Application of Weibull analysis and artificial neural networks to predict the useful life of the vacuum packed soft cheese

Aplicación del análisis Weibull y redes neuronales artificiales para la predicción de la vida útil de queso mantecoso envasado al vacío

Jesús Alexander Sánchez-González*, Jimy Frank Oblitas-Cruz

Facultad de Ingeniería, Universidad Privada del Norte. Av. vía de evitamiento norte s/n cuadra 15. C. P.06002. Cajamarca, Perú.

ABSTRACT: The objective of this work was to evaluate the capability of artificial neural networks (ANN) to predict shelf life and the acidity on vacuum packed fresh cheese. First, cheese samples, of 200 g per unit, were prepared; then these samples were stored for 2 to 4 days at temperatures of 4, 10 and 16 ° C and relative humidity of 67.5%. Throughout the storage, the acidity (AC) and sensorial acceptability were determined; this acceptability was used to determine the Shelf life time (SLT) by modified Weibull sensory risk method. A set of artificial neural networks (ANN) was created and trained; temperatures (T), maturation time (M) and failure possibility (F(x)) were used as inputs and SLT and AC as outputs. From this set, the networks with the lowest mean squared error (MSE) and best fit (R^2) were selected. These networks showed correlation coefficients (R2) of 0.9996 and 0.6897 for SLT and AC respectively, and good accuracy compared with regression models. It is shown that the ANN can be used to adequately model the SLT and, to a lesser degree, the AC of vacuum-packed fresh cheeses.

RESUMEN: El objetivo de este trabajo fue evaluar la capacidad de las redes neuronales artificiales (RNA) para predecir la vida útil y la acidez en el queso fresco envasado al vacío. En primer lugar, se prepararon muestras de queso de 200 g por unidad. Luego estas muestras se almacenaron en un intervalo de 2 a 4 días a temperaturas de 4, 10 y 16 ° C y humedad relativa del 67,5%. A lo largo del almacenamiento se determinaron la acidez (AC) y la aceptabilidad sensorial. Esta aceptabilidad se utilizó para determinar el tiempo de vida útil (TVU) por el método de riesgo sensorial Weibull modificado. Se creó y entrenó un conjunto de redes neuronales artificiales (RNA); como entradas se utilizaron la temperatura (T), tiempo de maduración (M) y posibilidad de fallo (F (x)) y TVU y AC como salidas. A partir de este conjunto, se seleccionaron las redes con el menor error cuadrático medio (ECM) y el mejor ajuste (R^2). Estas redes mostraron coeficientes de correlación (R2) de 0,9996 y 0,6897 para TVU y AC respectivamente y buena precisión en comparación con modelos de regresión. Se muestra que la RNA puede usarse para modelar adecuadamente TVU y en menor grado AC de quesos frescos envasados al vacío.

1. Introduction

The studies of shelf life in foods are useful to not undersize or oversize the time to market or distribute the product. The shelf life includes the elapsed time between the manufacturing and the moment in which significant changes appear in it, that could generate rejection by the final consumer. During this time, the product changes at microbiological, sensorial and/or physical-chemical level according to the production process, product nature and storage time, factors that produce changes in quality [1].

The soft cheese, a dairy product characteristic of Cajamarca Region (Peru) whose production exceeds the 120 tons [2], requires improving its production and commercialization; consequently, one of the most important conditions is to define methods for predicting the shelf life. The soft cheese production is performed in two stages: first, a junket is prepared; next it is mixed with salt, kneaded, molded and finally packed [3]. This cheese, which only is found in Cajamarca, has a long history of approximately two hundred years and its appearance is explained due to the particular isolation conditions of these Altiplano peasants and their need to increase the milk preservation period [4].

To evaluate the process capability to preserve quality in the food, we commonly use survival analysis; Weilbull distribution is applied to estimate the shelf life on the rejection of the product by the consumers [5-7]. In this method, it is necessary to know the probability of failure F(x), defined as the probability that a consumer rejects a product stored prematurely (x); in this case, the risk is focused on the rejection by the consumer. On the other hand, a technique known as artificial neural networks (ANN) has been used successfully for the study of dairy product deterioration [8, 9].

Considering the potentiality of the ANNs Weibull methodology for shelf life evaluation, as an objective of this research, it was proposed to develop a model of artificial neural networks that allows predicting the shelf life period of the vacuum packed soft cheese and compares its predictive capacity with mathematical regression models.

