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Using Computer Vision and Intelligent Classification Techniques for the Classification and Selection of Brazilian Nuts

Raphael Gava de Andrade[1], Valentin Obac Roda[1] and Jose Dalton Cruz Pessoa[2]

1. Depto de Engenharia Elétrica e de Computação, EESC/USP, Avenida Trabalhador Sãocarlense, 400, 13566-590, São Carlos (SP), Brazil

2. Embrapa Instrumentação - Rua XV de Novembro, 1452, 13560-970, São Carlos (SP), Brazil

Abstract: Aiming to improve the processes involved in the industrial beneficiation of the Brazilian nuts, this work used a new methodology based on concepts of computer vision and intelligent classification, with a focus on two of the various stages of the processing: classification according to the origin and selection. Using the proposed methodology for the selection of the nuts it was possible to distinguish between intact and broken nuts and between good and spoiled nuts with a very high percentage of correct identifications. Also to evaluate the efficiency of the proposed methodology, visual tests by human subjects were performed for the classification of the nuts, the results demonstrated that the intelligent techniques performed the same or better than the visual classification.

Key words: Brazilian nuts, classification techniques, computer vision, intelligent systems.

1. Introduction

The Brazilian nut, in some regions of Brazil also known as Para nut (Pará is a state of Brazil), Bertholletiaexcelsa HBK, is the seed of a tree of the botanical family Lecythidaceae native to the Amazon rainforest. The economic value of the Brazilian nuts is directly related to its oil and principally because of their nutritional value, making them also known as "vegetable meat".

The tree of the Brazil nut reaches up to 50 meters height and the fruit is harvested only after it falls to the soil, where it rests until the next visit of the collector. Meanwhile the fruit can be contaminated by Aspergillusflavus, a fungus that produces aflatoxin (a dangerous toxin to humans) [1]. In the agroindustry the fruits are handled to extract and shelling the nuts. The shelled nuts are then manually classified according to the integrity and size before packaging. The prolonged exposure to environmental and handling conditions in the industry is a potential source of contamination, especially by *E. coli.* [2]. These problems have been a strong obstacle to international commercialization of the nut, given the strict sanitary control imposed by the Europe and the United States.

The nuts are also exposed to injuries along the chain of production and processing where the seeds are submitted to different levels of moisture and intensity of mechanical impacts, compression and friction. Close to the end of the chain, the selection of nuts is costly and labour intensive [3] process and follows the specifications of the Brazilian Ministry of Agriculture that consider the size and external aspects.

Image processing has been used in many applications related to agriculture. Forti et al. [4] evaluated the techniques of image analysis for identification of damage caused by bugs in bean seeds, which can affect their germination. In a similar study

Corresponding author: Valentin Obac Roda, Ph.D., research field: electronics engineering.

using X-ray images, but with corn seeds, Wagner et al. [5] used computer vision for monitoring seed germination. Pinto el al. [6] performed tests using X-ray images on soybean seeds for assessment of stink bug damage. Teixeira et al. [7] used images to determine corn seed dimensions, from the processed images it was possible to obtain the width and length of seeds and classify them statistically. Shahin et al. [8] classified soybean seeds using image processing, calculating their dimensions and classifying them using statistical methods and neural networks.

As an example of application of intelligent techniques for seed segmentation in images, the work of Betancur et al. [9] used a fuzzy system algorithm (Fuzzy C-Means). Using this method it was possible to detect the contour of the seeds whose colors ranged from green, yellow and brown. In order to increase efficiency and processing speed, the algorithms were implemented by hardware using Field Programmable Gate Arrays (FPGAs) and Digital Signal Processors (DSPs).

Computer vision and artificial intelligence may be used in various applications beyond the characterization of seeds. Still facing agriculture and industrial environments, the work of Fojlaley et al. [10] classified tomatoes and showed the importance of defining the inputs for the classification neural network. Three neural networks were used in this work. The variables used as inputs of the first neural network were the red and green color channels of the RGB color space. The outputs of this first neural network were used together with the equatorial diameter of the tomatoes as inputs of a second neural network for their classification. The work of Simões et al. [11] was focused on the visual inspection of oranges. In this study, each of the pixels of the oranges images was added to the input layer of a neural network to determine their color. The colors were: dark green, light green, yellow, light orange, dark orange, white (background) and named colors for stains. Then, a fuzzy system for classification of fruits from the vectors of pixels created by the neural network was used.

This work presents a new methodology developed for the identification of Brazilian nuts according to their origin and their classification according to their weight, shape and preservation. The developed methodology used computer vision techniques for the segmentation of the nuts over a conveyor belt and artificial intelligent techniques for the classification of the nuts, including artificial neural networks and fuzzy logic. The main characteristics of the developed methodology are the followings:

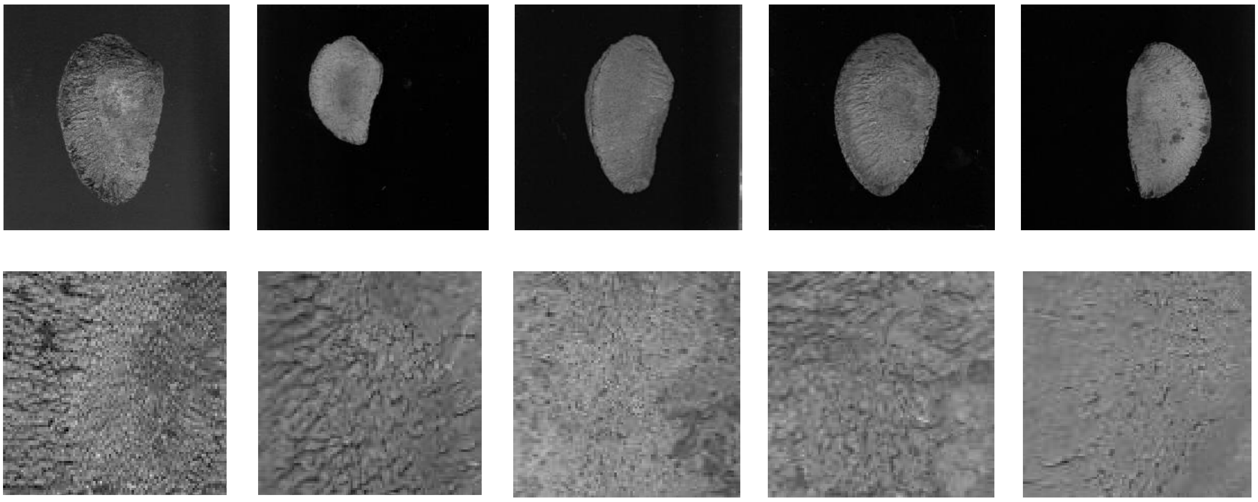
- Identify the source of the nuts through their physical characteristics.
- Classify the nuts (with or without peel) as whole or broken, good or spoiled and estimate and select the nuts by weight.

