Freshness and quality assessment of parsley using image processing and artificial intelligence techniques

Mohammad Hosseinpour Zarnaq[1], Mahmoud Omid[1*], Mahmoud Soltani Firouz[1], Mostafa Jafarian[2], Pourya Bazyar[1]

(1. Department of Agricultural Machinery Engineering, Faculty of Agricultural Engineering and Technology, University of Tehran, Karaj, Iran, Postal Code: 77871-31587

2. Department of Mechanical Engineering, Technical and Vocational University (TVU), Tehran, Iran, Postal Code: 1435761137)

Abstract: Fruits and vegetables are important components of healthy diet. Vegetable freshness is important for both the postharvest industry and consumer appeal. This study focused on freshness detection of parsleys using combined image processing and artificial intelligence techniques. A dataset of color and texture features computed from parsley images. Linear discriminant analysis (LDA) and principal component analysis (PCA) methods were used for feature reduction. Multilayer perceptron (MLP) neural networks, support vector machine (SVM) and decision trees (DTs) classifiers were used for classification. Results showed that MLP with LDA feature selection methods had higher performance and the overall accuracy, root mean square error (RMSE), mean square error (MAE) of MLP classifier (using LDA feature selection) were 97.22%, 0.17, and 0.03, respectively. This approach provided a rapid and nondestructive detection of parsley freshness without using chemical or colorimetric analysis. The results demonstrated that suggested approach could be employed satisfactorily for inspection, classification and automation of vegetables postharvest operations.

Keywords: parsley, vegetable's quality, grading, computer vision, freshness, artificial neural network

Citation: Zarnaq, M. H., M. Omid, M. S. Firouz, M. Jafarian and P. Bazyar. 2022. Freshness and quality assessment of parsley using image processing and artificial intelligence techniques. Agricultural Engineering International: CIGR Journal, 24(2): 282-290.

1 Introduction

Population growth and social concerns about healthy foods require guarantees of optimal quality of agricultural products (Blasco et al., 2017). Vegetables are an important source of food and nutrition to human (Yahia et al., 2019; Qiu et al., 2017). Consumption of less than 200 g of vegetables per person per day in a country, indicate poverty and poor medical services (Keatinge et al., 2011). Therefore, mechanization of vegetables postharvest operations is a necessary step for perfuming the objects of food security. Recently, automatic systems based on machine vision dramatically used in agriculture. Machine vision system has been demonstrated to be a powerful and standardized tool in quality monitoring and grading of different agricultural products (Bhargava and Bansal, 2018: Zhang et al., 2014; Arjenaki et al., 2013). Machine vision could measure the most important attributes such as color, texture, shape, size and volume, which can be utilized for grading of biological products or defect

Received date: 2021-06-13 **Accepted date:** 2022-01-03

* **Corresponding author: Mahmoud Omid,** Ph.D., Department of Agricultural Machinery Engineering, Faculty of Agricultural Engineering and Technology, University of Tehran, Karaj, Iran. Email: E-mail address: omid@ut.ac.ir, Tel: +98-263-2801038, Fax: +98-263-2808138.

inspection (Cubero et al., 2011; Costa et al., 2011).

The measurement of color has been frequently used as an alternative to distractive and time-consuming methods in a wide range of food industries. In recent years, researchers attempt to propose the automatic calibration methods to measure the color information without using any Colorimetric and spectrophotometry techniques as a reference for measurements (Minz et al., 2018; Cubero et al., 2018). Freshness is the key parameter of vegetables in the market. The quality of leafy vegetables has to be guaranteed for consumers for the whole postharvest period, usually limited to 5–7 days (Ferrante and Maggiore, 2007). The microbiological parameters and some important chemical characteristics (such as chlorophylls, ascorbic acid and total phenolic contents, and antioxidant activity) have been used to examine the effects of treatments to extend the shelf life of vegetables (Karaca and Velioglu, 2014; Ouzounidou et al., 2013). In addition, based on the standards of United States department of agriculture (USDA), the best quality of parsley is associated with good green color (USDA, 2007). Saba et al. (2018) reported that the sensory properties of vegetables were confirmed as the most important indicators of freshness and quality according to the consumers' opinions. Change of color is due to degradation of the leaf pigments or browning. These physiological processes occur when cell membranes lose their integrity and release enzymes (Ferrante and Maggiore, 2007).

