International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 16 (2018) pp. 12846-12853

Quality control system by means of CNN and fuzzy systems

Carlos Javier Enciso-Aragón
Mechatronic Engineer, Department of Mechatronics Engineering, Militar Nueva Granada University Bogotá, Colombia.

César Giovany Pachón-Suescún
Assistant Research, Department of Mechatronics Engineering, Militar Nueva Granada University Bogotá, Colombia.

Robinson Jimenez-Moreno
Professor, Department of Mechatronics Engineering, Militar Nueva Granada University
Bogotá, Colombia.

Abstract

Quality inspection processes in typical crop collection centers are carried out by operators, people who, during the course of the day due to fatigue, personal problems or illness, diverge from the concept of quality of a product. Derived from this reality, a fruit-oriented automatic quality inspection system is proposed, based on artificial intelligence algorithms using convolutional neural networks (CNN) and a fuzzy motor, that evaluate a series of physical aspects of vital importance to determine the quality of a Persian lemon, in order to minimize the factors of lack of objectivity that can cause an operator to diverge from criteria for the selection of the same type of fruit. The CNN trained through transfer learning obtained a 97.5% efficiency in the validation of characteristics, the methods proposed for the characterization process worked correctly, presenting problems only in the identification of defects generated by the ambient lighting. The proposed fuzzy system consistently classified each of the lemons studied in the three proposed ranges, according to the characteristics and rules established for the evaluation of these, according to quality standards.

Keywords. Quality, CNN, Transfer learning, Fuzzy logic.

INTRODUCTION

The design of systems for automatic quality processes in industry is focused on the extraction of characteristics and classification by means of machine vision systems and artificial intelligence algorithms, oriented to some type of product of interest, allowing the quality control of it, these designs currently take a great importance in industrial production processes [1-3]. Because quality inspection is now largely carried out by workers who in the course of the day, due to different situations such as work fatigue or stress, diverge their concept in relation to the quality of a product, the need arises to develop software tools and/or hardware that identify the quality of the products that are being offered, ensuring that they are reliable and suitable for the consumer.

Currently, different projects related to the field of agriculture have been proposed in this area, using image recognition and the application of different types of neural networks, with the disadvantage that it is not possible to determine the state of maturity of the fruit or detect defects in the surface that allow inferring whether the product is in good condition or not [4, 5]. In Colombia, projects of this type have been carried out using artificial vision systems such as those mentioned in [6, 7], It is also clear that, although there is an algorithm for the classification of fruits, it is still not possible to present a complete solution to the problem, since currently it is not possible to measure with patterns the aroma, texture of the pulp, hardness, the content of internal defects and the amount of sugar present in these fruits [8]. Although algorithms for extracting characteristics by machine vision usually leave these variables unidentified, they have been efficiently implemented in various industrial processes, including agriculture [9].

For this reason, the initiative to design an algorithm that allows initially identify the quality of Persian lemons that are currently available to a greater degree for consumers in Latin America, in addition to being qualified as the main global market in the period of 2011-2015 [10]. At the same time, it was sought to develop a software capable of evaluating the quality of a lemon, determining its physical state by means of a convolutional neural network (CNN), given the qualities with which they have respect to other types of existing techniques, as shown in [11]. Afterwards, the physical characteristics are extracted by means of image processing and sensory, to finally evaluate the quality by means of a fuzzy logic system that allows to classify in a parameterized way each fruit according to a weighting among the different extracted characteristics (Equatorial diameter, percentage of superficial defects and weight).

The Mexican standard NMX-FF-077-1996 [12] is chosen as a reference for this first development, which focuses on the classification of the product individually, where the classification parameters to be evaluated are established (see Table. 1).

Table 1. Classification by diameter [11].