2. Materials and Methods

2.1 Classification of the Brazil Nuts according to Their Geographical Origin

In order to classify the nuts according to their region of origin, nuts from five states of Brazil were tested. The nuts in the region of Acre were taken from the Philippine Rubber (Chico Mendes Extractive Reserve in the city of Epitaciolândia), the Extractive Reserve in Amapá Cajari River (municipality of Laranjal do Jari), the MatoGrosso in the Extractive Reserve Guariba Roosevelt (municipality of Colniza), the Pará plantations belonging to Embrapa Eastern Amazon and Rondônia were purchased in the region of Machadinho West. Images at 72 dpi of 50 nuts were acquired using an HP Scanjet 8250. Sub images of 100 × 100 pixels were analyzed according to texture and color data in three different color spaces (RGB, HSV, L * a * b). An illustration of some of the images used and their sub images is presented in Fig. 1.

A statistical approach based on the properties of the intensity histogram was used. The statistical approach



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

Fig. 1 Images of Brazil nuts (top) and their sub images (bottom) used for the classification according to the origin: (a) Acre; (b) Amapá; (c) MatoGrosso; (d) Pará; (e) Rondônia.

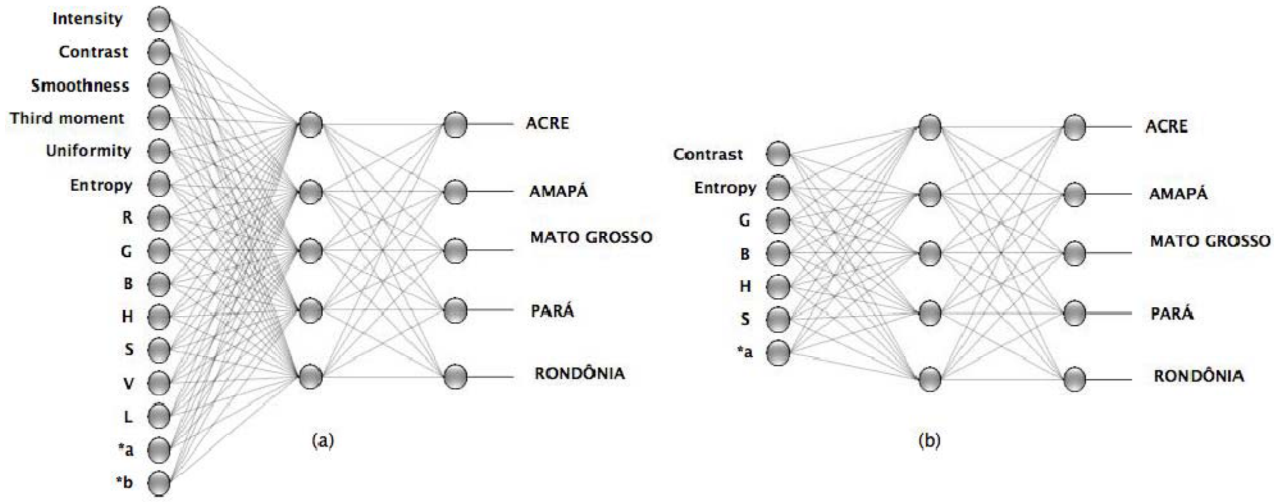


Fig. 2 Architectures of the MLP neural network used to identify the Brazil nuts by origin. (a) Using all the input variables (15 neurons for the input layer, 5 neurons for the intermediate layer and 5 neurons for the output layer); (b) Using a selection of the most relevant variables (7 neurons for the input layer, 5 neurons for the intermediate layer and 5 neurons for the output layer).

used relies on the statistical moments of the images, whose main descriptors are: mean, standard deviation, smoothness, third moment, uniformity and entropy [12].

The statistical moments plus the color information in the RGB color space, the average color converted to the HSV and L * a * b color spaces were initially used as inputs of a Multilayer Perceptron Neural Network (MLP), totalling 15 entries, as presented in Fig. 2a. To increase the processing speed, the input variables of the neural network that have the greatest influence on the process were selected.

The variable selection has the purpose to find the smallest subset of features, attributes eliminating redundant or irrelevant to the decision making of the intelligent system. For the selection of the more relevant variables, there are methods that depend only on properties of the data (filters) and those, which depend on the model of learning (wrapper) [13]. Despite its high computational cost, the wrapper algorithm is widely used in the selection of attributes for supervised learning problems and generally gives better results. The modified neural network, using a subset of the original variables, the most important for the process, was engineered using the software WEKA 3.6.0 [14] and the wrapper algorithm. With Weka, several tests were done using K-fold Cross validation in order to obtain the best MLP architecture, which is shown in Fig. 2b.

2.2 Nuts Selection by Size and Aspect

The next step in the classification of the Brazilian nuts was the classification of the nuts according to their size and aspect using images acquired by a video camera. The software developed for the classification of the nuts used C ++ Builder 6.0 and the Open CV computer vision library. The image acquisition system for selection of the nuts is composed of a CCD color video camera and a video card connected to a personal computer. The images of the nuts, with a resolution of 640 × 480 pixels were acquired with the nuts over a conveyor belt moving at approximately 7.5 cm/s. To increase the processing speed a region of interest with 640 × 320 pixels was set. With the described framework, it was possible to analyze 15 to 20 nuts simultaneously.