2. Methodology

2.1. Raw material

For this study, soft cheese samples were obtained (200 g per unit), in the training center for the dairy production of Centro de Formación Profesional Fe y Alegría (CEFOP) N° 7 in Cajamarca city. Figure 1 shows the production process.

2.2. Conservation

The conditions established for conservation stage were: relative humidity = 65 %; temperatures = 4, 10 and 16 °C; and maturation times = 2, 4 days. During the conservation lapse, it was evaluated the sensorial acceptability, using a semi-trained panel and acidity by titration.

2.3. Acceptability analysis

Analysis of acceptability was performed applying the Weibull modified sensorial risk method [4, 10, 11]. Table 1 shows the pre-set parameters for this evaluation.

2.4. Determination of shelf life

At this step, a 9-point hedonic scale test, previously proposed by Rojas [12], and the Eqs. (1) and (2), for accumulated risk and failure probability respectively, were used.
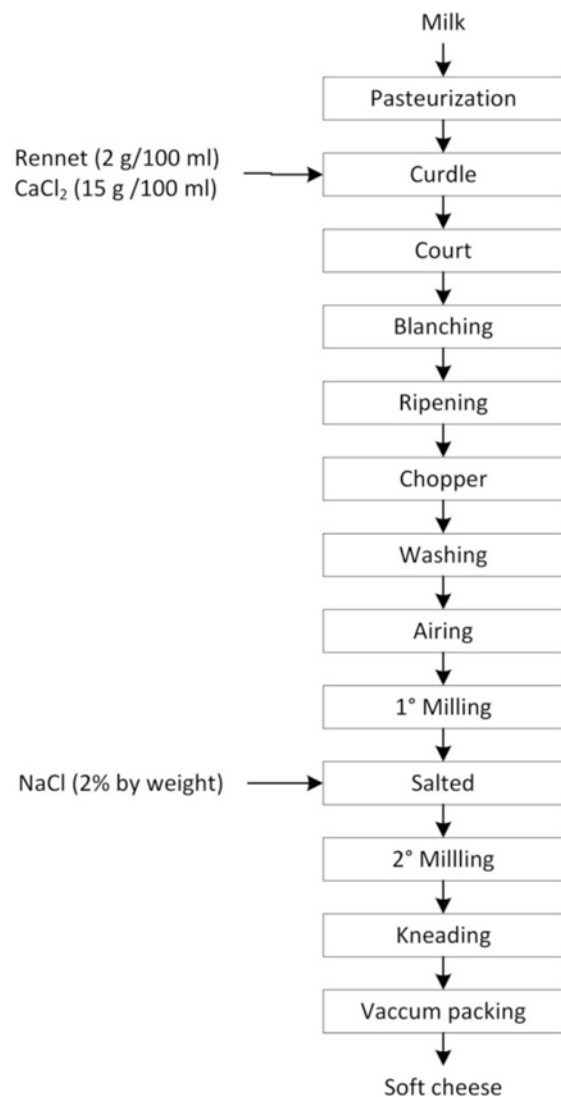

Figure 1 Flowchart for soft cheese production

$$H(x) = \left(\frac{x}{\alpha}\right)^{\beta} \tag{1}$$

$$F(x) = 1 - e^{\left(\frac{H(x)}{100}\right)} \tag{2}$$

Table 1 Parameters for sensorial evaluation of soft cheese

Maturation – M (days)		2			4		
Temperature – T (°C)		4	10	16	4	10	16
Hour	Initial	66	40	40	66	40	40
	Final	1648	1145	545	1506	785	329
Number of panelist	Initial	3	3	3	3	3	3
	Final	32	34	21	29	27	16

Where F (x) is the failure or rejection function; x is maturation time; β is the shape parameter and α is scaling parameter which represents the time value at 100% probability of rejection. The values β and α were analyzed for the reliability of the model fit.

The shelf life was calculated considering using failures probability of 25 and 50 %. Both times were statistically compared by mean a Chi-square tests (x^2) and Kolmogorov-Smirnov (K-S) at 95 % of significance level.

2.5. Creation and evaluation of artificial network

A set of multilayer artificial network (ANN), with two hide layers and a different number of neurons (4 - 18) and transfer function (logsig, tansig), were created and trained using back propagation (BP) and Levenberg-Marquardt (LM) algorithms for training and weight adjustment respectively.

