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# CLASSIFICATION OF TOMATO CULTIVARS FOR PROCESSING WITH ARTIFICIAL VISION AND EUCLIDIAN DISTANCE

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**ABSTRACT**

Industrialized tomato is the vegetable most consumed worldwide and due to its content of bioactive compounds and antioxidants, such as lycopene and carotene, is considered functional food. Color is one of the most important appearance parameters, which defines quality. With the recent advances in computer power and memory of personal computers, the artificial vision system can be applied in the selection or online classification of agricultural products. Thus, the present work proposes a methodology for the classification of different tomato cultivars based on the color model obtained from instrument (colorimeter) and digital image (RGB) of physicochemical characteristics (total soluble solids, pH and total titratable acidity), and pigment content. To this end, two pattern recognition techniques were used and compared: MLP (Multilayer Perceptron) and KNN (K-Nearest Neighbor) neural networks. In the case study, 330 tomato samples were used, 30 fruits of each cultivar. Analyzing the physicochemical characteristics, pigments and instrumental color analysis and digital image, cultivars formed three distinct groups, being H9992 cultivar isolated from the others, cluster II with HY37 and BRSena cultivars and cluster III with the other cultivars, most were grouped due to the presence of similarities. The cross validation results obtained quite high accuracy (%), since cultivars were analyzed in their full maturation stage, when their characteristics are very similar. Statistical models showed remarkable performance in the classification of cultivars. Of the two proposed models, KNN obtained 99.69% accuracy, being the best mathematical model proposed in this study.



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## INTRODUCTION

material for the production of purees, ketchup and other products. Brazil is one of the world's largest tomato producers for both fresh consumption and processing. The state of Goiás is one of the main Brazilian producers, and in 2014, its production was 1.1 million tons, about 65% of all tomato for processing produced in Brazil (Campo and Negócios, 2014). Tomato is a source of vitamin A and C is known as "orange of the poor". Among fruits and vegetables, this fruit occupies the 16th place as source of vitamin A and the 13th as source of vitamin C. It is a functional food due to its content of bioactive compounds, such as antioxidants (lycopene and β-carotene), which help prevent and neutralize free radicals, and ascorbic acid acts as an effective eliminator of superoxide, hydrogen peroxide, singlet oxygen, and other free radicals (Devi *et al*., 2019; Lucas, *et al*., 2014), in addition to providing red coloring to the fruit. However, many factors are known to affect the nutrient content of tomato, such as cultivar, climate, soil and water geochemistry and agricultural practices such as mineral fertilization (Canene-Adams *et al*., 2005). Various characteristics, such as soluble solids, acidity, pH, β-carotene, lycopene content and color are essential quality parameters for tomato, both for fresh consumption and for processing. The taste of tomato is dependent on the amount of sugars and acids present in fruits.

High content of soluble solids and acidity are required for better taste (Agbemavor *et al*., 2014). Color and chemical characteristics are considered as good fruit quality indicators, and understanding these attributes is fundamental to establish good management practices in industry (Maršić *et al*., 2011).

The color of tomato for processing is very important, since its derivatives must have intense red color; therefore, cultivars with high lycopene content have been developed, being a critical factor to obtain high-quality derivatives (Melo, 2012). Color has been one of the crucial issues of concern in the food industry, as well for the research and development of new products. In fruits, color is one of the most important attributes because it influences the consumer's decision to accept or reject a given product (Saldaña *et al*., 2013). The observation of color of agricultural products allows detecting certain imperfections and defects (Pedreschi *et al*., 2000; Du and Sun, 2004; Hatcher *et al*., 2004). Color can be numerically represented in the food industry by the Cielab scale (L*, a* and b*), measured by instrumental methods such as colorimeter and spectrophotometer, to provide a measure of color similar to that seen by the human eye (Wu and Sun, 2013). However, colorimeters are used to measure small areas, where samples may have homogeneous color (Gardner, 2007), and due to the size of fruits, they are highly heterogeneous. Surface, texture, brightness, shape and peculiarities of each type of product have influence on the human perception of color. When the material is heterogeneous, it is necessary to measure color in larger areas, or if the sample contains distinct colors, color should be measured in a different way, and digital image analysis can be an effective solution, since the camera provides images in which the colors of pixels are individually determined (van Dalen *et al*., 2014).

