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Recognition of coffee roasting degree using a computer vision system

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ABSTRACT

The definition of the coffee roasting degree is mainly based on the coloring of beans and is directly related to the beverage quality. This bean color reading usually occurs by visual inspection process or by using traditional instruments with scope limitations. Thus, the aim of this study was to construct a computational vision model that compares color patterns in CIE L*a*b* and grayscale with the numerical scale of roasting defined by Specialty Coffee Association of America. Artificial neural networks were used as a color transformation model and quadratic/cubic polynomial regression models and neural models for roasting index approximation. For whole beans, the applied Tukey test (95% of confidence level) showed that the neural model outperformed the polynomial ones for roasting index approximation, getting a R^2 factor of 0.99. For ground beans, the quadratic polynomial grayscale model was the best predictor, showing an average error of 0.93. Therefore, the proposed system is considered as effective in the identification and approximation of coffee bean color allowing greater automation and reliability in roasting degree analysis.

1. Introduction

Roasting is one of the most complex and important stages of the coffee production chain. During the roast process, several chemical reactions, such as hydrolysis, polymerization and pyrolysis contribute to the chemical and physical changes that occur in the beans. These chemical reactions produce volatile and non-volatile compounds that will compose the organoleptic properties of the drink such as aroma and flavor, and are also responsible for the color change of the coffee beans (Cheong et al., 2013). The change in bean coloring during roasting is due to the formation of melanoidins, which are dark and high molecular weight compounds resulting from complex chemical transformations of the Maillard reaction and the caramelization reaction (Ludwig et al., 2012). Both chemical reactions are closely related to the sensory properties, in this way the correct definition of coffee roast degree is of paramount importance as it directly influences the beverage quality (Kocadagli and Gökmen, 2015; Kucera et al., 2016).

Besides, as far as the coffee beans color is concerned, the industries and coffee shops may need to maintain a roasting pattern. However, few equipment help in the correct color reading of roasted coffee beans. Generally, the definition of the roast degree is made by masters of roast that show great sensory variability during this subjective color reading or by equipment, such as colorimeters and spectrophotometers which are expensive and not economically viable for small coffee industries. Although there are recent developments in coffee bean quality assessment, such as the analysis of hyperspectral images (Calvini et al., 2015; Chu et al., 2018; Kiani et al., 2018), color remains a significant factor in the marketing of the product.

The CIE L*a*b* system, a color standard implemented by the Commission Internationale de l'Eclairage' (CIE, 1986), has been used worldwide for color measurements because it has a uniform distribution and its color space is regardless of the used device. The color is described by the coordinates L*, a* and b*. The L* coordinate represents the luminance, while the a* and b*coordinates represent the change of color from red to green and yellow to blue, respectively. Differently from the RGB color space, the CIE L*a*b* one is perceptually uniform (Capitán-Vallvey et al., 2015). Traditional CIE L*a*b* color measurement equipment, such as colorimeters and spectrometers, typically capture a small and uniform sample. This limitation has generated the need of new systems of computer vision that aid in the color reading on non-uninform samples, as is the case of roasted coffee beans (Seginini et al., 1999; Papadakis et al., 2000; León-Roque et al.,

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2016; Oliveira et al., 2016).

Computer vision is a scientific area that aims to develop algorithms to automatically extract and analyze useful information about a given object or scene from an observed image, image set or image sequence (Brosnan and Sun, 2003; Wu and Sun, 2013; Wan et al., 2018). In this sense, it extracts quantitative color information from digital images using image processing and analysis, resulting in a non-contact and fast color measurement, besides providing a cheaper and more versatile path than traditional color measurement instruments (León et al., 2006; Costa et al., 2015; Sanaeifar et al., 2016; Vidal et al., 2018).

The color tone for roasted coffee beans can vary widely depending on the roasting time and temperature, air pressure in the chamber, type of coffee, among others. This hinders a reliable visual definition or the use of equipment that requires constant calibrations. Thus, the aim of this work was to develop a calibrated computer vision system to measure the roast degree of coffee samples (whole and ground beans) in a universal color space based on a roast index defined by the Specialty Coffee Association of America (SCAA, 2017).