For ANN training, the following inputs were used: maturation time of soft cheese (days) M, temperature in storage (°C) T, and failure probability during storage time F (between 0.01 and 0.9). Also, the following outputs were used: x shelf life (days), and A titrable acidity (g lactic acid/100 ml).

Then, for all topologies. During training and simulation, the mean squared errors (MSE), and coefficient of determination (R^2) were obtained and compared, selecting the topologies with the smallest MSE and R^2 nearest to 1.

2.6. Modeling by multivariate regression

In order to validate the ANN model, mathematical regression models (RM) were created, for the output variables, using the DataFit 9.0.59 software. Then it was selected the model with the highest value of R^2 to be compared with the selected ANN

2.7. Statistical analysis

The values obtained using ANN and RM were evaluated using the effect of three treatments in a completely randomized block design (α=0.05) and 15 validation units. Next, the Levene's tests were applied to acidity values, for independent or paired samples respectively.

3. Results and discussions

3.1. Shelf life of soft cheese by Weibull method

The shelf life and activation energy of soft cheese show that soft cheese ripened during 2 days presents more time of acceptability compared with the soft cheese ripened during 4 days, see Table 2 and Figure 2. Likewise; this method determined activation energy, of 14.7 and 20.0 kcal/mol for 2 and 4 days respectively, within the ranges of other dairy products reported by Hough and Fiszman [5].
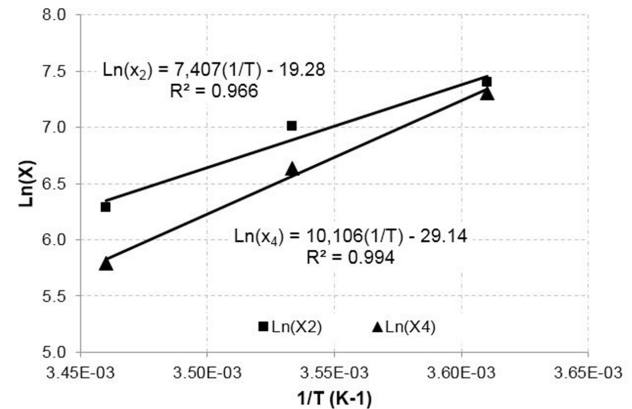

Figure 2 Shelf life (x) of soft cheese vs inverse of the storage temperature (1/T) (x_2, x_4 = 2 and 4 days of maturation)

The selected panel, using the criterion of [6], has a tendency acceptable in the decisions, because the values of parameter β (Table 2) are between 2 and 4 [11].

The shelf life period of the soft cheese changed as a result of the temperature (Table 2), the higher the cooling temperature the lower the shelf life. On the other hand, the samples stored at 4° extend their shelf life over 55 days; this is due to the control of maturation parameters, as the low temperature in the maturation warehouse, short maturation time (2 and 4 days), final product vacuum packing, previous pasteurization treatment, disinfection of the water to wash the junket. Similar results were obtained in buttery cheese [12], where the estimated useful life is very high, due mainly to the type of preservation, since it is vacuum packed. The sensory shelf life of double cream

Table 2 Shelf life determined by the Weibull modified risk method

M (days)		2			4		
T (°C)		4	10	16	4	10	16
X (days)	50 %	68.0	46.1	22.4	62.2	31.7	13.7
	25 %	53.9	36.4	16.3	49.9	23.5	10.8
Value *α*		1,798.0	1,221.5	611.1	1,638.7	862.0	362.1
Value *β*		3.8	3.7	2.8	4.0	2.9	3.7
-Ea (kcal/mol)			14.7			20.06	

cheese using survival statistics, at two fat levels, stored at 4 °C and packed under vacuum, was determined to be about 60 days [13].

Evaluation of the Mean Squared Error (MSE) and R^2 of predictions

When the 43 training predictions were compared with the expected values (Table 3), it was noted a good correlation of the storage time (x) values; such event is related to a decrease of the MSE during training of the ANN (Figure 3); this is not the case of the titratable acidity (A).
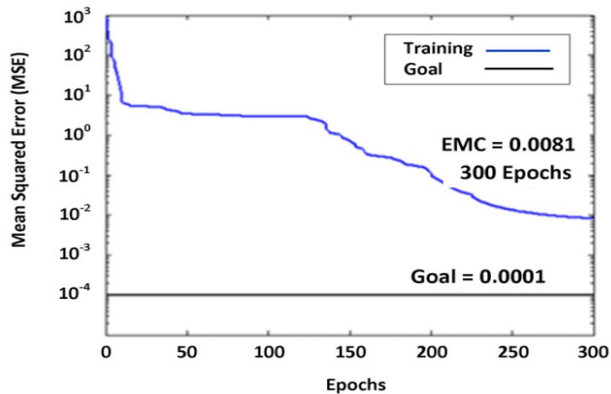
Figure 3 Decrease of the mean squared error during training

