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Neural Networks in Food Industry

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Abstract

In the present review we study the application of artificial neural networks in food industry, classifying the information obtained in different categories and the most used programs for its development. The prediction of parameter on operation such as drying, heat treatment, food classification and quality analysis are the main objective for RNA application. Multilayer with feedback propagation is the model most used being Matlab, the software par excellence for its development. Application of artificial neural network in food industry proved to be a useful tool to determine their quality through non-invasive, low-cost and real time processes**.**

Kewords: Parameter predictions, Process control, Network architecture, Food industry

1. Introduction

Artificial neural networks (RNA) are a technological tool that consists of a set of nodes and interactions that allow us to model different behaviors of a process [1] without the need to make assumptions such as those required by common mathematical models [2], these have a functioning analogous to the human brain through neurons and dendrites, also have a great ability to learn and solve specific problems in different fields [3]. The advantages of RNA are that they allow the analysis of data and the determination of parameters through different learning algorithms that facilitate the performance of teaching tests for the subsequent predicttion of the output values according to the input values by means of simulations, in addition to the fact that the proposed models have dynamic systems adaptable to the conditions of the process, even if a new situation arises, these responses are given in real time, which is why it represents one of the main advantages compared to other systems for determining parameters [4], [5].

The fundamental points to consider within the concept of RNA are: problem data, learning models, network structure, algorithms and simulation. These fundamental points are the result of the great modifications that have been made throughout history in RNA, in search of their optimization [5].

Neural networks arose from artificial research and have been seen with interest and applied successfully through an extraordinary range of problem domains, in diverse areas such as finance, medicine, engineering, geology and physics. The RNAs offer several advantages over conventional models, because without adequate knowledge about variable process relationships, the system can be modeled [4]. The main element of a neural network are the neurons, arranged in input and output layers. An important feature of a neural network is its ability to learn how to improve performance. Improving network performance offers several advantages over digital computing due to its higher data processing speed, learning capacity and fault tolerance [4].

RNA models were constructed by interconnecting many non-linear calculation elements, known as neurons or nodes, operating in parallel, and organizing them in patterns similar to biological networks. In the last 50 years there has been an interest increase in the RNA use as a means of solving problems of classification and analysis of data, among others [6], applying in areas such as medicine, biology, neuroscience, computer intelligence, computer science, engineering, physics and chemistry [5]. In food industry case, there is a large number of operations related to the different stages of production processes and quality control of final products, this has made it necessary to develop techniques that allow the performance of analytical tests with in order to determine different properties closely related to the quality of type products, seeking to avoid problems related to adulteration and toxicity of the same. In some cases, these tests are based on perceptual measurements, which makes them little objective and in other cases, information that is not available is required [6], so this technology has been implemented specifically in food industry in the determination of parameters related to thermal processes, drying, mass transfer, cooking [2], [7], [8] among others.

The architecture of the networks refers to the way in which network neurons are organized (number of layers and neurons present in each layer within the network), they are important because they allow carrying out the processes of analysis of the networks. Data entered due to this distribution may vary the results obtained with the network [9]. The multilayer perceptron is the most used neural network architecture for pattern recognition [6], which consists of a network formed mainly by three layers of neurons: an input, an output and a hidden layer where the entire process is performed analytical [7]; In terms of training algorithms, the most used is the backpropagation algorithm, which allows the prediction error of the network to be minimized, feeding it back as an input until the minimum acceptable error is reached [6], these are the most used due to the excellent results obtained in various investigations in the area [10]. This review allows us to delve into the latest applications of RNAs, showing a general outline regarding the specific areas where they are most used, as well as their predictive efficiency, providing useful information for the development of subsequent studies and allowing to generate new alternatives where to focus future investigations on the subject.

2. Neural networks: applications in food industry

This study shows some published works related to food industry, it was found that applications are focused on aspects of product quality, focusing mainly on food classification and parameter prediction. The RNA application also focused on process optimization and its combination with the Response Surface Methodology (RSM).

According to the keywords for technological surveillance, it was found that between 2009 to date, approximately 770 articles related to neural networks in food industry have been published. For the years 2014 and 2016, the largest number of publications was made with 120 and 119, respectively. 72% of the publications were made with a scientific article, followed by 19% for event reports, while 5% of the publications were review articles.