Size Code	Diameter range (mm)	Average Interval (mm)
1	58-67	62.5
2	53-62	57.5
3	48-57	52.5
4	46-52	49.0
5	43-46	44.5
6	38-43	40.5

Based on the established size codes, it was determined to divide into three quality classes the lemons evaluated: low, medium and high, in which the parameters of weight and percentage of damage to the surface of the lemon are made, although they are not standards that are contemplated in the norm, they are sensory indications of the people to assess the quality of a product of this type. This type of classification is the approach that is given to fuzzy systems, not only taking into account the parameters determined by the standard, but also the experience and reasoning processes of the people who would normally perform those tasks [13, 14]. Next, the methods and materials used are presented, later the results obtained are analyzed and finally the conclusions obtained related to the general functioning of the algorithm.

MATERIALS AND METHODS

This article presents the structure of a software which is composed of three main parts, where the first is a convolutional neuronal network (CNN) responsible for determining which lemon is suitable for consumption and which is not, this consists of four stages which are the taking of the database, the adaptation of the architecture, the training process and the verification using test images. The second part is focused on extracting the necessary characteristics to determine the quality of the fruit that is being evaluated, making use of image processing to define the damaged area of the surface and the size of the lemon, and using sensory to determine its weight. Finally, the third part classifies each lemon according to the parameters extracted using a fuzzy system. Figure 1 illustrates the overall operation of the algorithm and what sequence is followed to establish a quality criterion. Additionally, it is necessary to point out the importance of this type of development, since initially this project is aimed at quality inspection of Persian lemons, but likewise this algorithm can be applied to any fruit that has quality standards for its sale.

In the first place, for the CNN evaluation of the input image, an architecture known as "Alexnet" [15] was used, which is widely recognized in the scientific field due to its depth and the great number of categories it uses [16, 17], which was adapted to the needs that are had for the development of this algorithm, through the scheme known as Transfer Learning. The modifications that were made in the architecture are focused on the layer called Final Fully Connected, which was originally made up of 1000 categories, but in this case, for the development of this application only 2 categories need to be recognized, Fresh or Spoiled (see Table. 2), to be able to determine which lemons are suitable for consumption and which are not. This seeks to optimize the final classification process, since discriminating from the beginning the lemons that are not suitable for consumption, will allow processing less unnecessary data and these will be focused only on the lemons that will finally be marketed.

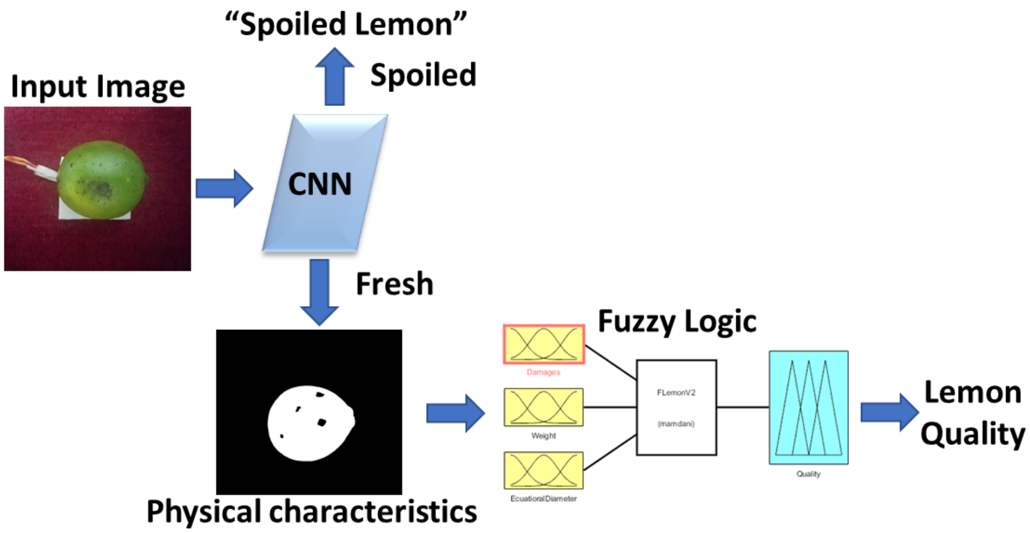

Figure 1. General scheme of the algorithm.

Table 2. Modified Alexnet architecture.