To improve the quality of the images for the selection of the features for the classifier, the following steps, as illustrated in Fig. 3, were taken. Initially, the B-channel (RGB color space) of the background image was subtracted from the B-channel of the original image. The result of this subtraction is the isolation of objects in relation to the background image. The resulting images were converted to two level images (binary) and to improve the blurring of the images caused by the motion, mathematical morphology operations were used. The images were eroded and then dilated by a 3 × 3 pixels cross shaped structuring element. This operation is known as opening.

Once the nuts were detected the next step was to extract information about the shape and color of the nuts. The shape features used in the analysis were the following: area, perimeter, major axis, minor axis, eccentricity, rectangularity, circularity, thinning ratio, perimeter-area ratio and thinning-circularity ratio. Area and perimeter were used to enclose the objects to be recognized, the features extraction was done only if the detected objects reach the minimum number of 1250 pixels in area and 200 pixels in perimeter. Then, the center of mass was determined. The center of mass is used to acquire the neighborhood average (template 5 × 5) of the color channels B (RGB space), H and S (HSV space) and also as the starting pixel (seed) for the color filling for the classification.

To identify if the nuts are whole or broken, an MLP neural network was used. The features of the nuts extracted from the images were used as input network. The wrapper algorithm was also used for selecting the best variables for this architecture. Fig. 4 shows the architecture after the variables' selection.

In assessing the preservation of the nut (good or spoiled) color data in the vicinity of the center of mass was used. The nuts without the peels have higher contrast than the nuts with peel when compared to the spoiled nuts. When a nut suffers some type of mechanical shock, it becomes exposed to humidity and temperature or fungus, and tends to lose oil becoming with a spoiled appearance. These are the critical situations where the nuts should be removed from the conveyor and discarded. However, there are cases where the colors in the peel of the good nuts are similar to the colors of the spoiled nets. Also there are nuts that are not fully covered by the peel, and this can confuse the system. Fig. 5 illustrates some of those cases mentioned.

Because of the many factors involved in identifying the good and the spoiled nuts, a fuzzy classification was used. The developed fuzzy system used as inputs three color variables, B of RGB color space and H and S of the HSV color space. Each of the variables has two membership functions that can be seen in Fig. 6

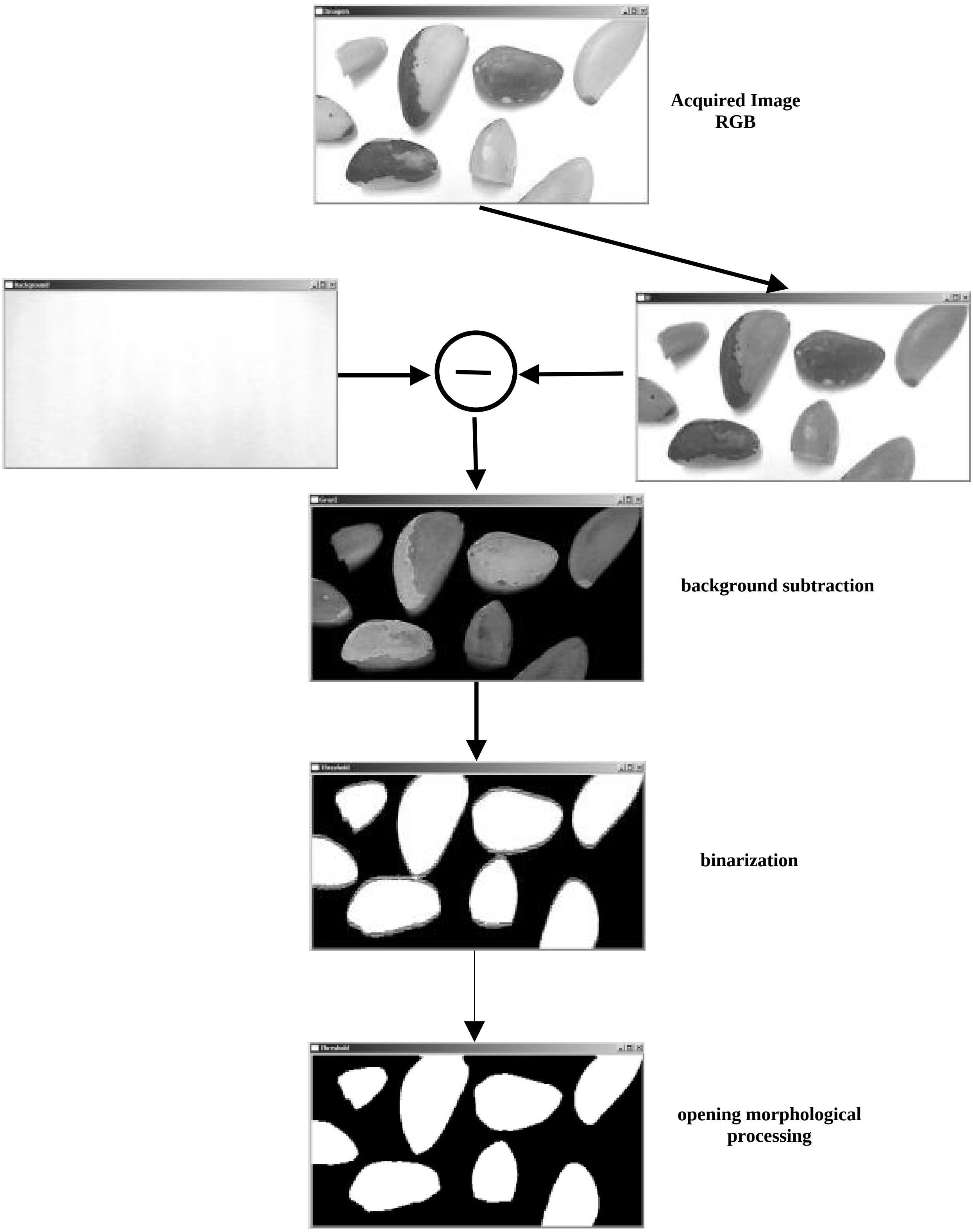


Fig. 3 Image processing steps to improve the images for the classifier.

