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Non-invasive analysis with dynamic infrared thermography to calculate dry matter in Hass avocado via neural networks

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Abstract

By using dynamic infrared thermography was possible to obtain the percentage of dry matter in Hass avocado fruits. Two groups were worked on the fruits, one of them was stimulated with a high-power laser and the other one with halogen lamps. Were acquired more than 17000 images during the cooling stage in 300 fruits. An algorithm constructed previously in Matlab allowed segmenting the registered images in order to extract statistical characteristics with which a neural network model was trained to quantify the dry matter.

1. Introduction

The technological advances in the last twenty years, both in the functionality of the thermographic cameras, as well as in the best performance of computer equipment and information processing techniques, have been enhancing the multiple applications of infrared thermography (IRT), making it a valuable tool for the non-destructive study of fruits and vegetables [1]. In particular, IRT technique has been used to characterize the mechanical damage produced in fruits [2] such as apples, pears, and blueberries, allowing identifying, for example, the number of soluble solids and water losses that occur during the freezing process of potatoes [3].

Thermographic images are data matrices in which each temperature value corresponds to a pixel, according to radiation emitted by a material which depends on its thermal properties. Therefore, if a fruit or a vegetable is thermally stimulated, without affecting its maturity, the quantification of the rate of cooling or heating could be directly related to these properties; making the dynamic infrared thermography (DIRT) technique an adequate tool to studying the behavior of these thermal effects [4].

Hass avocado is a climacteric fruit and therefore it does not ripen on the tree, so two types of ripening are identified: harvest ripening and consumption ripening. The process of collecting this fruit is determined taking into account the harvest maturity, which has been usually determined through a destructive test of dry matter which must be above 18%, the higher the dry matter the higher the oil content, and therefore the better palatability [5].

Villaseñor et al. have proposed the use of IRT for the measurement of the dynamic emissivity of the Hass avocado, establishing that the dynamic emissivity of the peel is related to the ripening process of the fruits and, in turn, to their oil content and dried matter content [6].

2. Methodology

The experimental process was developed in two groups, A and B. Group A corresponded to 157 fruits acquired in market centers, and group B corresponded to 143 fruits from a collection center. For group A, the fruits were exposed to a NdYAg laser, with a wavelength of 900 nm and a power of 100 mW for a short time of 4.5 minutes, and then a Fluke TI 300 thermographic camera was used with the goal to acquire images during the cooling process during 5 minutes (100 images for each fruit). On the other hand, for group B, a pair of halogen lamps of 500 W each was used, stimulating the fruits for a lapse of one minute, and posteriorly, using the same camera, were registered images during the cooling process. Every three seconds for a period of 45 seconds were captured images, for a total of 12 images per fruit, for B group.

After acquiring the images in both groups, a destructive dry matter test was performed, and these data were used for training and validation of the implemented algorithms. Algorithms for segmentation and noise removal in each of the images were built, during preprocessing phase. Then, group A images underwent continuous wavelets decomposition using different mother wavelets, and levels decomposition of 128 (with steps of 1.0 and 0.5), and 256 (with a step of 1.0) were considered. Subsequently, the coefficients and scalograms were taken and correlated with those of the other fruits; the highest correlations were associated with similar percentages of dry matter.

3. Results

The results in group A showed that for the scale of 128 with steps one by one, the best result was obtained using rbior1.3 as the mother wavelets with an effectiveness of 70.7% (table 1.a). For the 128 scale with steps of 0.5 the best results are obtained with the same mother wavelets and the same effectiveness (table 1.b) and for the 256 scale, the best results correspond to the gauss1 mother wavelets with an effectiveness of 70 .1% (table 1.c).

Wavelet	Coefficient	Scalogram	Mean
Haar	66,2	65,0	68,8
Db4	65,6	65,6	68,8
Db5	65,0	65,6	67,5
Db9	66,9	66,2	67,5
Db11	68,8	65,0	67,5
Sym1	66,2	65,0	68,8
Bior 1,1	65,5	65,0	69,4
Bior 1,3	64,3	65,0	67,5
Rbior 1,1	66,2	65,0	68,8
Rbior 1,3	65,6	64,3	70,7
Rbior 1,5	65,6	65,6	67,5
gauss1	65,0	64,3	68,8