Identifying, selecting, or classifying fruits is an arduous and complex task due to the amount of information that must be considered. Resources for color measurement and extraction using an artificial vision system offer a potential solution for pattern recognition. The application of artificial neural networks (ANNs) and artificial vision has received increasing acceptance in the food industry. These techniques prioritize classification, pattern recognition and prediction of harvests and physical changes in products (Figueredo-Ávila and Ballesteros-Ricaurte, 2016). ANNs, which are computational techniques that mimic the behavior of the human brain and extract knowledge from a set of data obtained during training, are considered as calculation models that use very efficient algorithms, allowing the development of cognitive tasks such as learning patterns, classification and optimization (Veites-Campos *et al*., 2018). Unlike conventional computing techniques, in which a computer program needs to be developed to solve a given problem, artificial neural networks learn to solve problems through learning and experience, as occurs with humans (Mingoti, 2007). They are alternatives to the use of statistical techniques for classification and natural grouping among available variables. For artificial neural networks to be used, it is not necessary to know the statistical distribution of data, unlike many of the statistical techniques commonly used (Silva Junior *et al*., 2008). The K-nearest neighbors (KNN) method is a simple algorithm that classifies an object by performing a major grouping of the K nearest neighbor classes using Euclidean distance, applying a weight to each neighbor inversely proportional to the distance (Lochne *et al*., 2016). In view of the above, the present work proposes a methodology for the classification of different tomato cultivars based on the color model obtained from digital image (RGB). Data obtained from physicochemical analyses, pigment content, information extracted from the colorimeter, as well as data obtained through digital image processing algorithms, executed on the digital photographs of fruits from eleven tomato cultivars for industrial processing, were analyzed. Two pattern recognition techniques were used: MLP (Multilayer Perceptron) and KNN (K-Nearest Neighbor) neural networks.

## MATERIAL AND METHODS

**Fruits used in the experiment:** Fruits from industrial tomato cultivars (IT761, H9953, AP533, Advance, N901, BRSena, U2006, HY26, HY37 and HY68) were supplied by Cargill Agrícola S.A Company, Hidrolândia, Goiás, Brazil. All fruits were similar in terms of maturation stage, firmness, shape and size, free from external defects.

**Harvesting and preparation of fruits:** Fruits were manually harvested from June to September 2013. Fruits were transported in low-density polyethylene bags washed in running water and submitted to sanitization by immersion in sodium hypochlorite solution at 150mg $100^{-1}$ for 20 min, and allowed to air dry.

**Physicochemical characteristics**: Three tomatoes with seed and bark were ground in domestic blender for better homogenization before physicochemical characterization. For pH, 5.0mL of pulp added of 50mL of distilled water were used, and reading was carried out in digital potentiometer, previously calibrated with buffer solutions of pH 4 and 7. Total soluble solids (TSS) were obtained by direct reading in refractometer (ºBrix); titratable acidity (TA) was determined by titration with 0.1 N sodium hydroxide using 1% phenolphthalein as indicator. Results were expressed as citric acid concentration (g $100g^{-1}$), and the TSS / TA ratio was calculated. Analyses were determined at 25ºC in triplicate, according to AOAC methodologies (Association of Official Analytical Chemists; 2012).