Figure 4 shows that, from all the selected topologies, only that with 300 training stages and with 'Logsig-Logsig' transfer functions, in the two hidden layers, of 6 and 14 neurons in the first and the second respectively, show the highest value of the coefficient of determination (R^2 = 0.6885) by relating the predicted and expected values of the titratable acidity (A) during the training.

Final Topology of ANN

The training of the ANNs was performed by essay and error because there is no a defined method or rule, that determines the optimum number of hidden layers and neurons in them [14, 15].

The following architecture was obtained (Figure 5): Type of a ANN (*Feed forward*), with supervised learning, BP training
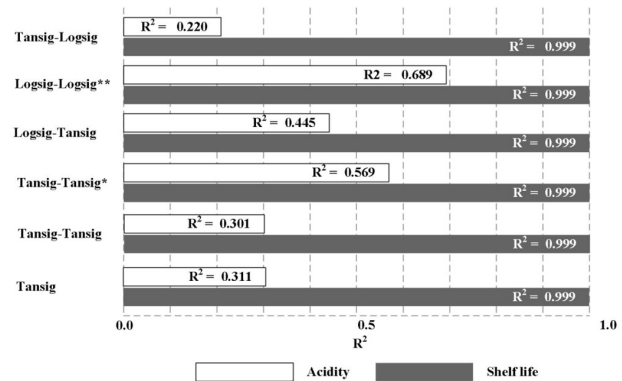
Figure 4 Comparison of R^2 among 15 for storage time (x) and titratable acidity (A)

algorithm (*Back propagation*), weight adjustment algorithm: LM (*Levenberg-Marquardt*), three neurons in the input layer, two neurons in the output layer, linear transfer function ('Purelin') in the output layer, two hidden layers, six neurons in the first hidden layer, sigmoid logarithmic transfer function ('Logsig') in the first hidden layer, 14 neurons in the second hidden layer, sigmoid logarithmic transfer function ('Logsig') in the second hidden layer, learning rate: 0.01; moment coefficient: 0.5; 300 stages or cycles of training, target error: 0.0001; weight and bias update function: moment with downward gradient ('*learngdm*') and function or criterion to evaluate the network performance: Mean Quadratic Error (MSE). In the case of Bp type ANN, the training is supervised and is constituted as one of the most versatile learning functions and are used with good results in the applications of series of time, analysis and prediction [16]; likewise, [17] an ANN with 'Logsig' transfer function was used, both in hidden layers and output layers, to estimate the storage time of yogurt; which shows the versatility of topologies for finding the best prediction indicators.

On the other hand, a series of experiments has been performed to estimate the shelf life of the processed cheese, taking as input variables: the texture, aroma and taste, humidity, free fat acids and the sensorial score as output variable, stored at 30°C, applying the ANN, based on back propagation cascade algorithm (BPCA) [18], just like an additional ANN model of radial basis function (RBF) [19] and the models of simple delayed time (SDT) and Multilayer [20]; and to predict the shelf life of the processed cheese

Table 3 Coefficients of determination in ANN training stage for shelf life and titratable acidity