Therefore, freshness of postharvest vegetables could be detected with the determination of plant leaves color based on machine vision and artificial intelligence (Huang et al., 2019). Wongpatikaseree et al. (2018) Used different machine learning methods for assessing freshness of hydroponic produced lettuce and reported that the fresh and withered lettuce could be precisely classified by using image processing techniques and decision tree algorithms. Manninen et al. (2015) examined the color change of green vegetables such as lettuce, cucumber and basil during heat treatments and reported that the determining of fractional coefficient of b component in Lab color space is a good key to color measurement. Another study showed that the luminance measurement could perfumed perception of vegetable freshness (Arce-Lopera et al., 2015). In addition, hyperspectral imaging is a nondestructive and powerful method in agricultural products quality measurement, which provide the wide spectral range images to detection of decay and fresh vegetables (Simko et al., 2015; Zhu et al., 2019).

Evaluating fresh herbs quality is an essential task to postharvest industry in order to meet consumer’s demands. In this study, the freshly harvested parsley, as one of common and important types of vegetables, were selected as a case study. It which has similar attribute to other green leafy herbs. The objective of this study was to develop a computer vision-based method for automatic evaluation of vegetables freshness with the intention of automation of herbs preparing process.

2 Material and methods

2.1 Samples preparation

For detecting parsley freshness, the flat-leaf parsley (Petroselinum crispum var. neapolitanum) samples were bought from a local farmer market around Karaj city in Alborz province, Iran. The samples packaged and stored in a refrigerator at 5°C. Measurements were conducted each day and lasted for 12 days. Prior to each experiment, the plants were taken out of the refrigerator and allowed to rest at room temperature for 10 min. In total, 20 images of samples in each day were acquired. An experimental imaging system was fabricated by Mohi-Alden et al. (2019). The system was fabricated from a wooden cube with dimensions of 500×400×500mm. A digital camera takes images of the parsley samples and the computer saved and processed the images (Figure 1).

In order to automatic detection of freshness, image processing techniques are used for the extraction of color and texture features and finally artificial intelligence methods are used for classification. For classification, sensory panel test results were used as a reference to categorize the parsleys based on storage time. Parsleys are categorized as grade A (proper for fresh consumption and processing), grade B (proper for processing) and grade C (waste) (Figure 2).