2.1 Prediction of bioactive compounds and physicochemical characteristics

Cortes and Prieto [3] evaluated the properties of antioxidant activity of essential oils as part of their research with RNA, due to the extensive information available about them. A multi-layered artificial neuronal network with 30 input neurons, 42 hidden layers and a neuron at the exit was developed using the Fast Artificial Neural Network software, taking as input the chemical composition of 32 essential oils, their antioxidant activity determined by DPPH and linoleic acid. The results showed an adequate prediction of the model with an error of 3.16% for the determination of antioxidant activity and 1.46% for the determination of linoleic acid. On the other hand, Cimpoiu et al., [11] studied RNA application for the prediction of antioxidant activity and the classification of teas using a multi-layered feedback architecture formed by a hidden layer with 3-4-1 neurons. It was shown through an error value lower than 0.4%, a high closeness between the results obtained experimentally and those obtained by the neural networks used.

Likewise, RNA has been used with a multi-layered architecture fed back with four neurons in the input layer, four in the hidden layer and one in the output layer to evaluate the relationship between content of total polyphenols, flavonoids, anthocyanins and tannin content, associated With the antioxidant activity and classify the wine according to its variety, year of harvest and cava, the results showed correlation coefficients of 0.992 and 0.963 for the wine classification and antioxidant activity, respectively [12]. In the same way, a model was designed to predict optimal conditions of 15 properties of the bean (L. Viciafaba) (length, width, thickness, arithmetic and geometric diameter, sphericity index, image area, gravity, weight, real density, apparent density, volume, porosity, stability of fill angle and emptying) depending on the moisture content (17% and 28%), this being the input variable, for this, a model based on Fuzzy Logic was used from experimental data. R2 values of 0.9999 and 0.9995 were found for the moisture contents of 17% and 28%, respectively, showing an adequate design of the model [13].

Other studies such as the one developed by *León-Roque et al*. [14] used a multilayer perceptron with a feedback algorithm for determining the fermentation rate of cocoa beans based on color changes, through measurements of free amino acids. These parameters were evaluated by experimental values and compared with the proposed model, showing that there was no statistical difference between them.

2.2 Determination of shelf life and maturity stages

One of the most frequently functions used of RNAs is predicting the shelf life of food and the determination of the states of maturity, this tool provides quality characteristics in a short time, allowing companies to take preventive or corrective actions about the process In a study of the kinetics related to the shelf life of Basundi, an Indian dairy dessert, Ruhil et al. [15] evaluated the physicochemical characteristics (pH, hydroxymethylfural, apparent density and solubility index) and their dependence on temperature in order to predict a sensory model of the quality of the Basundi mixture. In addition, a multilayer connection model with a posterior propagation algorithm was used to predict the product's useful life, using the Matlab software. Quality indices were the input parameters, while sensory perception and taste were the output parameters. It was found that the proposed model presented better quality predictions than the kinetic models used, this was determined by the correlation coefficients that were 0.94 and 0.96 for the taste and sensory score parameters, respectively and 0.74 and 0 , 86 for the parameters mentioned above, for the proposed kinetic model.

In a study conducted by Kono et al., [16] the optimum cold storage temperature of cooked rice was predicted through RNA with a hidden layer between the input and output layers using an algorithm backpropagation type. The cooked rice samples were frozen and stored at (-5, -15, -30 and -45) °C for (1, 5, 10, 30 and 90) days. Sensory and texture attributes were evaluated in 690 panelists and the size of crystals obtained after cold storage was compared to obtain a correlation. The RNA model was found to require a storage temperature below -25 °C and microwave heating below -15 °C to maintain the acceptability of the samples for more than 40 days. On the other hand, *Soto-Barajas* [17] used RNA for the prediction of maturation time and the variation of milk mixtures (cow, sheep and goat) for cheese making, using the content of 19 fatty acids as input values. and near infrared spectral values (NIR). Four models were developed, two of which use the fatty acid information as input data and the other two, using the NIR values as input data. These are the models that took the NIR spectra as input values obtained 100% and 50% correct classification at the time of maturity and type of milk, respectively, at the same time, the model that took the concentration of fatty acids as input data obtained correct classification percentages of 80% and 75% in ripening time and milk type, respectively.