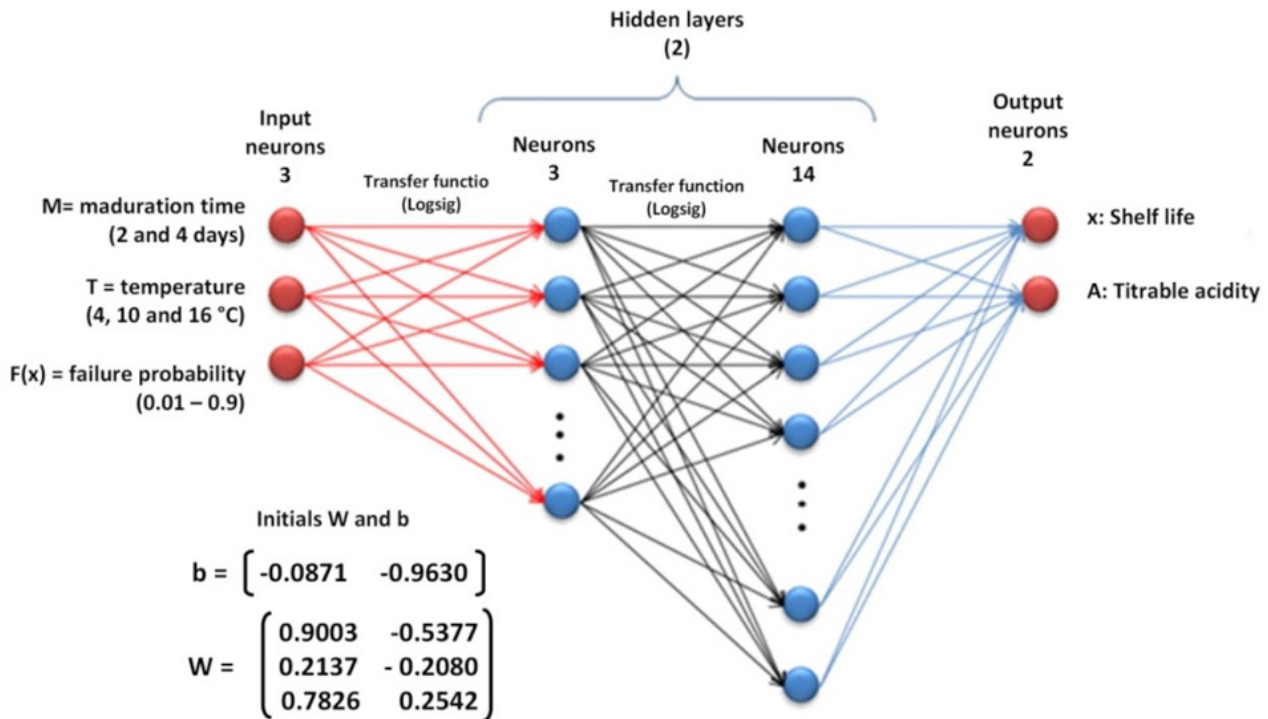| Hidden layer	Number of neurons	Transfer function	Stages	R^2 (Training)	
				x	A
1	16	'Logsig'	300	0.9999	0.6821
	9	'Tansig'	300	1.0000	0.7651
2	4, 18	'Tansig', 'Tansig'	50	0.9999	0.8008
	11, 15	'Logsig', 'Tansig'	300	1.0000	0.6978
	6, 14	'Logsig', 'Logsig'	300	0.9999	0.7818
	13, 12	'Tansig', 'Logsig'	300	1.0000	0.7809

Figure 5 Final topology of BP Artificial Neural Network

stored at 7 - 8°C. Elman ANN models with a simple layer and multilayer were also used [21]; as well as linear layer (LL) and generalized regression (RG) [22] ANN models. Other studies, in which the input variables were the soluble nitrogen, pH; standard counting in plate, fungi and yeasts and spore counting; and output variable, sensorial score, were applied: the ANN-BPCA model [23], as well as LL and RBF artificial intelligence models [24] to estimate the shelf life of the processed cheese stored at other temperature between 7 and 8°C. On the other hand, [25] the Elman model was also developed to predict the processed cheese stored at 30°C.

When the 15 data obtained by simulation is compared with the expected data, for the storage time (x) the value of R^2 is seen close to the unit ($R^2=0.9996$); this indicates a good prediction of data [26].

When the data obtained by simulation are compared against the expected data, for storage time (x), it is observed that the value of R^2 is close to the unit ($R^2 = 0.9996$). This indicates a good prediction of the data [26].

Validation of the ANN with the Regression Models

The mathematical regression models that allow obtaining a better adjustment of the data where y_1 is the shelf life (x), y_2 the titratable acidity (A) are shown in Eqs. (3) and (4).

$$y_1 = \exp\left(ax_1 + bx_2 + cx_3 + d\right)$$

(3)

$$y_2 = ax_1 + bx_2 + cx_3 + d$$

(4)

Where: x_1 is maturation time in days; x_2, cooling temperature (°C); x_3, Weibull probability of failure. For both equations, the correlation coefficients (R^2) were 0.9519 and 0.5495 in shelf life and acidity equations, respectively.

