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Artificial neural network for predicting the physicochemical composition of milk from physical analyses

Andreza Márcia da Silva, Larissa Souza Teixeira, Gerson de Freitas Silva Valente *, Giovana Maria Pereira Assumpção and Wellington de Freitas Castro

Federal Institute of Education, Science and Technology of Southeastern Minas Gerais, Barbacena, Brazil.

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Abstract

The aim of the research was to predict, using Artificial Neural Network (ANN) the physicochemical composition of milk from physical analyses. Forty-three milk samples were analyzed for fat, solids-non-fat, protein, lactose, and mineral salts. In addition to temperature, freezing point, and density by means of an ultrasound milk analyzer. The network architecture used was feed-forward multilayer, with data divided into 70% for training and 30% for ANN testing. The artificial neural network transfer function was Relu, Adam as the training algorithm for weight change with a constant learning rate. The number of neurons in the hidden layer was determined using the mean square error and coefficient of determination for training and test data. Twenty neurons in the hidden layer were analyzed and considered appropriate. The ANN model was able to predict the physicochemical composition of milk, the result obtained was a robust coefficient of determination, with values above 0.88.

Keywords: Artificial intelligence; ANN; Machine learning; Milk collection; Dairy industry

1 Introduction

The physicochemical composition of milk is an important parameter because it is related to the industrial yield in the production of dairy products and can be used in the system of payment for quality from the dairy to the producer [1].

Milk is a mixture of different substances that are quantitatively distributed on average 87% water and 13% solids, called milk solids (MS) being, 4.8% carbohydrates, 4% fat, 3.5% proteins and 0.7% vitamins and mineral salts and represent the nutritional part of milk [2].

The milk presents a stability becoming a basis for performing tests to indicate the occurrence of setbacks that may alter its composition [3].

Upon arrival at the industries reception platform, it is necessary to meet the requirements of the normative sector established in Normative Instruction (IN) 76/2018 of the Ministry of Agriculture, Livestock and Supply [4] following the physical-chemical parameters that establishes: Titratable acidity between 0.14 and 0.18 grams of lactic acid/100 mL; Alizarol stability at the minimum concentration of 72% v/v; Relative density at 15 °C between 1.028 and 1.034; Cryoscopic index between -0.530 °H and -0.555 °H, corresponding to -0.512 °C and -0.536 °C. The minimum content of: Fat 3.0 g/100 g; Total protein 2.9 g/100 g; Lactose 4.3 g/100 g; Non-fat solids 8.4 g/100 g and milk solids 11.4 g/100 g; Temperature 7 °C. The analyses employed to perform the physical-chemical evaluations of milk require specific equipment and there are dairies that do not have the necessary instruments to perform them. From this, artificial neural networks appear as an alternative method.

* Corresponding author: Gerson de Freitas Silva Valente; Email:gerson.valente@ifsudestemg.edu.br

Artificial neural networks have been widely used in the food industry to improve process efficiency, optimize product quality, and increase food safety. One of the most common applications of artificial neural networks in the food industry is demand forecasting. Companies can use historical data on sales, weather, seasonal events, and other variables to train neural network models that predict future demand with high accuracy. This allows companies to adjust their production and inventory according to predicted demand, reducing food waste and storage costs [5].

Another important application of artificial neural networks in the food industry is automatic food classification. Artificial Neural networks can be trained to identify and classify different types of food based on their characteristics, such as size, color, texture, and shape. This is useful for the classification of agricultural products, such as fruits and vegetables, as well as for the automatic selection of ingredients in food production lines [6, 7].

Artificial Neural networks can also be used to optimize food production processes. For example, companies can train neural network models to automatically control temperature, humidity, and other variables at different stages of the production process, ensuring that final products are of the desired quality. In addition, artificial neural networks can be used to detect anomalies in the production process, such as machine failure or contamination, allowing companies to take immediate action to correct the problem [8].

Finally, artificial neural networks can also be used to improve food safety. Companies can train neural network models to automatically detect bacteria and other pathogens in food, reducing the risk of foodborne illness. In addition, neural networks can be used to automatically identify and remove foods that do not meet quality or food safety standards [9, 10, 11].

