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REGULAR ARTICLE

Radial base neural network for the detection of banana maturation stages: perceptron multilayer network comparison

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ABN: Conceptualization and supervision; VFdaSF: Collecting experimental data and writing the manuscript; WPLdosS: Literature review and experimental data collection; JMdeM: Experimental data collection and data analysis; AVdeS: Experimental data collection and data analysis.

Abstract

Agriculture is one of the pillars of human existence since it allows for the obtention of food as well as other products for food production processes. In this regard, there are some crops, such as climactic fruits, that face difficulties especially regarding classification of their maturation stages at the time of harvest, which is the case of bananas, the focus of this work. Therefore, there are some techniques that use artificial neural networks to classify them, such as multilayer networks. Examples of such networks are Perceptron, widely used in several areas, and Radial Base Functional networks (RBF), whose studies are incipient and have little use in agricultural areas. Hence, the objective of the present work was to carry out a comparison between these two neural networks to verify which provides the highest accuracy. In this work it was possible to verify that radial base functional neural networks provide a faster and more efficient categorization for the stages of bananas maturation, because they do not require training and, therefore, have low computational cost, saving more energy, when compared to a Multilayer Perceptron. Therefore, it can be inferred that Radial Base Functional Artificial Neural Networks (RBF ANN) can be widely used in agriculture, enabling the improvement of different cultures and different processes, such as harvesting.

Keywords

Radial base. Maturation stages. Multilayer Perceptron. Musa acuminata. Artificial neural networks.

Introduction

Agriculture is one of the pillars inherent to human survival, due to the fact that, from it, it is possible to obtain food as well as other products that can be used in food production processes (CONTRERAS et al, 2011; MINISTRY OF HEALTH et al, 2014; JOMORI et al, 2008). Accordingly, the UN (United Nations) proposed the SDGs (Sustainable Development Goals) to be met by 2030 (UN, 2022), which have, as their main objective, the promotion of sustainable and conscious development, food security, and prosperity for all (UN, 2019).

In this sense, agriculture in Brazil represented more than 25% of the Brazilian GDP (Gross Domestic Product) in 2020 (CEPEA, 2022), which places it as one of the countries that most exports food in the world. Therefore, Brazil is among the main countries that must meet the SDGs, in order to have sufficient and quality agricultural production (IPEA, 2019).

Considering the territory with continental dimensions, the variation of climates and biomes, Brazil is a country that has a vast diversity of cultivars (BARBOSA et al, 2018). However, it is possible to note that there are difficulties in the production of some crops, especially those of climacteric fruits, that is, fruits which the organoleptic characteristics such as placement, flavour, aroma, and nutritional parameters can be easily modified, with greater emphasis on the stage at which they are harvested. In light of this, one of the climacteric fruits that is most difficult to produce are bananas, since they must be harvested at the correct ripening point, have adequate storage and logistics, so that they reach the market still green, with a fresh appearance and good quality (MINISTRY OF THE ENVIRONMENT, 2022; VIEIRA, 2019; FERREIRA, 2008).

Bonini et al. (2022) used an ANN (Artificial Neural Networks), with the objective of classifying the maturation stages of bananas, which consisted of a feedforward backpropagation network, employing physical, physical-chemical, and biochemical parameters in the input layer. The ANN presented an excellent result for the validation and test phase, that is, the classification of samples that were not part

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of the training, presenting correct results in more than 89% of the cases, in three configurations.

Difficulties in banana production can be mitigated by using more accurate management, associated with the detection and forecasting of pest, disease, and weather attacks, which would greatly assist in decision-making in harvesting, logistics, storage, and even pricing. (SHIRATSUCHI, L.S; EMBRAPA et al, 2014). In view of this, several tools have been developed, in order to solve such problems. Among the main ones, it is possible to highlight the ANN (Artificial Neural Networks) MLP (Multilayer Perceptron), through which it is possible to discover the amount of error in the output compared to backpropagation technique, which is a generalization of the least squares algorithm in the linear Perceptron. However, MLP are slower than other networks when it comes to learning, since they go through an iterative process, needing to start with random weights, because the inner product is between the input vector and the weight vector (ICMC USP, 2009; PUTTI et al, 2017).

In Bonini et al. 2021, it was proposed to develop a graphical interface for estimating the production of Marandu grass, using artificial neural networks and the graphical properties provided by the software. Good results were obtained, with a mean square error around 10-3 for training, proving the efficiency of the model application.