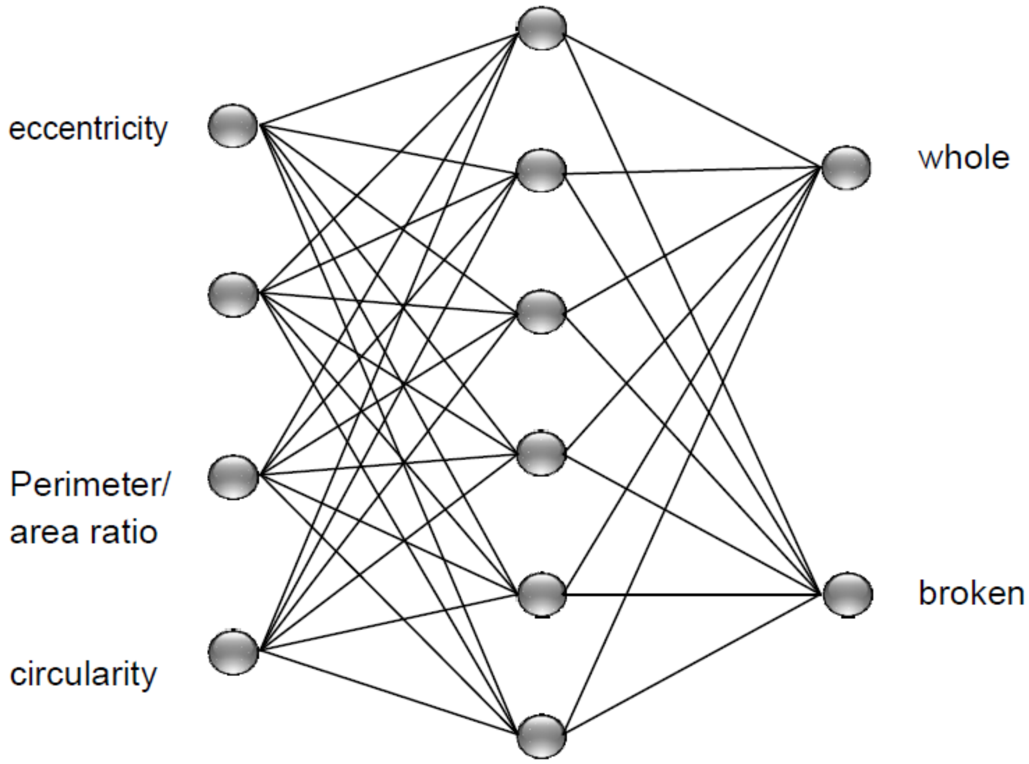


Fig. 4 MLP neural network architecture, after wrapper, for the classification of the state of the nuts: whole or broken.

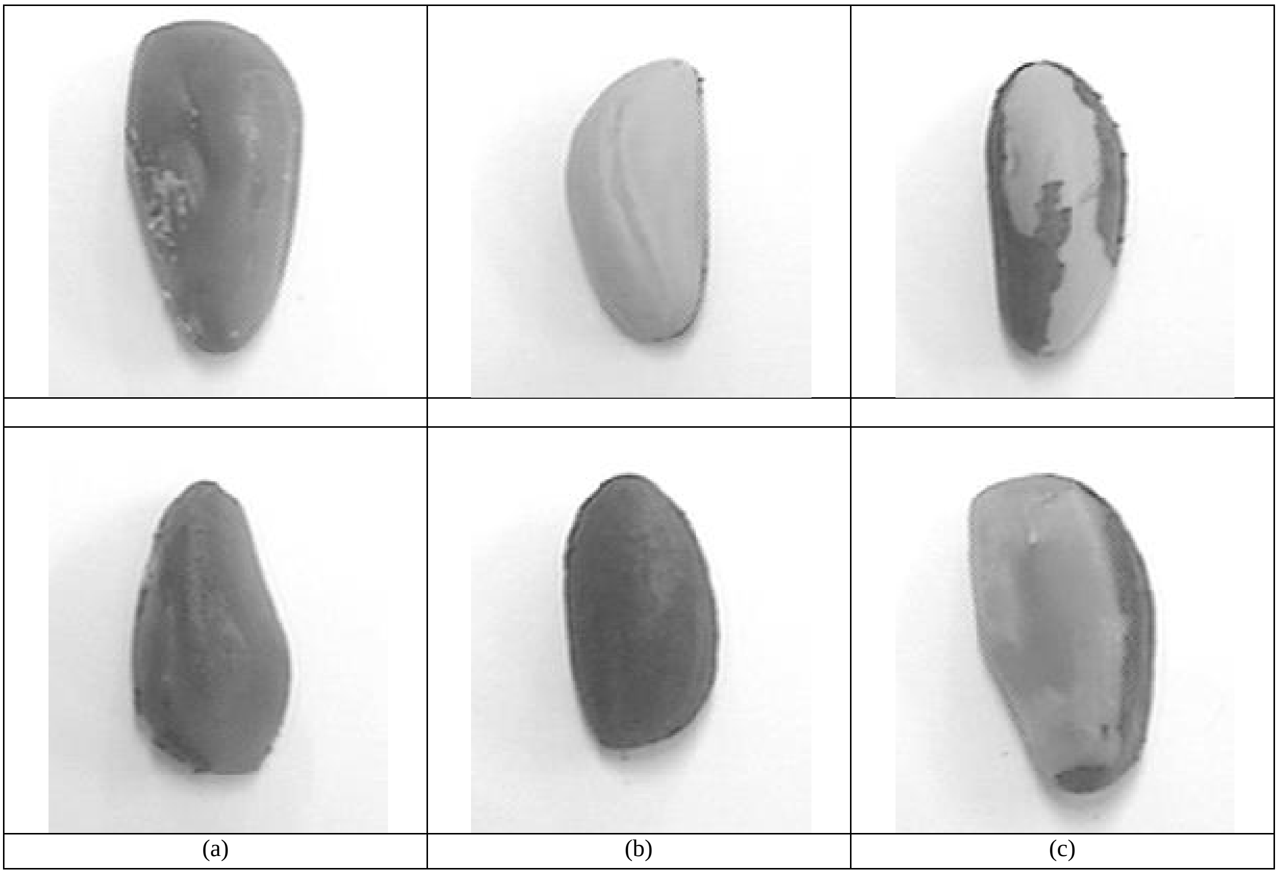


Fig. 5 Images of the nuts: (a) spoiled; (b) with and without peel; (c) with some peel and loosing oil.