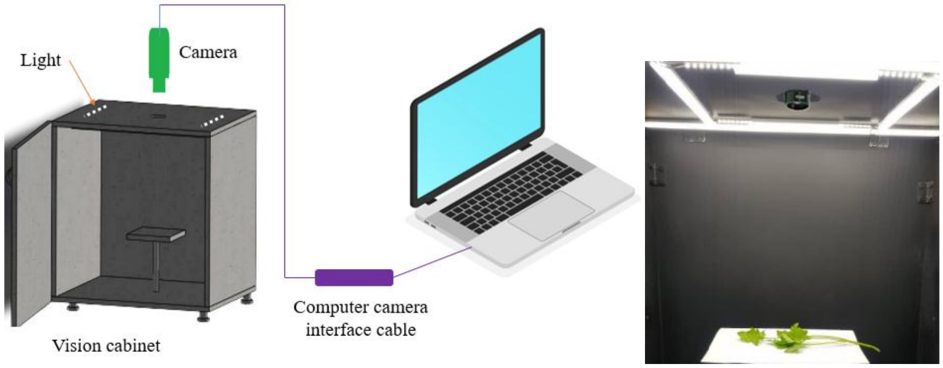


Figure 1 Schematic of the set-up test framework

(a) grade A (b) grade B (c) grade C

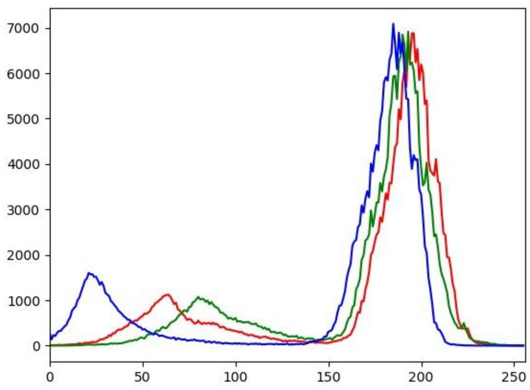
Figure 2 Parsley grades

2.2 Image processing procedure

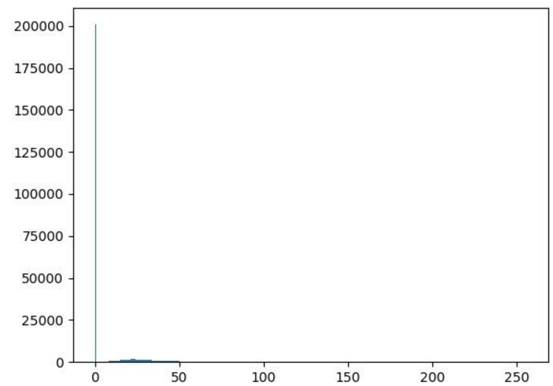
For image acquisition, a CCD color camera (mod. ace1300-200uc, Basler, Germany) was used. All steps of detection methodology are carried out using python programming platform. The algorithm run in a laptop having a core i7 CPU, 2 GHz, and 8 GB memory. The samples were placed in front of the camera and computer takes the images. Images cropping, resizing as preprocessing step perfumed for reduce the complexity of the algorithm and decreasing processing time.

In this study, different color spaces were analyzed to find the most appropriate color component for automatic images segmentation (Wu and Sun, 2013). Results showed that blue component (B) in RGB color space had better performance. Automatic Otsu's histogram thresholding method is performed on B-component for segmenting (Otsu, 1979). This approach can transform grey images effectively into black and white images (Figure 3c). Finally, image background separated from object (Figure 3d) and statically analysis of color is performed for feature extraction.

(a) (b) (c) (d)



(e)



(f)

(a) Cropping and resizing of RGB image, (b) B-component of image, (c) Thresholding by Otsu's method and morphological opening operation, (d) Final image after segmentation, (e) Histogram of R, G and B-components before segmentation, and (f) B-component histogram after segmentation

Figure 3 Image processing procedure

2.3 Feature extraction

In this study, various features including color and texture are extracted from the images of parsley samples. So, 4 statistical parameters were extracted from each color components in RGB color space include mean (*m*) – Equation 1 , standard deviation (*sd*) – Equation 2, kurtosis (*k*) – Equation 3, and skewness (*s*) – Equation 4, respectively (Donis-González, et al., 2013; Sabzi et al., 2018).

$$m = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

$$sd = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{2}$$

$$k = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^4}{[\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2]^{\frac{4}{2}}} \tag{3}$$

$$s = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^3}{[\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2]^{\frac{3}{2}}} \tag{4}$$

Where x_i is the gray level of each pixel in the image and *n* is the number of pixels. Hence, four color features were obtained from each color component and totally 12 color features were computed. For texture analysis grey level co-occurrence matrix (GLCM) performed as a statistical method introduced by Haralick et al. (1973). In the GLCM the image texture studies are based on the statistics of pixel intensity distributions and considering the spatial relationship of pixels. Here, 4 important features extracted from the co-occurrence matrix were contrast, energy, homogeneity, and correlation (Table 1) (Grassi et al., 2018). These parameters were obtained in zero and 45 orientation degrees and one-pixel distance of GLCM structure. Therefore, eight texture features were obtained from each color component. In total, 24 texture features were computed.

Table 1 Statistical features and their formula obtained from GLCM

Statistical features formula
$\text{Contrast} = \sum_{i.j} \lvert i-j \rvert^2 \times p(i.j)$
$\text{Energy} = \sum_{i.j} (p(i.j))^2$
$\text{Homogeneity} = \sum_{i.j} \frac{p(i.j)}{1+\lvert i-j \rvert}$
$\text{Correlation} = \sum_{i.j} \frac{(i-\mu i)(j-\mu j)p(i.j)}{\sigma_i \sigma_j}$

Note: Element i,j of the GLCM matrix define as the number of times which two samples of intensities i and j occur in specified Spatial relationship.