In summary, artificial neural networks have a wide range of applications in the food industry, including demand forecasting, automatic food sorting, production process optimization, and improving food safety. As technology continues to advance, it is likely that food companies will continue to explore new ways to harness the power of artificial neural networks to improve the efficiency, quality, and safety of their products [12].

According to Furtado [13] artificial neural networks are a set of mathematical methods and computational algorithms specifically designed to predict results from input values. Functionally, an artificial neural network can be thought of as a kind of processing box that can be trained to form one or more outputs from a set of input data.

Thus, the objective of this work was to use artificial neural networks from the data of physical analysis of milk to predict the physicochemical composition to allow the producer to have the possibility of checking the quality of his product.

2 Material and methods

We collected 43 milk analysis data on random production days during a 6-month period, between July and December, at the facilities of the Instituto Federal do Southeast de Minas Gerais, Barbacena, Brazil. The samples used were samples that had not undergone any type of adulteration. The analysis was performed by ultrasound milk analyzer equipment (Master Complete-ASKO®) which determined the percentage of fat, non-fat solids, protein, lactose, temperature, freezing point, mineral salts, and density [14]. The data from the analyses were tabulated in a spreadsheet. The architecture class used for artificial neural network was the multilayer feed-forward network that features one or more hidden layers. According to Furtado [13] these hidden neurons have the function of intervening between the input and output layers of the network in some useful way. This network maps better to more complex problems due to the addition of one or more layers.

The data was divided into 70% for training, 30% for testing the ANN, and standardized with zero mean and standard deviation equal to 1.0. The ANN architecture was developed using the Python software version 3.7. The number of neurons in the input layer was stipulated by the variables milk temperature at analysis and milk density at 15 °C. The output layer corresponds to the prediction of the following components: fat content (%), solids not fat (%), protein (%), lactose (%) and mineral salts (%). The number of neurons in the hidden layer was defined by trial and error using as parameter the least mean square error given by Equation 1:

$$\text{MSE} = \frac{1}{Q}\sum_{1}^{Q}(t(k) - a(k))^2 \text{ .... } (1)$$

Where t(k) is the real value and a(k) the value predicted by the ANN and Q the number of samples.

A second parameter used to evaluate ANN performance was the coefficient of determination (R^2) between the real data and the data predicted by the artificial neural network for the training and test data. Graphs showing the correlation between experimental data and values predicted by the artificial neural network have been drawn.

3 Results and discussion

The physicochemical parameters of the milk samples presented minimum and maximum values as shown in Table 1.

Table 1 Variation of physical-chemical parameters of milk samples used in the construction of ANN

Variable	Minimum - Maximum	Limits - IN n° 76/2018
Fat (%)	2.64 - 3.33	min 3.0
SNF (%)	7.73 - 9.04	min 8.4
Protein (%)	3.17 - 3.33	min 2.9
Lactose (%)	4.70 - 4.95	min 4.3
Mineral Salts (%)	0.69 - 0.72	-
Temperature (°C)	7.30 - 21.00	4
Density (g L-1)	1,031.00 – 1,032.64	1,028.00 a 1,034.00

The physical-chemical standards are established by IN 76/2018 [4] (BRASIL, 2018). For fat content, part of the samples did not meet the minimum expected value, where it was found in some samples a minimum value of 2.64 g /100 g. In density, all samples met the required standard values. In solids not fat, only one sample presented a value below the standard. In relation to the content of protein, lactose, and total solids, all the samples presented values above the minimum required by the legislation. The minimum and maximum values found during the temperature analyses were 7.30 and 21.00. According to the guidelines of the Master Classic equipment, the milk samples must be between 5 and 35 °C. Non-standard values are important for ANN training because it improves the prediction of new cases.

Figure 1 shows the architecture of the multilayer feedforward artificial neural network, with the representation of the input layer, hidden neurons, and output layer.