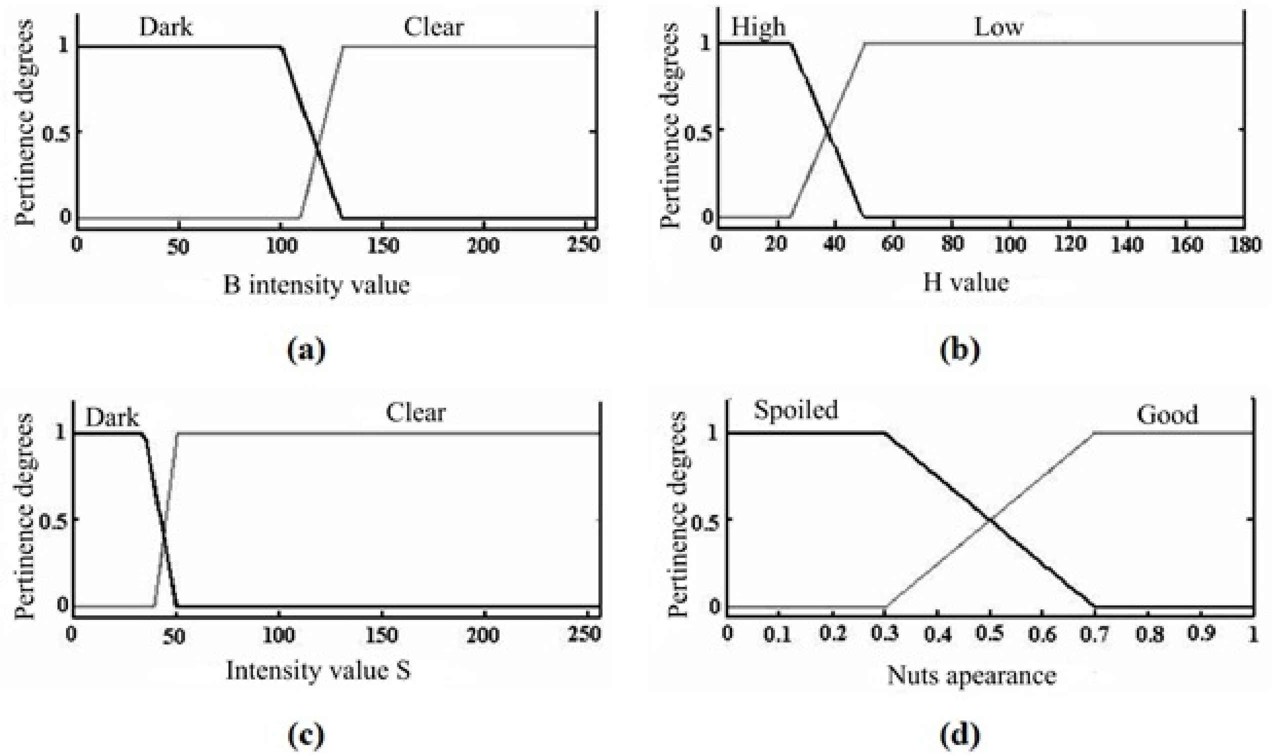


Fig. 6 Universes of discourse used for the fuzzy system: (a) B intensity; (b) H value; (c) S intensity value; (d) Nut appearance.

together with the output universe of discourse (aspect of the nut). For this configuration of the universes of discourse the rules shown in Table 1 have been developed and used. The system also used the Mandani implication operator, aggregation was carried out with maximum values, the composition with Max-Min and the defuzzy fication with the centre of area method.

3. Results

3.1 Results on the Classifications of the Brazil Nuts according to Their Origin

Two types of analysis were performed with the architectures presented in Fig. 2, one using only 100 samples and the second using all the samples (250). Based on the cross validation tests, 10 training files were created. For the first analysis the file contained 90 samples, while for analysis 2 the file contained 240 samples. Thus, the test file always contained 10 samples, i.e., 10 folds with 10 equal samples for both analyses. Fig. 7 shows the percentage of correct identification of the analysis for each training and test files for the two architectures. Table 2 shows the overall averages of these files.

The percentage of correct identification of training in architecture 2 was lower in most subsets than architecture 1, which was confirmed in the overall average. Nevertheless, there was an increase in the overall average of the second architecture, with some subsets where percentage of correct identification was 100%. The quadratic medium error ranged from 0.42 at the worst case (40% correct identifications) to 0.09 in the best case (100% correct identifications).

To evaluate the classification efficiency carried by the devised MLPs, visual tests by human subjects were used. Visual analysis was performed by four women, biologists of the same age, who identified the region of origin of the nuts for all 10 samples from 10 sub-images. Due to the reduced number of samples the human testers were trained previously. The training consisted on presenting sets of images, the same as those used for the extraction of features, properly

Table 1 Universes of discourse rules used for identifying the good and the spoiled nuts.

Rule 1:	IF Intensity value of B is Clear Then Nut is good
Rule 2:	IF Intensity value of B is Dark and H value is High and Intensity value of S é Dark Then Nut is good
Rule 3:	IF Intensity value of B is Dark and H value is Low and Intensity value of S é Clear Then Nut is spoiled
Rule 4:	IF Intensity value of B is Dark and H value is Low e Intensity value of S é Dark Then Nut is good