This work proposes a color transformation model that converts the RGB (Red Green Blue) color space to the independent CIE L*a*b* using artificial neural networks (ANNs) (Haykin, 2009), considering whole and ground coffee beans images. In addition, it is proposed a roasting degree recognition system capable of predicting the Agtron/SCAA value of each sample, using polynomial regression models and ANNs for colored and grayscale images.

2. Material and methods

2.1. Coffee samples

Two types of commercial coffees (*Coffeaarabica L.*) were selected, the first being dry processed (natural coffee) and the second wet processed (peeled coffee cherry), originating from the 2014 harvest in the state of Minas Gerais, Brazil. The coffees were stored in sealed containers with CO_2 injection until the roasting time in order to preserve their physical and chemical characteristics (Borém et al., 2013).

For the roasting procedure, 150 samples were selected, 75 for each type of processing, containing 150 g each. These samples were submitted to roasting in a test roaster (Probat - Leogap TP2) with initial temperature of 150 °C and roasting time ranging from 8 to 12 min. The final roasting temperature ranges between 200 and 240 °C. Similar as used in (Alessandrini et al., 2008), after roasting, each sample of 150 was divided in a half part (75 g), and ground in 3.5 mesh granulometry to create two model types, one of whole beans (75 g each), and another for ground beans, total 300 samples.

2.2. Computer vision system

The computer vision system developed in this study used the imaging system UVDI-254 of the Major Science company, which has a 8″ color TFT display and front access for sample exchange. In its top, there is a Canon (Canon®) camera, model Powershot G12 of 10MP resolution (Fig. 1). The system has inside two LED lamps of 3 W each and 57 cm length with color temperature of 6500 K.

The camera has been set up in order to capture images without flash or zoom, with white fluorescent light balance, f/6.0 aperture, 1/10 sec exposure, ISO speed equal to 160, and fixed focus.

After internal storage in a SSD card, the images were transferred to a personal computer with image processing and analysis software.

The images were captured with the maximum aspect of the camera (16:9) and saved with the uncompressed Canon's raw image (CR2) standard. The images were converted to the TIFF file format, thus maintaining a high number of colors per channel in the RGB model. This process provides 16 bits of depth (2^{16}), 65,536 colors per pixel per channel.

Fig. 1. Image acquisition system.

2.2.1. The color space transformation model

The CIE L*a*b* color space has its origin in the mathematical transformation of light according to its wavelength based on the human ability to see colors (CIE, 1986). The coordinates are divided into three dimensional Cartesian coordinate system as follows: (i) L* or luminescence relates the gloss degree of the material, ranging from 0 (totally black) to 100 (totally white); (ii) a* is the axis representing the wavelength from red to green, ranging from −120 to +120°; and (iii) b* is the axis from blue to yellow, ranging from −120 to +120°.

Since an image obtained in RGB is affected by several factors, such as incident lighting and camera configuration parameters, the direct conversion from RGB to the CIE L*a*b* color space is not possible. Thus, it is necessary to construct a color transformation model as discussed in (León et al., 2006). Consequently, processing the information requires more consumption of resources and is not as immediate as other spaces (Capitán-Vallvey et al., 2015).

The methodology presented in Fig. 4 was used in this study to construct the color space transformation model according to (León-Roque et al., 2016). The following steps were performed:

1. Selection of color charts: based on the eight Agtron/SCAA color disks (Fig. 2), a dataset was built with 165 color charts, aiming to obtain a wide range of values to ensure the maximum generalization of the model. Some examples of charts are shown in Fig. 3.
2. Measurement of the CIE values: L*a*b* of each chart were measured using the Minolta CM 300 colorimeter. For each value was done a triplicate and calculated the average as the result of the chart. The colorimeter head uses diffuse illumination with 0° display geometry, set for D65 luminance, with core temperature at 6500 K, 2 CIE, calibrated white plate L* (97), a* (0.25), and b* (1.78).
3. Recording of images from color chart using uncompressed camera format (CR2).
4. Conversion of images to 16-bit TIFF format.
5. Reading of TIFF files using MATLAB software that returns a three-dimensional array for each image with RGB color space.
6. Identification of the color transformation model using the MATLAB® software based on RGB values of each card as input and their

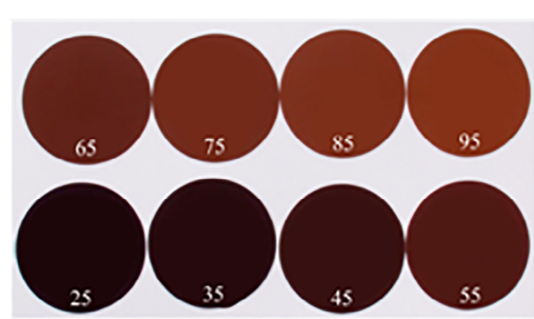

Fig. 2. SCAA color disks, where numbers correspond to SCAA values.