Pan et al., [18], evaluated the quality of cold stored peaches between the interaction of a hyperspectral imaging system and an RNA. The proposed RNA model consisted of three layers: an input layer, a hidden layer and an output layer; the input layer had 420 nodes corresponding to spectral response values for each fruit, the output layer with two nodes corresponding to the classification of the state of the peaches. For the prediction of the quality of stored peaches, an accuracy of 95.8% was found for fruits that suffered cold damage. Siripatrawan and Jantawat [19] conducted a study to predict the shelflife of rice snack varieties packed in polypropylene and polyethylene bags. The RNA used to evaluate the life consisted of a multilayer perceptron with backpropagation algorithm with input capacity, a hidden layer and an output layer. The results showed that the RNA is a good alternative to evaluate the shelflife of these products, with coefficients of determination of 0.9918 and 0.9554 for the snacks types.

Another study compared the Arrhenius model with RNA in the study of the quality of rainbow trout fillets during storage at different temperatures, for it used an input layer with two neurons and an output layer with four neurons. One to eight neurons were tested in the hidden layer, obtaining the best results with the network of six hidden neurons, which generated a correlation coefficient of 0.9697 with an average square error of 0.0042 [20]. Likewise, a method to predict the rancidity of butter cookies using RNA was evaluated. Parameters such as moisture content, acidity and peroxide values were determined by conventional methods and subsequently related to partial regression of least squares and backpropagation using a multispectral imaging system. The results showed that the model through partial regression had a better fit than the proposed RNA. However, it was demonstrated that the multispectral imaging system is a useful tool to measure the quality of food in real time [21].

2.3 Food quality prediction

The use of RNA is a tool to improve quality characteristics in food products, this was demonstrated by the study carried out by Keeratipibul et al., [22] where they studied the prediction of the amount of coliform bacteria and Escherichia Coli present in tomato (*Solanum lycopersicum*) and lettuce leaves (*Lactuca sativa*) after carrying out a disinfection process with hypochlorous and peracetic acid. RNA is used to predict the relationship between bacterial load, type of plant, concentration and concentration of sanitizers and residual microorganism levels after disinfection. A backpropagation model with a hidden layer feedback was used, three occult neurons for coliforms and five neurons for E. Coli. A correlation coefficient of 0.85 and 0.72 was obtained for coliforms and E. Coli, respectively. In addition, it was shown that the effectiveness of the disinfection depended on the characteristics of the fruit or vegetable and the type of sanitizer. Goyal and Goyal [23] studied the prediction of the sensory quality of aromatized drinks with instant coffee, using a cascade model and a feedback model, when testing the different configurations in both cases, it was found that the one that provided the best predictive results was the network conformed by 17 neurons in the hidden layer, with a correlation coefficient of 0.998 and an average error of 0.0013, for the cascade model and with a configuration with seven neurons in the hidden layer, a correlation coefficient of 0.996 and an average error of 0.0028 for the model with feedback, which exhibits the advantages of feedback over the cascaded model. In addition, in a study conducted by Argyri et al. We compared the detection of decomposed meat fillets, using Fourier Transform Infrared Spectroscopy (FTIR) and through an RNA, testing several network architectures. A network consisting of seven input neurons, two output neurons and 20 neurons in the hidden layer was able to correctly classify 22 of 24 fresh samples, 32 of 34 decomposed samples and 13 of 16 semi-fresh samples, with a percentage of efficacy of 91.7%, 94.1% and 81.2%, respectively. The combination of the FTIR technique with RNA is an optimal tool to predict damage in meat samples in real time [24].

2.4 Application of RNA in thermal treatments

The application of thermal treatments in food industry is one of the main stages to obtain a product of good quality, whether applied in the pre-treatment or transformation stage [25]. A feedback-type RNA was used with Levenberg-Marquardt backpropagation and weight-adjustment training algorithms, with two input neurons, six output layers, a hidden layer and 18 neurons in the hidden layer, to evaluate the concentration and temperature in a solution of fructooligosaccharides in parameters such as mass, moisture, volume, and solids in dehydrated yacon cubes, in addition to evaluating the diffusion coefficient by comparing its values with and without shrinkage. An average global error of 3.44% was found and correlation coefficients between the predicted and experimental values, greater than 0.99. The response variables that had the best adjustment were mass and humidity. No significant differences were found between the experimental values, the values predicted by the RNA and predicted values by means of second-order regression [26]. It was also evaluated the thermal conductivity of different fruits and vegetables (apple, carrot, corn, pear, potato, rice, among others), in wide ranges of temperature, focusing on the development of a model where an RNA and a system were combined of diffuse inference and was compared with a conventional RNA model and a polynomial regression model, obtaining a correlation coefficient of 0.978, 0.950 and 0.931, for each proposed model, respectively [27].