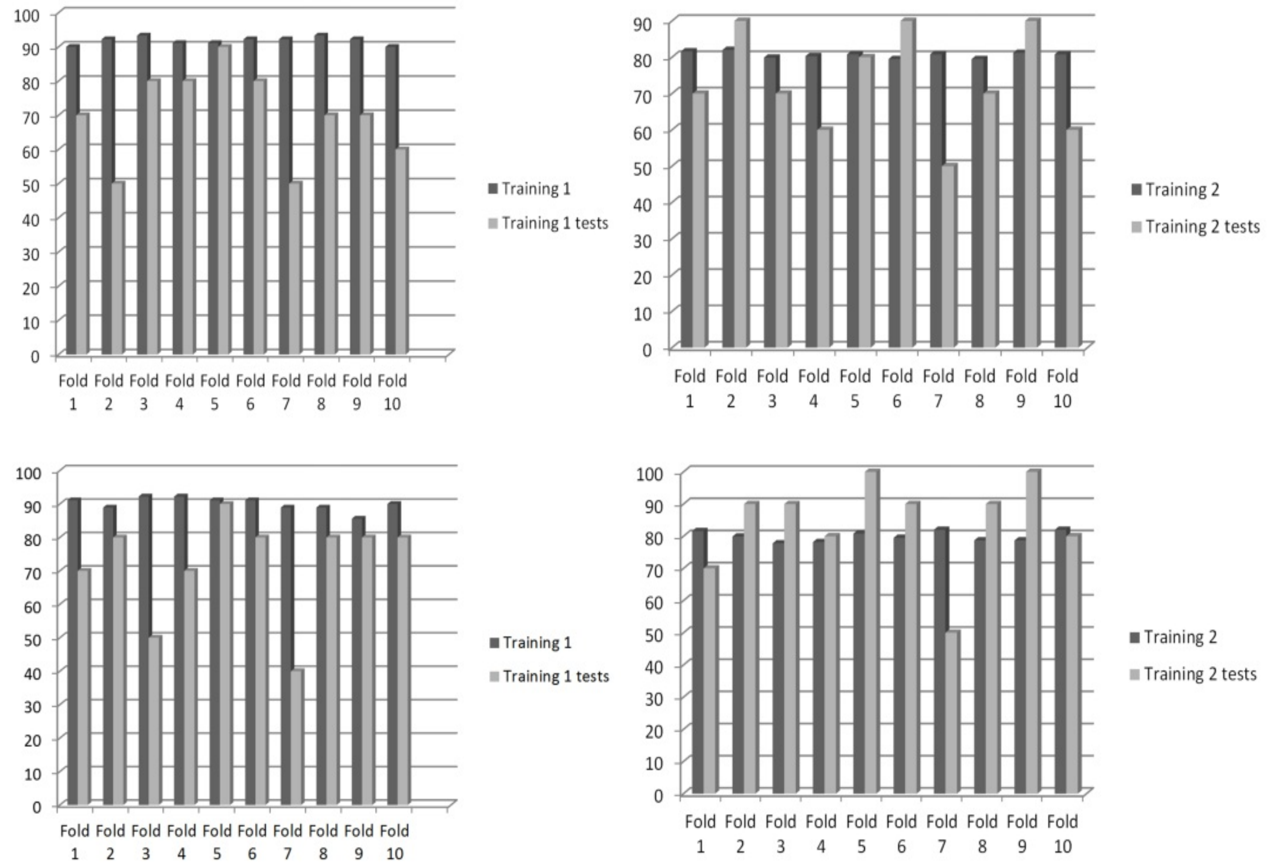


Fig. 7 Percentage of correct identification of the nuts. (a) MLP architecture using all the input variables (Top). MLP architecture (bottom) with reduced input variables, selected after wrapping.

Table 2 Average of correct identification (%) of the folds for each architecture.

	Correct identifications (%)			
	Training 1	Training 1 test	Training 2	Training 2 test
Architecture 1	91.8	70	80.6	73
Architecture 2	90	72	79.9	84

identified by their region of origin. The visual identification was based on color and texture. The results of the visual identification are presented in Fig. 8.

In order to compare the results obtained using the MLP architectures and the visual tests obtained by human observers a statistical t Student test was used. The t Student test is divided into two categories: paired and unpaired. For this validation, we used the paired t test, because the samples are not distinct in their features. In this test, there are always two hypotheses: null (H0) and alternative (H1). H0 can be accepted or rejected by the test. Considering the methodology, H0 was considered for this analysis as being the same or worse (or less) and H1 was considered as being better (higher) than the visual analysis.

The result of the comparison of the test, for each person, considering the training tests of the MLP first architecture is presented in Table 3.

3.2 Results of the Nuts Selection by Size and Aspect

The nuts have their size classification defined by the Brazilian Ministry of Agriculture. This classification is given by the quantity of nuts in each 453 g, and there may be nuts of various sizes in a set defined as large. The nuts classification ranges from tiny (more than 180 nuts per 453 g) to extra-large (less than 102 nuts in each 453 g). In order to improve the size classification, relations between the weight of the nuts and features extracted from the images were obtained. Also, calculations were made considering the approximation of the two almond shapes: triangular prism, and ellipsoid. The processing system used two-dimensional images, the lack of depth data was a constraint in the calculations of the relationship between the nuts features and weight. The equation used to calculate the weights of the nuts was the equation resulting from linear regression between the actual weight and area of the nuts in the image. The