Fig. 3. Examples of color charts used to define the transformation model.

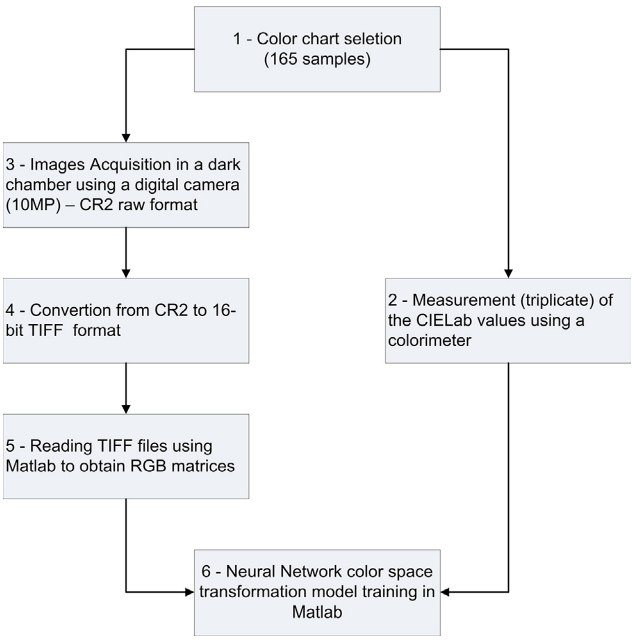

Fig. 4. Steps used to build the RGB and CIE L*a*b* transformation model.

respective average values of the colorimeter, with CIE L*a*b* as output.

The color transformation models can have several structures, whether linear or non-linear, polynomial models estimated by the least squares algorithm (Stõderstrõm and Stoica, 1989), models of direct transformation (Hunt, 1991), and non-linear models based on intelligence techniques, such as ANNs (Haykin, 2009; Dębska and Guzowska-Świder, 2011). For this study, ANNs were used because they are considered as universal approximators (Cibenko, 1989) and have satisfactory results proven in previous studies (León et al., 2006; Oliveira et al., 2016).

In order to obtain better results, three distinct ANNs were implemented, one for each component (L*, a* or b*) of the feedforward type (Fig. 5), composed of a hidden layer with five neurons each and with a non-linear activation function (hyperbolic tangent) where the RGB data are the inputs used to predict a single output value of L*, a* or b*. The network training was based on the Levenberg-Marquardt algorithm (Haykin, 2009). This same procedure was also adopted in (Oliveira et al., 2016).

The dataset with 156 color charts was divided initially into two parts: training data (80%) and validation data (20%). The ANN structure (such as numbers of nodes, number of training epochs, non-linear activation function, and others) was obtained based on 500 iterations from the hold-out cross validation method (Bishop, 1996).

The network error was evaluated according to criteria defined by (León et al., 2006):

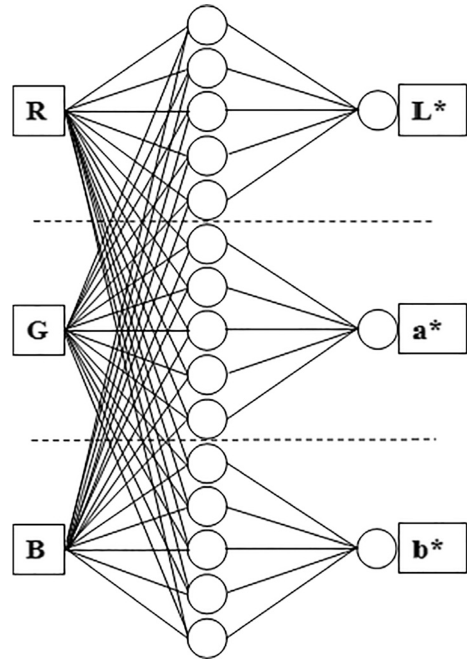

Fig. 5. Structure of the three artificial neural networks (ANN) used to transform RGB to CIE L*a*b* color spaces. Each ANN yields one color unit as output.

