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A method for classifying oranges based on image processing and neural networks

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ABSTRACT

In recent days, there have been many recommendations on social media about eating healthy fruits to strengthen the immune system and corona resistance. Therefore, it is very important to identify spoiled fruits at this time when human society is concerned about coronavirus and the human body needs healthy fruits in case of this disease. This paper proposes a method to identify the type of defects found in oranges fruits. We used a machine vision system to capture sample images, which includes a charge-coupled device camera, black box, lighting system, and personal computer. The citrus fruits are classified into eight classes, including Wind scar, Stem-end breakdown, Snail bites, Thrips scar, Scale injury, Medfly, Rings, and Calyx, depending on the type and model of the defects. In the proposed method, classification by the neural network with the help of co-occurrence matrix for four angles θ=0°, 45°, 90°, and 135°, were extracted to identify various defects and 24 features related to the areas with defect in citrus. For the final classification of defects in citrus, after evaluating many classification tools from various tools available, Feed-forward Back Propagation Neural Network (FFBPNN) is used. The result of the neural network classifier was obtained with the help of the co-occurrence matrix by taking four angles (horizontal, right diagonal, vertical, and left diagonal) with an accuracy of 89.65%. The evaluation shows acceptable results compared with similar studies. It is a reliable method in the food classification industry with reasonable accuracy.

1. Introduction

Coronavirus created many problems for the human being in the real world, in general, and in business and economic areas, in particular. One of the problems is some fluctuation in demand for the purchase of products such as sour lemon, fresh ginger, orange, and garlic in the market. Many recommendations have been made on social media in recent days about the consumption of healthy fruits to strengthen the body's immune system and corona resistance. Opportunists have been abused to sell these products expensively. The main problem, here, is to identify the destructive fruits. Many systems have been developed for agricultural purposes and most systems are applied using non-destructive techniques not only for classification but also for determining fruit ripeness. However, many studies have focused on using a single method to identify fruit ripeness. Some commercial and scientific incentives usually make us tend to exploit computer vision systems and use a smart algorithm to have a mechanized system to classify fruits. One of the powerful tools for the applications of automatic inspection of fruits and vegetables is artificial vision systems. The aim of these applications is grading, estimating the quality of external parameters or internal features, and monitoring the processing of fruits and vegetables during production, processing, packaging, and labeling. Generally, an inspection of the external quality of fruits and vegetables is carried out concerning size, shape, color, texture, and defects manually. The manual process is very laborious, tedious, time-consuming, and expensive, and is easily affected by the environment (1). Therefore, the use of an automatic and intelligent system is inevitable for defect detection in fruit (2-5). Since consumers usually recognize

