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RESEARCH ARTICLE

NEURAL NETWORK MODELING OF MANGO (Mangiféra indica L.) SLICE DRYING

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ABSTRACT

Mango is a seasonal fruit subject to significant post-harvest losses due to its high water content. Drying is an effective method of reducing water content. It prolongs the shelf life of dried mangoes and can be carried out naturally or artificially. The main objective of the study is to develop a mathematical model capable of predicting the drying kinetics of mango slices in hot air, using artificial neural networks (ANN).To achieve this, machine learning algorithms were used to analyze the drying data and create a predictive model. The parameters studied include slice thickness, temperature, drying time, initial moisture content and mango Brix level. The optimal neural network identified is of 5-6-1 architecture. Results with it give high coefficients of determination (R^2) and low root mean square errors (RMSE), indicating good agreement between predicted values and experimental data. The R^2 values for the training, test and validation sets are 0.9827, 0.9885 and 0.9836 respectively, with an RMSE of 0.004, demonstrating the effectiveness of the RNA model in predicting the drying process.

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INTRODUCTION

Côte d'Ivoire's economy is based mainly on agriculture, with a heavy reliance on the export of cash crops such as cocoa, coffee, oil palm and rubber (Akmel *et al.*, 2008). Among exported fruits, pineapple, banana and mango occupy a prominent place (CBI-MFA, 2019). Mango is grown in Côte d'Ivoire, particularly in the north of the country, which enjoys favorable climatic conditions. Since its first export to France in 1981, mango has become the country's third-largest agricultural export after cotton and cashew nuts. It accounts for around 4% of national GDP and 10% of the country's agricultural GDP (FAO, 2023).Côte d'Ivoire is thus positioned as Africa's leading exporter and the world's third largest exporter of mangoes, with over 30,000 tonnes exported each year (FruiTrop, 2024). However, despite these massive exports, only a small proportion of mango production is processed locally, leaving a large proportion unsold and subject to wastage due to a lack of conservation facilities (CBI-MFA, 2019). Mango losses are estimated at around 30-60%, mainly due to pests responsible for orchard diseases, as well as marketing challenges linked to the saturation of the domestic market (CBI-MFA, 2019).

Yet mango is a highly nutritious fruit (Kafana, 2023).Its nutritional properties, notably its richness in provitamin A, vitamin C, minerals and fiber, make it a valuable dietary supplement. With its pulp composed mainly of water (around 82%), mango offers an excellent source of carbohydrates (Kanté-Traoré, 2019). In addition, its flavor is highly appreciated by populations for its attractive gustatory qualities (Abouo *et al.*, 2020; Abouo *et al.*, 2021). Given the numerous post-harvest losses recorded, the limited data on this subject and the scientific advances made thanks to the drying of various agricultural matrices, it seems pertinent to conduct research that will help provide solutions to the problem of mango post-harvest losses by modeling drying kinetics.The processing of fresh mango into by-products such as dried mango, mango juice and jam is being considered (Akmel *et al.*, 2008). Drying foods, including fruits such as mango, is a crucial step in post-harvest processing aimed at extending their shelf life by removing much of their water content (Afoakwa *et al.*, 2013). Mango drying can be carried out using either solar energy or an electric oven (Abouo *et al.*, 2020). Understanding mango drying kinetics is essential for optimizing drying parameters and improving end-product quality. Artificial neural networks (ANNs), mathematical models inspired by the functioning of the human brain, are increasingly used to predict physical drying parameters (Ramesh *et al*., 1995; Sreekanth *et al*., 1998; Hernandez-perez *et al*., 2004). In Côte d'Ivoire, research has been carried out on the method of drying mango pulp of the Kent variety using an electric kiln, with temperatures varying between 40°C and 60°C (Abouo *et al*., 2020). However, there is a lack of available data concerning the modeling of drying kinetics by artificial neural networks (ANN). In this study, machine learning algorithms were used to analyze mango slice drying data and create a mathematical model describing how the water content of mango slices decreases over time under the effect of hot air.This model will be used to predict the time required to dry mango slices to a specific moisture content level. To achieve these objectives, the work consists in:

- Characterize some of the mango's physical parameters
- Carry out drying tests on mango slices in hot air
- Model the drying kinetics of mango slices using neural networks.