Another tool that is emerging, to assist in a more precise management and decision-making, are the RBF (Radial Base Networks), which are little studied, mainly in the agricultural area, and can be used for classification, approximation of functions, and time series forecasting. However, these differ significantly from MLP networks, as they contain a hidden layer with radial basis functions, and their activation occurs through the distance between the input vector and a prototype vector, which causes it to have several positive points, such as faster and more efficient training, faster learning, as well as no need to start with random weights, since it goes through incremental training (VASCONCELOS et al, 2020; CERQUEIRA et al, 2002).

With that, the present work aims to make a comparison between these two networks. The objective is to verify which one will perform better, in view of their accuracy, efficiency, and processing time.

Materials and methods

The experiment is of a quantitative and laboratorial nature, with emphasis on experimental procedures, in order to analyse the RBF neural networks and their benefits when compared to the MLP. The classification of the maturation stages of bananas has a descriptive character, through output binary data. From this point of view, the study was conducted in the city of Tupã, São Paulo State, Brazil, with a total of 120 selected samples of fruits from a commercial banana plantation of the 'Nanição' cultivar, a type of Musa acuminata (AAA) of the Cavendish subgroup (YOKOMIZO, 2011).

Therefore, each sample is composed of 4 input data, which are chlorophyll a, chlorophyll b, anthocyanins, and carotenoids; all from the fruit peel, verified in Souza et al. (2021).

Among these, it is worth highlighting the carotenoids which are from a family of fat-soluble pigments, synthesized by plants and microorganisms, responsible for the yellow, orange and red colours of many plants. The methodology used to determine the pigments chlorophyll a, chlorophyll b, carotenoids, and anthocyanin was adapted from Sims and Gamon (2002). In this method, spectrophotometric reading was performed, and the results were expressed in mg $100g{-}1$ fresh mass.

The network output data were described as follows, representing the banana maturation stages: (0, 0) green, (0, 1) almost ripe, (1, 0) ripe, (1, 1) stale. The two desired output data (binary) are used only for the training phase of the MLP network, that is, each binary output (2 data) corresponds to an input (4 data). This is necessary for the network to be able to learn and, so, be able to classify data that were not part of the training.

In radial basis networks, unlike MLP, there are no iterative training processes, but an incremental training. This means the weights are updated after the presentation of each training example. Thus, the incremental approach is generally faster, especially if the training set is large and redundant. Another advantage of this technique is that it requires less memory (BISHOP, 1995; HAYKIN, 1999).

To create the network, Matlab® (Mathworks, 2021) software was used. The radial basis artificial neural network used has 4 input data. After input, the centres are adjusted and, with this, the input data are used by the radial basis functions (120 radial basis functions were used in this work - as shown in Figure 2). Above all, it is worth highlighting the Gaussian functions because, through these, the values of the radii of the functions can be considered equal for problems of function approximation.

Subsequently, the data obtained in the radial basis functions are used in linear functions resulting in the output (Yob) which is the maturation of the bananas. Then, the error of each output is calculated (difference between the value desired Ydes and the output Yob). A model of the radial basis neural network used is shown below in Figure 1 (MINUSSI, 2008).

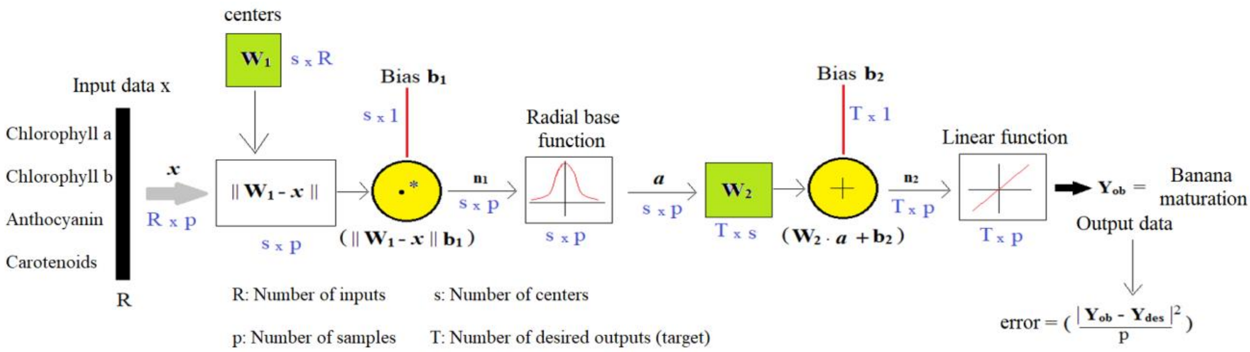

Figure 1: Radial Base Functional Artificial Neural Networks (RBF ANN) used in this work