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fruit quality and taste from its appearance (6), fruit appearance is an important feature that can have a more effective role in fruit price and customer's choice. Lopez-Garcia et al. (8) offered a technique that information on texture and color are put into a principal component analysis (PCA) model to detect skin defects in four citrus cultivars. For this purpose, RGB values in every pixel and their neighborhood, in windows of 3×3 and 5×5, are used. The results show a success rate of around 91.5% in diagnosing individual defects, while the classification ratio of damaged/sound in the samples was 94.2%. In another research, a hyperspectral imaging system in the spectral range of 400 to 1000 nm has been provided to detect common defects in oranges (9). In this study, hyperspectral images of the samples were examined using PCA. The purpose was to select many wavelengths that can potentially be used in an online multi-spectral imaging area. Finally, using this method, a defect detection algorithm with an accuracy of 93.7% was obtained. However, the disadvantage of the proposed algorithm was a failure to detect the types of defects. Another similar work has been conducted to detect citrus rot caused by Penicillium fungus using machine-learning techniques (6). The proposed method, which uses a hyperspectral computer vision system, allows more functionality in differentiation. They have used decision trees and neural networks. Also, they have used the minimum redundancy maximal relevance (MRMR) method to reduce the number of input parameters for classification models. The accuracy of the proposed method was around 98%. Blasco et al. (10) provided a computing vision system with the ability to detect external features of apples, peaches, and citrus such as shape, size, as well as external defects. Then, this system can pick out them according to the preset rules. The system is not able to identify and separate defect types. In fact, the current commercial systems for fruit inspection are able to detect skin defects, based on machine vision. However, the automatic detection of any defect type remains a challenge. By identifying any type of defect separately, one can optimize the economic performance of fruit and take necessary measures to prevent the occurrence of such defects in the future (6). Another study aimed at developing a strong chemical method to verify the benefits of high-quality European organic orange juice (11). The metabolic fingerprint and volatile contour of commercial orange juice were performed using HS-SPME-GC-MS and HPLC-HR-MS. In order to validate and classify the purposes of orange juice, three different analyses, including principal components, hierarchical cluster, as well as partial least square, have been used, which provided reasonable and acceptable results. In this study, data aggregation strategies were experienced, and from the correlation of data at the intermediate level, an optimal model for classifying organic or conventional orange fruit juices with 100% sensitivity and specificity was obtained. In recent years, the use of machine vision systems for grading oranges can ensure that only good quality fruits are exported (12). This research provides an efficient orange grading system (defective and normal) based on color and texture characteristics. As part of the feature selection process, this research provides a packaging approach with a genetic algorithm to search and identify a subset of informative features for the classification problem. The selected features were exposed to three classifiers, including a support vector machine, the neural network of backpropagation, and auto-associative. The results show that the auto-associative neural network provides the highest accuracy of other classifiers. Another research focused on measuring antioxidant capacity with the aim of finding out a standard technique for the problem (13). In this research, Folin-Ciocalteu (F-C) and four other common tests (FRAP, ORAC, TEAC, CUPRAC) were used to measure antioxidant capacity for fruit-based beverages. In the samples examined, a total antioxidant power composite index was calculated by assigning each test equal weight so that the ranking of antioxidants could be performed. In addition, the research provides an assessment of the antioxidant potential of total phenolic beverages, anthocyanins, and ascorbic acid through principal component analysis. In the results, the authors recommend the use of F-C to compare the antioxidant power of fruit-based beverages. A study based on mango classification was performed using a combination method (14). This study combined the techniques of image processing and odor measurement in a particular system. The first technique, image processing, is applied using the color image, which is the HSV image color method, to determine the amount of fruit ripening based on the skin of the fruit by changing the color when ripe. The second technique, the odor measurement, is performed using an array of sensors to determine the rate at which the fruit arrives by changing the odor when the odor arrives. To create the dataset, mangoes of "Harumanis" and "Sala" were collected based on two different and unsuitable harvesting conditions, using image processing and an odor sensor. The support vector machine method is employed as a classifier for training and testing operations based on the information obtained from both techniques. The results show that the combined method offers a correct classification range of 94.69%. Another study proposed a method to identify and classify apple quality by image processing based on convolutional neural networks (15) that aims to accurately and quickly calibrate the quality of apples. The model captured specific, complex, and useful visual features for detection and classification. Compared to existing methods, the proposed model can better learn the high-order properties of two adjacent layers that are not in the same layer. Channels were highly relevant but the proposed model was trained and validated, with the best training and validation accuracy of 99 and 98.98% at the 2590th and 3000th steps, respectively. The overall accuracy of the proposed model tested using the independent 300 apple dataset was 95.33%. The results showed that the training accuracy, overall test accuracy and training time of the proposed model was better than the Google Inception v3 model and the traditional imaging method based on histogram-oriented gradient (HOG) were the characteristics of the gray level co-occurrences matrix (GLCM) and support vector machine (SVM). Defect detection on fruit skin usually requires an extensive and developed program capable of analyzing images of fruit. Due to its high differentiating ability, texture examination plays a significant role in identifying and classifying defects in the grading systems. According to the capability of the machine vision system considered in previous research, this study focuses on the assessment of the external quality of identifying defects on the orange and classifying them into eight classes of the defect. Since detecting stem and calyx ends is important in fruits (as stem and calyx should not be confused with other defects), in this paper, in addition to detection and classification of the defect type, we have also identified calyx. The structure of the remaining sections is as follows: Section 2 presents the related works on the matter. In section 3, the material and method are presented. In section 4, we provide the results and discussion. Finally, section 5 is considered for the summary and conclusion.