**Bioactive components (pigments):** For the extraction of lycopene and β-carotene pigments, 1g of liquefied pulp was weighed and added of solvents (10mL of ethanol, 10mL of acetone and 20mL of hexane). The mixture was refrigerated at 3°C in tube wrapped with aluminum foil and lid; after complete depigmentation, another 10mL of ethanol, 10mL of acetone and 20mL of hexane were added, filtering on Whatman filter paper nº 2. Then, 50 mL of distilled water was added, and the mixture was transferred to a separation funnel, discarding the lower fraction. In the later phase, absorbance was read at wavelengths of 503 and 450nm for lycopene and β-carotene, respectively (Rodriguez-Amaya, 2001). Another technique using only acetone P.A. was used for pigment extraction. For the calculation of the lycopene and β-carotene content in both techniques, the equations developed by Lime *et al*. (1957) and Georgé *et al*. (2011) (Equations 1 and 2) were used, and results were expressed in μg $g^{-1}$. Pigment analyses were performed in triplicate, respectively.

$$C_{\beta\text{-carotene}} = 4{,}624xA_{450} - 3{,}091xA_{503}$$

$$C_{lycopene} = 3{,}956xA_{450} - 0{,}8061xA_{503}$$

In which:

$C_{\beta\text{-carotene}}$ and $C_{lycopene}$: β-carotene and lycopene concentrations in μg $g^{-1}$;

$A_{450}$ and $A_{503}$ = absorbance at wavelengths of 450 and 503, respectively.

**Colorimetric analysis:** The color of tomatoes was determined in the Cielab system using colorimeter (Color Quest II, Hunter LabReston, Canada). Readings in three areas of the fruit (shoulder, equator and apex) were performed. In the Cielab system, L* represents how light or dark the sample is, which ranges from -100 (black) to +100 (white). Chromaticity coordinates are: + a* = red and -a* = green; + b* = yellow and -b* = blue, according to the International Commission of (CIE, 2014).

**Color image analysis:** Fruits were photographed by digital camera (Samsung WB1000, Manaus, Brazil) with 12.2 megapixel resolution. Tomatoes were placed on a black surface, and digital images were taken immediately after harvest and preparation samples under controlled lighting of two electronic lamps (Philips, white color, 20W), arranged at an inclination angle of 45º, and D65 illuminant (Silva, 2006). Camera lens was positioned at an angle perpendicular to the fruit surface and distance of 40cm from the black surface (Figure 1).

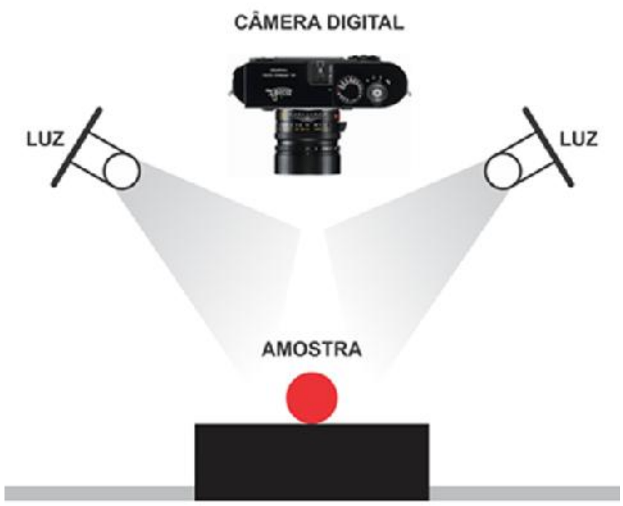


**Figure 1. Layout of the digital image acquisition system of tomato fruits (*Solanum lycopersicum*)**

With the aid of the Microsoft Paint software, an area of approximately $5x5cm^2$ was selected in the central area of the digital image of fruits, which was converted into average RGB value, using the Paint pixel color reading. Image color analyses were performed thirty times. Data were read out in Matlab (high performance interactive software for numerical calculation), according to Table 1.

**Statistical analysis:** For the implementation of the evaluated neural network and KNN, WEKA software was used. In this research, two supervised pattern recognition algorithms were proposed: Multilayer Perceptron (MLP) and K-Nearest Neighbor (KNN) artificial neural networks, which use supervised learning techniques. In MLP and KNN neural networks, the cross-validation procedure was used to measure the accuracy of classifiers. Similarity measures were calculated using the Euclidean distance through Statistica 7.