Layer	Kernel	Filters
Input	227x227x3	-
Convolution	11x11 S=4 P=0	96
Maxpooling	3x3 S=2 P=0	-
Convolution	5X5 S=1 P=2	256
Maxpooling	3X3 S=2 P=0	-
Convolution	3X3 S=1 P=1	384
Convolution	3x3 S=1 P=1	384
Convolution	3x3 S=1 P=1	256
Maxpooling	3x3 S=2 P=0	-
Fully-Connected	1	4096
Fully-Connected	1	4096
Final Fully-Connected	1	2
Softmax	-	-

The database collected for training the neural network has a total of 320 images, of which half correspond to lemons in good condition and the other half are not suitable for consumption according to established standards. Finally it was defined that, of the 160 images of each category, 110 would be selected in a random way for the training, this in order to avoid that during the training of the CNN there is a bias towards only one of the categories, in this same way, 30 images were assigned to the network test, which will help to check the trained CNN and finally the remaining 20 images were assigned to the validation process to avoid overfitting of the network.

The Training Learning Rate value was adjusted to 0.001 so that the weights will not vary drastically, for the Batch size, the total number of images is divided into 5 to define its size, therefore this value is defined as 44, in this way it is avoided to overuse the GPU, there were use 30 epochs to perform the training of the CNN, this value is chosen from training tests being sufficient for this particular case and to validated the network during the training, since the overall process has 150 iterations, 5 validations where done, which is why every 30 iterations will be checked to avoid the overfitting of the network. In the results section it can be observed the behavior of the training with the previously set parameters.

It was continued with the second stage of the algorithm, focused only on lemons that can be marketed and consumed thanks to the results of the previous stage. The measurement of the physical parameters of the lemon can be summarized in the flowchart shown in Figure 2, where, in the first place, an image treatment is performed to identify the lemon within the work area. For this, a filter based on the HSV color format was used, since it is robust to changes in lighting compared to other color spaces and its chromatic organization is similar to that of the human eye [18, 19], facilitating the configuration of the filter, in which the ranges of 0.125-0.399 were defined for H, 0.2-1 for S and 0-1 for V. Once the binarized image is generated, an area filter is applied to eliminate noise in the image and only take into account the groups of significant pixels (> 10 pixels).

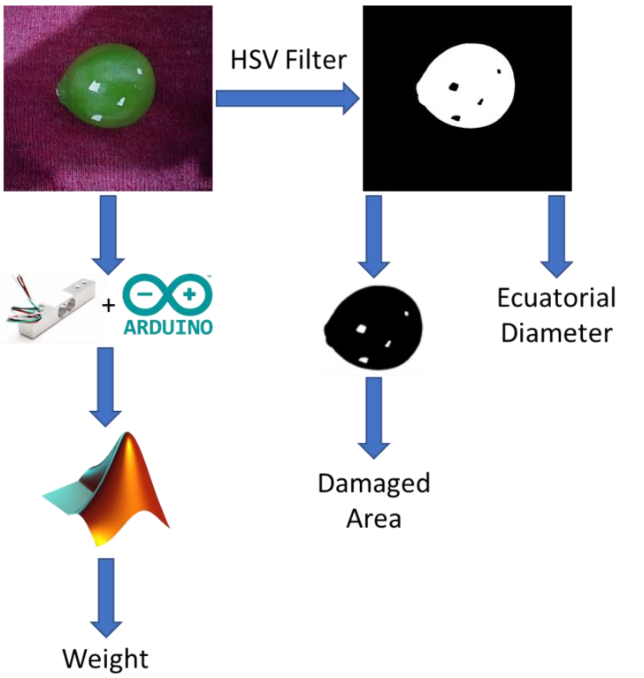

Figure 2. Extraction of characteristics.

