous matrix, visual characteristics such as color, texture, shape, and size can vary significantly even within the same product category. Machine vision technology can effectively replace visual inspection systems in various applications such as harvesting, quality control, sorting and classification, portioning, and label inspection. It also enables more objective and standardised evaluation of food quality parameters over a large number of samples (Anand and Priya, 2019).

Machine vision systems are excellent tools for automated inspection of fruits and vegetables. In automated inspection, vision systems are typically used to sort, classify, and estimate quality based on external metrics or internal product qualities. The powerful and broad application of the technology stems from the fact that machine vision systems provide a considerable amount of information about the nature and characteristics of objects present in a scene. Furthermore, machine vision systems have the potential to objectively analyze long-term processes or events that occur outside the visible range, which is beyond the human capabilities (Zude, 2008). Due to the biological nature of agricultural products, automated inspection can detect defects that may not be found in other areas. Agricultural products often have similar colors, shapes, sizes, and other external characteristics, while fruits and vegetables can have a wide range of characteristics. The morphological characteristics of fruits and vegetables, such as color and texture, change after harvest and these features depend on their maturity and storage method. All these limitations confirm that there is a great challenge in the machine vision application in agricultural product quality inspection and evaluation. Fruits and vegetables, external characteristics, appearance and defects are factors that influence consumer preferences; therefore, these characteristics play an important role in the quality evaluation of fruits and vegetables (Ma et al., 2016). Because the technology is non-invasive and non-destructive, it is widely used for the inspection and classification of fruits and vegetables. Various studies have been conducted over the past decade and encouraging results have been obtained.

1.2. Computer Vision Technology in Detecting Fruit Quality

Appearance of fruit products is very important quality control factor and always determines the acceptability of the product by the consumers. Xiao-bo et al., (2010) developed an in-line detection system in order to detect apple defects using three cameras system. Each camera was capturing three images from each apple. The multithreshold approach was used to segment the apple from the images. In each image, Regions of interest (ROIs) were segmented and counted, including the stem ends and calyxes. This provided a good and clear distinction between normal and defective apples. The classification error of unwarranted acceptance of defective apples decreased from 21.8% for a single camera to 4.2% for the three-camera system. The divided region was used to extract statistical, textural, and geometric data for the study. Statistical and syntactic classifiers were utilized and trained to categorize the fruits into two or more categories based on these characteristics. The results showed that feature selection performed better by retaining only the most discriminative features, and that statistical classifiers outperformed their syntactic counterparts, achieving good recognition rates (93.5% overall accuracy) in the results (Unay et al., 2011). Another evaluation of bicolored apples was performed by Kang & Sabarez (2009). Here, a new simple segmentation algorithm was applied to analyze dried apple slices, which is also appropriate for measuring multiple objects. Since consumers are more likely to look for skin defects when selecting fruits, especially oranges, a multivariate image analysis approach was combined with a computer vision system to detect orange skin defects. A success coefficient of 100% was obtained when evaluating oranges with lesions at the stem end (Blasco et al., 2007a). Blasco et al. (2007a) proposed a region-based segmentation algorithm to detect the most common citrus peel defects. The proposed algorithm was tested on photos of many varieties of oranges and mandarines that highlighted flaws without the requirement for additional training between batches or even types of citrus fruits. For defect detection, the algorithm could achieve a high accuracy rate of 95%. Since mangoes are so popular in many parts of the world due to their colorful, unique taste, and nutritional content, several studies have been conducted using computer vision and image processing to assess the product's quality. (Zheng and Lu, 2012). Their research developed a LS-SVM classifier to detect the degree of browning of mango fruit. The best categorization accuracy of the degree of browning was up to 99% according to the findings. A computer vision system was utilized to observe the ripening of mangoes and evaluate their quality (Kang et al., 2008). The method also allowed for a quantitative analysis of the product's color properties. Enzymatic browning in pear slices, bananas, and avocados was also detected using vision systems (Quevedo et al. 2009; Quevedo et al. 2011).