2.4 Feature selection

Principal component analysis (PCA) and linear discriminant analysis (LDA) used for reduction of data dimension. The mentioned methods compute new variables, so they widely used for reducing data dimension and clustering purposes (Kim et al., 2007; Gu et al., 2011; Cao et al., 2003). Therefore, a fewer variable could be used instead of many original variables with these dimension reduction methods. In this study, LDA with two components and PCA with five principal components were used.

2.5 Classification

Multilayer perceptron (MLP) neural networks used for classification. The nets input layer feed by the extracted original features and selected features. MLP structure contained one hidden layer with 12 neurons. All of the neurons used a sigmoid function. The network was trained using stochastic gradient descent algorithms with a learning rate of 0.3 and a momentum of 0.2. In addition, for comparing MLP performance with the other powerful and popular classifiers, namely support vector machine (SVM) and decision trees (DTs) (Table 2).

Table 2 SVM and DT Classifiers structure used in the research

SVM	DTs
Implementation method = one-vs-one algorithm	Implementation method = CART
Kernel = polynomial	Tree depth=20
Regularization parameter = 1	

The confusion matrixes indicated a classifiers performance (Omid, 2011). Some important parameters, which extracted from confusion matrixes, were precision (*PR*) (Equation 6), Sensitivity (*SE*) (Equation 7), Specificity (*SP*) (Equation 8), the area under ROC curve (*AUC*) (Equation 9) and overall accuracy (Equation 10) (Hosseinpour-Zarnaq et al., 2022):

$$\text{C.M.}:\begin{bmatrix} TP & FN \\ FP & TN \end{bmatrix} \quad (5)$$

$$\text{PR}\ (\%) = \frac{TP}{TP+FP} * 100 \quad (6)$$

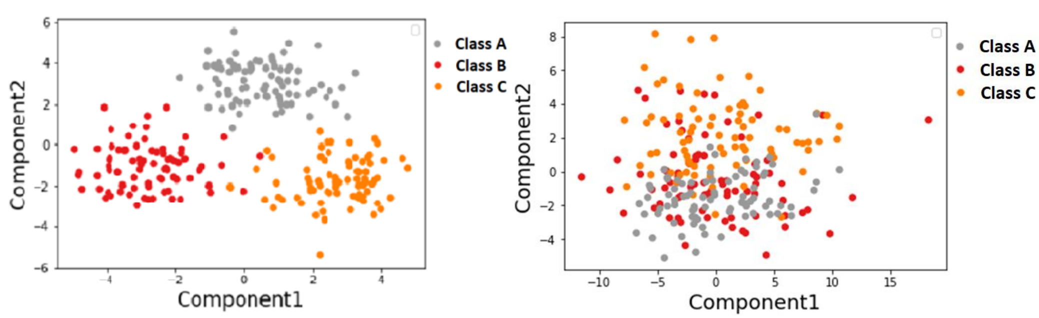
$$\text{SE}\ (\%) = \frac{TP}{TP+FN} * 100 \quad (7)$$

$$\text{SP}\ (\%) = \frac{TN}{TN+FP} * 100 \quad (8)$$

$$\text{AUC}\ (\%) = \frac{1}{2}\left(\frac{TP}{TP+FN} + \frac{TN}{TN+FP}\right) * 100 \quad (9)$$

$$\text{OAC}\ (\%) = \frac{TP+TN}{TP+TN+FP+FN} * 100 \quad (10)$$

Where *TP*, *FP*, *TN*, and *FN* are the number of true positives, false positives, true negatives, and false negatives, respectively. MLP Performance were further investigated based on mean square error (MSE).