The calculation of the percentage of area damaged or with defects in the surface of the fruit was made based on the number of pixels of the fruit, as well as the sum of the small areas that represent the present defects, for this the binarized image obtained by the HSV filter is inverted and the number of pixels that compose each defect are added within the area corresponding to the lemon, once these two values are taken, the percentage of affectation is calculated. In Equation 1, it can be seen the mathematical expression for the calculation of the percentage of area with defects in the surface of the lemon ($\%DA$), where nod is the number of defects, Ad_i refers to the area of defect i and AL to the total surface area of the lemon.

$$\%DA = \sum_{i=1}^{nod} \frac{Ad_i * 100}{AL} \quad (1)$$

On the other hand, for the calculation of the equatorial diameter it was necessary to formulate an equation to perform the conversion of pixels to a real measurement, this formula was calculated by measuring 13 specimens and later associating these measurements with a certain number of pixels, where it must be taken into account that all the pictures were taken in identical conditions. Finally, this result is tabulated and, drawing a trend line, it is determined which is the equation that correctly de-scribes the relationship between the number of pixels and the equatorial diameter in millimeters (see Figure 3).

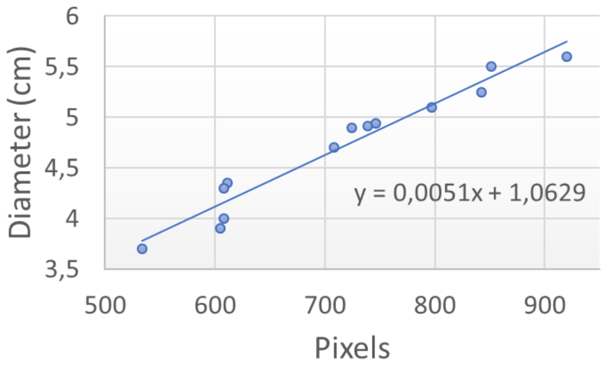

Figure 3. Equation for the determination of the equatorial diameter from the binarized image.

To obtain the weight of the lemons, it was used a load cell and an Arduino acquisition card, which receives an analog signal from the cell with a voltage amplification, then, from this analog value, the fruit weight is obtained and sent via serial communication to a computer equipment for further processing by means of MATLAB®. Once the complete characterization is finished, it is possible to proceed to the third and final stage of the algorithm, which is based on a fuzzy motor and from the measurements obtained for each of the characteristics, to apply an inference of the category or quality that the lemon that is being evaluated at this moment has.

The fuzzy system works from the obtained inputs and a series of established rules (See Table 3), these rules relate the characteristics to each other with a determined result, for example, a lemon with ideal characteristics results in the highest possible quality in the fuzzy system. Once the rules for each of the possible combinations of characteristics were established, the following result surfaces of the fuzzy motor were obtained (see Figure 4).

Table 3. Rules in the Fuzzy System.

Damages	Weight	Ecuatorial Diameter	Quality
Low	Heavy	Large	High
Low	Heavy	Normal	High
Low	Heavy	Narrow	Medium
Low	Normal	Large	Medium
Low	Normal	Normal	Medium
Low	Normal	Narrow	Low
Low	Light	Large	Medium
Low	Light	Normal	Low
Low	Light	Narrow	Low
Medium	Heavy	Large	High
Medium	Heavy	Normal	Medium
Medium	Heavy	Narrow	Low
Medium	Normal	Large	Medium
Medium	Normal	Normal	Medium
Medium	Normal	Narrow	Low
Medium	Light	Large	Medium
Medium	Light	Normal	Low
Medium	Light	Narrow	Low
High	Heavy	Large	Medium
High	Heavy	Normal	Medium
High	Heavy	Narrow	Low
High	Normal	Large	Medium
High	Normal	Normal	Low
High	Normal	Narrow	Low
High	Light	Large	Medium
High	Light	Normal	Low
High	Light	Narrow	Low