Ajasa, et al., [28] studied the prediction of the thermal conductivity of bakery products in Nigeria, based on the temperature, moisture content and apparent density of the same. Different RNA models were used as retropropagation algorithm with a hyperbolic tangent transfer function, choosing as optimal model a network of eight neurons in two hidden layers and a simpler model with a hidden layer and 10 neurons. The adjustment of the models was evaluated through the mean relative error (ERM), mean absolute error (EAM) and the standard error (EE) of the models, being 4.878 * 10-2%, 0.0054 W / m K and 0.0015 W / mK for the optimal model and 3,388 * 10-2%, 0.0034 W / mK and 0.0011 W / mK for the simplest model. Although the error values of the two models were approximately equal to zero, the simplest model obtained lower values. On the other hand, Ochoa Martinez [2] developed an RNA model for the prediction of mass transfer parameters (water loss and solids gain) in the osmotic dehydration of the apple, correlating six process variables (temperature, concentration of the osmotic solution, immersion time, surface area, proportion of fruit in the solution and level of agitation). The proposed model (a hidden layer and four neurons) predicted values of water loss and solids gain with a standard error of 13.9% and 4.4% and a regression coefficient of 0.96 and 0.89, respectively. These results had a better fit than a conventional multi-variable linear regression.

In a study conducted by Neethu et al., [29] the prediction of the convective heat transfer coefficient during pantoa frying by means of RNA was studied, obtaining a correlation coefficient for the results derived from the network of 0.9984, using a multilayer network with feedback and a learning algorithm of backpropagation, one of the most common neural network architectures. Arjona-Román et al [30] developed an RNA model that allowed the determination of the calorific capacity (Cp) of the defrosting of pork with variables not associated with said measurement. For this process, two RNAs with different input variables were used: five for the first model and seven for the second. The model used was a three-layer network, a layer at the entrance, a hidden layer and a layer at the exit. It was found that for the first proposed model (five input variables) an error of 0.0082 and R^2 of 0.9992 was obtained, while for the second proposed model an error of 0.00079 and R^2 of 0.9989 was obtained.. In another study, a multilayer perceptron with a layer at the entrance with four neurons and an exit layer with two neurons was used to predict percentages of water loss and solids gain in the osmotic dehydration of aubergines by modifying sodium chloride concentration (5%, 10% and 15%), osmotic solution rate (1:10, 1:15 and 1:20) and temperature (30 ° C, 45 ° C and 60 ° C). Type 4-25-2 and 4-16-2 models were generated (neurons in the input, hidden and output layer) with correlation coefficients of 0.9825 to 0.9761, respectively [31]. On the other hand, Das and Golder [32] evaluated the parameters of microwave-assisted dehydration of aloe vera gel, combined with an optimization process through response surface methodology and the modeling of an artificial neural network (RNA). The microwave power, the amount of aloe gel and the drying time were evaluated on the humidity ratio. The optimization process was carried out with a central design composed of a centered face, the results obtained were the basis to obtain the architecture of the RNA. The Levenberg-Marquardt backpropagation algorithm showed an adjustment of 0.999 indicating the correct modeling of the process. *Azadbakht et al.* [33] found that for the determination of dehydration parameters of potato cubes, such as energy and exergy efficiency and the use of energy, the use of RNA provided better response approaches than traditional mathematical models, using the Levenberg-Marquardt as a means of learning and obtaining correlation coefficients for energy efficiency, energy utilization, loss and exergy efficiency, values of 0.9927, 0.9984, 0.9979 and 0.9839, respectively.