(a) (b)

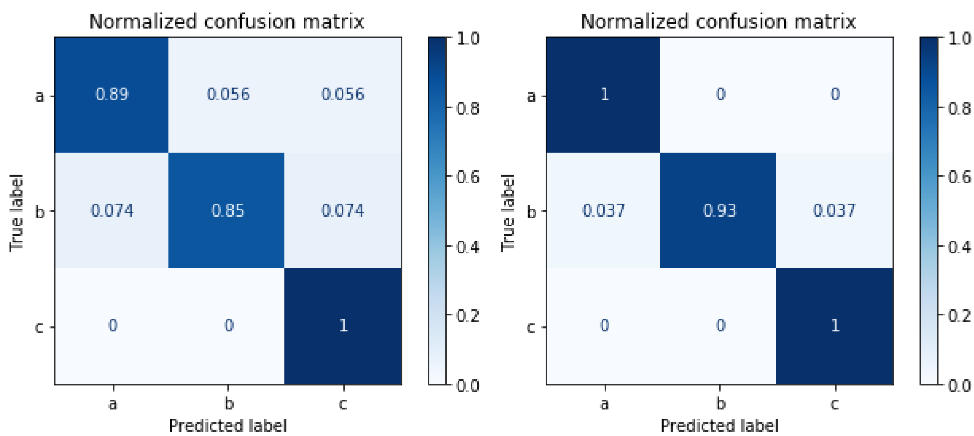
Figure 4 Data visualization with various dimension reduction methods a) LDA and b) PCA

3 Results and discussions

Vegetables sensory attributes are related to consumer perception of freshness. Visual features including color and texture can provide useful information for automatic detection of freshness. In this study, the color and texture features are computed from parsley sample images. After implementing LDA method, two of the best features were selected as inputs to the MLP classifier. In addition, the effect of using PCA as feature selection methods for intelligent model input were investigated. Results showed that the performance of the MLP classifier with reduced features by LDA was better than PCA (Figure 4).

In order to evaluate the performance of the classifier, the confusion matrix was computed (Figure 5). The performance parameters are presented in Tables 3-4. The confusion matrices show the distribution of predictions for each grade. Comparing the results showed that using LDA for feature selection increased the performance of classification, model interpretability, and computational cost. The overall accuracy of the optimum MLP with LDA were 97.22% (Table 4.). The average per class of AUC was 98.1%. RMSE error of the MLP-LDA and MLP-PCA methods were 0.17 and 0.35 respectively.

Grade A were correctly classified with sensitivity of 100% (Table 3). As shown in Table 3, the performance parameters of MLP-LDA including precision, sensitivity, specificity and AUC for predicting grade A were 94.7%, 100%, 98.1%, and 99.1%, respectively.



(a) without feature selection (b) with LDA feature selection

Figure 5 Confusion Matrix for MLP classifier

The proposed algorithm could detect all grade A samples correctly (SE=100%). Suggested approach only misclassified about four percent of grade B samples like that waste and about four percent of grade B class as grade A. The misclassified images were distributed near the main diagonal of the confusion matrix, which means that they were predicted close to the correct classes.

Table 3 Performance measurements of MLP with and without LDA feature selection

	MLP with all features			MLP with selected features		
class	**A**	**B**	**C**	**A**	**B**	**C**
PR (%)	88.9	95.8	90	94.7	100	96.4
SE (%)	88.9	85.2	100	100	92.6	100
SP (%)	96.3	97.8	93.3	98.1	100	97.8
AUC (%)	92.6	91.5	96.7	99.1	96.3	98.9

Table 4 Overall performances of MLP classifiers for freshness classification

	MLP	MLP-LDA
Average PR (%)	91.6	97.1
Average SE (%)	91.4	97.5
Average SP (%)	95.8	98.6
Average AUC (%)	93.6	98.1
MSE error	0.12	0.03
Overall Accuracy (%)	91.66	97.22

Grade A had no misclassified images, which confused with grades B and C. Only about 7% of grade B samples were classified as grades A and grade C. In this research, fresh parsleys could be detected precisely. Detection of grade A (completely fresh vegetable) is very important according to the consumer's opinions. The performance of MLP classifier compared to SVM and DTs methods is shown in Figure 6. It can be conducted from Figure 6 that the overall performance of the MLP classifier was higher as compared to other classifiers (SVM and DTs) with and without feature selection methods.