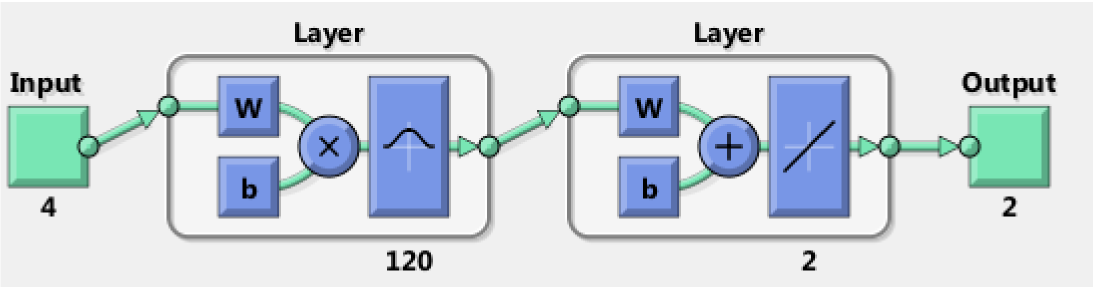

Figure 2: Demonstration of the RBF Artificial Neural Network (ANN) layers used in this work

The RBF ANN used to compare the results is from the feedforward backpropagation network with five layers and an input with 4 neurons. For output, there were 2 neurons (stages of maturation) and these follow the same model as the RBF ((0, 0) green, (0, 1) almost ripe, (1, 0) ripe, (1, 1) stale). The big difference between these two networks is that MLP have their output determined by the function of the input and the values of the weights, that is, for the desired outputs to be obtained it is necessary to make an adjustment in the weights of the network. Therefore, MLP do not have feedback loops (HAYKIN, 1994; SIMPSON, 1989).

A consequence of this is that it is necessary to train the network (these correspond to an iterative process of adjustments which are applied to the weights) and, when calculating the squared error of the output neurons, the error must be propagated in the reverse direction (from output to input) (WIDROW & LEHR, 1990). RBF ANN, on the other hand, do not need training, since they perform an incremental process, which makes obtaining the output data faster and, consequently, more accurate and with a smaller error (ZUBEN, 2021).

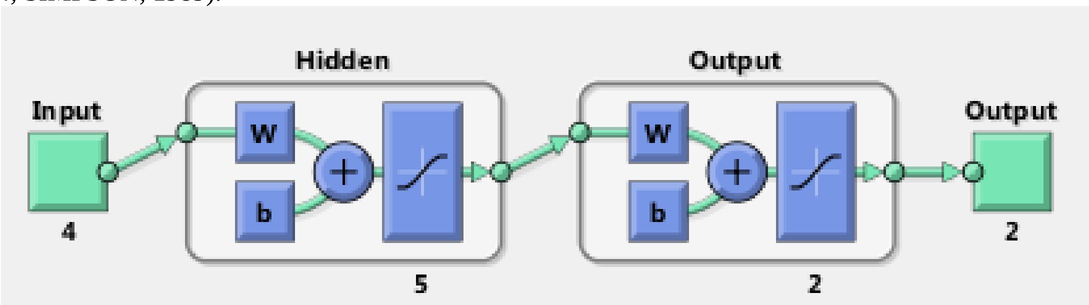

Figure 3: Demonstration of the Multilayer Perceptron (MLP) ANN layers used in this work

Results and discussion

Initially, the MLP ANN training was performed, the results of which are shown in Figure 4. The first graph expresses what would be the correct answer for each output data, that is, it demonstrates whether the output data is (0, 0) green (0, 1) almost ripe, (1, 0) ripe, (1, 1) stale, thus evidencing the answer with the smallest possible error. That is because the theoretical answer (represented by the red line) is the same as the correct answer (represented by the blue one).

The second graph shows the results obtained after training the network, which occurred in a period of 4 seconds of processing, performing a total of 100 iterations, with a performance of 0.0250 for the MSE (mean squared error) with 5 neurons in the middle layer. Therefore, it is important to emphasize that responses with a variation greater than 0.5 are considered network errors, since as they are binary responses (0 and 1) the smallest accepted response is < 0.5.