2.5 Prediction of parameters with digital analysis methodology

One of the non-invasive techniques for predicting food characteristics is done through computer vision in combination with artificial neural networks. A study by Fan et al., [34] evaluated five texture characteristics (hardness, elasticity, cohesiveness, chewiness and gumminess) by means of a TPA texture analysis and two color space characteristics: HSI (hue angle, saturation e intensity) and Lab (Luminosity, red-green space, yellow-blue space) by means of a Computational Vision System (SVC) to extruded products. A multi-layered RNA model with feedback was used, using the Trainbm training algorithm using the Matlab software (The Math-Works, Inc., USA).The adjustment was compared with a conventional linear adjustment showing favorable results with the proposed model. The gummity and hardness variables were the best fit with correlation coefficients of 0.97 and 0.98, respectively. Likewise, Shafiee et al [35] proposed RNA models to transform RGB (Red, Green, Blue) values to CIELab colorimetric parameters and predict values of antioxidant activity (AA), total polyphenol content (CPT) and ash content (CC) from honey image color characteristics using a computer vision system. In this study two feedback networks were used, the first network consisted of an input layer that had three neurons that corresponded to values of R, G and B, with an output layer with three neurons that corresponded to values of L, a and b. The second network consisted of an input layer with 15 neurons that corresponded to of color characteristic extracted from honey samples, an output layer with a neuron representing AA, CPT and CC measurements. For the conversion of RGB color parameters to Lab, an error of 1.01 0.99 was obtained. In addition, correlation values of 0.99, 0.98 and 0.87 were found for CC, AA and CPT, respectively, showing the effectiveness of the proposed model.
The application of RNA models was also evaluated as a tool for the determination of the maturation state of papaya (Carica papaya) in a non-invasive way through image processing. For the study, a multilayer perceptron RNA was proposed for the conversion of RGB color parameters to Lab, and pattern recognition techniques

were also used.. A relationship was found between the color index (obtained from Lab values) and the state of maturity of 91%. In addition, this tool allowed designing a software to establish the state of maturation of the papaya by digital image [36]. Dara and Devolli also proposed an integration algorithm for image processing and RNA for the classification of apples within the size groups (small, medium and large). For this study, a backpropagation network model was developed with an input layer, a hidden layer and an output layer. The results showed an error of 1.1% for the proposed model, achieving a correct prediction at high speed and low cost [37].

2.6 Prediction and parameters optimization with response surface methodology

Astray et al., [38] compared the use of artificial neural networks (RNA) with the response surface methodology (RSM) to optimize the production of oligosaccharides from sugar beet pulp. The model used three independent or input variables and 10 response variables. For this test 19 experiments were done, with five repetitions in average values, which were used for the development of the RSM. For RNA, three layers were used at the entrance, five hidden layers and one layer at the exit (corresponding to the 10 response variables). It was found that the model proposed by RNA improved the response variables between 5.58% and 61.78% compared to MSR, however, four of the response variables failed to be adjusted by RNA. On the other hand, a study conducted by *Khawas* et al., [25] evaluated the influence of temperature, thickness and type of pretreatment, texture of color and texture during vacuum dehydration of banana *(Musa* ABB). For this, a comparison was made between the response surface and an artificial neural network for the prediction of the parameters mentioned above. The optimization through RSM was done with a factorial experimental design, this design was the basis for obtaining a retropropagation type RNA model. It was found that the proposed RNA model obtained better predictions for the values of rehydration rate, sweep rate, color and texture, than the model proposed by the RSM.
Anastácio, et al., [39], also compared the use of RNA and RSM for the modeling and optimization phenolic compounds extraction from sweet potato peel (Ipomoea batatas L.). The composite central design was applied using the solid / solvent ratio, time and temperature as independent variables, and the measurement of phenolic compounds and antioxidant activity by two extraction methods: ABTS (2,2'-azino-bis-3) ethylbenzothiazoline-6-sulfonic acid) and DPPH (1,1-diphenyl-2-picrylhydrazyl) as response variables in the RSM. For RNA, a simple structure was used with three layers at the entrance, six hidden layers and nine exit layers. It was demonstrated that the optimization was carried out successfully using both the RNA method and the RSM method.