## RESULTS AND DISCUSSION

The three experiments were carried out to verify the most relevant information for the classification of tomato cultivars for processing. Physicochemical data, bioactive compounds, and color parameters by means of colorimeter and digital image were analyzed. In the first experiment, only physicochemical attributes (total soluble solids, pH, total titratable acidity) and bioactive compounds (lycopene and β-carotene, extracted with acetone and a mixture of hexane, acetone and ethanol) were used to identify cultivars (Table 2). Both classifiers achieved high success rate in the analysis of physicochemical data and pigments, and results for the classification of pigments extracted with acetone using MLP obtained relatively higher accuracy rate (98.48%), compared to those extracted with the mixture of reagents (93.93%), whose error percentage was four times higher. For KNN, results were the same, both for the extraction of pigments with the mixture of reagents and for extraction with acetone alone, and all presented very good accuracy rate (2.13%).

The percentage of correctly reclassified diagnoses was presented as a confounding matrix. Vélez-Rivera *et al*. (2013) evaluated the classification of damages in climacteric fruits with different classifiers and obtained better result using the KNN classification model, with accuracy rate of 97.9%, similar to that obtained in this study. However, Arzate-Vázquez *et al*. (2011), classified three maturation stages of Hass avocado with KNN, achieving 81.9% accuracy rate using six texture and color parameters by image (RGB), which result is lower when compared to that observed for the study of the physicochemical characteristics and color of tomato cultivars in the present study. In a palm oil color study using MLP neural network, Farahani *et al*. (2012) obtained 94% accuracy rate in results and verified that both algorithms proved to be good parameters for the classification of maturation and other fruit characteristics, as observed in this study. The extraction of pigments by the solvent mixture presented greater confusion among cultivars, and HY26 and H9992 cultivars presented six and five samples erroneously classified, respectively, obtaining accuracy rate of 93.93% (Table 2). Of the 11 tested cultivars, four (AP533, BRSena, U2006 and HY37) presented 100% accuracy. The hierarchical clustering analysis using Euclidean distance, constructed from physicochemical characteristics and pigments of the different tomato cultivars for processing, showed cluster architecture at various similarity and dissimilarity levels (Figure 2).

The vertical lines extended for each cultivar in several similarity and dissimilarity values, and these lines were connected to other observations with horizontal lines. In the composite binding method, two groups (A and B) composed of three clusters were formed according to similarities between physicochemical characteristics and pigment contents. Group A was formed by cluster I and by two subclusters, which included (Advance and AP533) and (U2006 and H9553) cultivars, and these are close to each other. Group B was formed by clusters II and III. Cluster II was composed only of BRSena cultivar (single), while cluster III, with six cultivars (HY68, HY37, HY26, N901, H9992 and IT761) showed similarity between their physicochemical characteristics (total soluble solids, pH and total titratable acidity) and lycopene and β-carotene content. IT761 and H9992 cultivars formed a subcluster and showed greater similarity with each other in relation to the physicochemical characteristics and pigment

**Table 1. Description of the physicochemical characteristics, pigment content, L*, chroma a*, chroma b* color parameters of Cielab, and RGB characteristics with their respective number**

| Description of the physicochemical characteristics | |
|---|---|
| Characteristic 1 | Total soluble solids |
| Characteristic 2 | pH |
| Characteristic 3 | Total titratable acidity |
| Description of the physicochemical characteristics of pigments | |
| Characteristic 4 | Lycopene (hexane, acetone and ethanol) |
| Characteristic 5 | Lycopene (acetone) |
| Characteristic 6 | β-carotene (hexane, acetone and ethanol) |
| Characteristic 7 | β-carotene (acetone) |
| Description of Characteristics Cielab per fruit region | |
| Shoulder | |
| Characteristic 8 | L* |
| Characteristic 9 | a* |
| Characteristic 10 | b* |
| Equatorial | |
| Characteristic 11 | L* |
| Characteristic 12 | a* |
| Characteristic 13 | b* |
| Apical | |
| Characteristic 14 | L* |
| Characteristic 15 | a* |
| Characteristic 16 | b* |
| Description of RGB characteristics of fruit images | |
| Characteristic 17 | Red color (R) |
| Characteristic 18 | Green color (G) |
| Characteristic 19 | Blue color (B) |