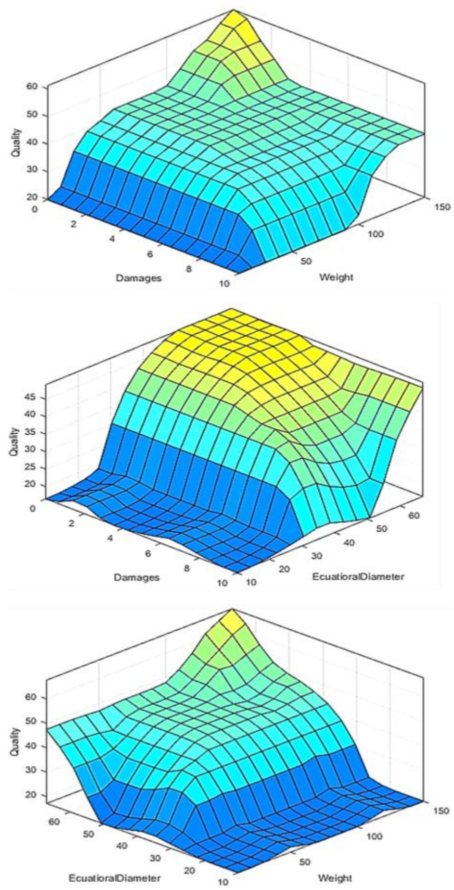

Figure 4. Response surfaces of the fuzzy system.

Observing Figure 4, it can be shown which are the combinations to obtain a high or low quality result, for this specific case the maximum quality that can be obtained is 83.7%, while the lowest quality is 16.3%, this is due to the operation of fuzzy systems that are rarely able to reach 0 or 100%, even though they have all the characteristics that would presumably result in these results.

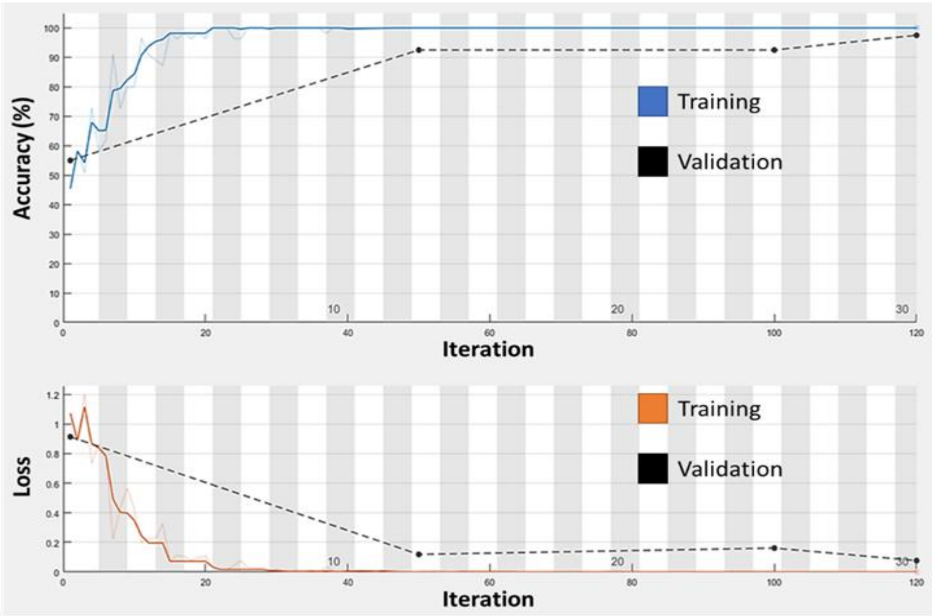

Figure 5. CNN training process.

Results

Once the convolutional neuronal network was trained, 100% accuracy was obtained in the images of the last period in the training images, with losses in the batch of 0.01%, while in the validation 97.5% were obtained, with losses of 3.7%. In Figure 5, the CNN training process can be evidenced, where the percentage of accuracy that the network has in each iteration with respect to the classification of the batches in their respective categories, in addition to the five validations made to avoid overfitting the network. The lower graph shows the losses of the training batches in each iteration and the losses in the validation images.

From the trained CNN, a confusion matrix was obtained (Figure 6), evaluating 60 test images, where the classification by categories was 100% correct, in this way it is established that the results achieved by the CNN are robust enough to continue with the remaining stages of the algorithm.

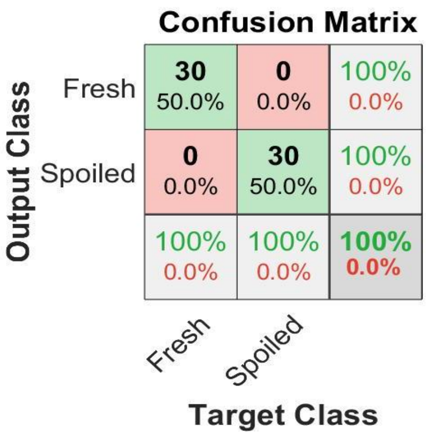

Figure 6. Confusion matrix resulting from CNN training.

