Artificial Neural Network-based Model Used to Determine Citric Maturity Level

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Abstract
One of the most important tasks in price determination of a product is the classification for its quality, color, maturity, etc. Usually vegetables and fruits are classified manually. This process is complex and usually some errors in the product categorization occur due to the subjectivity of persons with limited skills and long hours' work. A possible alternative is the automatic selection of products using classifiers based on computer vision systems. These systems capture the image of the product and determine its class in real time. In this paper a model capable of establishing the level of maturity of oranges, using artificial neural networks, is proposed.

Keywords
Computer Vision Systems, Artificial Neural Networks, Multi Layer Perceptron, image classification.

1. Introduction

The visual properties of fresh vegetable products result in very important criteria considered by consumers during the selection at the market. Also, these properties have great relevance in price definition. A visual impression of the product is created by the combination of color, size, shape and texture [10]. In order to satisfy consumer demands, farmers classify their products in a processing line and the selection is made by human beings. However, human perception can be easily misled, apart from that, experienced inspectors are not only difficult to find, but also expensive to pay for. Moreover, it is extremely difficult to standardize the classification results. Consequently, it is necessary to establish objective selection criteria.

Progress in technology has become important and useful to introduce objective quality controls using computer vision systems (CVS). Camera-computer systems consist of light source, digital cameras, computer and image management software. The use of these systems has increased dramatically in the agriculture and food industry. CVS application examples can include evaluation of pork meat color, cereal grains classification, measurement and classification of corn whiteness, automated sorting of pistachios, inspection of Golden Delicious apples, detection of pinhole damage in almonds and bone detection in fish and chickens [4] [7] [8] [19].

Recently, several applications for the inspection of food quality and modeling and control of biological processes have been successfully developed using artificial intelligence techniques as statistical learning, fuzzy logic and artificial neural networks (ANNs).

ANNs are models that simulate the human learning process [3] [7] [13]. The combination of CVS and ANNs produces a good tool for machine vision inspection. The ANNs do not use threshold values for the inspection of samples and this represents a significant advantage. In recent years, ANNs have been applied for classification, prediction and segmentation of foodstuff quality. Some of the studies on the implementation in CVS and

ANN include cereal grains and vegetables, fruits, nuts classification and other foods such as meat, fish and beans [7] [16].

There are several methods that use ANNs for fruit image classification. Nakano [18] proposed an ANN model for distinguishing five levels of apples quality (superior, excellent, good, poor color and injured). The ratios for superior, poor color, and injured were very high: 92.5%, 87.2%, and 75.0% respectively. However, the ratios for excellent and good are not adequate, with only 33.3% and 65.8% respectively. Kavdir and Guyer [14] sorted Empire and Golden Delicious apples using MLP model and spectral imaging. A 2-class and a 5-class classification were performed. The classification success rates were between 89.0% and 100%. Using X-ray imaging technique, Casasent et al [5] developed an improved version of the piecewise quadratic ANN to classify pistachios. The classification ratios were 88.0% and 89.3% for the test and training sets, respectively. Kondo et al [17] utilized a neural model to find the correlation between image characteristics and the sugar content or pH level for Iyokan oranges. All mentioned models require some type of image preprocessing.

In this article, an ANN-based model of classifications of citric images is described. In section 2 some image descriptors used in classification process are explained, ANN characteristics are mentioned in section 3. In section 4 the proposed model is described. The simulations and results are showed in section 5. Finally, conclusions and future work are presented in sections 6 and 7 respectively.

2. Image Descriptors

Images are made up of features that describe them, such as color, texture, pixel, etc. For their representation, image descriptors are used. They allow to emphasize some elementary characteristics and transform all pixel set into a quantitative representation that identifies them. Descriptors can be used to characterize complete images, their divisions or shades, such as Red-Green-Blue (RGB) tones [11] [12]. By using the descriptors in fragmented images for some property, greater representation is achieved. It permits better differentiation between the different images. Image descriptors[1] commonly used are [6]:

- Arithmetic Mean (M):

$$\overline{X} = \frac{X_1 + X_2 + \cdots + X_n}{n} \tag{1}$$

where $\bar{X} = mean, X_i = observations, n = all\ observations$

- Median (Me):

$$\bar{x} = \begin{cases} X_{\left(\frac{n+1}{2}\right)} & if\ n\ is\ odd\ number \\ \dfrac{X_{\left(\frac{n}{2}\right)} + X_{\left(\frac{n}{2}\right)+1}}{2} & if\ \ n\ is\ even\ number \end{cases} \tag{2}$$

where $\bar{x} = median, X = observations, n = all\ observations$

- Variance (V):

$$s^2 = \frac{\sum_{i=1}^{n}(x_i - \overline{x})^2}{n} \tag{3}$$

where $s^2 = variance, x_i = observations, \overline{x} = mean$

[1] All image descriptors calculation variables are expressed in 2D arrays.