2.7 Parameters of Classification in food industry

Besides the prediction of parameters, the use of RNA is mainly used to classify food types or some characteristics of them, obtaining high correlation percentages in most of the studies found. In a study conducted by Dębska and Guzowska-Świder [6] they evaluated characteristics of a beer brand, taking into account parameters such as clarity, color, flavor, degree of fermentation, pH, acidity, among others, through an RNA, in which was classified as "good" or "bad". A multilayer perceptron was used, which consisted of an entrance layer, one or more hidden layers and an exit layer with a radial base pattern. The implementation of RNA allowed the discrimination between the quality of the samples with a 100% efficiency in the prediction of the drinks studied. On the other hand, Górska-Horczyczak [40] sought to differentiate neck, loin and ham from frozen pork, fresh and spoiled, in order to avoid adulteration in the sale of the same. This study was carried out using an electronic nose supported with an RNA model, this model was based on three layers of non-linear perceptron.. The results indicated an effective recognition of 90%, 85% and 80% for the samples of spoiled, frozen and fresh pork, respectively, showing the utility of this method for its speed, effectiveness and low cost.

Another study proposed a methodology to classify four types of oil: canola, sunflower, corn and soybean from different tools, including the use of RNA with three layers, each one with four neurons. Fluorescence spectral values were used as input data. It was found that the proposed model was able to classify the oil with 72% efficiency [41]. In the same way, a methodology was proposed using RNA for the authentication of origin of extra virgin olive oil, using the multilayer perceptron model and the Scaled Conjugate Gradient algorithm. For the classification, three methodologies were applied: meteorological services, near infrared data and nuclear magnetic resonance, obtaining greater capacity to classify the crops in the last mentioned methodology, with precision values higher than 99% [42]. Hajimahmoodi et al., [43] sought to classify five types of vinegars (distillate, apple, grape, pomegranate and unclassified) from the measurement of their organic acid composition using the high-performance liquid chromatography (HPLC) method, using a RNA with feedback multilayer type backpropagation. He found the proposed model, a level of accuracy of 88.6%, successfully classifying various types of vinegar, even unclassified samples. Three fish species from Rio de Janeiro were classified in a study conducted by *Hauser-Davis* et al., [44] using a multilayer perceptron with four hidden layers and six neurons in each of these, obtaining this list with 100% of correct distributions, comparing these results with those used with the use of a discriminatory analysis, 92% was generated of correct classifications. *Cevoli* et al., [45] classified cheese type Pecorino using an analysis of volatile components and artificial neural networks, the latter were made with architectures varied in the number of input units: 19, 6 and 184 of these. The best results were obtained in each case with 10, 4 and 35 neurons in the hidden layer correspondingly and reaching a correct classification percentage of 100%, 75% and 100%, respectively.

On the other hand, *Almeida* et al., [46] performed the preparation of gelatin from chicken legs with different formulations. A classification was developed from sensory tests with 50 untrained tasters and through the use of Kohonen-type RNA allowing to identify the acceptability of the gelatins, obtaining highly satisfactory results with the use of the network, *Anjos* et al., [47] studied the use of RNA for the determination of the biological origin of honey used in their tests, using 14 different architectures and obtaining the best results with a configuration of 25 neurons in the hidden layer and four input variables (color, conductivity electrical, content of total polyphenols and ashes) which generated 100% of the correct determinations. Similarly, the results obtained with an architecture of 25 neurons in the hidden layer and three input variables, were the least satisfactory with 20% of the correct determinations and *Muñiz-Valencia*, et al., [48] performed the classification of Mexican coffee using a multilayer perceptron with six neurons in the input layer, five neurons in the hidden layer and four in the output layer, using coffee from four different origins. The percentages of exposure were 100%, 94%, 94 and 81%, for coffee from Chiapas, Colima, Oaxaca and Veracruz, respectively.

2.8 Other applications

In addition to the prediction parameters mentioned above, the use of RNA has applications for example in the agro-industrial area, determination of food stability, concentration of compounds, etc. Table 2 shows some of the RNA applications in food industry.

Table 1. Other applications in food industry.