1.3. Computer Vision Technology in Detecting Quality of Vegetables

The classification of vegetables before use is a very important process that has a significant impact on quality. Potatoes, for example, are simple to grade due to their various sizes, shapes, and regularities. Using computer vision and image processing technology different works have been performed in order to classify potatoes into various grates. An automated computer vision system has been used by (ElMasry et al., 2012) in order to sort potatoes into multible grates. In the study, a special algorithm was developed and programmed for image acquisition and processing, controlling the entire process and monitoring the progress of all operations. For each image in the database, eight shape parameters were derived from the size features, as well as the Fourier transform. All of the shape parameters were used in a stepwise linear discriminant analysis to obtain the most relevant and discriminative factors that best described potato regularity. In-line classification of moving potatoes was shown to be 96.2 percent successful in the testing. At the same time, the well-shaped potatoes were identified by size with 100% accuracy, demonstrating that the created machine vision system has a lot of potential for autonomous identification and sorting of deformed products. A real-time computer vision system was also employed to defect detection and size sorting, with a color-based classifier that had a classification accuracy of 95%(Razmjooy et al., 2012). To detect surface defects in tomatoes, a deep learning-based computer vision system was deployed. The dataset was substantially skewed towards the healthy class. Using feature extraction and fine-tuning, deep residual neural network classifiers were trained to detect external defects. On the test set, this model had an overall accuracy of 94.6%, where The optimal classifier has an 86.6 % recall while securing a 91.7 % precision (Da Costa et al., 2020).

1.4. Computer Vision Technology in Detecting Quality of Nut Products

Computer vision technology has been widely used to detect defects in nut products and has shown successful results in numerous studies. A computer vision system based on pattern recognition was used to discriminate wormy chestnuts (Figure 1). A classification accuracy of 100% was achieved for both normal and wormy chestnuts (Wang et al., 2011).

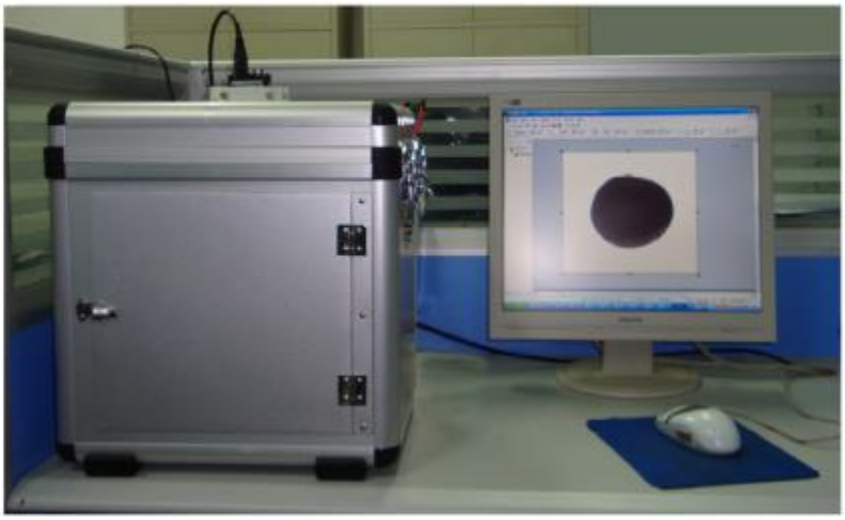

Figure 1. Chestnut sorting test platform based on machine vision

Mathanker et al. (2011) used AdaBoost and Support Vector Machine, traditional machine learning classifiers, to improve classification accuracy for pecans. Good and defective pecan samples were taken as X-ray images, segmented, and features extracted. Average classification accuracy values of 92.3% and 90.1% were achieved using AdaBoost and Support Vector Machine, respectively. In addition, color, texture and geometric features were evaluated using computer vision images to study chestnut grading and an overall accuracy of 89.6% was achieved. (Donis et al., 2013). Table 1 summarizes the technology's application in evaluating the quality of nut products, taking into account the items evaluated, the type of application, and the technology.

Table 1. Application of machine vision system in agro-product quality inspection

Products	***Application***	***Technology used***	***References***
Almond	Defected, roasted, and foreign material classification	RGB Digital camera	(Delila and Turajlic, 2017)
Almond	Pinholes detection	X-Ray imaging	(Kim and Schatzki, 2001)
Pistachio	Sorting different types of defects	X-Rayimage histogram features	(Pearson et al., 2001)
Chestnuts	Insect infestation	NIR spectral tec.	(Moscetti et al., 2014)