Taking into account the above, a completely different test group was established against the fruits used for the CNN training and the test, in order to determine how accurate, the result was with the lemons that were in physical for tests in the final work environment. A total of 26 pictures were taken, half were lemons in good condition and the others had defects that qualified them as unsuitable for sale. Evaluating these new images in the neural network results in the fact that 100% of the images used for this new test were correctly classified.

Subsequently, it was proceeded with the acquisition of data for each of the characteristics that would be entered into the fuzzy system. Additionally, a verification was made to calculate the equatorial diameter where there was a maximum error of 3.03% of the measurement thrown by the algorithm with respect to the real specimens.

The data obtained previously are entered into the fuzzy system to determine which category belongs to each evaluated lemon, it should be noted that in the output quality parameter, three categories were distinguished: low, medium or high, which are included in the percentages of quality of 0-34%, 34.1-67% and 67.1-100% respectively, but even the lemons classified as low class are suitable for sale and consumption, what this label represents is that it does not have some characteristics that are more determining to establish the quality of the fruit with respect to other specimens.

Finally, a user interface is created in which the result can be visualized for each of the stages of the algorithm, obtaining the quality of the lemon that is being evaluated. On the left side there are the result gotten by CNN, in the central part it can be

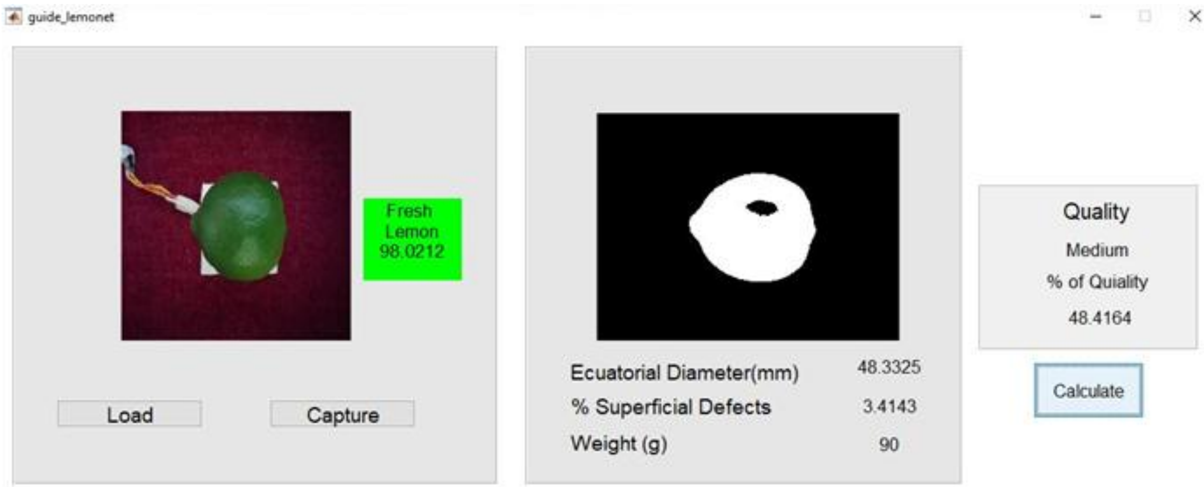

Figure 7. Test in the graphical user interface

seen the binarized image in addition to the physical characteristics of the lemon and, on the right side, the quality rating obtained by the fuzzy system (see Figure 7).

Making use of the proposed graphical user interface (see Figure 7), Table 4 is constructed, where it can be observed the results obtained using the fuzzy motor, according to the characteristics of each lemon and the classification score thrown by CNN.

It should be noted that the values reflected in the Score column refer to the percentage they have to be classified in the Fresh category, which means that if a lemon has a value of 0.01%, it means that it is 99.99% Spoiled.