MATERIAL AND METHODS

Sample collection: Mangoes were purchased in Korhogo and shipped to Abidjan. The mangoes used were commercially ripe, continuing to ripen after harvest until perfect ripeness was reached (Dick *et al*., 2009). The initial moisture content of the fresh Kent variety at commercial and advanced maturity is 79.2% and 80.4% respectively (Anselme *et al*., 2003).

Sample preparation: Once the mangoes have been received, they are transported to the Biochemistry laboratory for further processing. The selected mangoes are ripe and firm, to facilitate cutting. The surface of the fruit naturally carries impurities, insects and micro-organisms. During cutting, the mangoes are peeled and pitted using a stainless steel knife (Michel *et al*., 2009). The mangoes are cut into slices 1 and 1.5 cm thick (Figure 1).

Drying mango slices: The slices were placed on the trays in such a way as to leave space between them to facilitate adequate air circulation and uniform drying. Next, the mango slices were placed in an oven at different temperatures : 50°C and 60°C to carry out the drying process (figure 2). The drying tests were carried out by measuring the mass loss of the sample using a balance. Weighing was carried out every hour to obtain the mass loss data (Abouo *et al*., 2020). We assumed that weighing times (a few minutes) had no influence on drying kinetics. Lamellae are considered dry when their weights no longer vary considerably. (Belhamidi *et al*., 1995). The percentage moisture content is determined by measuring the difference in weight before and after drying, and calculated using the method (AOAC, 2005).

Physico-chemical analysis

Determination of water content and Brix level: Moisture content is determined by the AOAC (2005) method. Brix level corresponds to the percentage of soluble dry matter. This parameter was determined using the refractometry method. A fine portion of the crushed pulp was placed on a specific part of the refractometer. The Brix value was read directly from the refractometer screen (Abouo *et al*., 2023).

Figure 1. Sample of mango slice (A: 1 cm / B: 1.5 cm)

Figure 2. Oven-dried samples

Modeling the drying process

Artificial neural network architecture: The neural network used here is a multilayer perceptron. The network used here is characterized by five (5) neurons in the input layer (I.L) (five parameters) and one (1) neuron in the output layer (O.L) (one parameter). Thus, the number of neurons in the hidden layer (H.L) is varied from 1 to 10 to achieve the optimum architecture. Selecting the right input parameters is crucial to optimizing calculations and minimizing errors, aiming for the best possible result. This choice is guided by parameter relevance, redundancy and availability (Abouo *et al*., 2023).Input layer neurons were used to represent the input variables, which are respectively slice thickness (X_1), temperature (X_2), drying time (X_3), initial water content of mango slices (X_4) and mango Brix degree (X_5). The selection of output parameters is dictated by the variables to be controlled (Abouo *et al*., 2023). In this case, the focus is on the amount of water present in the mango slices at the end of drying (Y). The activation function used in the hidden layer was the hyperbolic tangent (Tanh), while a linear function was employed as the activation function for the output layer (Assidjo *et al*., 2006). Prior to processing, the experimental data set was normalized to the interval [-1; 1].The learning phase was supervised using the Levenberg-Marquardt algorithm (Assidjo *et al*., 2006). According to the composite matrix, thirty (30) trials were carried out for each type of thickness (120 in total). Fifty percent (50%) of this experimental database was used to form the training base for the artificial neural network (ANN). Twenty-five percent (25%) of the experimental data were used for validation. Finally, to assess the generalization quality of the ANN, 25% of the experimental data, which had not been used for either learning or validation, were used. Initially, a single neuron was used in the hidden layer. The network was built using Matlab R2016a software (MathWorks Inc., Massachusetts, USA).

Optimizing and stimulating the artificial neural network: To obtain the optimum neural structure, we optimized the number of neurons in the hidden layer. This optimization involved varying the number of neurons from 1 to 10. It should be noted that there is no universal rule for determining the optimal number of neurons in a hidden layer (Laïdi *et al*., 2012). Each neuronal structure was subjected to 2000 computational repetitions. Then, for each structure the coefficient of determination (R^2) and root mean square error (RMSE) were determined. The best ANN was selected on the basis of the highest R^2, lowest RMSE and minimum topology. Once selected, this optimal ANN was used to simulate randomly selected trials. Simulation quality was assessed using R^2 and mean absolute error (MAE) (Nogbou *et al*., 2015). In other words, the process involved evaluating several structures, selecting the one with the best performance, and then using it to simulate test data for subsequent evaluation.
General formula

$$Y = \sum_{i=1}^{N} Wi.yi + B \quad (1)$$

Wi is the weight of the connection between the hidden layer neuron Ni and the output layer neuron.