In general, few studies have been conducted on hazelnuts in this area compared to other crops. One of the studies that have been conducted was the identification of hazelnut defects using RGB image analysis and color gram techniques (Giraudo et al., 2018). They developed a color-gram based system for the detection of defective hazelnuts. The half-cut RGB hazelnut images were taken with a digital camera after being classified by industry experts into three reference categories; healthy, rotten, and infested by pests. The colorgrams were obtained by converting RGB images, and then Partial Least Squire Discriminant Analysis (PLS-DA) was developed and used as a classification model. To better distinguish the previously defined classes, the Interval Partial Least Square Discriminant Analysis algorithm (iPLS- DA) of Norgaard et al. (2000) was applied to select the most informative regions of the color signals. The whole defective hazelnuts were detected by Kivrak and Gürbüz (2019) using image processing and machine learning techniques. The goal of the work was to distinguish intact hazelnuts from damaged or defective ones. Images of hazelnut samples were captured using a cell phone and processed using image labelling techniques. Satisfactory results were obtained using the supervised learning method. Furthermore, a computer vision system was used to classify the partly skin removed hazelnut kernel, skin removed and rotten hazelnuts kernels. The processed hazelnut kernels are classified with a classification accuracy rate of 93.57 % (Guvenc et al., 2015). Solak and Altinisik, (2018) classified and detected hazelnuts using image processing and clustering techniques. The size and area features were extracted from hazelnut images and hazelnuts were divided into three classes. The use of mean-based classification and K-means clustering algorithms yielded 100 detection and classification accuracy. For classifying shelled hazelnuts according to type and commercial definitions, an accuracy rate of 84 % was reached. Image processing and machine learning techniques were also used to determine hazelnut kernel quality using size and shape characteristics. Hazelnut cultivars were classified also by Caner et al., (2020) using Gradient Boosting and Random Forest classifiers. Classification accuracy of 94% and 100% was achieved by Gradient Boosting and Random Forest, respectively. Recently, a study proposed to identify hazelnut varieties using computer vision-deep learning technic that was developed by Taner et al. (2021). In this study, a Convolutional Neural Network classifier was suggested to classify 17 commonly planted hazelnut cultivars in Turkey. The results showed that the proposed model can accurately classify the varieties with a 98.63 % overall accuracy.

2. CONCLUSION

In this work, a comprehensive literature review was conducted on the application of computer vision and image processing techniques in evaluating the quality of agricultural products. In this paper, the application of computer vision and image processing techniques in evaluating the quality of fruits, vegetables and nut products is presented. Successful results have already been obtained and applied in wide areas of the food industry to increase the marketability and acceptance of these products. However, we have found that much research is still needed in the quality control of hazelnuts using the same technology to facilitate the processing of hazelnuts in the food industry, improve the quality of hazelnuts, and increase the national and international marketability of nuts.

REFERENCES

Anand, S., and Priya, L. (2019). A Guide for Machine Vision in Quality Control: *Applied spectroscopy*, 54(3), 413–419.

Blasco, J., Aleixos, N., Gómez, J., and Moltó, E. (2007a). Citrus sorting by identification of the most common defects using multispectral computer vision. J*ournal of food Engineering,* 83(3), 384-393.

Blasco, J., Aleixos, N., and Moltó, E. (2007b). Computer vision detection of peel defects in citrus by means of a region oriented segmentation algorithm. *Journal of food Engineering,* 81(3), 535-543.

Caner, K., Gerdan, D., Emin, M. B., YegüL, U., Bulent, K., and VatandaŞ, M. (2020). Classification of hazelnut cultivars: comparison of DL4J and ensemble learning algorithms. *Notulae Botanicae Horti Agrobotanici Cluj-Napoca,* 48(4), 2316-2327.

Da Costa, A. Z., Figueroa, H. E., and Fracarolli, J. A. (2020). Computer vision based detection of external defects on tomatoes using deep learning. *Biosystems Engineering*, 190, 131-144.

Delila, H. E. S., Emir Turajlic. (2017). Almonds classification using supervised learning.pdf.

Donis, I. R., Guyer, D. E., Leiva-Valenzuela, G. A., and Burns, J. (2013). Assessment of chestnut (Castanea spp.) slice quality using color images. *Journal of food Engineering*, 115(3), 407-414.

ElMasry, G., Cubero, S., Moltó, E., and Blasco, J. (2012). In-line sorting of irregular potatoes by using automated computer-based machine vision system. *Journal of food Engineering*, 112(1-2), 60-68.

Giraudo, A., Calvini, R., Orlandi, G., Ulrici, A., Geobaldo, F., & Savorani, F. (2018). Development of an automated method for the identification of defective hazelnuts based on RGB image analysis and colourgrams. *Food Control*, 94, 233-240. doi:10.1016/j.foodcont.2018.07.018

Guvenc, S. A., Senel, F. A., and Cetisli, B. (2015). Classification of processed hazelnuts with computer vision. *Paper presented at the 2015 23nd Signal Processing and Communications Applications Conference* (SIU).

Kang, S., East, A., and Trujillo, F. (2008). Colour vision system evaluation of bicolour fruit: A case study with 'B74'mango. *Postharvest Biology and Technology*, 49(1), 77-85.

Kang, S., and Sabarez, H. (2009). Simple colour image segmentation of bicolour food products for quality measurement. *Journal of food Engineering*, 94(1), 21-25.