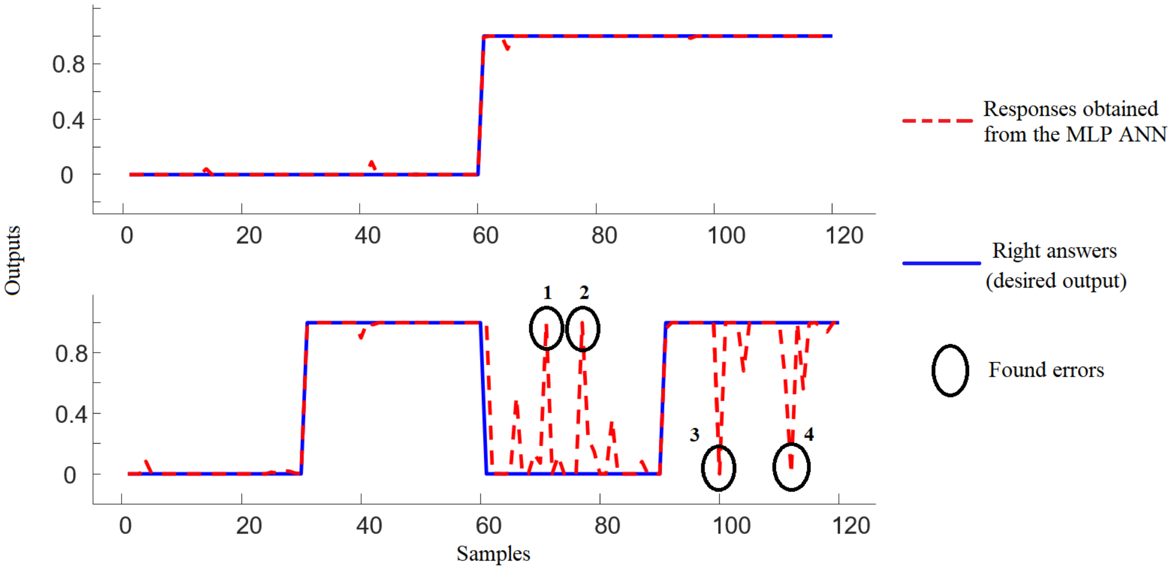

Figure 4: Graphics of the MLP ANN

This way, 4 errors were found with a MSE greater than 0.5, which are highlighted with a black circle in Figure 4. It is necessary to highlight that these 4 errors refer to 4 samples of the 120 presented as input, which represents an error percentage of 4.8%, that is, an accuracy of 95.2% was presented.

Subsequently, the output data of the RBF ANN were obtained, the results of which are shown in Figure 5. The first graph expresses what would be the correct answer for each output data, that is, it demonstrates whether the output data are (0, 0) green, (0, 1) almost ripe, (1, 0) ripe, (1, 1) stale, thus evidencing the answer with the smallest possible error. That is because the theoretical answer (represented by the red line) is the same as the correct answer (represented by blue).

The second graph shows the results obtained after the incremental process which had a processing time of 1 second (already 4 times less than the processing time of the MLP ANN) with a performance of 0.0169 for the MSE, with 120 neurons in the middle layer of the radial basis functions.

Analogously to MLP ANN, it is important to emphasize that responses with a variation greater than 0.5 are considered network errors, since as they are binary responses (0 and 1) the smallest accepted response is < 0.5.

