Study of the feasibility of using Near Infrared Spectroscopy and Neural Networks for predicting Iberico dry cured ham sensory attributes

Pangborn 2019

Revilla I., Hernández-Ramos, P., González-Martín, I., Vivar-Quintana, A.M., Martínez-Martín, I.
Food Technology Area. Higher Polytechnic School of Zamora Avenida Requejo 33, 49022 Zamora. Spain **University of Salamanca**

INTRODUCTION & OBJECTIVES

Spanish Iberico dry-cured ham is a very popular meat product owing to its sensory profile, its nutritional quality and long shelf life.
Ibérico ham represent a large part of the meat products hosted under Quality Distinctions in Spanish market and stands out among them as a high-quality product of increasing economic relevance. To assure the quality of these products their sensory analysis according to the ISO 17025 norm is compulsory.

However, sensory analysis is expensive and time-consuming. Then, some instrumental technique such as NIRS technology has been studied to predict sensory attributes but it has hardly been used for meat products. The aim of this study was the quantification of sensory attributes of Spanish Iberian dry-cured ham using NIR technology and Artificial Neural Networks.

MATERIALS & METHODS

In order to do so, 91 dry-cured hams from "Ibérico" pigs elaborated according to traditional technology and matured for 24 to 36 months were selected. The sensory attributes (28 descriptors) were generated by a panel of 10 expert tasters trained by means of QDA and assessed on a scale of 9 points. The sensory evaluation of each parameter and sample were the expected outputs of the ANN.
Recording of the NIR spectra from 1100 to 2000 nm at intervals of 2 nm was accomplished by direct application of the fiber optic probe to the samples. The 451 data from each sample were the inputs of the ANN.