**Table 2. Results of physicochemical characteristics recognition (total soluble solids, pH, total titratable acidity) and lycopene and β-carotene pigments extracted with the mixture of reagents (hexane, acetone and ethanol) and acetone in the neural network (MLP) and K-Nearest Neighbor (KNN) of tomatoes (Solanum lycopersicum) for processing. Goiânia, GO, Brazil**

| Problem | MLP Mixture | MLP Acetone | KNN Mixture | KNN Acetone |
|---|---|---|---|---|
| Pigments, physicalchemical characteristics[1] | 93,93% | 98,48% | 97,87% | 97,87% |
| Error[1] | 6,06% | 1,51% | 2,13% | 2,12% |

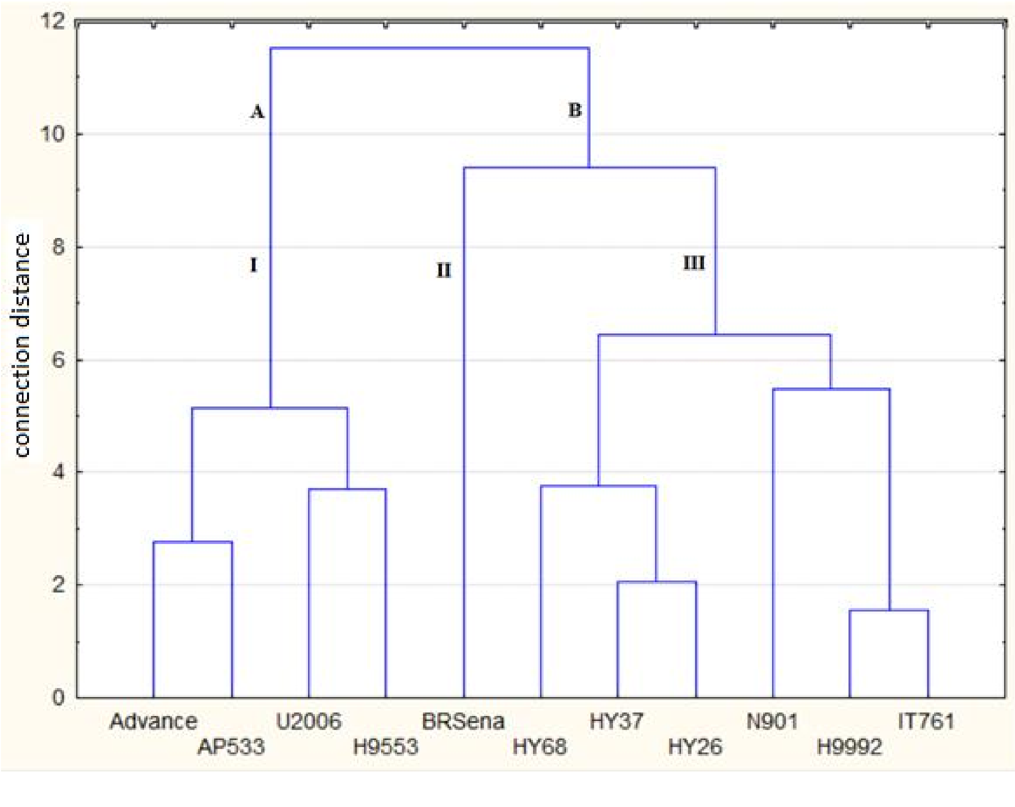


**Figure 2. Dendrogram showing similarity among tomato cultivars (*Solanum lycopersicum*) for processing using physicochemical characteristics (total soluble solids, pH and total titratable acidity) and contents of pigments lycopene and β-carotene extracted with the mixture of reagents (hexane, acetone and ethanol) and acetone. The smaller the bars that bind two cultivars, the greater the similarity between them in relation to the evaluated characteristics.**