$$\bar{e} = \frac{e_L + e_a + e_b}{3}, \tag{1}$$

where,

$$e_L = \frac{1}{N}\sum_{i=1}^{N}\frac{|L_i^* - \hat{L}_i|}{\Delta L},$$

$$e_a = \frac{1}{N}\sum_{i=1}^{N}\frac{|a_i^* - \hat{a}_i|}{\Delta a},$$

$$e_b = \frac{1}{N}\sum_{i=1}^{N}\frac{|b_i^* - \hat{b}_i|}{\Delta b},$$

where the terms ΔL, Δa, and Δb refer to the length of the variation intervals of each component of the color space CIE L*a*b*, i.e., $0 \leq L \leq 100$, $-120 \leq a \leq 120$ and $-120 \leq b \leq 120$, $\Delta L = 100$ and $\Delta a = \Delta b = 240$, and N is the number of observations.

2.2.2. *Roasting index estimation*

The images of roasted coffees beans, whole and ground, were obtained from beans arranged in an 18 cm diameter acrylic plate, positioned in the center of the dark chamber under a black surface (Fig. 6a). After conversion to TIFF (16 bits), the files were loaded in the Matlab®

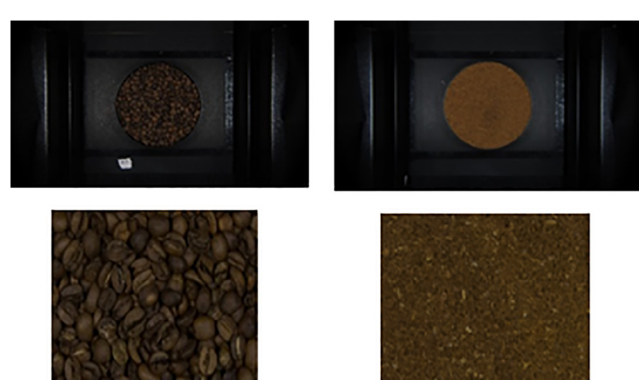

Fig. 6. Examples of image acquisition of whole and ground coffee samples.

software and their region of interest cropped so that all samples had the same final size, according to Fig. 6b.

All the cropped images were submitted to two transformations:

- Conversion from RGB to CIEL*a*b* through the obtained neural transformation model. Thus, each sample has a value for L*, a* and b*.
- Image conversion in RGB colors to grayscale image using the *rgbtogray* function that obtains an estimated average index of the image by function ($Ind = 0.2989\ R + 0.5870\ G + 0.1140\ B$) via Matlab® software.

In order to obtain the roast degree defined by SCAA, five measurements per sample were performed in the Agtron spectrophotometer (M-BASIC II), which has read variations according to the sample position, besides being necessary repeated calibrations with two reference disks.

With the average values from the spectrophotometer together with the results from the color space conversion (RGB-CIEL*a*b*) plus the grayscale intensity values (RGB-Ind) for each sample, it was possible to implement six types of models, being five polynomial models and one ANN model, for the two sets of samples (whole/ground), totaling 12.

These six models were used in two problems:

- Transformation from the sample image average L*a*b* value to SCAA/Agtron (two polynomial models and one ANN).
- Transformation from the sample image average grayscale (*Ind*) value to SCAA/Agtron (three polynomial models).

Obtaining a model that converts values from the CIE L*a*b* space to SCAA/Agtron is justified to develop a mathematical equation that relates these two important entities, being able to be used by other users that obtain the CIE L*a*b* values from their samples by other methods.

However, obtaining a model that relates grayscale values from the image to the SCAA/Agtron value from the samples is interesting in the sense of implementing automation in low cost devices. Grayscale imaging can be performed by simple devices and data processing can be done with a lower demand for computer processing, such as on single board computers.

Therefore, the six models used to solve these problems were:

- Linear polynomial model (P1), quadratic polynomial model (P2), with regressors based on the average value of the image in the CIE L*a*b* color space:

$$RI_{P1}(L, a, b) = [L \quad a \quad b \quad 1]\theta_{P1},$$

$$RI_{P2}(L, a, b) = [L^2 \quad a^2 \quad b^2 \quad L \quad a \quad b \quad La \quad Lb \quad ab \quad 1]\theta_{P2},$$

where $\theta_{P1} \in \mathbb{R}^{1\times4}$ and $\theta_{P2} \in \mathbb{R}^{1\times10}$ are the parameters to be estimated of polynomial models P1 and P2, respectively, and RI (Roasting index) is the output of each model.