Dinnella et al. (2014) studied the relationships between sensory properties (appearance, odor, taste and texture) and perception of freshness for ready-to-eat mixed salads leaves. They found that the perception of freshness was positively linked to appearance attributes such as green color. Wongpatikaseree et al. (2018) evaluated the performance of image processing and machine learning technologies for distinguishing between fresh and withered lettuce. The results showed that the accuracies of MLP and deep neural network classifiers were 90% and 93.65%, respectively. Huang et al. (2019) evaluated quality of postharvest spinaches based on machine vision and electronic nose. Machine vision with MLP classifier achieved a classification accuracy of 85.42% and MLP model based on data fusion of machine vision and electronic nose features improved the freshness detection accuracy to 93.75%. Zhu et al. (2019) used hyperspectral imaging for freshness detection of spinach leaves during storage and they reported that both Vis-NIR and NIR imaging could satisfactorily predict the storage date with accuracies above 92%. Qiu et al. (2017) studied the freshness of postharvest leafy vegetables using chlorophyll fluorescence (ChlF) measurement. ChlF parameters classified spinach and cabbage with an average correct rate of 89.5% and 76.75%, respectively. For real time applications, the machine vision-based systems could precisely detect the quality of vegetables.

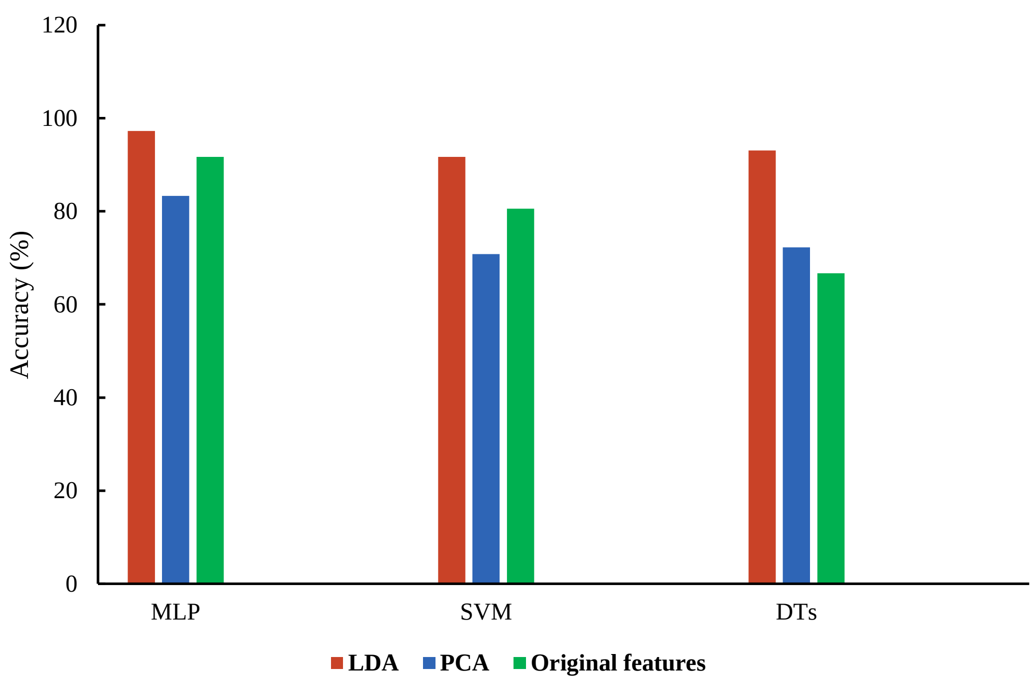


Figure 6 Comparison of the MLP, SVM and DTs accuracy with different feature selection methods for freshness detection

Therefore, it can be concluded that the proposed method could detect the freshness of herbs with very high accuracy and this provides confidence that the machine vision equipped systems can be efficiently employed for automation of vegetables grading and packaging operations.

4 Conclusions

In this work, an intelligent model based on image processing techniques and artificial neural networks developed for freshness evaluating of parsleys. The proposed method distinguished fresh samples under different storage days. In this research, several color and texture features were extracted from preprocessed images. To improve the learning efficiency of the classifier, original features dimension was reduced with the LDA methods. It gave a satisfactory performance in freshness detection of parsleys using suggested methods. The accuracy of MLP classifier with original features was 91.66%, whereas the accuracy of MLP with LDA feature selection was 97.22%. These results indicated the feasibility of the proposed method for freshness determination of leafy vegetables.