- Standard Deviation (D):

$$s = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{x})^2}{n}} \qquad (4)$$

where $s = standard\ deviation, x_i = observations, \overline{x} = mean$

- Kurtosis Coefficient (K):

$$k = \frac{\sum_{i=1}^{k} f_i(x_i - \bar{x})^4 / n}{s^4} \qquad (5)$$

where $k = kurtosis, s = standard\ deviation, x_i = observations, \overline{x} = mean$

- Correlation coefficient (C):

$$r = \frac{\sum_{i=1}^{k}(X_i - \bar{X})(Y_i - \bar{Y}) / n}{S_x\, S_y} \qquad (6)$$

where $X_i = observations\ of\ X\ and\ Y_i = observations\ of\ Y$

$S_x = \sqrt{\frac{\sum(X_i - \bar{X})^2}{n-2}}$, $S_y = \sqrt{\frac{\sum(Y_i - \bar{Y})^2}{n-2}}$, $\bar{X}\ and\ \bar{Y}\ are\ mean\ of\ X\ and\ Y\ respectively$

3. Neural Network

Computer technology called artificial neural network consists of a mathematical computational model that simulates the structure and functioning of a biological neuronal network [13]. They can be used in a large number and variety of commercial [2], medical [1] [15] and communication [9] applications and there are many different types of neural networks, each of whom has a particular and more appropriate application, e.g. character recognition [3], exploitation of databases, pattern and image recognition [3], control process, etc [1] [13] [15].

It can be said that neural network is a parallel massively distributed processor made up of simple processing units, which has a natural propensity to store experimental knowledge and make it available for use. The procedure used to perform the learning process is called a learning algorithm, the function of which is to modify the synaptic weights of the network in an orderly fashion to attain a desired objective [13]. Thus, ANNs are capable of learning from experience, generalizing from previous cases to new cases, abstracting essential characteristics from inputs, etc.

So, one of the main properties of this system is the ability to learn and generalize from real examples. Generalization refers to the neural network producing reasonable outputs for inputs not encountered during training (learning) [3]. To do that an important class of ANN called Multilayer Perceptron (MLP) is used. It consists of a set of input neurons (input nodes) that constitute input layer, one o more hidden layer of computation nodes and one output layer of computation nodes. Inputs to the network are passed to each node in the first layer. The outputs of the first layer nodes then become inputs to the second layer, and so on. The outputs of the network are therefore the outputs of the nodes lying in the final layer. Usually all the nodes in a layer are fully connected to the nodes in adjacent layers, but there is no connection between nodes within a layer and no connecting bridging layers. The input-output relationship of each hidden node is determined by the connection of synaptic weights and the node activation function.

MLP has been applied successfully to solve some difficult and diverse problems by training them in a supervised manner [13].

4. Recognition MLP-based Model

The proposed model in this paper uses an MLP capable of recognizing images of navel oranges (of navelina variety) and categorizing them. The images were captured from one hundred oranges using a digital camera. The examples showed different maturity levels and they were visually classified into five classes according to their color.

Once the classes were defined, all descriptors mentioned in section 2 were calculated. The main idea was to use all of them for the recognition procedure, since the images had not been preprocessed. However, as each descriptor is calculated for each of the RGB tone, there has been an increase in the number of entries for the network. In order to reduce the number of entries all combinations of two and three descriptors were tested[2]. Then, each combination of descriptors was used to train an MLP and the classification results were analyzed. Finally, from descriptors mentioned in section 2, Arithmetic Mean (M), Kurtosis Coefficient (K) and Correlation Coefficient (C) were used because they showed better categorization of examples. Therefore, MKC descriptors for each image (according to each RGB tone) were extracted and the training patterns [input; target output] were built as [MKC descriptors; class].This pattern set is divided into training set (used for learning process) and test set (used for determining the network generalization level).

Learning process consists of two phases through different network layers: a forward pass and a backward pass. In a forward pass, each MKC descriptors of training set is applied to input layer, and its effect propagates through the network layer by layer and it calculates error for each target output. During the backward pass all synaptic weights are adjusted in accordance to error calculated and process continues until the training error is acceptable. At the same time, the test set is used to calculate the test error which indicates if the classification of patterns not used in the training process is correct. When learning process if finished, the MLP is able to recognize patterns unseen before.