**Table 3. Results of physicochemical characteristics recognition (total soluble solids, pH, total titratable acidity), lycopene and β-carotene pigments extracted with the mixture of reagents (hexane, acetone and ethanol) and acetone, instrumental color (L*, a* and b*) and digital image in the (MLP) and K-NearestNeighbor (KNN) neural network of tomato (*Solanum lycopersicum*) for processing**

| Problem | MLP Mixture | MLP Acetone | KNN Mixture | KNN Acetone |
|---|---|---|---|---|
| Pigments, physicalchemical characteristics, instrumental color and digital image[1] | 97,57% | 99,39% | 99,39% | 99,69% |
| Error[1] | 2,42% | 0,60% | 0,60% | 0,30% |

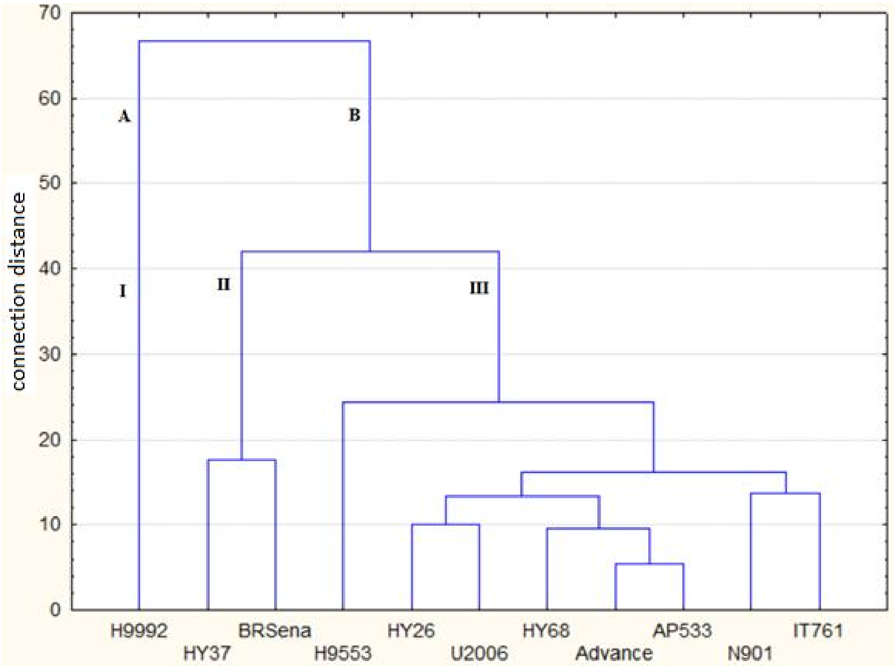


**Figure 3. Analysis of clustering of tomato cultivars (*Solanum lycopersicum*) for processing based on physicochemical characteristics (total soluble solids, pH and total titratable acidity), lycopene and β-carotene pigment contents extracted with the mixture of reagents (hexane, acetone and ethanol) and acetone and the color verified by colorimeter and digital image. The smaller the bars that bind two cultivars, the greater the similarity between them in relation to the evaluated characteristics**