Yi is the output of the hidden layer neuron Ni

B is the general bias of the network

$$yi = \text{Tanh}\left(\sum_{j=1}^{X}(Wij.Xi) + bi\right) \quad (2)$$

Wij is the weight of the connection between input Xj and neuron Ni

Xj is the input j of the network

Bi is the bias associated with neuron Ni

$$R^2 = \frac{\sum_{i=1}^{N}(X^*{}_{exp,i}-X^*{}_{pre,i})^2}{\sqrt{\left[\sum_{i=1}^{N}(X^*{}_{exp,i}-X^*{}_{pre,i})^2\right]*\left[\sum_{i=1}^{N}(X^*{}_{exp,i}-X^*{}_{pre,i})^2\right]}} \quad (3)$$

$$RMSE = \left[\frac{1}{2}\sum_{i=1}^{N}(X^*{}_{exp,i} - X^*{}_{pre,i})^2\right]^{\frac{1}{2}} \quad (4)$$

$$MAE = \frac{100}{N}\sum_{1}^{N}\frac{X(eqi,exp - Xeqi,pre)}{Xeqi,pre} \quad (5)$$

STATISTICAL ANALYSIS

Statistical analyses were carried out using a computer program using multilayer perceptron-type artificial neural networks (ANNs), developed and integrated into MatLab R2016a software. This program was used to determine the optimal neural structure (Nogbou *et al*., 2015).

RESULTS AND DISCUSSION

RESULTS

Drying curve: The evolution of the differential loss of sample mass during drying is illustrated in figure 3. The mass loss shows a general decreasing trend. Three (03) drying phases can be identified. Mass loss is rapid at first, then slows as the remaining water becomes harder to evaporate. After 15 hours, the slice has lost most of its water, reaching a stable mass. Initial phase (0-2H): Rapid loss of free water from mango slices. Intermediate phase (2-7H): Transition where the drying rate slows down, probably corresponding to the loss of less easily extractable bound water. Final phase (7-15H): Stabilization where mass loss becomes minimal, corresponding to the loss of strongly bound or residual water. The curve shows significant mass loss initially, then a gradual decrease until a plateau is reached. This is typical of drying processes where free water is first rapidly evaporated, followed by slower evaporation of bound water. The stabilization point at around 15H indicates that most of the water has been evaporated by this time.

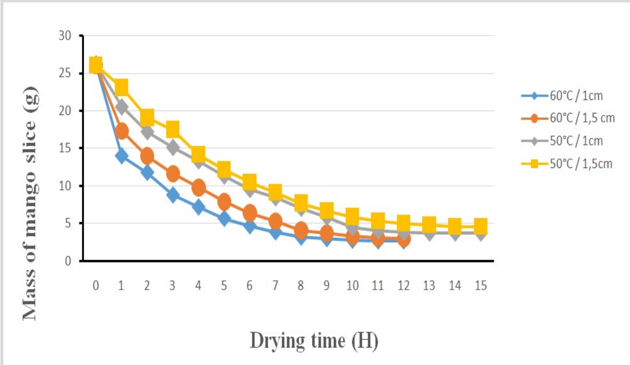

Figure 3. Evolution of differential mass loss of mango slices during drying

Artificial neural network (ANN) modeling: Table 1 summarizes the performance of the best neural configurations for each hidden layer. Examining this table, we see that the coefficient of determination (R^2) during the learning phase varies between 0.8852 and 0.9827. This indicates a strong overall correlation between the values predicted by the neural networks and the experimental values of the training set. Moreover, analysis of the root mean square error (RMSE) confirms this observation, with values oscillating between 0.0046 and 0.0973, testifying to satisfactory convergence between predictions and real data. Overall, the performance of the different neural configurations is fairly similar. However, the 5-6-1 configuration (5 neurons in the input, 6 neurons in the hidden layer and 1 neuron in the output) stands out for having the highest R^2 (0.9827; 0.9885 and 0.9836) and the lowest MSE (0.0046) during the learning, testing and validation phases. It is thus considered the most suitable neural model. Details of the weights, linear coefficients and biases of this configuration are given in Tables 2 and 3. All in all, this configuration stands out for its outstanding performance in data prediction.