Table 4. Results of the different stages of the algorithm.

Lemon	Score (%)	Category	Equatorial Diameter (mm)	Surfaces damaged area (%)	Weight (g)	Quality (%)	Quality
1	99.69	Fresh	53.58	0	150	83.62	High
2	99.03	Fresh	58.79	0.37	147	79.91	High
3	99.78	Fresh	54.01	0	132	67.85	High
4	98.37	Fresh	51.28	0	131	66.81	Medium
5	97.92	Fresh	47.55	0	93	51.15	Medium
6	98.02	Fresh	48.33	3.4	90	48.41	Medium
7	96.97	Fresh	48.67	0	77	45.98	Medium
8	96.62	Fresh	46.75	0	75	45.45	Medium
9	99.23	Fresh	41.51	0	49	38.95	Medium
10	94.98	Fresh	41.78	0	34	33.72	Low
11	99.08	Fresh	41.62	0	31	31.99	Low
12	99.72	Fresh	41.43	0	22	23.90	Low
13	97.95	Fresh	37.88	0	19	21.21	Low
14	3.93	Spoiled	N/A	N/A	N/A	N/A	N/A
15	2.58	Spoiled	N/A	N/A	N/A	N/A	N/A
16	24.32	Spoiled	N/A	N/A	N/A	N/A	N/A
17	0.16	Spoiled	N/A	N/A	N/A	N/A	N/A
18	0.02	Spoiled	N/A	N/A	N/A	N/A	N/A
19	0.22	Spoiled	N/A	N/A	N/A	N/A	N/A
20	0.07	Spoiled	N/A	N/A	N/A	N/A	N/A
21	19.30	Spoiled	N/A	N/A	N/A	N/A	N/A
22	3.36	Spoiled	N/A	N/A	N/A	N/A	N/A
23	8.81	Spoiled	N/A	N/A	N/A	N/A	N/A
24	14.68	Spoiled	N/A	N/A	N/A	N/A	N/A
25	0.01	Spoiled	N/A	N/A	N/A	N/A	N/A
26	4.08	Spoiled	N/A	N/A	N/A	N/A	N/A

CONCLUSIONS

The CNN built from Alexnet using the transfer learning method was sufficiently robust, obtaining Scores in average of 98.25% for the classification of fresh lemons and 93.73% for the spoiled lemons, for this reason the coupling with the rest of the algorithm was possible, allowing discarding from the initial stage those lemons that are not directly suitable for consumption, which reduces the processing times in the other stages.

The system proposed for the extraction of characteristics, in each of its parameters (damaged area, equatorial diameter and weight), worked correctly and the image treatment was sufficiently robust in the defined environment, although there were problems in the ambient lighting, since the lemon bark generates a reflection on its surface with great ease, creating non-existent defects such as lemon 6 (see Figure 7).

The proposed fuzzy system correctly classified each lemon in the three classes proposed, taking into account the characteristics of each one. It is an alternative to consider in this class of developments since they eliminate the possibility of divergence between the opinion of an operator and reality, besides this is a robust and scalable system, allowing the inclusion of other characteristics that are wanted to take into account to evaluate an object of study, depending on the perception of the people or established rules.

It is important to highlight the importance of this type of algorithms in different areas of the industry, since in this specific case the development was made taking Persian lemons as an object of study, if the necessary adaptations are made in the CNN, in the characterization process and the fuzzy system, it could be adapted to any kind of product, in order to raise the quality standards of the companies that use them.

ACKNOWLEDGMENT

The research for this paper was supported by Davinci research Group of Nueva Granada Military University.

REFERENCES

[1] Albers, A., Gladysz, B., Pinner, T., Butenko, V. and Stürmlinger, T., 2016, “Procedure for defining the system of objectives in the initial phase of an industry 4.0 project focusing on intelligent quality control systems,” Procedia Cirp, 52, pp.262-267. doi: 10.1016/j.procir.2016.07.067.

[2] Chow, Z.S., Ooi, M.P.L., Kuang, Y.C. and Demidenko, S., 2012, “Automated visual inspection system for mass production of hard disk drive media,” Procedia Engineering, 41, pp.450-457. doi: 10.1016/j.proeng.2012.07.197.