2. Materials and methods

2.1. Machine Vision System

In this section, the material and methods are explained. At first, the overall system with a machine vision is described. Then, the stages of preparing the data set, calculating the co-occurrence matrix, extracting the features, and classification are expressed. We used a machine vision system to capture sample images (Fig.1). The proposed system contains a Charge-Coupled Device (CCD) camera (Sony XC-003P with 768 × 576-pixel resolutions), black box, lighting system, and personal computer. The camera was placed at about 300 mm above the background surface and nourished by a 24 V power supply. As shown in Fig. 1, the lighting system consists of three fluorescent lamps that are situated on the top, right, and left sides of the black box to provide uniform illumination and be free from the shadow images of fruits.

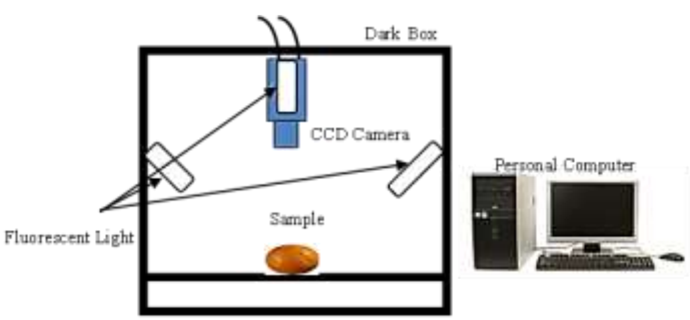

Fig. 1. A schematic of the machine vision.

The light source and camera were mounted on a frame. In order to obtain images from the defected area of the orange, fruits were manually rotated so that the defective part is covered 100%. The images of fruits were captured by a camera, moved to the personal computer through the USB cable, digitized, and put into the storage of the computer for further analysis. To detect defects of oranges in practice, a personal computer system with a central processor (Intel Core i5 4200U 1.60GHz up to 2.60 GHz), Memory RAM (4 GB - type DDR3), a graphics processor (AMD RADEON HD 6470M) along with MATLAB programming software were used.

2.2. Preparing the data set

In the first stage, a data set of 550 oranges with external defects was analyzed in the laboratory within two months. By taking into account the defects on the skin of the fruit, the image was taken so that the entire surface defects were covered. According to experts' discretion, among 550 data, 290 were approved, classified, and labeled according to the type of defect. This data formed the training data for the classification step. As there is no well-established criterion for classifying defects in citrus, this study was conducted only on the seven most common types of defects found in citrus along with calyx. The defect identified for the current work is shown in Fig. 2. To remove the background of the images and increase continuity between pixels, the Global thresholding method and morphology operator were used, respectively. Then the information related to the continuous components was extracted from the images. The area of the largest object was found, and cutting operation on the original image as large as the area determined was done. In fact, by doing so, fruit images were cropped from the background, and subsequent operations were performed on the cropped image.

2.3. Calculating co-occurrence matrix

The texture is the most significant quality feature frequently used in grading and inspection systems of external quality to assess the quality of agricultural products that can play an important role in image segmentation (1). This study used the co-occurrence matrix method to extract texture features. For the first time, Haralick et al. (16) proposed this method to study different texture structures. In gray-level co-occurrence matrix (GLCM) not only the intensity distribution of pixels but also the position of the pixels is considered. Since the co-occurrence matrix works on gray images, in the first step, digital images should be converted to gray images (16). Three parameters are considered to describe an image through GLCM (1- the number of gray levels, 2-orientation angles, and 3-displacement length). The number of gray levels is an important element in calculating the co-occurrence matrix because more levels provide more accurate texture information. However, with this increase, the computational cost may increase. To form the co-occurrence matrix, 64 gray levels were considered with orientation angle at four levels (θ = 0°, 45°, 90°, 135°), and displacement length as the value 2. These parameters can be changed to improve the features. The flowchart of the proposed defect detection method is shown in Fig. 3. The following steps must be achieved in the process:

- Step 1-Categorizing: the database input from 290 color images is categorized into eight categories from citrus defects.
- Step 2-Pre-processing: the pre-processing of the data is consisting of (a): Sorting and categorizing folders by name

and labeling; (b): Calling the “crop image” function to remove the background and (c): Improving the histogram using “adapthisteq” command.