The mathematical expression of the neural model selected is as follows:

$Y=0.0888*\text{Tanh}(0.7094X_1 - 0.7264X_2 + 1.0205X_3 + 0.0321X_4 + 1.7439X_5 - 2.076)-0.0737*\text{Tanh}(-0.2138X_1 - 1.2378X_2 + 1.1098X_3 + 0.0047X_4 + 0.6096X_5 +0.9201) + 0.1183*\text{Tanh}(1.1138X_1 -0.5499X_2 + 0.6739X_3 -0.1409X_4 - 0.8696X_5 +0.0749) -0.0589*\text{Tanh}(-0.7068X_1 + 0.1545X_2 + 0.0916X_3 -1.1113X_4 - 1.3331X_5 -0.7462) + 0.1923*\text{Tanh}(1.5108X_1 - 0.1876X_2 +0.1343X_3 - 0.8939X_4 + 0.6740X_5 + 1.2606) + 0.1723*\text{Tanh}(1.2060X_1 + 0.9391X_2 -1.1189X_3 + 0.0413X_4 + 0.5143X_5 + 2.0613) - 0.2796$

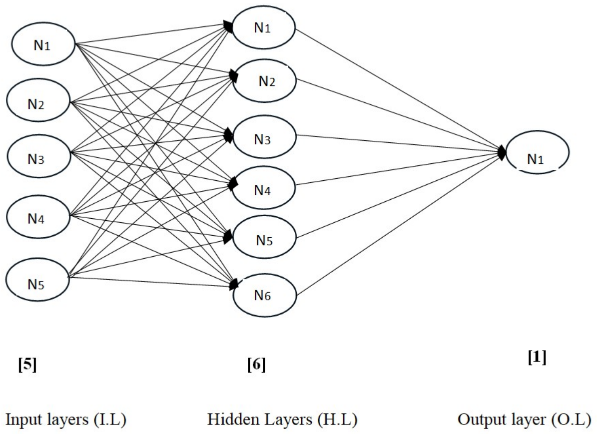

Figure 4. Selected multilayer perceptron (ANN 5-6-1)

Simulation of the selected neural model (5-6-1): Figure 5 shows the global simulation of drying mango slices at different temperatures and thicknesses. Analysis of this figure shows a very good match between experimental and predicted values. This is reflected in the random and uniformly distributed mean absolute errors around the straight line with equation Y=0.

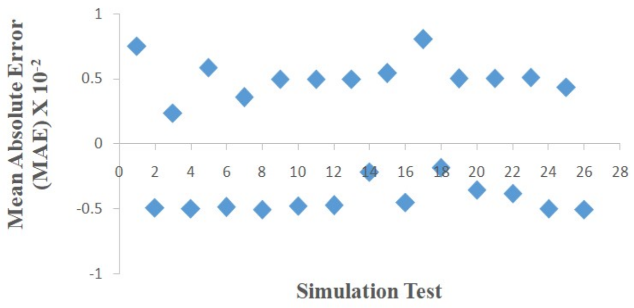

Figure 5. MAE fluctuation during the simulation

DISCUSSION

The drying curve showing differential loss of moisture content is comparable to that observed for other agricultural products in several studies on hot-air drying (Abouo *et al*., 2020). It shows a decreasing exponential trend, indicating that water loss depends on the time/temperature couple, as shown by the work of Chekroune (2009) on date drying. The process of modeling the drying of mango slices using an artificial neural network (ANN) takes place in two distinct stages. In the first stage, the objective is to determine the optimal neural configuration capable of adapting well to the experimental data. To this end, a technique for adjusting the number of neurons in the hidden layer is used as a method for optimizing the neural structure.To this end, a technique for adjusting the number of neurons in the hidden layer is used as a method for optimizing the neuronal structure. This approach has been applied in various previous research works, such as those by Özkaya *et al*, (2008), Murphy *et al*, (2012) and Kouamé *et al*, (2013), making it possible to explore several neural structures (10) and analyze their performance using measures such as coefficient of determination (R^2) and root mean square error (RMSE).After testing different structures, the best configuration, in this case a 5-6-1 ANN, was selected on the basis of its high R^2 and low MSE. These criteria indicate a satisfactory generalization capability of the model, i.e. its ability to provide accurate predictions even for data not used in the initial training. These results are consistent with other similar studies involving the modeling of osmotic dehydration of mango (Mangifera Indica L.), those carried out by N'goran *et al*., (2009) and in the case of the modeling of intermittent drying of cocoa beans (Théobroma cacao L.) by Nogbou *et al*., (2015).In the second step, once the optimal ANN of 5-6-1 has been identified, it is used as a prediction tool to simulate the drying behavior of mango slices.