Acknowledgments

The financial support provided by the Research Department of University of Tehran, is duly acknowledged.

References

Arjenaki, O. O., P. A. Moghaddam, and A. M. Motlagh. 2013. Online tomato sorting based on shape, maturity, size, and surface defects using machine vision. *Turkish Journal of Agriculture and Forestry*, 37(1): 62-68.

Arce-Lopera, C., T. Masuda, A. Kimura, Y. Wada, and K. Okajima. 2015. Model of vegetable freshness perception using luminance cues. *Food Quality and Preference*, 40(2): 279-286.

Bhargava, A., and A. Bansal. 2018. Fruits and vegetables quality evaluation using computer vision: A review. *Journal of King Saud University-Computer and Information Sciences*, 33(3): 243-257.

Blasco, J., S. Munera, N. Aleixos, S. Cubero, and E. Molto. 2017. Machine vision-based measurement systems for fruit and vegetable quality control in postharvest. *Measurement, Modeling and Automation in Advanced Food Processing,* 161: 71-91.

Cao, L. J., K. S. Chua, W. K. Chong, H. P. Lee, and Q. M. Gu. 2003. A comparison of PCA, KPCA and ICA for dimensionality reduction in support vector machine. *Neurocomputing,* 55(1-2): 321-336.

Costa, C., F. Antonucci, F. Pallottino, J. Aguzzi, D. W. Sun, and P. Menesatti. 2011. Shape analysis of agricultural products: a review of recent research advances and potential application to computer vision. *Food and Bioprocess Technology,* 4(5): 673-692.

Cubero, S., N. Aleixos, E. Moltó, J. Gómez-Sanchis, and J. Blasco. 2011. Advances in machine vision applications for automatic inspection and quality evaluation of fruits and vegetables. *Food and Bioprocess Technology,* 4(4): 487-504.

Cubero, S., F. Albert, J. M. Prats-Moltalbán, D. G. Fernandez-Pacheco, J. Blasco, and N. Aleixos. 2018. Application for the estimation of the standard citrus colour index (CCI) using image processing in mobile devices. *Biosystems Engineering,* 167: 63-74.

Dinnella, C., L. Torri, G. Caporale, and E. Monteleone. 2014. An exploratory study of sensory attributes and consumer traits underlying liking for and perceptions of freshness for ready to eat mixed salad leaves in Italy. *Food Research International*, 59: 108-116.

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

Ferrante, A., and T. Maggiore. 2007. Chlorophyll a fluorescence measurements to evaluate storage time and temperature of Valeriana leafy vegetables. *Postharvest Biology and Technology*, 45(1): 73-80.

Grassi, S., E. Casiraghi, and C. Alamprese. 2018. Fish fillet authentication by image analysis. *Journal of Food Engineering*, 234: 16-23.

Gu, Q., Z. Li, and J. Han. 2011. Linear discriminant dimensionality reduction. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases,* Editor: Dimitrios Gunopulos, 549-564. Berlin, Heidelberg: Springer.

Haralick, R. M., K. Shanmugam, and I. H. Dinstein. 1973. Textural features for image classification. *Studies in Media and Communication*, SMC-3(6):610-621.

Hosseinpour-Zarnaq, M., Omid, M., Taheri-Garavand, A., Nasiri, A. and Mahmoudi, A., 2022. Acoustic signal-based deep learning approach for smart sorting of pistachio nuts. *Postharvest Biology and Technology*, 185: 1111778.

Huang, X., S. Yu, H. Xu, J. H. Aheto, E. Bonah, M. Ma, and X. Zhang. 2019. Rapid and nondestructive detection of freshness quality of postharvest spinaches based on machine vision and electronic nose. *Journal of Food Safety*, 39(6): e12708.

Karaca, H., and Y. S. Velioglu. 2014. Effects of ozone treatments on microbial quality and some chemical properties of lettuce, spinach, and parsley. *Postharvest Biology and Technology*, 88: 46-53.

