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Determination of the Ripeness State of Guavas Using an Artificial Neural Network

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Abstract. The determination of the ripeness state of fruits is an essential element in the agriculture research field. This is because the ripeness is related with quality and it can affect the commercialization of the product. In this paper, a classification system of the ripeness state of guavas is proposed. The guavas are classified into three states: green, ripe and overripe. The classification system is based on Artificial Neural Network (ANN) which uses color features as input. The characteristics used in our proposal are extracted from three different color spaces: RGB, CIELab and CIELuv. Specifically, we only use the components R, G, a and u, which gave us the best separability within classes. The system was tested using real images of guavas obtaining 97.44% of accuracy.

Keywords: Guavas, ripeness state, color, ANN.

1 Introduction

Nowadays, image analysis is of great interest for the development of applications in agriculture-oriented tasks. The determination of the ripeness state of fruits is an essential element in agriculture tasks because ripeness is highly related with quality and therefore, with their commercialization. The main issue is that only trained personnel can perform this task and a large amount of time is required to analyze each piece of fruit. The development of systems to determine fruits quality is very important. Specifically, guavas are of great interest in our society because, taking into account the benefit in the health, the guavas [5] have high content in quercetin, vitamin A and C which prevents the development of cataracts and the other diseases. Due to this, the global market of guavas [1] has achieved the exportation of 1.2 millions of tons per year.

Recently, a wide number of classification systems have been developed for the determination of the ripeness state of fruits. Such methods can be classified into two groups: destructive and non-destructive. Destructive methods take a sample of the crop an it is chemically analyzed in order to determine its glucose composition. The main disadvantage of these methods is the destruction of the fruit. On the order hand, non-destructive methods analyze images of the fruit to determine the ripeness state. Among these approaches, different image features and classification methods have been proposed. In [8], color features are extracted from images of bananas with two different illuminations: natural and ultraviolet, and the corresponding images are submitted to a set of if-then rules for classification. On the same way, in [2] color features are extracted from bananas using two color spaces CIElab and HSV. Tomatoes images are analyzed in [15], where color features are extracted. In this case, the authors use two different cameras: conventional and near infrared. The classification is performed through an integration and analysis of the color variation in red-green. Using variation of color, in [14] an algorithm is developed to determine the ripeness state of watermelons. Another method used in classification tasks is the fuzzy logic, for example in [6] color features and texture features are extracted from images of tomatoes and they are submitted to an if-then rules system to get a classification. Different studies corresponding to the ripeness state of a fruit have been proposed using Artificial Neural Networks (ANN). For example, in [4] a system to determine the level of ripeness in palm oil using color features is proposed. The features are submitted as input to the ANN. Oranges are analyzed in [9], where color features and weight features are used for their classification.

In this paper, a classification system of guavas depending of their ripeness state is proposed. The guavas are classified into 3 states: green, ripe and overripe. The images were taken with a conventional camera and natural light. Color features are extracted from images using three color spaces RGB, CIElab and CIEluv. These features are used as input to the ANN where only the components R, G, a, u are used. Our system is tested with real images of guavas, attaining a high accuracy level. The rest of the paper is organized as follows: in the Section 2 the methodology is presented where it is described each state to details, Section 3 results and the accuracy percentage of the system is presented. Finally, in Section 4 conclusion is presented.

2 Methodology

The automatic determination of ripeness state of guavas is of a great interest. In this work, a system for the classification of guavas is proposed. In order to have a good set of guavas with exportation quality, a person has to classify each piece of fruit. For our application, image samples in three main states are studied: green, ripe and overripe. Samples of each state are shown in Figure 1. For this system, 72 images of guavas in different ripeness states were taken. All the images were taken in the same conditions and the guavas were pre-classified by an expert. The images are grouped in two sets training and testing, ensuring that these two sets are completely different.

a) Green b) Ripe c) Overripe

Fig. 1. Guavas in different ripeness states.

The proposed system is developed in two main stages: training and testing. The first stage is performed in three steps: image segmentation, features extraction, neural network training. The second step is achieved in four steps: image segmentation, features extraction, neural network testing and ripeness state classification. The process is shown in Figure 2. Each phase is described in detail in the next subsections.

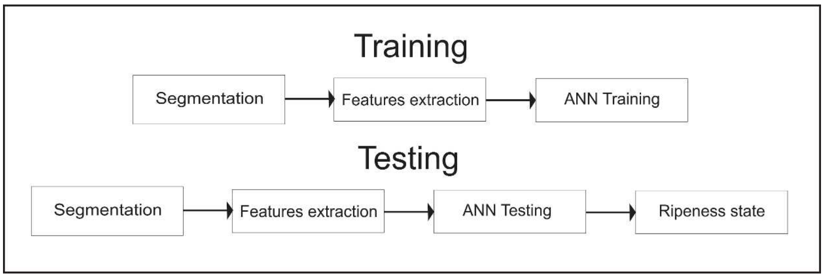

Fig. 2. Classification system.