[3] Dias, A.P., Silva, M.F., Lima, N. and Guedes, R., 2015, “IDENTIFICATION OF MARKS ON TIRES USING ARTIFICIAL VISION FOR QUALITY CONTROL,” International Journal for Quality Research, 9(1).

[4] Zhang, B., Huang, W., Li, J., Zhao, C., Fan, S., Wu, J. and Liu, C., 2014, “Principles, developments and applications of computer vision for external quality inspection of fruits and vegetables: A review,” Food Research International, 62, pp.326-343. doi: 10.1016/j.foodres.2014.03.012.

[5] Stein, M., Bargoti, S. and Underwood, J., 2016, “Image based mango fruit detection, localisation and yield estimation using multiple view geometry,” Sensors, 16(11), p.1915. doi: 10.3390/s16111915.

[6] Sandoval Niño, Z.L. and Prieto Ortiz, F.A., 2007, “Caracterización de café cereza empleando técnicas de visión artificial,” Revista Facultad Nacional de Agronomía, Medellín, 60(2), pp.4105-4127.

[7] Montoya Holguin, C., Cortés Osorio, J.A. and Chaves Osorio, J.A., 2014, “Sistema automático de reconocimiento de frutas basado en visión por computador,” Ingeniare. Revista chilena de ingeniería, 22(4), pp.504-516. doi: 10.4067/S0718-33052014000400006.

[8] Pencue, E.L. and León-Téllez, J., 2003, “Detección y clasificación de defectos en frutas mediante el procesamiento digital de imágenes,” Revista Colombiana de Física, 35(1), pp.148-151.

[9] Latha, M., Poojith, A., Reddy, B.A. and Kumar, G.V., 2014, “Image processing in agriculture,” International Journal of Innovative Research In Electrical, Electronics, Instrumentation And Control Engineering, 2(6).

[10] Arias, F. and Suarez, E., 2017, Comportamiento de las exportaciones de limón persa (Citrus latifolia tanaka) al mercado de los Estados Unidos.

[11] Zeiler, M.D. and Fergus, R., 2014, “Visualizing and understanding convolutional networks,” In European conference on computer visión, Springer, Cham, pp. 818-833. doi: 10.1007/978-3-319-10590-1_53.

[12] Banco Nacional de Comercio Exterior, “NMX-FF-077-1996. PRODUCTOS ALIMENTICIOS NO INDUSTRIALIZADOS PARA CONSUMO HUMANO FRUTA FRESCA. LIMÓN PERSA (Citrus Latifotia L.) ESPECIFICACIONES. NORMAS MEXICANAS. DIRECCIÓN GENERAL DE NORMAS”, available: https://www.colpos.mx/bancodenormas/nmexicanas/NMX-FF-077-1996.PDF. Consult date: July 30, 2018.

[13] Perrot, N., Ioannou, I., Allais, I., Curt, C., Hossenlopp, J. and Trystram, G., 2006, “Fuzzy concepts applied to food product quality control: A review,” Fuzzy sets and systems, 157(9), pp.1145-1154. doi: 10.1016/j.fss.2005.12.013.

[14] Melin, P. and Castillo, O., 2007, “An intelligent hybrid approach for industrial quality control combining neural networks, fuzzy logic and fractal theory,” Information Sciences, 177(7), pp.1543-1557.

[15] Krizhevsky, A., Sutskever, I. and Hinton, G.E., 2012, “Imagenet classification with deep convolutional neural networks,” In Advances in neural information processing systems, pp. 1097-1105.

[16] Vedaldi, A. and Lenc, K., 2015, “Matconvnet: Convolutional neural networks for matlab,” In Proceedings of the 23rd ACM international conference on Multimedia, pp. 689-692.

[17] Lu, H., Li, Y., Chen, M., Kim, H. and Serikawa, S., 2018. Brain intelligence: go beyond artificial intelligence. Mobile Networks and Applications, 23(2), pp.368-375. doi: 10.1007/s11036-017-0932-8