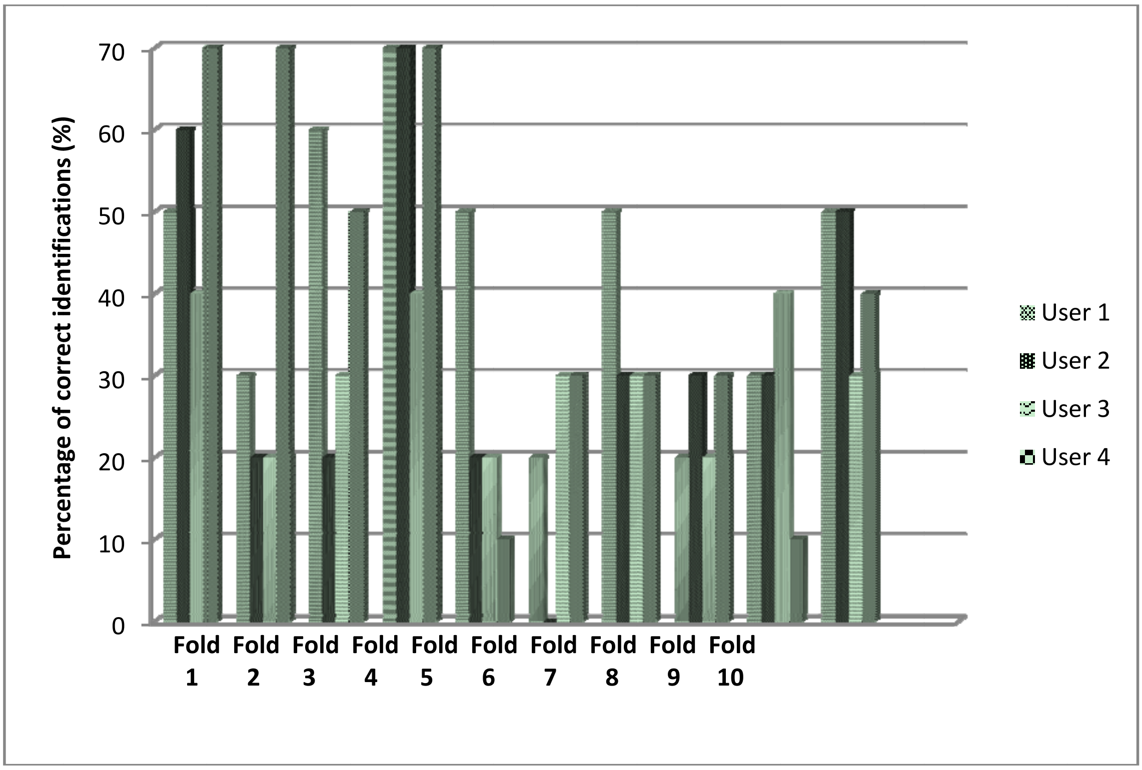


Fig. 8 Percentage of correct classification (vertical axis) by human subjects.

Table 3 Statistical T Student test results comparing the results obtained using the MLP architecture and the visual tests obtained by human observers.

	Training 1				Training 2			
	Person 1	Person 2	Person 3	Person 4	Person 1	Person 2	Person 3	Person 4
Value of T	4.3864	4.5278	8.4853	3.0973	3.3541	4	7.6955	3.4026
Significance level (p)	0.0009	0.0007	< 0.0001	0.0064	0.0042	0.0015	< 0.0001	0.0039