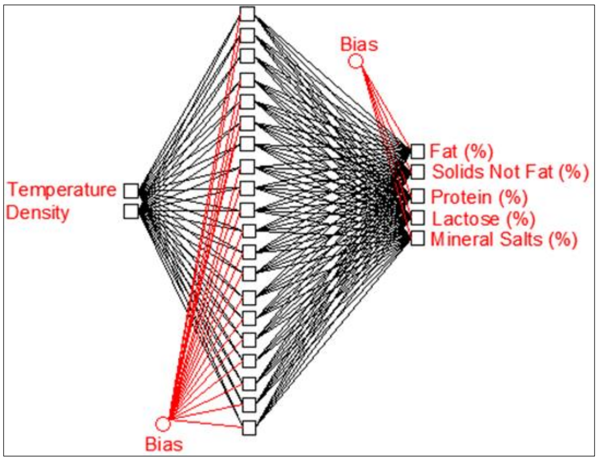

Figure 1 Architecture of the artificial neural network with the representation of the input layer, hidden neurons, and output layer

The transfer function of the artificial neural network was Relu, and the Adam algorithm was used to adjust the weights with a constant learning rate. To build the ANN architecture, the results of 43 analyses were randomly divided into 70% for training and 30% for testing.

The weights of connections in the constructed ANN are shown in Table 2.

Figure 2 shows the number of neurons in the hidden layer defined by the mean square error (MSE), where it was analyzed that 20 neurons in the hidden layer would be adequate because the artificial neural network with a higher number of neurons did not show a significant variation in error reduction (MSE). In this work, we chose to use 20 neurons in the hidden layer, and the prediction capability of the artificial neural network for training and test data was verified by means of the coefficient of determination.

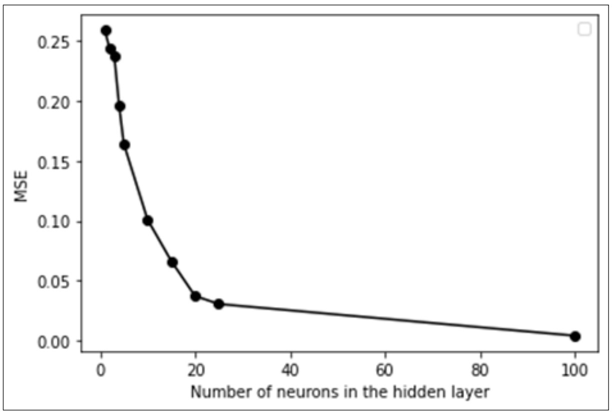

Figure 2 Number of neurons in the layer

Even after training, artificial neural networks may present lower calibration errors and high prediction errors, or rather, overfitting, which occurs due to a high number of neurons used in the hidden layer [15]. ANNs that have few neurons in the hidden layer tend to show better generalization ability, which is related to the performance of identifying patterns in the test set [16].

Figure 3 shows a parallel between the values predicted by the ANN and the experimental values for training and test data.

Statistically, the coefficient of determination is the measure for the degree association between two variables [17]. The coefficient of determination, also known as R^2, is a statistical measure that indicates the degree of adjustment of a linear regression between two variables, this coefficient varies from 0 to 1. The coefficient of determination is an important measure in regression analysis because it indicates the degree of regression fit and the proportion of the variation explained by the variable. [18].

The data support that, in comparison with the experimental results, the ANN accurately predicted the physicochemical composition of milk from density and temperature. The fat content, protein, lactose, and mineral salts showed linear degree of association with coefficient of determination greater than 0.92. It was observed that only for the mineral salts presented lower coefficients of 0.88, which are still considered good.

Artificial neural networks have been applied in several areas in food science, with various purposes of solving adversities, facilitating access to information, calculating and predicting results, avoiding errors and waste, for example, helping in the organization of stocks and reducing costs, performing activities by image recognition, classifying and quantifying impurities, and fraud detection, among others.

Through the use of artificial neural network [19] in search of the best model to quantify fraud in powdered milk, by the addition of whey powder used models with alternating parameters and the best model obtained was the third model. This model used routine analyses in dairies such as cryoscopy, defatted dry extract, fat and total solids, reaching an ANN capable of satisfactorily predicting the analyzed fraud from analyses that are considered routine in dairies.

Santos et al. [20] employed ANN in an attempt to classify traditional Minas cheese from the Serro, Canastra, and Araxá regions. The linear function used was able to identify 100% as a function of the physicochemical parameter. The creation of a model based on routine analyses is important in the automatic control system, which would be able to collaborate with the veracity and pprotected designation of origin of the cheeses of each region.