- ANN model, shown in Fig. 7. The entries of this model are the average values of L, a, and b of the image.
- Linear polynomial model (P1G), quadratic polynomial model (P2G), cubic polynomial model (P3G), based on gray scale intensity values (*Ind*):

$$RI_{P1G}(Ind) = [Ind \quad 1]\theta_{P1G},$$

$$RI_{P2G}(Ind) = [Ind^2 \quad Ind \quad 1]\theta_{P2G},$$

$$RI_{P3G}(Ind) = [Ind^3 \quad Ind^2 \quad Ind \quad 1]\theta_{P3G},$$

where $\theta_{P1G} \in \mathbb{R}^{1\times2}$, $\theta_{P2G} \in \mathbb{R}^{1\times3}$ and $\theta_{P3G} \in \mathbb{R}^{1\times4}$ are the parameters to be estimated of polynomial models P1G, P2G and P3G, respectively, and RI (Roasting index) is the output of each model.

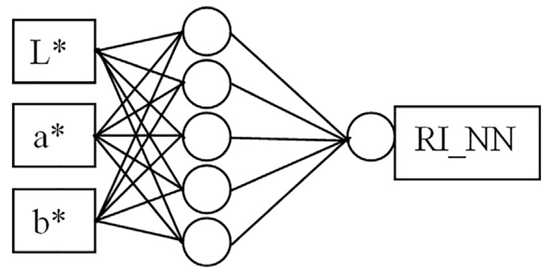

Fig. 7. Artificial neural network structure used to transform CIE L*a*b* value into roasting index.

The polynomial models were adjusted using the least squares estimator, while the neural model was estimated using the back-propagation algorithm with weight adjustment using the Levenberg-Marquardt algorithm with Bayesian regularization.

To compare the performance of models, the samples were randomly selected and separated, being 120 (80%) used for training and 30 (20%) for validation (at each execution). The parameters of each model were calculated, and training and validation errors were verified, with their respective deviations and absolute mean errors for the 2000 executions for each model (hold-out cross-validation procedure).

3. Results and discussion

3.1. Color space transformation model

Based on the Tukey test, it was verified that the neural networks with five neurons in the hidden layer obtained the best results for transforming RBG to CIE L*a*b*. The mean errors obtained by the transformation model after 500 iterations from hold-out cross-validation procedure are shown in Table 1.

The results obtained in this study are 0.4984% ± 0.6805% for the training set and 0.8170% ± 0.7146% for the validation data (Eq. (1)); these values are lower than those reported by (Papadakis et al., 2000), which found error equal to 1.20% ± 1.24% for training and 1.15% ± 1.01% for validation. However, it is important to note that this study used a color tone scope aligned to the color standards of whole and ground roasted coffee beans.

In agreement with CIE (CIE, 1986), the difference of spaces among colors in the CIE L*a*b* model can be expressed by:

$$\Delta E^*_{ab} = \sqrt{(\Delta L^*)^2 + (\Delta a^*)^2 + (\Delta b^*)^2} \tag{2}$$

where the variation ΔE^*_{ab} for the human capacity of distinguishing different colors is between 2.2 and 4 units of the model (Valous et al., 2009). The transformation model developed in this study reached the value 1.6434 ΔE^*_{ab} units per tested data, surpassing the 2.97 ΔE^*_{ab}described in (Oliveira et al., 2016), thus confirming that they were well estimated and can be used for analysis in small variations of roasting degree for coffee beans samples.