There is a similarity among the shelf life period values obtained by prediction with the ANN and with the actual values (Figure 6); contrary to the data of the titratable acidity in which it is noted a high variability between the predicted values and the real values (Figure 7).
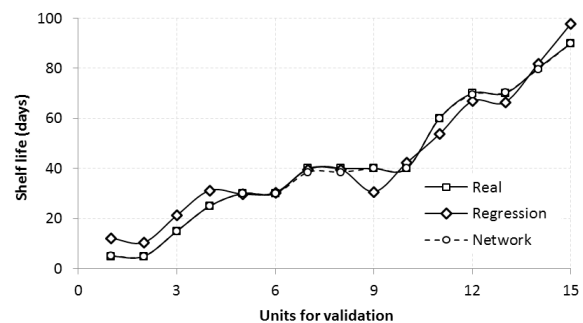

Figure 6 Shelf life period real and calculated with the regression and ANN

From the randomized block analysis, comparing the 15 actual simulation data and the data obtained by prediction,
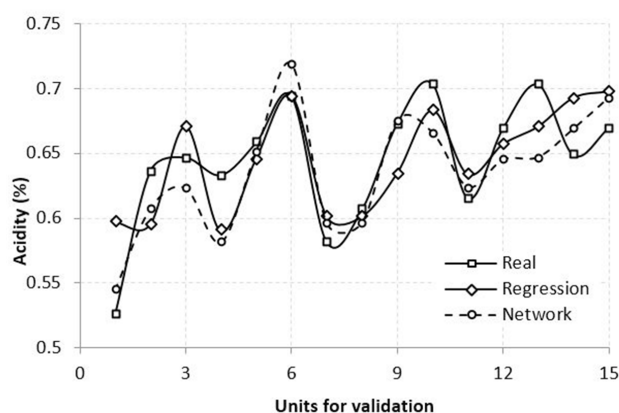
Figure 7 Titratable acidity real and predicted

both with ANN and with mathematical regression model; both ways offer the same possibility of prediction. It is necessary to clarify that the ANN operates with one topology in parallel, while the mathematical regression model proposes two different equations for each of the dependent variables, which confirms the ANN power for prediction, as well as the imperfection of the regression models when they are compared with the ANN [15].

The results indicate that the tendencies for acidity values during time do not show differences between the 2 and 4-day maturation treatments for the samples stored at temperatures of 4°C and 10°C.

When the titratable acidity of the soft cheese is statistically evaluated, it could be established during the shelf life period that only the samples of soft cheese stored at 16 °C show different effects among the groups of cheese obtained by maturation during 2 and 4 days; however, the sensorial acceptability marked evident differences in the shelf life period as a result of the maturation time, the samples of soft cheese subject to storage at 10 °C and 16 °C show different effects among those groups ripened during 2 and 4 days; confirming what is indicated by [11] about the difference between the sensorial attributes and other physical-chemical and microbiological variables.

4. Conclusions

The shelf life of the packed vacuum soft cheese was predicted with a *Feedforward* ANN, with *Backpropagation* training algorithms, *Levenberg-Marquardt* weight adjustment algorithms and 300 training stages; with three con 3 inlet neurons (maturation time of cheese, storage temperature and probability of failure or rejection of the soft cheese during the storage time), and 2 outlet neurons (x: storage time or shelf life of soft cheese and A: titratable acidity) with linear transfer function; with 6 and 14 neurons in the first and second hidden layer, respectively, and sigmoid logarithmic transfer function in both layers. The ANN has more predictive capacity than the mathematical regression models, regarding the actual values, when the coefficients of determination (R^2) of 0.9996 and 0.6897 are evaluated for x and A, respectively. The sample of soft cheeses ripened

during 2 to 4 days and vacuum packed, showed activation energy of 14.7 and 20.06 kcal/mol respectively.