- Step 3-Determining parameters: determine d and θ values and create a co-occurrence matrix.
- Step 4-Extracting: (a): extract the statistical features of the co-occurrence matrix, (b): Extract the Feature of Self-image.
- Step 5-Distributing: The 290 samples are distributed randomly with a ratio of 70 to 30 between the training set and test set.
- Step 6-Training: The training set is sent to the feed-forward back propagation neural network for training-the bias/weight of the neural network is adjusted through MSE.
- Step 7-Evaluating: The test dataset is used to evaluate the learning classifier's performance. And finally, the confusion matrix and classifier output are calculated.

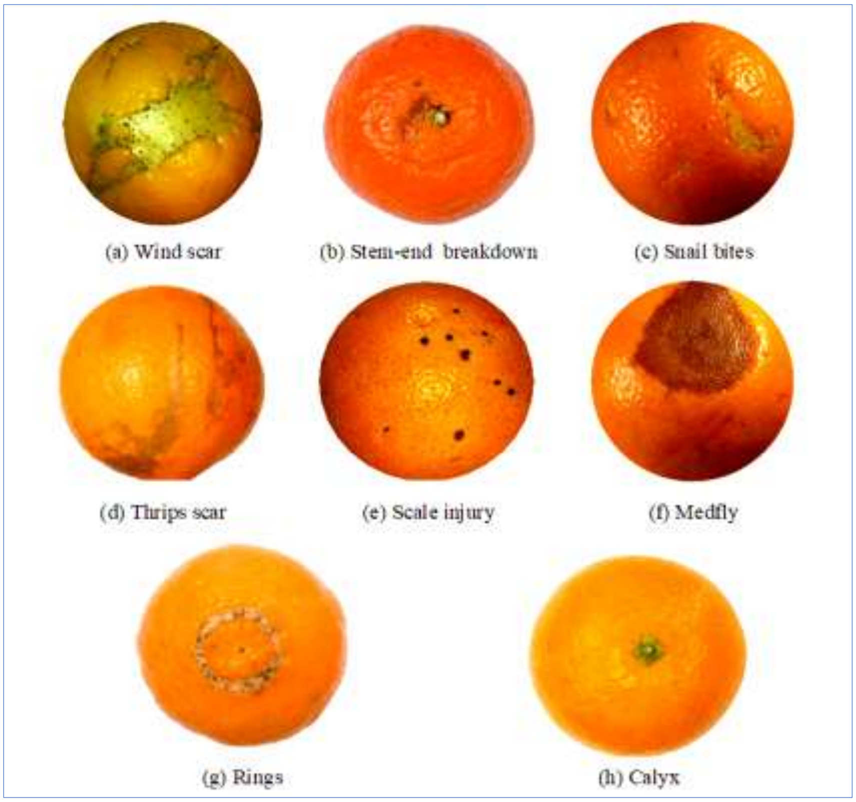

Fig. 2. Different samples from the analyzed defect groups.