Table 1
Mean ± standard deviation of error (Eq. (1)), obtained by the color space transformation models based on Artificial Neural Networks (ANN).

n° = 5	Training error (%)	Validation error (%)
NN 1 (L*)	0.9011 ± 0.7768	1.6884 ± 0.9300
NN 2 (a*)	0.2207 ± 0.2601	0.2892 ± 0.1098
NN 3 (b*)	0.3735 ± 0.3674	0.4734 ± 0.4031
ē	0.4984 ± 0.6805	0.8170 ± 0.7146

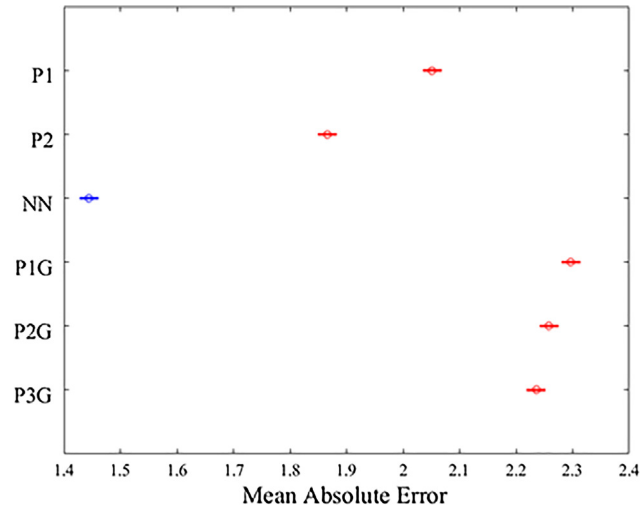

Fig. 8. Comparison of absolute errors among approximation models for whole coffee beans samples.

3.2. Roasting index estimation

3.2.1. Whole roasted beans

To compare the performance of the proposed regression models in whole beans, the Tukey test was used again with a 95% confidence level in the mean absolute validation errors. Fig. 8 shows the test where the vertical axis presents the estimated models.

It is possible to observe that the ANN model showed significantly the smallest error, being therefore defined as estimation model of the roasting degree based on CIE L*a*b* values for whole beans.

Based on performance analysis of all networks, one whose R^2 factor was 0.99 was chosen to present the mean squared error. Fig. 9 shows a comparison between the ANN output and the experimental values. The obtained error is small, being that the mean absolute error found was 1.44 and the deviation was 1.17.

3.2.2. Ground roasted beans

As shown in Fig. 10, the results of the polynomial grayscale approximation model (P2G) obtained the best fit, where the Tukey test with 95% confidence was performed. The mean absolute error found by this model was 0.9361 ± 1.3097. This model is expressed by:

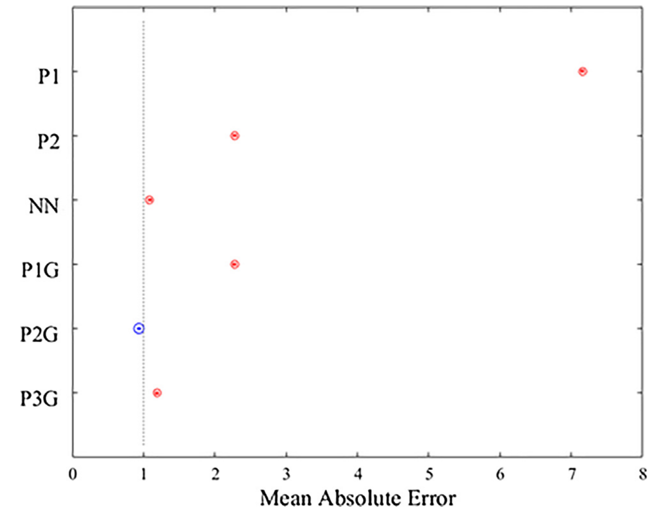

Fig. 10. Comparison of absolute errors among approximation models for ground coffee beans samples.

$$RI_{P2G} = -2.839 \times 10^{-7} Ind^2 + 1.551 \times 10^{-2} Ind - 43.85, \quad (3)$$

where Ind^2 and Ind were obtained by transforming the RGB image to grayscale. The chosen model faithfully estimates Agtron/SCAA roasting index, as can be observed in Fig. 11.

It is interesting to observe that although Artificial Neural Networks reached better performance for whole beans, a simple model such as the P2G (second order polynomial model with grayscales values) was able to estimate the roasting degree of ground beans with good accuracy. This can be explained by the fact that images of ground coffee samples are much more homogeneous than those of whole samples.