Table 2 Weight matrix between the input and hidden layers (W_1) and weights between the hidden and output layers (W_2) for the final structure of the ANN

W_1 (weights)						**W_2(weights)**		
Input			**Neuron**	**Output**				
Temperature	**Density**	**Bias**	**Hidden layer**	**Fat**	**SNF**	**Protein**	**Lactose**	**Mineral salts**
1.02186629	1.44405825	1.85479668	1	0.642257065	-5.06153019	-1.08720894	-2.30708219	-1.70665009
3.81772814	0.12550089	-0.54369016	2	-3.27457395	0.365998584	-2.24864394	0.143877958	3.01352059
-2.51374819	-1.38025452	-0.72634111	3	1.89408884	-4.1445052	-0.48832831	-1.3526362	-1.3999381
1.08809276	0.41946601	-1.98842252	4	3.30772218	1.33187624	0.285682982	0.563052962	0.810542549
-2.70760954	0.8896559	0.3783436	5	-2.64046456	0.124710727	-0.986555246	-0.869523785	-0.818973511
1.60044818	-1.5117755	0.68630023	6	-3.7348026	$-6.94299729 \cdot 10^{-4}$	-0.256767446	-0.316635646	-1.02955052
0.0626933	1.12295031	1.12810377	7	1.55517247	-3.36063232	0.0773233225	0.121765513	-1.41702117
1.99097598	0.61452869	1.00454304	8	-5.24488182	-1.64820705	-3.2463589	-2.86808671	-0.0323613265
0.06653385	-0.00975206	-0.33424409	9	$-3.24236122 \cdot 10^{-4}$	$-3.16807881 \cdot 10^{-7}$	0.00215140093	-0.0010533395	-0.00456794838
-1.97885517	1.68505038	1.96137745	10	2.34686767	-2.44750456	1.5269246	2.16107817	-0.00680987732
-0.37636655	-1.864924	-1.01248928	11	-0.740683732	1.24773244	1.36337565	1.38708835	1.6708918
1.41624251	-1.47389818	1.26868629	12	3.58978656	0.324979704	0.900792741	0.863671559	0.741617865
1.5228652	-0.64022314	-1.88359403	13	-2.75056865	-2.52083656	-0.565284566	-0.692568004	-1.28600407
4.18059075	1.17289912	1.2838418	14	5.1546421	-2.38141106	1.21626144	1.28826714	1.14083927
0.43054407	-1.60015322	-1.49029974	15	1.36488639	-2.24393977	-3.18703068	-3.52148107	-0.137240093
1.86003969	0.85097521	0.73820273	16	-4.53032062	5.49455408	2.30181741	2.47877268	1.24476993
2.2032064	0.81197118	0.63789797	17	-0.51656777	5.89743462	1.08141321	0.0826230755	-3.00124887
-1.16039044	1.17435071	1.59750463	18	-1.30649194	8.17116401	-0.442428269	-1.01514439	2.71970293
3.09516726	-0.64894348	-1.10463485	19	4.53597141	-0.459468912	2.27519117	0.136791801	-2.10726325
-0.37412885	-1.15246855	-1.33275881	20	-5.2959215	6.83290359	-0.208789111	2.11024424	0.818841163
			Bias	2.8567948	1.40717709	-1.25966861	-0.00322026	-0.73617886

