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Artificial neural network modelling of the antioxidant activity and phenolic compounds of bananas submitted to different drying treatments

Raquel P.F. Guiné [a,*], Maria João Barroca [b], Fernando J. Gonçalves [a], Mariana Alves [c], Solange Oliveira [c], Mateus Mendes [d]

[a] Polytechnic Institute of Viseu, Research Centre CI&DETS/Dep. Food Industry, Quinta da Alagoa, Estrada de Nelas, Ranhados, 3500-606 Viseu, Portugal
[b] Polytechnic Institute of Coimbra, ISEC, DEQB, Rua Pedro Nunes, Quinta da Nora, 3030-199 Coimbra, Portugal
[c] Polytechnic Institute of Viseu, Dep. Food Industry, Quinta da Alagoa, Estrada de Nelas, Ranhados, 3500-606 Viseu, Portugal
[d] Polytechnic Institute of Coimbra – ESTGOH/Institute of Systems and Robotics of the University of Coimbra, Department of Electrical and Computer Engineering, University of Coimbra, Pinhal de Marrocos – Polo II, 3030 Coimbra, Portugal

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ABSTRACT

Bananas (cv. *Musa nana* and *Musa cavendishii*) fresh and dried by hot air at 50 and 70 °C and lyophilisation were analysed for phenolic contents and antioxidant activity. All samples were subject to six extractions (three with methanol followed by three with acetone/water solution). The experimental data served to train a neural network adequate to describe the experimental observations for both output variables studied: total phenols and antioxidant activity. The results show that both bananas are similar and air drying decreased total phenols and antioxidant activity for both temperatures, whereas lyophilisation decreased the phenolic content in a lesser extent.

Neural network experiments showed that antioxidant activity and phenolic compounds can be predicted accurately from the input variables: banana variety, dryness state and type and order of extract. Drying state and extract order were found to have larger impact in the values of antioxidant activity and phenolic compounds.

1. Introduction

The antioxidant compounds can be defined as substances that in small concentrations, compared to the oxidizable substrate, significantly delay or prevent the initiation or propagation of oxidising chain reactions. These natural chemical compounds are generally aromatic and contain at least one hydroxyl group and are called bioactive substances, including, among others, phenolic compounds that are part of the constitution of various foods. Phenolic compounds are widely present in the plant kingdom, have simple or complex structures, and are essential for growth and reproduction of plants, besides being responsible for the colour, astringency and aroma in several foods (Sharma, 2014). These compounds, being antioxidants, fight free radicals (Rodrigo & Gil-Becerra, 2014), prevent heart diseases (Jiang, 2014; Khoo & Falk, 2014), neurodegenerative disorders (Hamaguchi, Ono, Murase, & Yamada, 2009), circulatory problems (Medina-Remón, Tresserra-Rimbau, Valderas-Martinez, Estruch, & Lamuela-Raventos, 2014), cancer (Fernández-Arroyo et al., 2012), inflammation (Wen, Chen, & Yang, 2012), and inhibit lipid oxidation (Maqsood & Benjakul, 2010). Thermal processing may destroy the amount or the bioavailability of these compounds, thus reducing beneficial health effects (Agcam, Akyıldız, & Akdemir Evrendilek, 2014; Al Bittar, Périno-Issartier, Dangles, & Chemat, 2013).

Bananas belong to the genus *Musa* from the family Musaceae and are one of the most popular fruits worldwide. They have a strong ability to protect themselves from the oxidative stress caused by intense sunshine and high temperature by increasing their antioxidant levels. Bananas contain vitamins (A, B, C and E), β-carotene and phenolic compounds, such as catechin, epicatechin, lignin, tannins and anthocyanins (Huang et al., 2014; Sulaiman et al., 2011), and are notably perishable, as they ripen rapidly causing significant changes of physicochemical, biochemical and sensory attributes (Huang et al., 2014). Hence drying represents

* Corresponding author. Tel.: +351 232446641; fax: +351 232426536.
E-mail addresses: raquelguine@esav.ipv.pt (R.P.F. Guiné), mjbarroca@gmail.com (M.J. Barroca), fgoncalves@esav.ipv.pt (F.J. Gonçalves), mgalves.2100@gmail.com (M. Alves), sol_10890@hotmail.com (S. Oliveira), mmendes@isr.uc.pt (M. Mendes).

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one of the possible preservation methods to prevent deterioration and extend the shelf life.

Drying is a very ancient way of preserving foods, and is still in use nowadays due to its ability to inhibit microbial growth and enzymatic modifications, owing to the low moisture and water activity of the dried products. However, the advantages of drying surpass the preservation capacity (Guiné, Pinho, & Barroca, 2011). Drying, and particularly air drying, usually implies an exposure to high temperature for some time, and that may affect the product properties, either at the physical or chemical levels (Coimbra, Nunes, Cunha, & Guiné, 2011; Guiné, 2011). Polyphenols, which are sensitive to high temperatures, may be affected by heat treatment, leading to some reduction on their content and antioxidant capacity (Ahmad-Qasem et al., 2013).