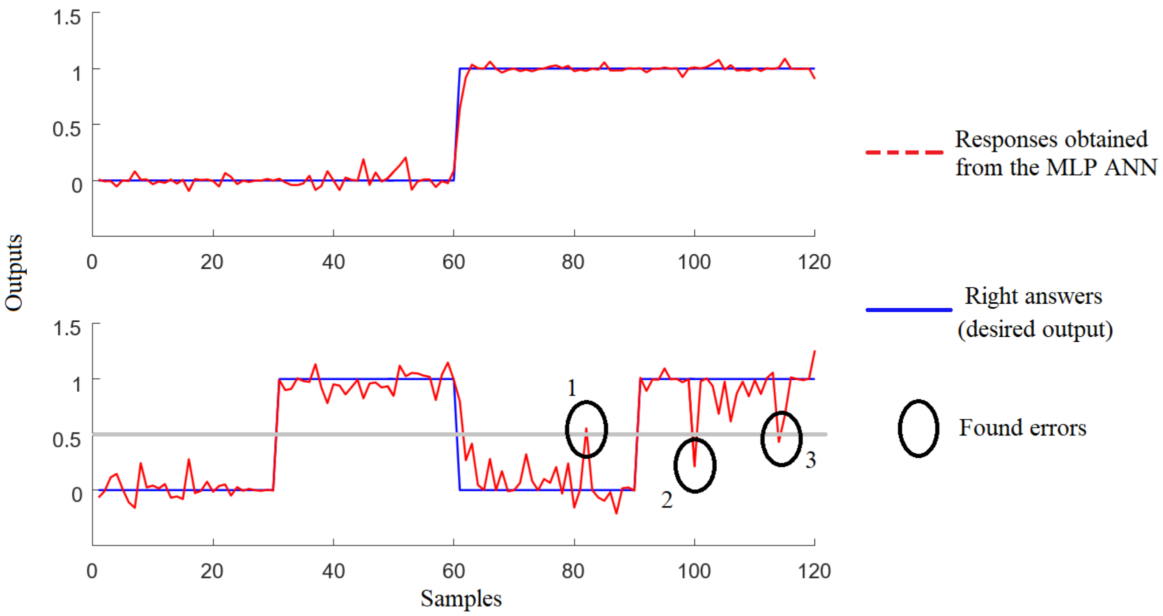

Figure 5: Graphics of the Radial Base Functional Artificial Neural Networks (RBF ANN).

In view of the results obtained from the two ANN, it is necessary to compare them. In this aspect, in order to generate a graph with more accurate data, it was necessary to mitigate the error allowed through the software and, with that, the number of errors found consequently tends to be greater since the error tolerance was attenuated.

Thus, Figure 6 was generated, demonstrating the results obtained in both MLP and RBF ANN, following the same metric (if these data had a variation > 0.5, it would be considered an error).

It is important to highlight that the networks used are exactly the same, the only change made was in the accuracy of the data accepted and, thus, the MLP ANN continues with 5 intermediate layers and 2 output layers, accepting binary results, and the RBF ANN with 120 neurons in the middle layer of the radial basis functions, accepting binary results indicating banana maturation.

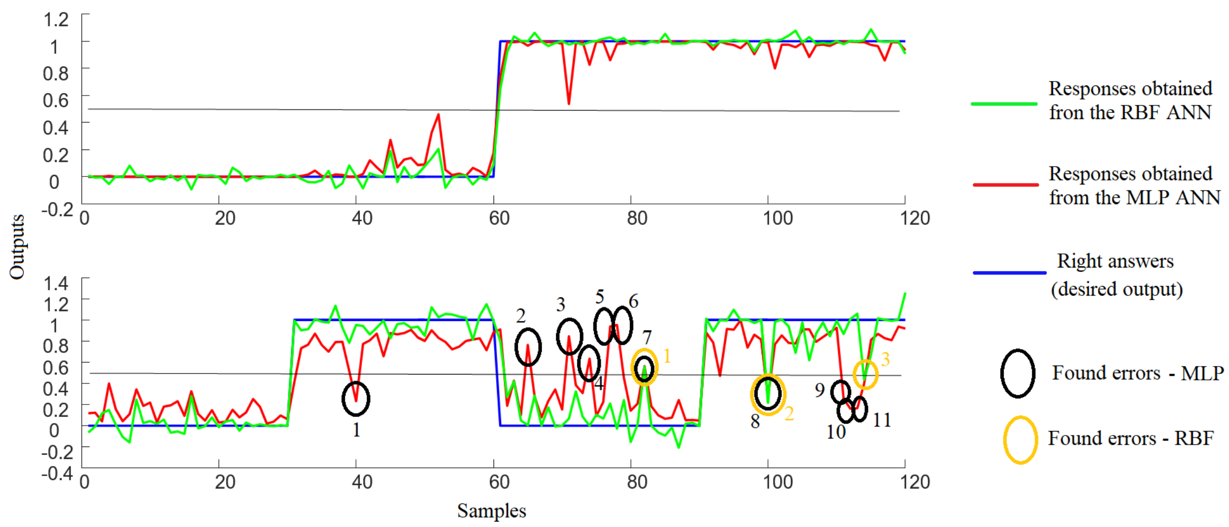

Figure 6: Comparison graphs between MLP and RBF artificial neural networks

From Figure 6, attached above, it is possible to describe that 11 errors were found in the MLP ANN since it has a variation greater than 0.5 and, therefore, this network had a 90.84% accuracy. The RBF ANN, on the other hand, presented only 3 errors greater than 0.5, thus having an accuracy of 97.5%, which demonstrates that it performed better than the MLP. Furthermore, RBF is even faster for classifying the data, because it does not perform an iterative process, but rather an incremental process. Therefore, it is possible to infer that the RBF ANN had a performance of 6.66% higher in accuracy when compared to MLP ANN, in addition to not needing to be trained.

Conclusions

Based on the results obtained, it is possible to infer that Radial Base Functional (RBF) Artificial Neural Networks (ANN), are more efficient for classifying banana maturation stages in both tests. Results with RBF performed better than with Multilayer Perceptron (MLP) ANN, which is already widely used. In addition, RBF ANN are still faster in classification since they do not need to be trained and, therefore, have a lower computational cost, saving more energy, and presenting more accurate results.

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