Keatinge, J. D., R. Y. Yang, J. D. Hughes, W. J. Easdown, and R. Holmer. 2011. The importance of vegetables in ensuring both food and nutritional security in attainment of the Millennium Development Goals. *Food Security*, 3(4): 491-501.

Kim, H., B. L. Drake, and H. Park. 2007. Multiclass classifiers based on dimension reduction with generalized LDA. *Pattern Recognition*, 40(11): 2939-2945.

Manninen, H., M. Paakki, A. Hopia, and R. Franzén. 2015. Measuring the green color of vegetables from digital images using image analysis. *LWT-Food Science and Technology*, 63(2): 1184-1190.

Minz, P. S., I. K. Sawhney, and C. S. Saini. 2018. Algorithm for automatic calibration of color vision system in foods. *Journal of Food Measurement and Characterization*, 12(3): 1787-1794.

Mohi-Alden, K., M. Omid, A. Rajabipour, B. Tajeddin, M. Soltani-Firouz. 2019. Quality and shelf-life prediction of cauliflower under modified atmosphere packaging by using artificial neural networks and image processing. *Computers and Electronics in Agriculture*, 163: 104861.

Omid, M. 2011. Design of an expert system for sorting pistachio nuts through decision tree and fuzzy logic classifier. *Expert Systems with Applications*, 38(4): 4339-4347.

Otsu, N. 1979. A threshold selection method from gray-level histograms. *IEEE Transactions on Systems, Man, and Cybernetics*, 9(1): 62-66.

Qiu, Y., Y. Zhao, J. Liu, and Y. Guo. 2017. A statistical analysis of the freshness of postharvest leafy vegetables with application of water based on chlorophyll fluorescence measurement. *Information Processing in Agriculture*, 4(4): 269-274.

Ouzounidou, G., K. K. Papadopoulou, M. Asfi, I. Mirtziou, and F. Gaitis. 2013. Efficacy of different chemicals on shelf life extension of parsley stored at two temperatures. *International Journal of Food Science and Technology*, 48(8): 1610-1617.

Saba, A., E. Moneta, M. Peparaio, F. Sinesio, M. Vassallo, and F. Paoletti. 2018. Towards a multi-dimensional concept of vegetable freshness from the consumer's perspective. *Food Quality and Preference*, 66: 1-12.

Sabzi, S., Y. Abbaspour-Gilandeh, and G. García-Mateos. 2018. A new approach for visual identification of orange varieties using neural networks and metaheuristic algorithms. *Information Processing in Agriculture*, 5(1): 162-172.

Simko, I., J. A. Jimenez-Berni, and R. T. Furbank. 2015. Detection of decay in fresh-cut lettuce using hyperspectral imaging and chlorophyll fluorescence imaging. *Postharvest Biology and Technology*, 106: 44-52.

USDA. 2007. United States Standards for Grades of Parsley. Available at: https://www.ams.usda.gov. Accessed date: 20 July 2007.

Wongpatikaseree, K., N. Hnoohom, and S. Yuenyong. 2018. Machine learning methods for assessing freshness in hydroponic produce. In *2018 International Joint Symposium on Artificial Intelligence and Natural Language Processing IEEE*, 1-4. Pattaya, Thailand, Date: 15-17 Nov. 2018.

Wu, D., and D. W. Sun. 2013. Colour measurements by computer vision for food quality control–A review. *Trends in Food Science and Technology*, 29(1): 5-20.

Yahia, E. M., P. García-Solís, and M. E. M. Celis. 2019. Contribution of fruits and vegetables to human nutrition and health. *In Postharvest Physiology and Biochemistry of Fruits and Vegetables*, Editor: Elhadi M. Yahia, 19-45. Cambridge, United Kingdom, Woodhead Publishing.

Zhang, B., W. Huang, J. Li, C. Zhao, S. Fan, J. Wu, and C. Liu. 2014. Principles, developments and applications of computer vision for external quality inspection of fruits and vegetables: A review. *Food Research International*, 62: 326-343.

Zhu, S., L. Feng, C. Zhang, Y. Bao, and Y. He. 2019. Identifying freshness of spinach leaves stored at different temperatures using hyperspectral imaging. *Foods*, 8(9): 356.