The models identified in this work (color space transformation neural model, whole beans roasting estimation neural model and the polynomial ground beans roasting estimation model) achieved good accuracy performance making them suitable for implementation in real embedded systems. It is worth mentioning that the roasting degree mean absolute error achieved by the identified models are very small when compared to increments of 10 of the SCAA color disks, which are normally used for visual inspection of the roasting degree. Besides, the methodology here presented can be used elsewhere to develop other computer vision systems to predict the coffee beans color and roasting

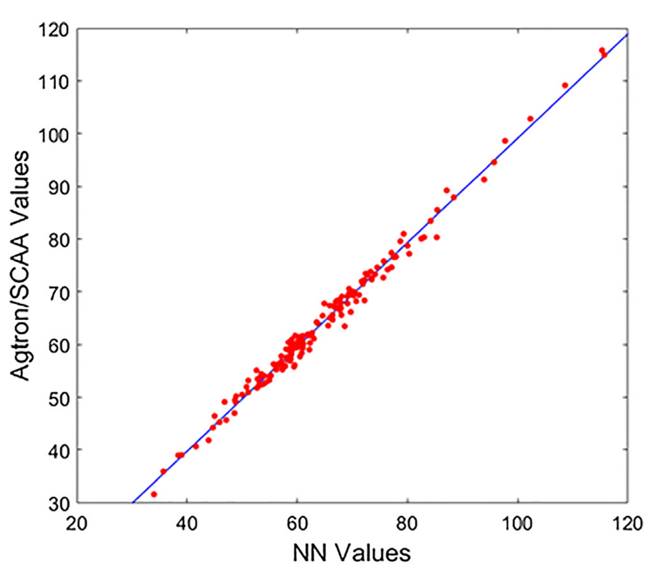

Fig. 9. Comparison between ANN simulated output and the Agtron/SCAA value measured for whole coffee beans samples.

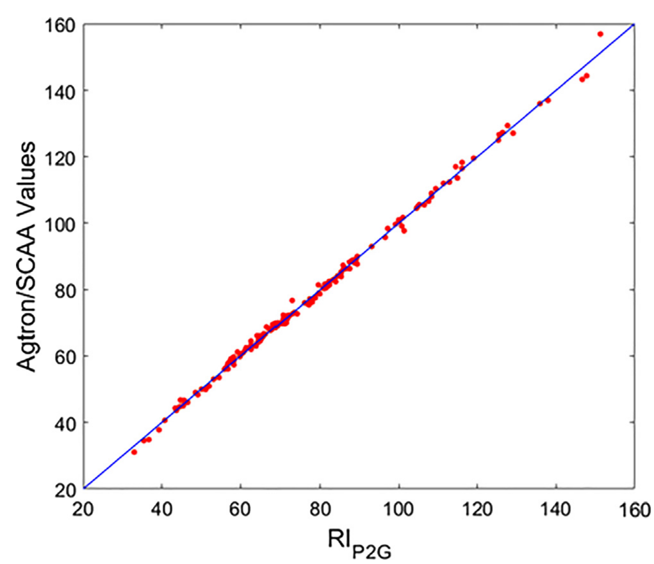

Fig. 11. Comparison between simulated output of the P2G polynomial model and the Agtron/SCAA value measured for ground coffee beans samples.

degree.

Food analysis, in general, has been improved by recent advances in science and technology. Image processing tools have been explored due to their applicability in several areas, such as in food analysis (Russ, 2015). Aiming at controlling the roasting process of coffee beans, several researchers have been developing reliable methodologies and easy handling and low cost equipments to meet their need to correctly determine the coffee roasting degree. The potential of artificial intelligence associated with image analysis techniques can contribute significantly to the elucidation of practical issues, as evidenced by the results presented in this work.

4. Conclusions

This study presents a computer vision system for analysis and identification of the coffee roasting degree by computer intelligence techniques. The results show that the development of regression models allows a precise and objective analysis of the roasting degree for both whole and ground beans based on the CIE L*a*b* color space or grayscale. It was observed that the estimation of the roasting degree in whole beans is more difficult than the estimation in ground beans, being necessary the use of ANNs for the first case whereas polynomial quadratic models was sufficient for the second. Satisfactory results were obtained for a wide sample range, concluding that the entire developed system is above human visual capabilities.

This simple, low cost assembly system can be used in industries, coffee shops, cooperatives and other establishments as a more reliable way of reading color and defining the coffee roasting degree. In addition, it can extend through other branches of the food industry, enabling improvements in the characterization of foods that undergo pyrolysis processes, hence improving the food quality.

Acknowledgments

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