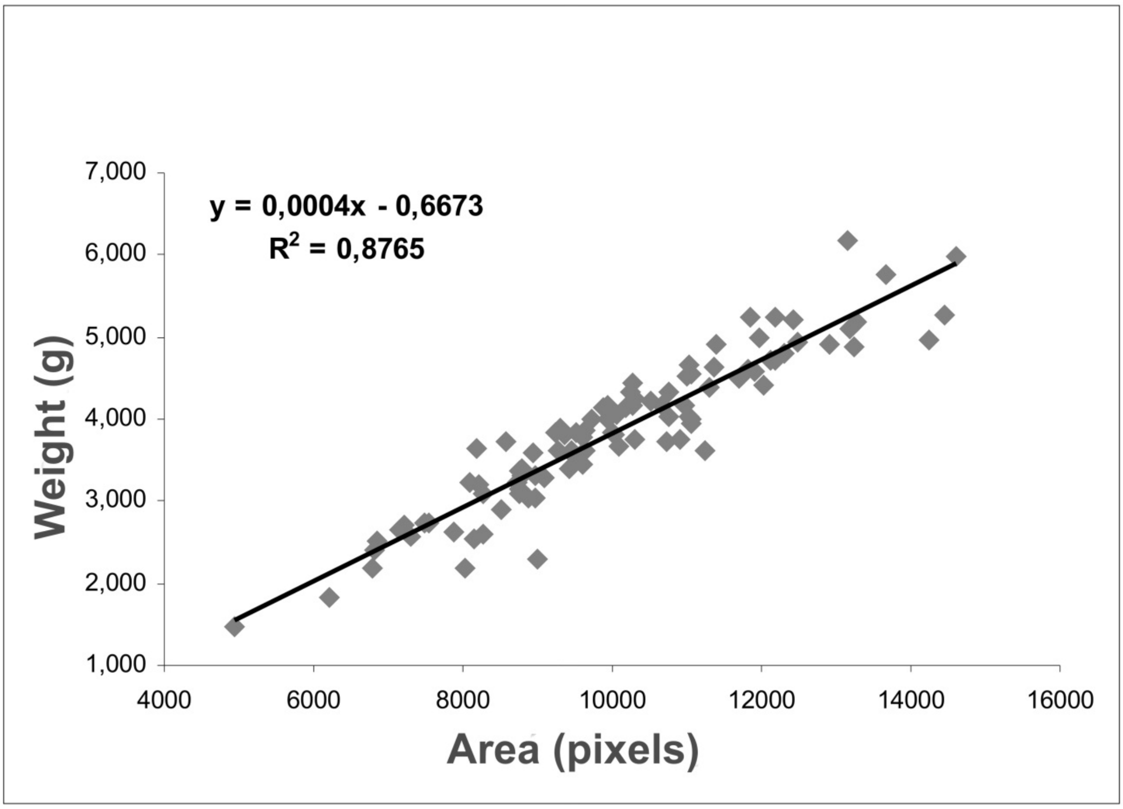


Fig. 9 **Relation between the nuts area (in pixels) and their weight.**

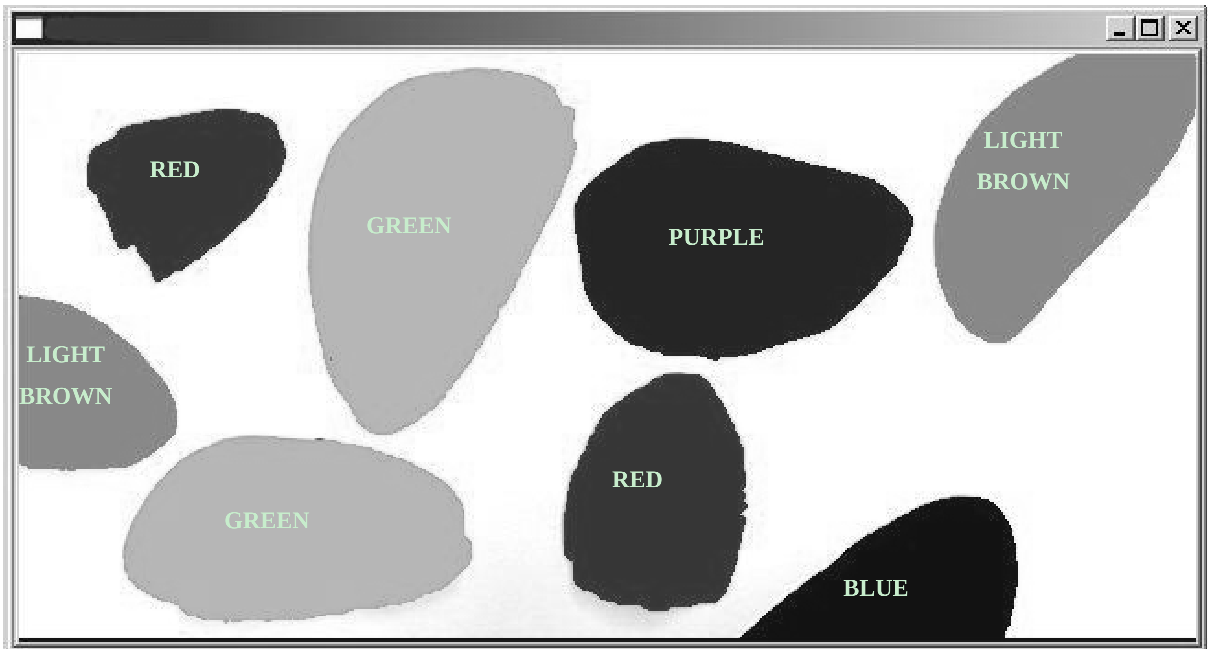


Fig. 10 **Classification of the nuts by color after the identification. In this figure labels replaced the colors of the original image; green—whole good nut; purple—whole spoiled nut; red—broken nut; light brown—out of the area of analysis; blue—end of analysis.**

Table 4 Percentage of correct identification of the shape of the nuts (whole or broken) using the MLP neural network with all the variables and the one with the selected variables after the wrapper.

File	Correct identifications (%)				
	Crossed validation	Training	Test 1	Test 2	Test 3
All variables	77	86	93.33	94.74	100
Selected variables (wrapper)	79	86	93.33	94.74	100

mean weight of the nuts analyzed was 3.86 g and the average of the residue (whether positive or negative) was 0.24 g, i.e., average error of 6.2%. Fig. 9 shows the graph of the regression and its equation.

The nuts were identified according to the shape (intact or broken) and to the aspect (good or spoiled) by the classifier which is shown in Fig. 4 and by the fuzzy system presented in Fig. 6. After the identification, the images of the nuts were filled with the coloring colors defined for each situation: green, good no broken; purple, probably spoiled; red, broken; light brown, cannot be analyzed because it is partially outside the area of analysis, i.e., the edges of the image; blue, regardless of its classification, came to the end the analysis. An image with the classified nuts is presented in Fig. 10.

Table 4 shows the percentage of correct identification of the shape of the nuts using the MLP neural network with all the variables and the one with the selected variables after the wrapper. It can be observed that there is no much difference in the tests results using both neural network architectures, therefore the MLP architecture with the fewer input variables was used.

For the classification of the aspect of the nuts the developed fuzzy classifier was tested with 10 images of spoiled nuts and 97 images of good nuts. The system was able to identify correctly 88.2% of the nuts.

4. Discussion

Aiming to improve the inspection and selection of the Brazilian nuts processing, computer vision and artificial intelligent techniques were used. The image pre-processing for segmenting the nuts in the images, acquired when the nuts were moving on a conveyor belt, included background image subtraction using the B channel of the RGB color space, conversion to binary form and mathematical morphology filtering to enhance the objects (nuts) to be segmented. Smoothing filters were also tested to enhance the objects in the image but this incurred in an increase in the processing time of about 40%, for this reason the mathematical morphology filters have been preferred.

Having segmented the nuts, shape, weight and colors features for each nut were determined; these data were used for the identification and classification of the nuts. For the identification of the whole and broken nuts, based on the shape features, multilayer perceptron neural networks were used. Tree sequence of tests were performed, with 30, 19 and 24 samples, leading to similar rates of correct identifications of about 94% of correct identifications. To identify good or spoiled nuts, fuzzy techniques based on color features were used. On a universe of 97 good and 10 spoiled nuts, 88.2% of correct identifications were achieved.

In order to validate the proposed methodology, classification of the nuts by human subjects was compared with computer classification. Results show that human subjects classification of the nut is the same or worse than by computer. The tests did not consider fatigue which could decrease the efficiency of the human subjects.

The proposed methodology, despite our implementation limitations, showed that computer based techniques including computer vision and artificial intelligent techniques could be applied to solve agricultural problems, including identification and classification of products with results that could overpass human subjects.

5. Conclusions

This article presents and discusses the results of a new methodology developed for the selection and classification of Brazilian nuts according to their region of origin, shape, weight and external aspects. Computer vision and artificial intelligence techniques were used, which guarantee the effectiveness and robustness required for an industrial system.

The selection of the nuts was made possible through shape descriptors and using their color data. The error in the identification of the shape of the nut was below the range prescribed by the industry which is 10%. To estimate its weight, a calibration was performed using the area of the object (nut) in the image. Since the classification of the nuts is performed by descriptors texture and color data. The model used for classification was compared with a visual analysis using the Student t test. As a result of the test, it was observed that the identification of the origin of the nuts was more effective using the developed methodology than by visual analysis.

The development system is ready to be incorporated in an automatic classifier system. Even with the hardware limitations, the total frame processing time averaged 50 ms. With speed and space used in the handling of almonds are, about four nuts per second can be classified, that is, more than 108,000 almond per eight hours of work. Considering an average weight of 5 g per nut, it is possible to classify 540 kg of nuts in an 8 hours journey. The system can be improved with the use of blue lenses optical filters which eliminate the need of the background subtraction and more efficient computer systems.

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