content, and N901cultivar showed proximity to these cultivars. Another subcluster was formed within group B in relation to the same characteristics, by HY26 and HY37cultivars, which showed similarity to each other, and are close to HY68 cultivar. Scholz *et al*. (2011) evaluated the physicochemical characteristics of coffee beans of different cultivars and observed that cultivars in the same group were similar, and distancing showed the effects of the genetic expression of each cultivar, which may also have occurred for tomato cultivars, even being cultivated in the same area and with the same cultural treatments. From the producer's point of view, the clustering methods based on several characteristics of cultivars and the particularities of each one is adequate for better decision making regarding the choice of cultivars, as well as for crop planning, and processing of batches of primary products (pulp and cubes) with characteristics specific to certain applications. When physicochemical characteristics, pigment contents, instrumental color parameters and image transformed into RGB were used, and both classifier reached higher accuracy rates (Table 3). With the use of MLP, lycopene extraction with the mixture of reagents presented relatively lower accuracy rate (97.57%), whereas with acetone alone, the result was the same as that of the KNN system using the mixture of reagents, with 99.39% accuracy rate. The percentage of correctly classified diagnoses was presented as a confounding matrix. In the MLP network using colorimetric values, color by digital image RGB, pigment extraction with the mixture of reagents, there were also greater confusions among cultivars, and H9992 and IT761 cultivars presented three and two samples erroneously classified, respectively, that is, these cultivars are those that most confused mathematical models. Rodrigue *et al*. (2014), evaluated the aging of "cachaça" in tons of different types of wood and found 100% accuracy rate for MLP and KNN, when sing physicochemical characteristics associated to RGB values. Monavar *et al*. (2011), worked with tomato fruit at red maturation stage (full maturation) and digital image processing converted into RGB values and reported average error of 3.85%, higher than that found in this study. However, both network methodologies, MLP and KNN, also used in this work, showed higher accuracy in relation to results obtained by the aforementioned authors, when RGB values were used. Clustering analysis of eleven cultivars based on physicochemical characteristics, pigment content with different extraction forms, Cielab and RGB color parameters evaluated is presented in Figure 3. When color was considered, two groups A and B and three clusters were formed. Group A, formed by cluster I presented only H9992 cultivar, which was isolated from the others. In group B, two clusters were verified; cluster II, composed of HY37 and BRSena cultivars, with greater similarity among them in relation to the evaluated parameters. Cluster III, composed of eight cultivars, formed three subclusters, H9553 cultivar as a single group, while (Advance and AP533), (HY26 and U2006) and (N901 and IT761) cultivars, within cluster III, showed the smallest variations among all evaluated parameters. HY68 cultivar showed similarities with Advance and AP533 cultivars. The main objective of the cluster analysis for this experiment was to determine the degree of affinity or the distance among cultivars in relation to physicochemical characteristics, pigment contents and color instrumentally analyzed and by digital image converted into RGB. Digital imaging techniques have been used in recent years in several areas, such as dentistry. One of the main advantages is the quantitative characterization of several physical characteristics, such as size, morphology, color and physicochemical characteristics using a simple digital image. In this research, the use of digital images converted into RGB values proved to be efficient in the classification of tomato cultivars. Farahani *et al*. (2012), used RGB components to study blue mold in apples, reaching accuracy rates between 80 and 100%, results that emphasized the importance of color by imaging in quantifying the severity of disease caused by mold. Ganiron (2014), used digital image to investigate the physical characteristics and lesions in mango, and images were used with the intention of classifying cultivars. It is not surprising that the digital image analysis technique is accurate and qualitative (Bock *et al*., 2008).

**Conclusion**

Analyzing the physicochemical characteristics, bioactive compounds and color by instrumental analysis and digital image, it was observed that cultivars formed three distinct groups, with H9992 cultivar isolated from the others; cluster II with HY37 and BRSena cultivars and cluster III grouped most cultivars due to their similarities. However, the cross-validation results obtained very high accuracy rate, above 90%, since these cultivars were analyzed in their full maturation and their characteristics are very similar. Based on results obtained, it could be concluded that the statistical models have remarkable performance in the classification of cultivars. Of the two models proposed, KNN obtained 99.69% accuracy rate, being the mathematical model most suitable for this type of study. The clustering analysis revealed little divergence of the physicochemical characteristics of Advance, AP533, HY68, HY26, U2006, N901 and IT761 tomato cultivars.

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