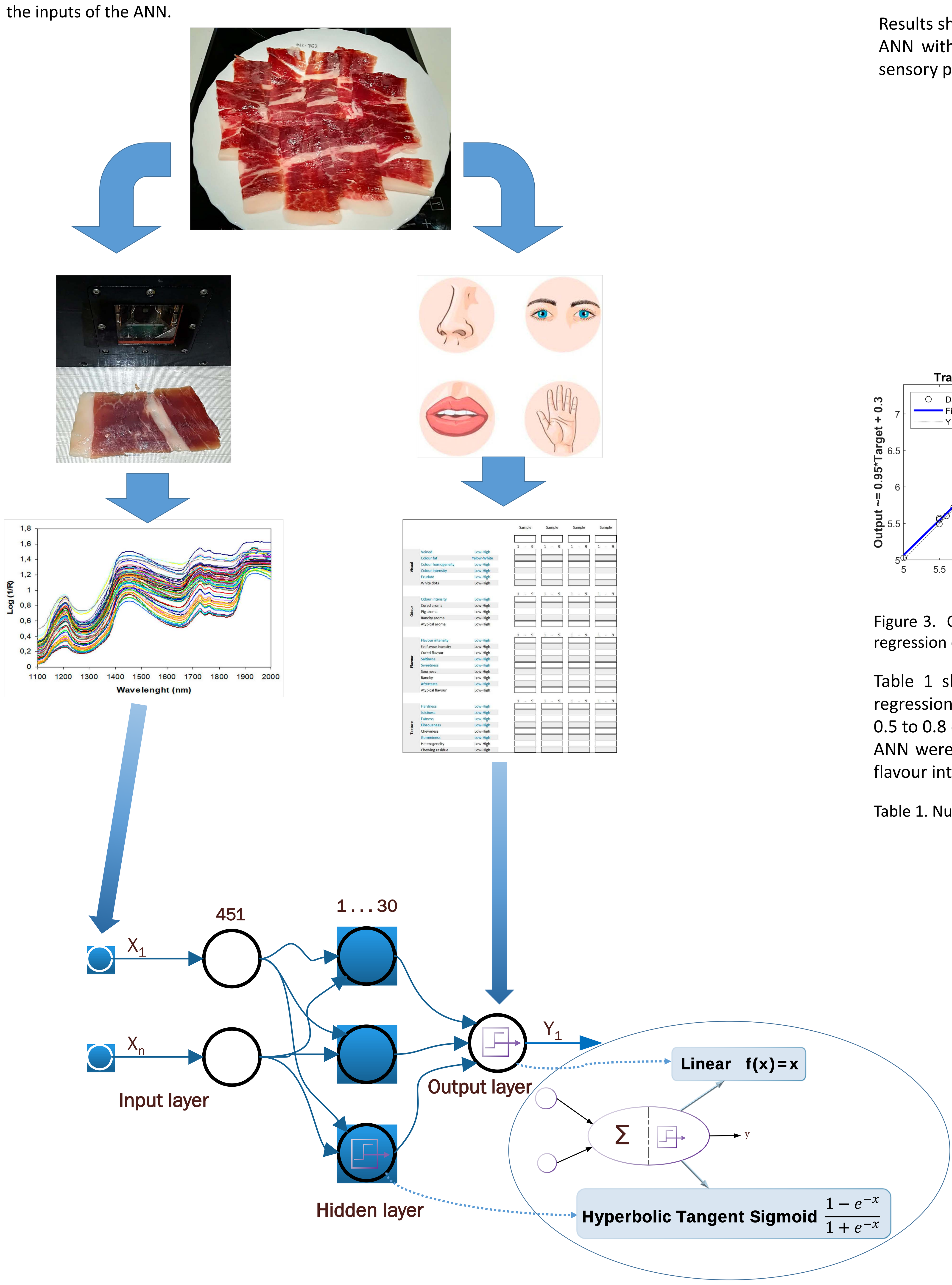

Figure 1. Analysis process using NIRS (1.100-2.000 nm / Δ=2nm), sensory panel and ANN.

The Neural Network used was the Multi-Layer Perceptron (MLP) feedforward ANN with 451 neurons in the input layer, one neuron in the output layer and one hidden layer with a variable configuration of between 1 and 30 neurons. The Hyperbolic tangent sigmoid and pure linear transfer functions were used in the hidden and output layers respectively.

Supervised learning by Backpropagation (BP) error was used for network training. The Scaled Conjugate Gradient, Bayesian Regularization and Levenberg-Marquardt ANN training algorithms were examined.
The original data set (91 observations) was divided at random as follows:

- 70% of the observations were used for network training
- 15% of the observations were used for network validation and for detecting the overfiting
- 15% of the observations were used for testing the accuracy of the trained network

For each number of neurons in the hidden layer, 30 training times were carried out with different inital weights randomly established.

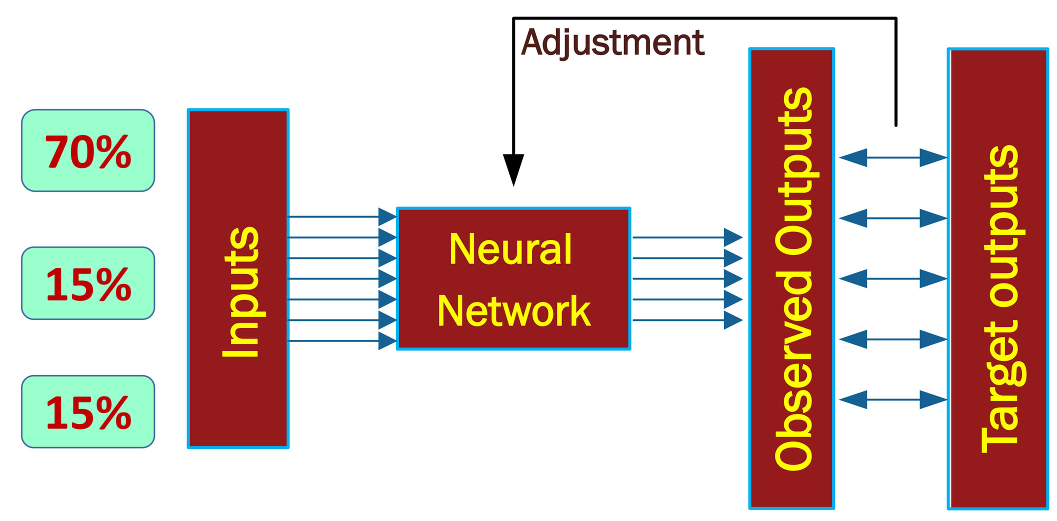

Figure 2. Training process to establish the connection weights. The suitability of the networks obtained was established by minimising the mean squared errors (MSEs) between the targets and the ANN outputs.

RESULTS & CONCLUSIONS

The error function (MSE) gradually decreases during network training (Figure 3a). This occurs indefinitely for the training data set but not for the validation and test sets. When the MSE stops being reduced for the validation data set, this indicates that the network begins to overfiting. It means that the network is memorizing the input data and is losing its ability to generalize to new data. The learning process must stop when the overfiting is detected. At this point, the network also increases its MSE for the test data set.

Results showed that the Levenberg-Marquardt (LM) training algorithm provided the largest number of ANN with acceptable values of R^2. Once the best network architecture had been established, the sensory parameters of dry ham were predicted (Figure 3, 1-4).