2.1 Images Segmentation

In order to estimate which pixels correspond to the guava and which to the background, images were segmented. The image segmentation is performed through a sequence of two steps. The first step is to transform the image from RGB space to CIELab color space. After that, the image is submitted to the K-means algorithm [11] using the color components of a and b. In this step, the images are separated into two clusters: background and object. In order to select the cluster corresponding to the guava, we take the cluster with the smaller number of pixels. Since the resulting image is not perfectly segmented, it is necessary to apply an additional processing. In this case, we perform a closure operation of mathematical morphology, in order to remove not desire segments. In Figure 3 the complete image segmentation process is shown.

a)Input b) Kmeans c) Closure d) Final Mask

Fig. 3. Image segmentation process.

2.2 Feature Extraction

For the feature extraction, we only use the pixels that correspond to the guava. In this case, we transform the original images in RGB to its representations in CIELab and CIELuv color spaces. Such spaces are defined as follows:

- RGB Color Model: The RGB (Red, Green, Blue) color model is the most important one in digital image processing because it is used by all electronic devices, such as monitors, cameras, etc. In the RGB model, a color is expressed in terms of the amounts of Red, Green and Blue lights.
- CIELab color space: This color space is most commonly known because it is independent of the illumination [13]. L* is the luminance or lightness component that goes from 0 (black) to 100 (white), the component a* goes from green to red, and b* from blue to yellow. The components a and b are the two chromatic components.
- CIELuv color space: This space is similar to CIELab and it is used in applications with low illumination[12]. L* is the luminance component that goes from 0 (black) to 100 (white), u* goes from green to red and v* from blue to yellow, which are the two chromatic components.
  The definition of L*a*b* and L*u*v* are based on the intermediate system CIEXYZ which emulates the human perception of color.

When the 3 corresponding images of each color space are obtained, only the pixels corresponding to the guava are used. In our application, we obtain the mean (see Eq.1) of each color component: R, G, a and u, which are the only features that we use for the ANN:

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i, \tag{1}$$

where x represent the value corresponding to the pixel intensity.

2.3 Artificial Neural Network for Guavas Classification

Artificial Neural Networks (ANNs) are a family of models inspired by biological neural networks which are used to estimate, or approximate functions that associate inputs and given outputs. The ANN can be designed using different parameters [7], in this work, the following factors have been taken: number of layers, number of neurons per layer, activation function, and the learning rate. In our approach, each one of these factors are varied in a range in order to determinate the best parameters for our specific task. For the number of layers we explore in the range of [2, 3]. The number of neurons in the hidden layer were varied in [5,6,..,15]. The learning rate was explored in [0.2,0.5,0.8]. Finally, the activation function was explored using two of the most popular ones: tangent sigmoid (TS) and logarithmic sigmoid (LS). This is in order to get the best combination of parameters and build the optimal ANN for our task. The structure of ANN is shown in Figure 4, where $X = \{x1, x2, x3, x4\}$ is the input vector and $Y = y1, y2, y3$ is the possible output with three options. In our system, $X = \{R, G, a, u\}$ and $Y = \{green, ripe, overripe\}$.

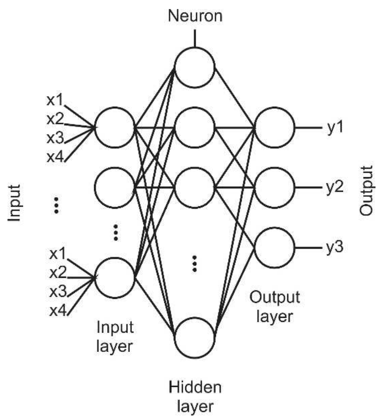

Fig. 4. Structure of Artificial Neural Network.

3 Results

At the end of our experiments, we have tested 786 different architectures with the different combinations of parameters. The performance of our system was evaluated using the number of images correctly classified. In our application, many architectures have achieved the same highest results of 97.44% of accuracy. However, the final results were obtained with the parameters: activation function = TS, learning rate = 0.2, two layers, input layer with 4 neurons and output layer with 3 neurons.

In Table 1 the confusion matrix for each class is shown. In this table we can see that the accuracy in each class is of 92.3%, 100%, and 100% for the green, ripe and overripe classes, respectively. As it was previously mentioned, 72 images were taken and they were grouped in two sets: training and testing, where 36 images were used to training and 36 for testing. As it can be seen in this table, our method proposes a novel methodology, which is able to detect 3 different states of guavas with an accuracy of 97.44%.

Table 1. Confusion matrix of the ANN in our proposal.

	Green	Ripe	Overripe	Average
Green class	92.30	7.69	0	92.30
Ripe class	0	100	0	100
Overripe class	0	0	100	100
			Total average	97.44

In order to evaluate the performance of our method with other approaches we select some of the most common classifiers: Naive Bayes and Fuzzy Inference. Results of such classifiers using the basic parameters and the same set of images and features, are depicted in Table 2. As we can see, Naive bayes achieves an accuracy of 89.4737% and the fuzzy system achieve an accuracy of 84.2105%. Our method attains a performance higher than 97%.

Table 2. Table of accuracy of different methods.

Method	Accuracy
Neural network [7]	97.44%
Classifier of bayes [3]	89.47%
Fuzzy System [10]	84.21%

4 Conclusion

A ANN-based system for the classification of ripeness state of guavas has been discussed. Our method uses color features from 3 different color spaces, which allows us to properly discriminate between the three states. The proposed methodology explores different parameters of the ANN in order to achieve the best architecture for this specific task. In this sense, we can see that our system is an appropriate option for the agricultural industry for the automatic determination of the ripeness state of guavas.

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