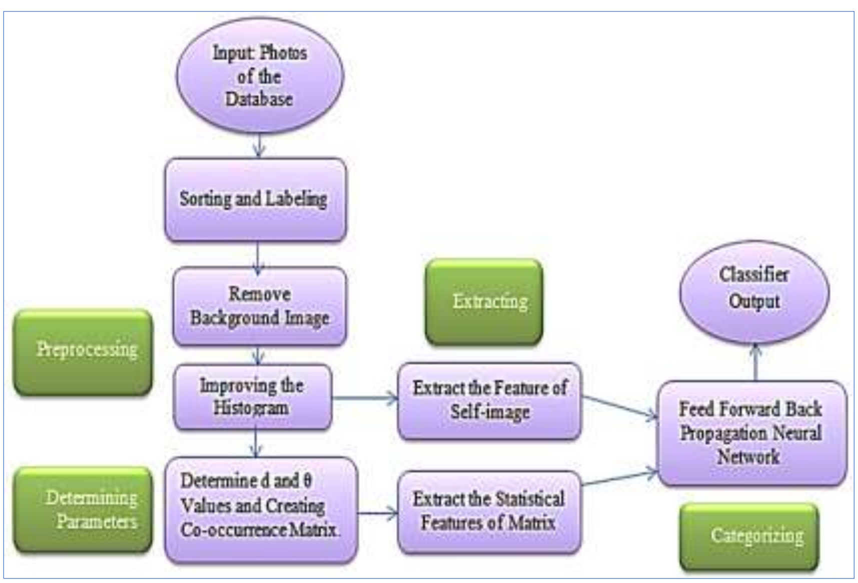

Fig. 3. Flowchart of the proposed method for identifying defects in orange fruits.

2.4. Extracting the features

After calculating the co-occurrence matrix, statistical measures begin mining the properties of the matrix. The next step is to determine the tissue features. The tissue features image appears indirectly using a co-occurrence matrix. GLCM is only a tool to start extracting the tissue properties. After creating a co-occurrence matrix, 13 indicators defined by Haralick et al. (17) in Table 1 along with eight indicators defined by (18) in Table 2 are calculated to extract features of tissue from this matrix. Moreover, to improve the result of classification, in addition to the features defined in Tables 1 and 2, features associated with contrast, solidarity, and homogeneity were extracted directly from the image itself.

Table 1. Thirteen features are defined in Haralick's theory (16) to extract texture features.

Feature	Description	Equation
1	Energy	$f_1=\sum_i\sum_j p(i,j)^2$
2	Contrast	$f_2=\sum_{n=0}^{N_g-1} n^2\left\{\sum_{i=1}^{N_g}\sum_{\substack{j=1\\ \lvert i-j\rvert=n}}^{N_g} p(i,j)\right\}$
3	Correlation	$f_3=\dfrac{\sum_i\sum_j (ij)\,p(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y}$
4	Entropy	$f_4=-\sum_i\sum_j p(i,j)\log(p(i,j))$
5	Inverse Difference Moment	$f_5=\sum_i\sum_j \dfrac{p(i,j)}{\lvert i-j\rvert^k}, i\neq j, k=1,2$
6	Sum Average	$f_6=\sum_{i=2}^{2N_g} i\ \mathrm{p}_{x+y}(i)$
7	Sum Variance	$f_7=\sum_{i=2}^{2N_g}(i-f_8)^2 p_{x+y}(i)$
8	Sum Entropy	$f_8=-\sum_{i=2}^{2N_g} p_{x+y}(i)\log\{p_{x+y}(i)\}$
9	Difference Variance	$f_9=\text{variance of }\mathrm{p}_{x-y}$
10	Difference Entropy	$f_{10}=-\sum_{i=0}^{N_{g-1}} p_{x-y}(i)\log\{p_{x-y}(i)\}$
11	Sum of Square: Variance	$f_{11}=\sum_i\sum_j (i-\mu)^2 p(i,j)$
12,13	Information Measures of Correlation	$f_{12}=\dfrac{HXY-HXY1}{\max\{HX,HY\}}$ $f_{13}=(1-\exp[-2.0(HXY2-HXY)])^{1/2}$ $HXY=-\sum_i\sum_j p(i,j)\log(p(i,j))$ where HX and HY are entropies of p_x and p_y, and $HXY1=-\sum_i\sum_j p(i,j)\log\{p_x(i)p_y(j)\}$ $HXY2=-\sum_i\sum_j p_x(i)p_y(j)\log\{p_x(i)p_y(j)\}$

Table 2. Eight parameters were defined by Soh et al. (18) to extract texture features from the co-occurrence matrix.