The entire Image recognition process using the trained MLP consists of: (a) image capture, (b) MKC descriptors extraction and (c) class determination using the MLP neural network. This process is depicted in Figure 1.

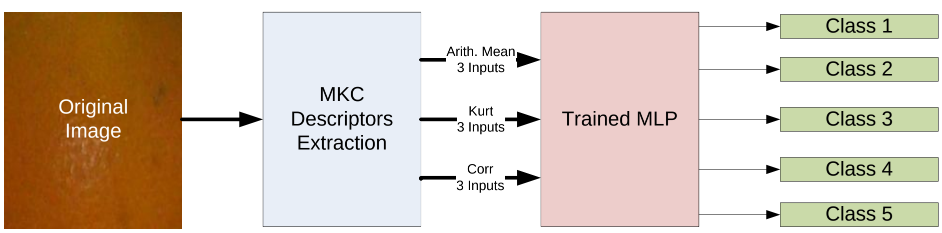

Figure 1. Process Description

The MLP has nine neurons in input layer, one for each MKC descriptor in each RGB of the images and five neurons in output layer, one for each image categories. There is no rule to determine the number of hidden layers or the number of hidden neurons. For this case several configurations must be considered in order to improve the recognition process.

[2] Currently, the Principal Component Analysis (PCA) method is being used to identify descriptors that produce a better classification of the samples.

5. Simulation and Results.

The main goal of simulations is to test if the model is capable of recognizing a citrus image and to classify it correctly. In order to test the proposed model, three MLP topologies are used (varying the number of neurons and hidden layer quantity). All topologies have nine input neurons corresponding to MKC descriptors and five output neurons corresponding to each citrus category.

One hundred images are randomly mixed and their MKC descriptors are obtained. The image descriptors are separated into training (70%) and test (30%) sets. Also, before training the MLP neural network, some parameters must be established. The following parameters were selected after comparing the performance of different training simulations:

- 100 training epochs.
- Learning rate equal to 0.4.
- Minimum acceptable average error equal to 0.
- The neurons in hidden layers use hyperbolic tangent transfer function because a better performance in the learning process is revealed. Output neurons use logistic transfer function.

After training, descriptors for each image of the test set are presented to the network and the corresponding outputs are calculated. The results are organized in tables for each proposed network topology and they are then compared to the target outputs (Table 1).

Table 1. *Target Outputs for Test Images*

Image	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Class 1	0	0	0	1	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	1	1	0	1	0	0	0	0	0	1	0
Class 2	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Class 3	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	1	1	0	1	0	0	0	0	1	0	0	0	0	0	1
Class 4	0	1	0	0	0	0	0	1	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Class 5	1	0	1	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	1	0	0

In Table 1, the test images correspond to the columns and the rows are the classes. For example, image 1 corresponds to class 5. Simulations were realized using different network topologies and the results are summarized in next subsections.

5.1 Simulation 1

The first topology has twenty hidden neurons disposed in a single hidden layer (Figure 2). The minimum value reached in training process is approximately 0.044 and the test error is approximately 0.06. Test error is calculated using thirty images which are not used for training process.

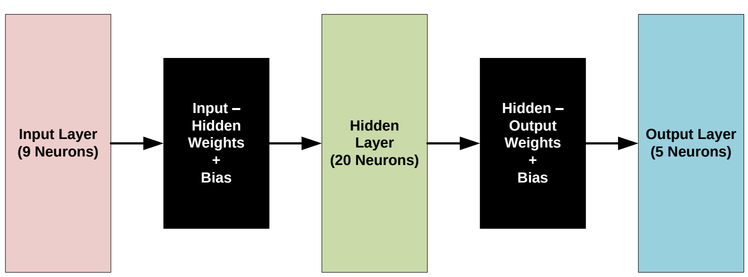

Figure 2. Network Topology 1

Both, training and test errors have the same tendency and their values are close. This means that the capacity of generalization of the network is good. Same test patterns were used to compare the target and real neural network outputs. The results are shown in Table 2. The highlighted columns correspond to wrong classifications. The average of correct classifications is 76.66%.