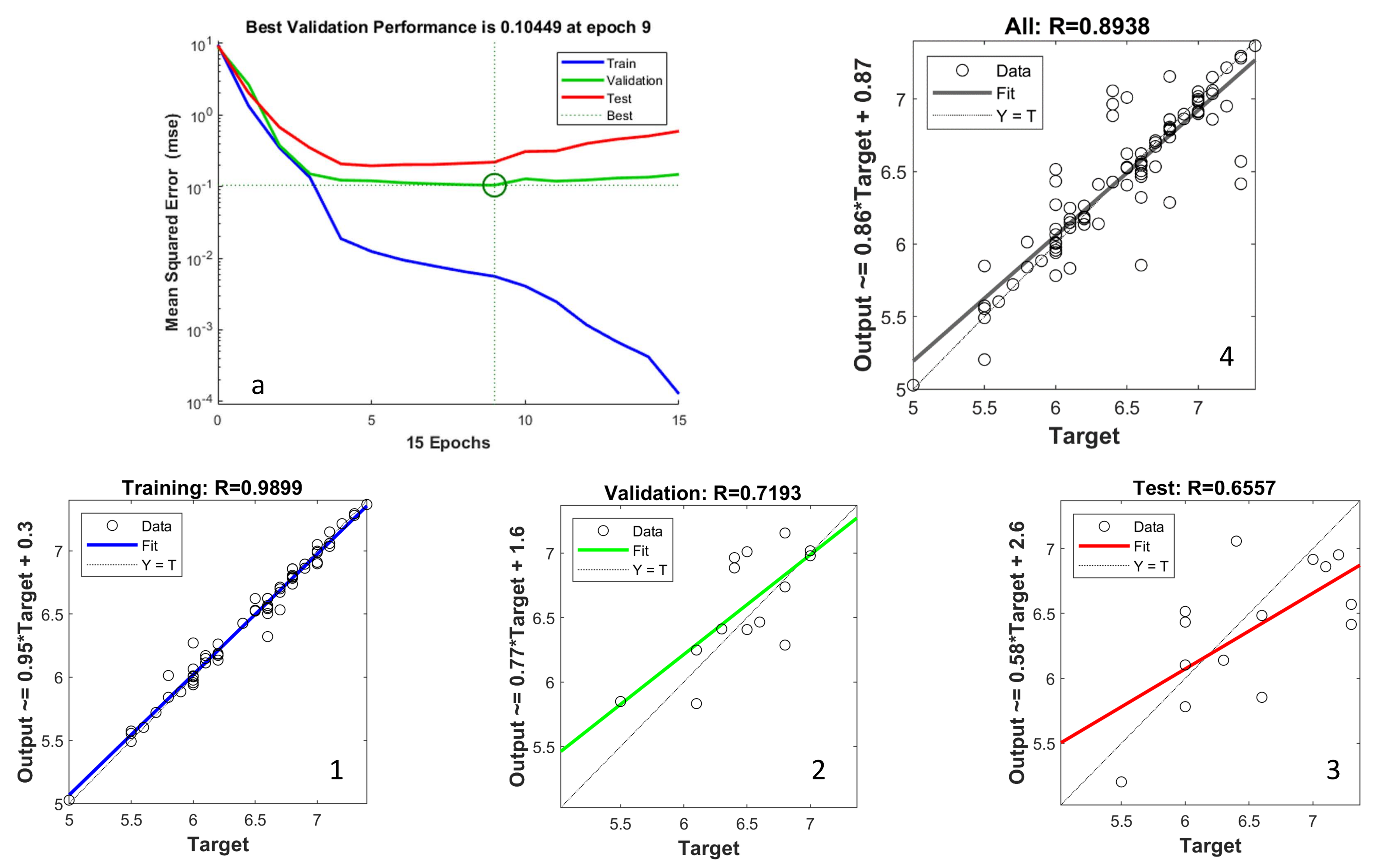

Figure 3. Overfiting detection (a), regression coefficient value for the three data sets (1, 2 and 3) and total regression coefficient (4) for aftertaste sensory parameter.

Table 1 shows that the number of neurons in the hidden layer were between 4 and 29, the regression coefficient (R) was between 0.7 and 0.9 and the determination coefficient (R^2) varied from 0.5 to 0.8 depending on the sensory parameter. The prediction of sensory parameters using NIRS and ANN were very good for descriptors such as colour intensity, exudate, cured aroma, cured flavour, flavour intensity, sweetness or aftertaste.

Table 1. Number of neurons and R^2 values for the best ANN architecture (in terms of obtaining the highest R^2)

Sensory		Nº Neurons	R^2
Visual	Veined	17	0.6111
	Colour fat	17	0.7786
	Colour homogeneity	8	0.6627
	Colour intensity	16	0.7910
	Exudate	26	0.7975
	White dots	4	0.7062
Odour	Odour intensity	10	0.6644
	Cured aroma	27	0.7450
	Pig aroma	27	0.5099
	Rancity aroma	25	0.7296
	Atypical aroma	16	0.4950
Flavour	Flavour intensity	14	0.7839
	Fat flavour intensity	18	0.6397
	Cured flavour	17	0.7496
	Saltiness	7	0.7241
	Sweetness	23	0.7487
	Sourness	16	0,5383
	Rancity	11	0.6769
	Aftertaste	27	0.7990
	Atypical flavour	13	0.6053
Texture	Hardness	29	0.6243
	Juiciness	15	0.7210
	Fatness	22	0.7040
	Fibrousness	16	0.7146
	Chewiness	7	0.5784
	Gumminess	15	0.5513
	Heterogeneity	7	0.6180
	Chewing residue	25	0.5343

Acknowlegment This study was made possible by funds from Reserch Projects from Junta de Castilla y León (Spain). Ref. SA039P17).