Kivrak, O., Gürbüz, M. (2019). Detection of Defective Hazelnuts by Image Processing and Machine Learning. *Natural and Engineering Sciences*, 4(3), 100-106.

Ma, J., Sun, D.W., Qu, J.H., Liu, D., Pu, H., Gao, W, H., and Zeng, X. A. (2016). Applications of computer vision for assessing quality of agri-food products: a review of recent research advances. *Critical reviews in food science and nutrition*, 56(1), 113-127.

Mathanker, S., Weckler, P., Bowser, T., Wang, N., and Maness, N. (2011). AdaBoost classifiers for pecan defect classification. *Computers and Electronics in Agriculture*, 77(1), 60-68.

Moscetti, R., Haff, R. P., Saranwong, S., Monarca, D., Cecchini, M., and Massantini, R. (2014). Nondestructive detection of insect infested chestnuts based on NIR spectroscopy. *Postharvest Biology and Technology*, 87, 88-94. doi:10.1016/j.postharvbio.2013.08.010

Naik, S., & Patel, B. (2017). Machine vision based fruit classification and grading-a review. *International Journal of Computer Applications*, 170(9), 22-34.

Norgaard, L., Saudland, A., Wagner, J., Nielsen, J. P., Munck, L., and Engelsen, S. B. (2000). Interval partial least-squares regression (iPLS): A comparative chemometric study with an example from near-infrared spectroscopy. *Applied spectroscopy*, 54(3), 413–419.

Pearson, T. C., Doster, M. A., and Michailides, T. J. (2001). Automated Detection of Pistachio Defects by Machine Vision. *Applied Engineering in Agriculture*, 17(5). doi:10.13031/2013.6905

Pinto, N., Cox, D. D., and DiCarlo, J. J. (2008). Why is real-world visual object recognition hard? PLoS. *computational biology*, 4(1), e27.

Quevedo, R., Díaz, O., Ronceros, B., Pedreschi, F., and Aguilera, J. M. (2009). Description of the kinetic enzymatic browning in banana (Musa cavendish) slices using non-uniform color information from digital images. *Food Research International*, 42(9), 1309-1314.

Quevedo, R., Ronceros, B., Garcia, K., Lopéz, P., and Pedreschi, F. (2011). Enzymatic browning in sliced and puréed avocado: a fractal kinetic study. *Journal of food Engineering*, 105(2), 210-215.

Razmjooy, N., Mousavi, B. S., and Soleymani, F. (2012). A real-time mathematical computer method for potato inspection using machine vision. *Computers & Mathematics with Applications*, 63(1), 268-279.

Kim, S., and Schatzki, T. (2001). Detection of Pinholes In Almonds. *American Society of Agricultural Engineers* ISSN, 0001–2351.

Sandoval, E. M., Rosas, M. E. M., Sandoval, J. R. M., Velasco, M. M. M. (2018). Machine Vision system - A Tool for Automatic Color Analysis in Agriculture. doi:10.5772/intechopen.71935

Solak, S., and Altinisik, U. (2018). Detection and classification of hazelnut fruit by using image processing techniques and clustering methods. *Sakarya University Journal of Science*, 22(1), 56-65.

Taner, A., Öztekin, Y. B., and Duran, H. (2021). Performance analysis of deep learning CNN models for variety classification in hazelnut. *Sustainability*, 13(12), 6527.

Timmermans, A. J. M. (1998). Computer Vision System For On-Line Sorting of Pot Plants Based On Learning Techniques. *International Society for Horticultural Science*, 421, 91-98. DOI:.

Unay, D., Gosselin, B., Kleynen, O., Leemans, V., Destain, M.-F., and Debeir, O. (2011). Automatic grading of Bi-colored apples by multispectral machine vision. *Computers and Electronics in Agriculture*, 75(1), 204-212.

Wang, C., Li, X., Wang, W., Feng, Y., Zhou, Z., and Zhan, H. (2011). Recognition of worm-eaten chestnuts based on machine vision. *Mathematical and Computer Modelling*, 54(3-4), 888-894.

Xiao-bo, Z., Jie-wen, Z., Yanxiao, L., and Holmes, M. (2010). In-line detection of apple defects using three color cameras system. *Computers and Electronics in Agriculture*, 70(1), 129-134.

Zheng, H., and Lu, H. (2012). A least-squares support vector machine (LS-SVM) based on fractal analysis and CIELab parameters for the detection of browning degree on mango (Mangifera indica L.). *Computers and Electronics in Agriculture*, 83, 47-51.

Zude, M. (2008). Optical monitoring of fresh and processed agricultural crops.

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