Table 2. *Network Outputs for Topology 1*

Image	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Class 1	0	0	0	1	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	1	1	0	1	0	0	0	0	0	1	0
Class 2	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Class 3	0	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	1	0	1	0	0	0	0	0	1
Class 4	0	1	0	0	0	0	0	1	1	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0
Class 5	1	0	1	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	1	0	0

5.2 Simulation 2

In this case ten neurons were added to hidden layer (Figure 3). The performance in training process shows a different behavior. Although the training error decreases significantly to 0.014, the capacity of generalization is worse than that in the previous case (the test error is about 0.081).

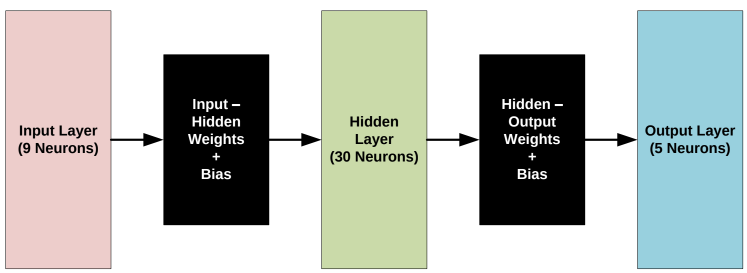

Figure 3. Network Topology 2

The comparison between target and obtained neural network outputs are shown in Table 3. For this topology, the average of correct classification is 73.33%. This percentage confirms that this topology has a worse performance than shown in the previous section.

Table 3. *Network Outputs for Topology 2*

Image	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Class 1	0	0	0	1	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	1	1	0	1	0	0	0	0	0	1	0
Class 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Class 3	0	0	0	0	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	1
Class 4	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0
Class 5	1	0	1	0	0	1	1	0	0	1	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	1	1	1	0	0

5.3 Simulation 3

For this case, a new hidden layer is added to neural network (Figure 4).
The topology has two hidden layers with twenty and ten neurons respectively. The performance in training process is similar to that in the previous case. The training error decreases to 0.023 but the test error increases its value to close 0.1.The comparison

between target and network outputs is shown in Table 4. The average of correct classification is 70.00%.

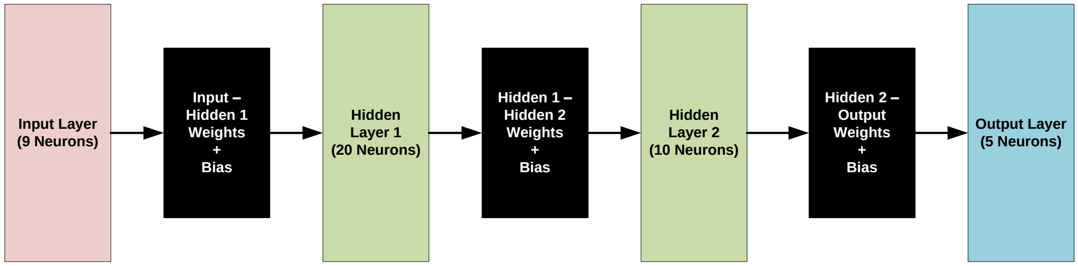

Figure 4. Network Topology 3

Table 4. *Network Outputs for Topology 3*

Image	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Class 1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0	1	0	1	0	0	0	1	0
Class 2	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Class 3	0	0	0	0	1	1	0	0	0	0	0	1	1	1	0	0	0	0	1	0	0	1	0	1	0	1	1	0	0	1
Class 4	0	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Class 5	1	0	1	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0

6. Conclusions

The proposed model based on MLP neural network can be used to classify images using their MKC descriptors. The implementation is simple and it does not require either high level of computational processing or great storage space.

The performance of recognition is over 75% without using image preprocessing. This ratio, although lower, is close to those obtained by similar models. This is an important issue because several techniques can be used to improve the image quality. Consequently, more precise descriptor values can be obtained in order to improve the model performance. Although the classification of the images used in this article was made in a manual way using five classes, it is possible to use this same model with any number of classes. In that case, only to redefine the number of input and output neurons is necessary.

The proposed model can be implemented as part of an automatic selection device that captures the citric image and determines its class in real time.

7. Future Work

The proposed model can be tested using non supervised neural networks. In this case, the classes can be determined using a competitive neural network and then, to use an MLP to compare the performances of models.

In addition to the mentioned image preprocessing, a Principal Component Analysis process of descriptors can be added. This has two goals: (1) to identify the descriptors that should be used to distinguish the different classes and (2) to reduce the dimension of input space. Both mentioned lines of work are carried out jointly.

Finally, the results presented in this article are currently being compared with those obtained by other methods (probabilistic methods, instance based learning, etc) in order to determine the proposed model performance.

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