Feature	Description	Equation
1	Homogeneity	$f_1 = \sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j)$
2	Autocorrelation	$f_2 = \sum_i \sum_j (ij)\, p(i,j)$
3	Dissimilarity	$f_3 = \sum_i \sum_j \lvert i-j \rvert . p(i,j)$
4	Cluster Shade:	$f_4 = \sum \sum (i+j-\mu_x-\mu_y)^3\, p(i,j)$
5	Cluster Prominence:	$f_5 = \sum_i \sum_j (i+j-\mu_x-\mu_y)^4\, p(i,j)$
6	Maximum Probability	$f_6 = \underset{i,j}{MAX} \quad p(i,j)$
7	Inverse Difference	$f_7 = \sum_i \sum_j \frac{P_{ij}}{1+(i-j)}$
8	Inertia	$f_8 = \sum_{i=1}^{n} \sum_{j=1}^{m} (i-j)^2\, p_{ij}$

2.5. Classification

The Feed-forward Back Propagation Neural Network (FFBPNN) with four layers was used to classify defects in citrus. It was composed of one input layer, two intermediate layers (hidden), and an output layer. The number of neurons of the first and second intermediate layers was selected as 50 and 30, respectively, by the trial-and-error method. The number of neurons of the output layer is eight which represents seven types of defects along with calyx in a fruit. In Fig. 4, an example of a feed-forward network with two hidden layers is shown.

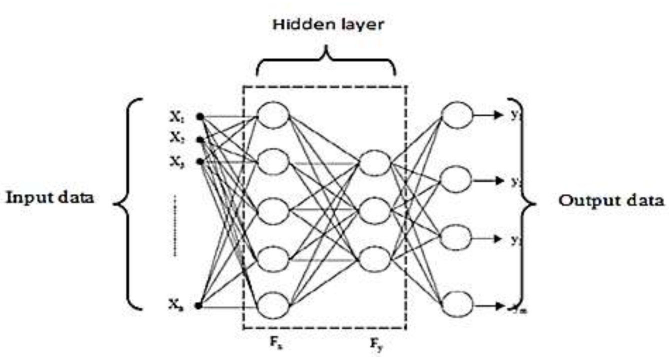

Fig. 4. Feed-forward network with two hidden layer structures.

In the network shown in Fig. 4, every neuron in a layer receives information from the neurons of the previous layer and then sends it out to the next layer neurons after processing. In this particular network, variable X represents the input data vector, variable Y represents the output data vector, and operator F is the function that processes the data (19). This network is expected to determine the defect classification of orange when presented with a sample of defect ranges.

3. Results and discussion

The study started with 290 samples for classifying the seven most common types of defects found in citrus along with calyx. Table 3 shows the test results of classifying different types of defects along with calyx. The first column shows the models of orange defects along with calyx, discussed in Section 3. The second column shows the percentage of correct diagnoses for each defect model.

Table 3. Rate of correct detection of each defect type in all samples.

Defect Type	Correct Detection
(a) Wind scar	95.95%
(b) Stem-end breakdown	100%
(c) Snail bites	92.50%
(d) Thrips scar	84.78%
(e) Scale injury	76.47%
(f) Medfly	92.31%
(g) Rings	77.78%
(h) Calyx	87.88%

The method proposed in the study (classification with feed-forward back-propagation neural network-FFBPNN) with the help of a co-occurrence matrix was compared with two classification methods mainly used in previous research (20). The first comparison method is based on distance. In distance-based classifications, two different methods are used: Nearest Neighbor (NN) and K-Nearest Neighbor (K-NN). Table 4 illustrates the results of the comparison of the proposed method with the mentioned methods. The column indicates the defect type in orange. The row shows the classifier used to detect defects. Each cell shows the rate of correct diagnosis. Relying on Table 4, one can conclude that the precision of the proposed method, in comparison with the nearest neighbor classifier, in all classes of defects, is very reasonable and acceptable. For example, the precision of the proposed method for the classes (a) and (c) is, in order from left to right, 95.95% and 92.50%, whereas the precision of the Nearest Neighbor classifier for the classes mentioned is 65.7% and 58.8%. Moreover, we compared the precision of the proposed method with K- Nearest Neighbor and concluded that in all classes, except for classes (c and d), the proposed method has high and good precision with precision (92.50% and 84.78%) compared with precision obtained by K-Nearest Neighbor for the same classes (94.1% and 92.8%). The most popular method for classifying infected oranges in the previous research was proposed by (20). This research was used in the recent comparisons (21-23) and identified eight infected classes including Wind scar, Stem-end breakdown, Snail bites, Thrips scar, Scale injury, Medfly, Rings, and Calyx (See Fig. 2). Hence, we compared the proposed method with the classification method based on neural networks used by (20) to classify citrus. To do so, the researchers used five features (mean, variance, range, kurtosis, skewness) as the features extracted from the image to classify fruit. Table 5 shows the results of comparing the proposed method with the mentioned method. According to the table, it can be concluded that the precision of the proposed method in all defects classes, except for class (c) with precision (92.50%), is acceptable and significant compared to the method used by (20).