Artificial neural networks have been used in the past years for modelling many processes in food engineering. Behroozi Khazaei, Tavakoli, Ghassemian, Khoshtaghaza, and Banakar (2013) used neural networks to model and control the drying process of grapes. Aghbashlo, Mobli, Rafiee, and Madadlou (2012) used artificial neural networks to predict exergetic performance of the spray drying process for fish oil and skimmed milk powder. Kerdpiboon, Kerr, and Devahastin (2006) used artificial neural network analysis to predict shrinkage and rehydration of dried carrots. Hernández-Pérez, García-Alvarado, Trystram, and Heyd (2004) proposed a predictive model for heat and mass transfer using artificial neural networks to obtain on-line prediction of temperature and moisture kinetics during the drying of cassava and mango.

The present study was undertaken to investigate the impact of drying conditions on the total phenolic compounds and antioxidant activity in bananas from two cultivars, as well as to model the process variables by means of artificial neural networks.

2. Materials and methods

2.1. Sampling

In this work samples from two varieties of banana, *Musa nana* (MN) and *Musa cavendishii* (MC) were used. The bananas were obtained from a local supermarket and then were peeled and cut into slices 8 mm thick before submitting them to the drying process. The initial moisture content of the bananas was calculated as an average of three tests made with a halogen Moisture Analyser (Operating parameters: temperature = 130 °C, rate = 3). For *M. nana* the initial moisture content was 67.37 ± 2.65% (wet basis), and for *M. cavendishii* it was 72.32 ± 2.36% (wet basis).

2.2. Processing

The convective drying was undertaken in an electrical FD 155 Binder drying chamber with an air flow of 0.2 m/s and over perforated trays. The samples were dried until a final moisture content lower than 10% (wet basis) was reached, in order to ensure good preservation characteristics as well as good final physical and chemical properties. The drying experiments were conducted at a constant temperature, having been tested two different temperatures: 50 and 70 °C. The drying of the bananas of cv. *M. nana* at 50 °C lasted 525 min and the obtained final moisture content (wet basis) was 9.36%, whereas the drying a 70 °C was faster, lasting only 270 min and the final moisture obtained was 4.71%. For *M. cavendishii* dried at 50 °C the process lasted 450 min and the final moisture content (wet basis) was 6.37%, while at 70 °C the process lasted 300 min and the final moisture was 8.83%.

Lyophilization was made using a Freeze Dryer TDF 5505 (Uniequip, Germany). The samples were frozen in a conventional kitchen freezer, and then left in the freeze-drier for 96 h at a temperature ranging from −52 °C to −49 °C and a pressure 0.7 Pa. The final moisture content was 2.32% and 2.14% (wet basis) for *M. nana* and *M. cavendishii*, respectively.

2.3. Analysis of total phenolic compounds and antioxidant activity

In the present work the extraction of phenolic compounds was performed in multiple successive steps, namely three times with methanol solutions followed by three times with acetone/water solutions. This procedure was adopted so as to extract the highest possible quantity of the phenolic compounds present in the original sample. Each sample was used to obtain extracts, rich in phenolic compounds, according to the method described by Soutinho, Guiné, Jordão, and Gonçalves (2013). Each of the samples was macerated and successively submitted to multiple extractions: first with a solution of methanol: three times with acetic acid (98:2), and following with an acetone/water solution (60:40) also three times. For each of the 6 extractions performed, the sample was left for 1 h in an ultrasonic bath at room temperature. This procedure resulted in three methanol extracts (M1, M2 and M3) and three acetone extracts (A1, A2 and A3).

The phenolic compounds were determined by means of the Folin–Ciocalteu reagent, using gallic acid as a standard, according to the conditions described by Gonçalves, Rocha, and Coimbra (2012). The results were expressed as milligrams of gallic acid equivalents (GAE) per gram of dried sample mass. The expression of the results in terms of dry mass instead of whole sample allows the direct comparisons of the results of the different samples, because in that way the effect of water content was eliminated.

The antioxidant activity was determined by the method based on the radical ABTS (2,2′-azino-bis(3-ethylbenzthiazoline-6-sulphonic acid)), as described by Miller, Rice-Evans, Davies, Gopinathan, and Milner (1993). The results were expressed as micromoles of Trolox per gram of dried sample mass.

2.4. Artificial neural network modelling

Artificial Neural Networks (ANN) models come from Artificial Intelligence, where they were first proposed for learning and function approximation. ANNs are an interconnected assembly of simple processing elements, known as artificial neurons. Each artificial neuron aims to mimic the functioning of a human neuron. The input for each neuron is one or more weighted variables, and the output is a linear or non-linear function of the weighted inputs. Neurons learn by adjusting the weights of the input variables. Those weights are adjusted in a way to minimise the error between the neuron's expected output and the measured output value.

In the present work, experimental data were modelled using artificial neural networks, trained and simulated in Matlab™. [1]

2.4.1. Data encoding and modelling

For ANN modelling, the data were first encoded in a manner suitable for ANN processing. Variety *M. nana* was encoded as 1, variety *Musa cavendishii* was encoded as 2. Banana state values 'fresh', 'dehydrated at 50 °C', 'dehydrated at 70 °C' and 'lyophilized' were encoded with integers from 1 to 4. Methanol and acetone extracts were encoded as 1 and 2, respectively.

The number of samples available from the experimental data to train and validate the neural networks was 264 for the output variable 'antioxidant activity' and 277 for the output variable 'phenolic compounds content'. To facilitate training and the analysis of the results, each output variable was processed separately. This simplification does not imply any loss of generality, for it is

[1] Matlab is a registered trademark of Mathworks. www.mathworks.com.