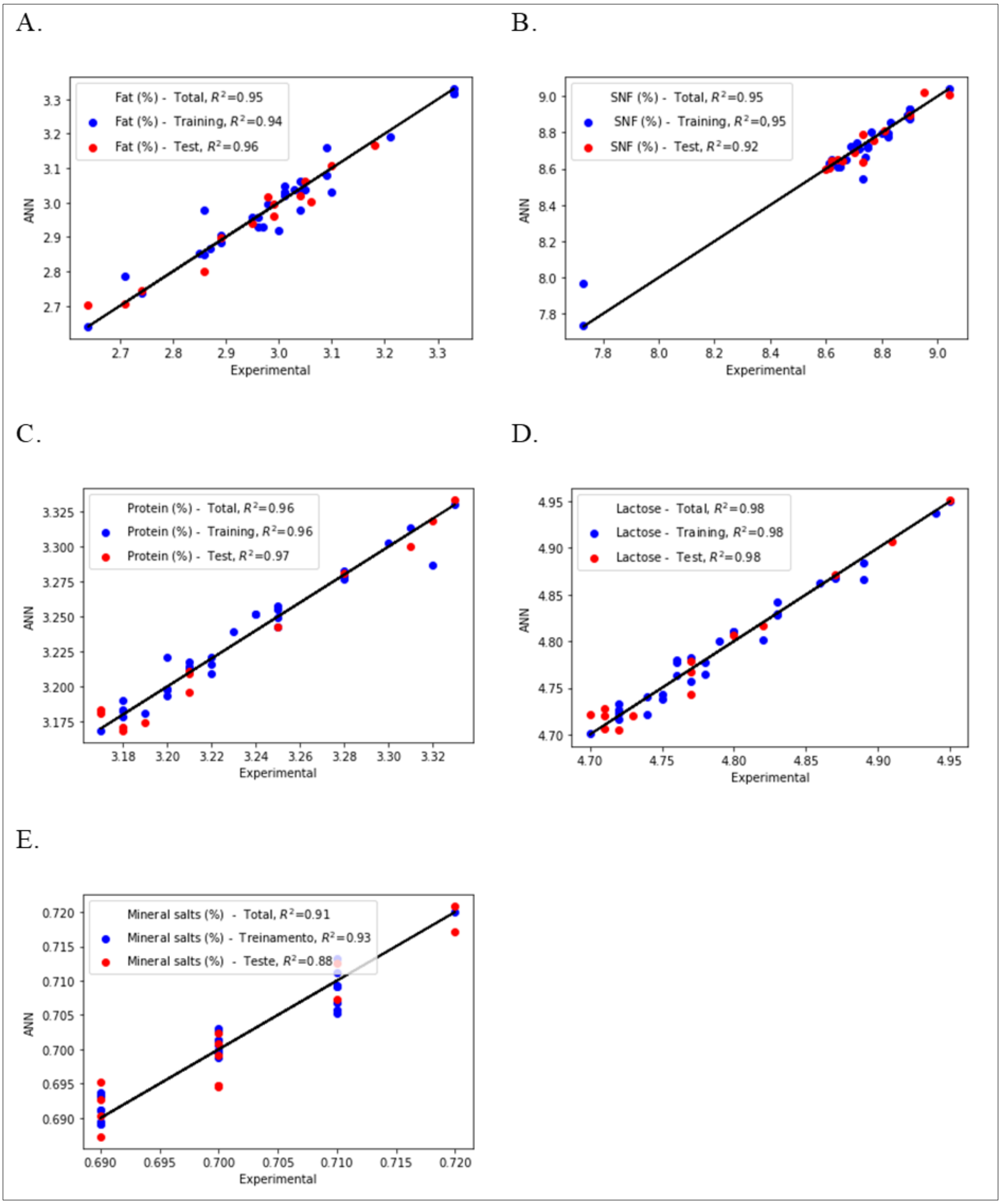

Figure 3 Comparison between the values predicted by ANN and the experimental values for training and test data

In order to classify commercial yogurts in the low fat content categories, Cruz et al. [21] used products of several commercial brands from several batches. According to the statistical data, distinct characteristics of yogurt categories were established, thus building the data for the neural model to be trained. The model used was 100% efficient and the process presented is a fast and interesting way to follow the reality of the products.

Artificial neural networks have a wide range of applications in the dairy industry, from quality control to demand forecasting and supply chain management. Artificial neural networks can be used to analyze milk quality data, identify patterns, and predict potential quality problems. They can also be used to optimize production processes, helping to maximize yield and minimize waste. In addition, neural networks are often used to forecast demand for dairy products, allowing companies to adjust their stocks and production more accurately. And finally, artificial neural networks can also be used to monitor the supply chain, helping to forecast raw material supply and ensure the timely delivery of finished products to customers. In this research, we can verify the possibility of predicting the physical-chemical composition of milk through artificial neural networks. From the prediction, there is the alternative of building smartphone applications that will allow, from easy-to-perform physical analyses, to evaluate the composition of milk at the time of collection from milk producers in Brazil.

4 Conclusion

The multi-layer feed-forward artificial neural network model was able to predict the physicochemical composition of milk from physical analyses, exhibiting great results. Artificial neural networks present themselves as a tool to predict milk composition without the need for chemical reagents and sophisticated equipment, assisting in good milk collection practices in farms and small properties.

Compliance with ethical standards

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To the Federal Institute of Southeastern Minas Gerais, Barbacena, Brazil.

Disclosure of conflict of interest

The authors declare that there is no conflict of interest.

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