Table 4. The result of the proposed method - (FFBPNN with the help of the co-occurrence matrix) and comparisons with two classification methods- Nearest Neighbor (NN) and K- Nearest Neighbor (K-NN).

Methods	(a) Wind scar	(b) Stem-end breakdown	(c) Snail bites	(d) Thrips scar	(e) Scale injury	(f) Medfly	(g) Rings	(h) Calyx
Nearest Neighbor (NN)	65.7	100	58.8	70.1	67.3	72.4	52.3	59.9
K-Nearest Neighbor (K-NN)	88.8	100	94.1	92.8	<50	85.1	74.3	67
FFBPNN with the co-occurrence matrix (Proposed Method)	95.95	100	92.50	84.78	76.47	92.31	77.78	87.88

Table 5. The precision of the classification obtained from the proposed method (FFBPNN) with the help of the co-occurrence matrix and the neural network classification method used by (20) (eight classes of infected oranges).

Methods	(a) Wind scar	(b) Stem-end breakdown	(c) Snail bites	(d) Thrips scar	(e) Scale injury	(f) Medfly	(g) Rings	(h) Calyx
NNET of MATLAB Toolbox [Used by (20)]	65.7	100	58.8	70.1	67.3	72.4	52.3	59.9
FFBPNN with the co-occurrence matrix (Proposed Method)	88.8	100	94.1	92.8	<50	85.1	74.3	67

4. Conclusion

One of the challenges in the post-harvest operation of oranges is the effective determination of skin defects, meaning the classification of fruits depending on their outside appearance. The color, size, shape, and texture are important parameters of grading that dictate the quality and value of many fruit products. In this study, a method of classification and detection of defects according to fruit skin of orange based on image processing was proposed. In the proposed method, classification with the neural network with the help of co-occurrence matrix for four angles θ=0°, 45°, 90°, and 135°, were extracted to identify various defects, 24 features related to the areas with a defect in citrus. The co-occurrence matrix is used to obtain features. For the final classification of defects in orange, neural networks were used. Finally, the result of the neural network classifier was obtained with the help of the co-occurrence matrix by taking four angles (horizontal, right diagonal, vertical, and left diagonal) with an accuracy of 89.65% that can be a reliable method in the food classification industry with acceptable accuracy.

References

1. Zhang B, Huang W, Li J, Zhao C, Fan SH, Wu J, Liu CH. Principles, developments and applications of computer vision for external quality inspection of fruits and vegetables: A review. *Science Direct on Food Research International*. 2014;62(1):326-43.
2. Zhao JW, Ouyang Q, Chen QS, Wang JH. Detection of bruise on pear by hyperspectral imaging sensor with different classification algorithms. *Sensor Letters*. 2010;8(4):570-6.