Sample	Research Objective	RNA Type	Results	Reference
Rice crops	Determination of factors that affect the performance in 27 districts of a city in India	Multilayer perceptron	Prediction percentage of 97,5 %	[49]
Extra virgin olive oil	Evaluation the stability of olive oil in polyethylene terephthalate bottles	Multilayer perceptron	Prediction percentage of 92,86 %	[50]
Jurel Fish protein	Modeling the hydrolysis degree of a function of the initial concentration of jurel fish protein	Feedback	Correlation coefficient of 0,98	[51]
Squid protein	Squid protein hydrolysis modeling	Multilayer perceptron	Correlation coefficients between 0.998 and 0.992	[52]
Prune juice	Predicción de flujo de jugo de ciruela roja permeada durante la clarificación de membrana	Multilayer feedback	Correlation coefficient of 0,86	[53]

3. Most used programs for neural networks treatment

Within the investigations in the area, it was possible to establish the different tools applied for the design of the RNA, in Table 2 the most used software is presented, its version and some of the investigations in which it was carried out.

Table 2. Most used software for the development of RNA.

Software	Version	Investigation
Matlab Neural Network Toolbox	R2014a 7.0 7.0.4.365 VR2007b R2011b 7.9.0	Exploitation of Artificial Neural Networks Approach to predict the thermal conductivity of food products in Nigeria [28]. Application of artificial neural network method to exergy and energy analyses of fluidized bed dryer for potato cubes [33]. Prediction of convective heat transfer coefficient during deep-fat frying of pantoa using neurocomputing approaches [29]. Prediction by Artificial Neural Networks (ANN) of the diffusivity, mass, moisture, volume and solids on osmotically dehydrated yacon (*Smallantus sonchifolius*) [26]. Cultivar classification of Apulian olive oils: Use of artificial neural networks for comparing NMR, NIR and merceological data [42]. Prediction of texture characteristics from extrusion food surface images using a computer vision system and artificial neural networks [34]. Cascade and feedforward backpropagation artificial neural network models for prediction of sensory quality of instant coffee flavoured sterilized drink [23]. Prediction of coliforms and *Escherichia coli* on tomato fruits and lettuce leaves after sanitizing by using Artificial Neural Networks [22]. Artificial neuronal network modeling of the enzymatic hydrolysis of horse mackerel protein using protease mixtures [51].

Table 2. (Continued): Most used software for the development of RNA.

Statistica	8.0 4.0 8.3	Classification of Pecorino cheeses using electronic nose combined with artificial neural network and comparison with GC–MS analysis of volatile compounds [45]. Application of artificial neural network in food classification [6]. Characterization of Mexican coffee according to mineral contents by means of multilayer perceptrons artificial neural networks [48]. Classification of food vegetable oils by fluorimetry and artificial neural networks [41].
Java Neural Networks Simulator (JavaNNS)	N.A.	Prediction of the type of milk and degree of ripening in cheeses by means of artificial neural networks with data concerning fatty acids and near infrared spectroscopy [17].
Fast Artificial Neural Network software FANN	N.A.	Application of artificial neural networks to the prediction of the antioxidant activity of essential oils in two experimental in vitro models [3].
Visual Basic Language Microsoft Excel	2010	Heat capacity prediction during pork meat thawing: Application of artificial neural network [30].

4. Conclusion

It was observed in the different articles consulted that artificial neural networks (RNA) have been expanding in the last years their field of action within food industry, being more commonly used for the classification and for the prediction of parameters that depend on the case studied. Most of the articles found are dedicated to the prediction of parameters, however, the classification of foods and beverages are widely used through RNA, with correlation coefficients with values between 0.70 and 0.99, which shows the use of artificial neural networks as a highly reliable tool. It was observed that the structure of the neural networks used for certain analyzes can vary depending on the desired inputs and outputs, likewise the references consulted indicate that having more neurons in one or another layer does not ensure better results, which makes the choice of the architecture a trial and error study to obtain the combination that generates the optimal values. The most used network is the multilayer with feedback, and as a learning algorithm, the most used is backpropagation algorithm, since they allow a reduction of the error and a highly efficient network learning process, reflected in the results obtained, as well as same, it was observed that the most used tool for the development of the networks is Neural Network Toolbox elaborated by Matlab for this purpose. In all cases, the results obtained indicate the high efficiency of RNA as a predictive and classificatory tool, this makes them a viable, low-cost and simple technique compared to other analysis methods that meet quality objectives, thanks to its efficiency to obtain satisfactory results where other techniques present diverse limitations.

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