Table 1. ANN performance criteria for learning, testing and validation

Hidden layer neuron	R^2 Learning	R^2 Testing	R^2 Validation	RMSE
01	0.8852	0.8764	0.8724	0.0910
02	0.8930	0.9071	0.8936	0.0973
03	0.8890	0.8745	0.8860	0.0747
04	0.8897	0.8754	0.8725	0.0558
05	0.8925	0.8865	0.8858	0.0763
06	0.9827	0.9885	0.9836	0.0046
07	0.8896	0.8730	0.8724	0.0667
08	0.9015	0.8769	0.8810	0.0583
09	0.8874	0.8625	0.8655	0.0531
10	0.8950	0.8651	0.8625	0.0482

Table 2. Weight values (I.L-H.L) and bias on the ANN hidden layer (5-6-1)

Hidden layer neuron	X_1	X_2	X_3	X_4	X_5	Bias (Bi)
N_1	0.7094	-0.7264	1.0205	0.0321	1.7439	-2.0174
N_2	-0.2138	-1.2378	1.1098	0.0047	0.6096	0.9201
N_3	1.1138	-0.5499	0.6739	-0.1409	-0.8696	0.0749
N_4	-0.7068	0.1545	0.0916	-1.1113	-1.3331	-0.7462
N_5	1.5109	-0.1876	0.1343	-0.8939	0.6740	1.2606
N_6	1.2060	0.9391	-1.1189	0.0413	0.5143	2.0613

Table 3 : Values of linear coefficients and bias of the ANN output layer (5-6-1)

Neuron output layer	Weight						General bias (B)
	N_1	N_2	N_3	N_4	N_5	N_6	
Y	0.0888	-0.0737	0.1183	-0.0589	0.1923	0.1723	-0.2796

The results obtained show high R^2 values and low RMSEs on the training, test and validation sets, indicating good agreement between the values predicted by the model and the experimental data. Indeed, the R^2s were 0.9827, 0.9885 and 0.9836 respectively for the three sets (learning, test and validation), and the MSE was 0.0046. The results obtained demonstrate satisfactory agreement between predicted values and experimental observations, confirming the effectiveness of the ANN (5-6-1) model in predicting the process of drying mango slices using hot air.The results obtained are close to those obtained by Abouo *et al*, (2020) in the case of mathematical modeling of oven drying (hot air) of mango slices using empirical models, the logarithmic model shows very high R^2 values (0.9984; 0.9984; 0.9981 ; 0.9987; 0.9988; 0.9985) and low values of χ^2 (2.43e-07; 1.58e-07; 1.25e-06; 2.02e-07; 4.56e-06 and 1.37e-06) and MSE (2.42e-04; 1.95e-07; 5.47e-04; 2.20e-04; 0.0010 and 5.69e-04) for the corresponding temperatures and thicknesses. This shows very good agreement with the experimental data. Kouamé *et al*., (2017) achieved an excellent match with optimal neural structure (7-2-7), obtaining coefficients of determination (R^2) exceeding 0.97 when modeling plantain growth. The work of Assidjo *et al*., (2006) has also successfully used artificial neural networks ($R^2 > 0.95$) to model processes such as alcoholic fermentation in brewing. Similar results were observed in the work of Karidioula *et al*., 2018 (R^2: 0.99718432 0.00181674 0.99220225 and MSE: 0.0057440) with a neural structure (2-2-1) in modeling the solar drying of cocoa beans by artificial neural network.

CONCLUSION

The aim of this study was to model the drying kinetics of mango slices using artificial neural networks. The results show that mango slices dry between 8, 10, 12 and 15H. Drying speeds are higher for higher temperatures (60°C) and for smaller thicknesses (1cm). The use of artificial neural networks to model the drying kinetics of mango slices proved effective. This ANN model presented the highest R^2 value (0.9827; 0.9885; 0.9836) and the lowest MSE value (0.0046). The results obtained show good agreement between the values predicted by the model and the experimental data, indicating good performance of the selected ANN model. ANNs can be integrated into industrial control systems to monitor and adjust drying parameters in real time, thus improving the consistency and quality of dried products.

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