3. Baranowski P, Mazurek W, Wozniak J, Majewska U. Detection of early bruises in apples using hyperspectral data and thermal imaging. *Journal of Food Engineering.* 2012;110(3):345-55.
4. Haff RP, Saranwong S, Thanapase W, Janhiran A, Kasemsumran S, Kawano S. Automatic image analysis and spot classification for detection of fruit fly infestation in hyperspectral images of mangoes. *Postharvest Biology and Technology*. 2013;86, 23-8.
5. Hu MH, Dong QL, Liu BL, Malakar PK. The potential of double K-means clustering for banana image segmentation. *Journal of Food Process Engineering*. 2014;37(1):10-8.
6. Blasco J, Aleixos N, Gomez-Sanch J, Molto E. Recognition and classification of external skin damage in citrus fruits using multispectral data and morphological feature. *Biosystems Engineering*. 2009;103(2):137-45.
7. Gomez-Sanchis J, Martin-Guerrero JD, Soria-Olivas E, Martinez-Sober M, Magdalena-Benedito R., Blasco J. Detecting rottenness caused by Penicillium genus fungi in citrus fruits using machine learning techniques. *Expert Systems with Applications*. 2012;39(1):780-5.
8. Lopez-Garcia F, Andreu-Garcia G, Blasco J, Aleixos N, Valiente JM. Automatic detection of skin defects in citrus fruits using a multivariate image analysis approach. *Computers and Electronics in Agriculture*. 2010;71(2):189-97.
9. Li JB, Rao X, Ying YB. Detection of common defects on oranges using hyperspectral reflectance imaging, *Computers and Electronics in Agriculture*. 2011;78(1):38-48.
10. Blasco J, Aleixos N, Molto E. Machine vision system for automatic quality grading of fruit. *Biosystems Engineering*. 2003;85(4):415-23.
11. Cuevas FJ, Pereira-Caro G, Moreno-Rojas JM, Muñoz-Redondo JM, Ruiz-Moreno MJ. Assessment of premium organic orange juices authenticity using HPLC-HR-MS and HS-SPME-GC-MS combining data fusion and chemometrics. *Food Control*. 2017;82,203-11.
12. Thendral R, Suhasini A. Automated skin defect identification system for orange fruit grading based on genetic algorithm. *Current Science*. 2017;112(8):1704-11.
13. López-Froilán R, Hernández-Ledesma B, Cámara M, Pérez-Rodríguez ML. Evaluation of the antioxidant potential of mixed fruit-based beverages: A new insight on the Folin-Ciocalteu method. *Food Analytical Methods.* 2018;11(10):2897-906.
14. Mavi MF, Husin Z, Badlishah AR, Farook RSM, Tan WK. Mango ripeness classification system using hybrid technique. *Indonesian Journal of Electrical Engineering and Computer Science*. 2019;14(2):859-68.
15. Li Y, Feng X, Liu Y, Han X. Apple quality identification and classification by image processing based on convolutional neural networks. *Scientific Report*. 2021;11,16618.
16. Renzetti FR, Zortea L. Use of a gray level co-occurrence matrix to characterize duplex stainless steel phases microstructure. *Fratturaed Integrità Strutturale*. 2011;16(1):43-51.
17. Haralick RM, Shanmugam K, Dinstein IH. Textural features for image classification. *IEEE Transactions on Systems, Man and Cybernetics*. 1973;6,610-21.
18. Soh LK, Tsatsoulis C. Texture analysis of SAR sea ice imagery using gray level co-occurrence matrices. *IEEE Transactions On geoscience and Remote Sensing*. 1999;37(2):780-2.
19. Ileana I, Rotar C, Incze A. The Optimization of feed-forward neural networks structure using genetic algorithms. International Conference on Theory and applications of Mathematics and Informatics, Thessaloniki, Greece. 2004. pp. 223-4.
20. Lopez J, Cobos M, Aguilera E. Computer-based detection and classification of flaws in citrus fruits. *Science Direct Neural Compute & Applic*, 2011;975-81.
21. Kasinathan T, Uyyala SR. Machine learning ensemble with image processing for pest identification and classification in field crops. *Neural Computing and Applications.* 2021;33,7491-504.
22. Mohamed AR, El Masry GM, Radwan SA, ElGamal RA. Development of a real-time machine vision prototype to detect external defects in some agricultural products. *Journal of Soil Sciences and Agricultural Engineering*. 2021;12(5):317-25.
23. Behera SK, Rath AK, Sethy PK. Fruit recognition using support vector machine based on deep features. *Karbala International Journal of Modern Science*. 2020;6(2):1-13.