Coefficient	Scalogram	Mean
66,2	65,0	68,8
65,6	66,2	69,4
65,0	65,6	68,2
66,9	65,0	66,9
68,8	65,0	67,5
66,2	65,0	68,8
65,0	65,0	69,4
64,3	65,0	67,5
66,2	65,0	68,8
65,6	64,3	70,7
65,6	65,6	67,5
64,3	64,3	68,2

Coefficient	Scalogram	Mean
65,6	65,6	67,5
64,3	65,0	66,2
65,6	65,6	68,2
65,0	65,0	66,9
65,0	64,3	69,4
65,0	65,6	68,2
65,6	66,2	68,2
65,6	66,2	68,2
65,6	66,9	68,2
65,6	68,2	68,8
65,6	64,3	70,1

Table 1. general results considering the application of differents wavelets and respective levels. The mean value correspond to the mean dry matter obtained with the algorithm .1(a) to level 128 with one to one step. 1(b) to level 128 with step of 0,5. 1(c) to level 256 with one to one step.

A Cascade Forward Network was trained through the Matlab function "newcf", using 100 hidden layers, a cross-validation of 70% of the data to train, and 30% to validate. The set of characteristics to make the training were extracted with group B. A Gaussian-type noise elimination filter with mean 0 and standard deviation of 2 was applied to the images, and the best training yielded an efficiency of 80.9%, a general determination coefficient of 0.82, and an average absolute error of 2.78% dry matter level.

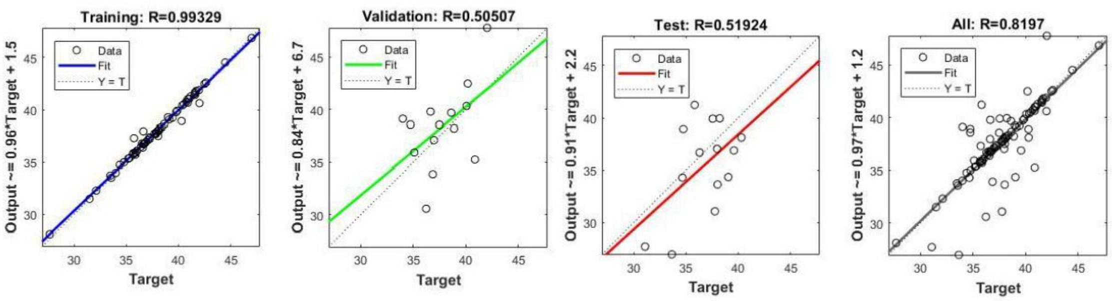

Figure 1. Neural network training result using halogen lamps for Hass avocado.

4. Conclusion

To the set of fruits stimulated by halogen lamps, the use of regression neural networks present better results than the correlation method used in the set of fruits stimulated by laser, showing that the use of machine learning considerably improves the results, increases the level of confidence in the algorithms and decreases the time of calculation.

REFERENCES

[1] P. Osinenko et al., “Application of non-destructive sensors and big data analysis to predict physiological storage disorders and fruit firmness in ‘Braeburn’ apples,” Comput. Electron. Agric., vol. 183, no. January, 2021, doi: 10.1016/j.compag.2021.106015.
[2] J. Kuzy, Y. Jiang y C. Li, «Blueberry bruise detection by pulsed thermographic imaging,» Postharvest Biology and Technology, vol. 136, pp. 166-177, 2018.
[3] L. Cuibus, M. Castro-Giráldez, P. J. Fito, and A. Fabbri, “Application of infrared thermography and dielectric spectroscopy for controlling freezing process of raw potato,” Innov. Food Sci. Emerg. Technol., vol. 24, pp. 80–87, 2014.
[4] T. A. E. da Silva, L. F. da Silva, D. C. Muchaluat-Saade, and A. Conci, “A computational method to assist the diagnosis of breast disease using dynamic thermography,” Sensors (Switzerland), vol. 20, no. 14, pp. 1–21, 2020, doi: 10.3390/s20143866.
[5] M. G. Solís, “Manual de cultivo, buenas prácticas de cultivo variedad Hass.” 2011.
[6] C. Villaseñor-Mora, P. Martínez-Torres, A. Gonzalez-Vega, G. Espinosa, S. E. Borjas-García, and V. H. Hernandez, “Correlation of post-harvest avocado ripening process with the thermal emissivity measured from the peel,” Appl. Eng. Agric., vol. 33, no. 2, pp. 267–272, 2017, doi: 10.13031/aea.11768.