5. References

1. T. Labuza, "Application of chemical kinetics to deterioration of foods," *Journal of Chemical Education*, vol. 61, no. 4, pp. 348-358, 1984.
2. S. Pezo, *Queso cajamarquino de calidad. Experiencia de la Coordinadora del Sector de Derivados Lácteos de Cajamarca - Codelac*. Lima, Peru: Soluciones Prácticas-ITDG (Intermediate Technology Development Group), 2007.
3. F. Boucher and M. Guégan, *Queserías rurales en Cajamarca*. Lima, Peru: ITDG (Intermediate Technology Development Group), 2004.
4. F. Boucher and D. Desjardins, "La concentración de las queserías rurales de Cajamarca: retos y dificultades de una estrategia colectiva de activación," *Agroalimentaria*, vol. 10, no. 21, pp. 13-27, 2005.
5. G. Hough and S. Fiszman, *Estimación de la vida útil sensorial de los alimentos*, 1st ed. Madrid, Spain: CYTED, 2005.
6. E. Al-Kadamany *et al.*, "Determination of shelf life of concentrated yogurt (labneh) produced by in-bag straining of set yogurt using hazard analysis," *J. Dairy Sci.*, vol. 85, no. 5, pp. 1023-1030, 2002.
7. C. Cardelli and T. Labuza, "Application of Weibull Hazard Analysis to the Determination of the Shelf Life of Roasted and Ground Coffee," *LWT - Food Science and Technology*, vol. 34, no. 5, pp. 273-278, 2001.
8. S. Goyal and G. Goyal, "Predicting shelf life of dairy product by using artificial neural networks (ANN) and statistical computerized methods," *International Journal of Computer Engineering Research*, vol. 3, no. 2, pp. 20-24, 2012.
9. J. Paquet, C. Lacroix, and J. Thibault, "Modelling of pH and Acidity for Industrial Cheese," *J. of Dairy Sci.*, vol. 83, no. 11, pp. 2393-2409, 2000.
10. Indecopi (Instituto Nacional de Defensa de la Competencia y de la Protección de la Propiedad Intelectual), "Norma Técnica Peruana, NTP 202.151. Leche y productos lácteos. Queso. Determinación de acidez. Método de titulación", Indecopi, Lima, Perú, 1998.
11. W. Duyvesteyn, E. Shimoni, and T. Labuza, "Determination of the end of shelf-life for milk using Weibull Hazard Method," *LWT - Food Science and Technology*, vol. 34, no. 3, pp. 143-148, 2001.
12. J. Sánchez and J. Pérez, "Sensory shelf life of mantecoso cheese using accelerated testing," *Scientia Agropecuaria*, vol. 7, pp. 215-222, 2016.
13. N. Lópes and C. Novoa, "Evaluación de la vida útil sensorial del queso doble crema con dos niveles de grasa," *Rev. Med. Vet. Med. Zoot.*, vol. 55, no. 2, pp. 91-99, 2008.
14. J. Rojas and V. Vásquez, "Predicción mediante redes neuronales artificiales (RNA) de la difusividad, masa, humedad, volumen y sólidos en yacón (*Smallantus sonchifolius*) deshidratado osmóticamente," *Scientia Agropecuaria*, vol. 3, no. 3, pp. 201-214, 2012.

15. V. Vásquez and C. Lescano, "Predicción por redes neuronales artificiales de la calidad fisicoquímica de vinagre de melaza de caña por efecto de tiempo-temperatura de alimentación a evaporador-destilador flash," *Scientia Agropecuaria*, vol. 1, no. 1, pp. 63-73, 2010.

16. P. Ponce, *Inteligencia artificial con aplicaciones a la ingeniería*, 1st ed. City of Mexico, Mexico: Alfaomega, 2010.

17. A. Sofu and F. Ekinci, "Estimation of Storage Time of Yogurt with Artificial Neural Network Modeling," *J. Dairy Sci.*, vol. 90, no. 7, pp. 3118-3125, 2007.

18. S. Goyal and G. Goyal, "A Novel Method for Shelf Life Detection of Processed Cheese Using Cascade Single and Multi Layer Artificial Neural Network Computing Models," *ARPN Journal of Systems and Software*, vol. 2, no. 2, pp. 79-83, 2012.

19. S. Goyal and G. Goyal, "Radial Basis (Exact Fit) and Linear Layer (Design) ANN Models for Shelf Life Prediction of Processed Cheese," *International Journal of u- and e- Service, Science and Technology*, vol. 5, no. 1, pp. 63-70, 2012.

20. S. Goyal and G. Goyal, "Artificial Neural Expert Computing Models for Determining Shelf Life of Processed Cheese," *International Journal of Electrical and Computer Engineering* (IJECE), vol. 2, no. 3, pp. 333-338, 2012.

21. S. Goyal and G. Goyal, "Artificial Neural Network Simulated Elman Models for Predicting Shelf Life of Processed Cheese," *International Journal of Applied Metaheuristic Computing*, vol. 3, no. 3, pp. 20-32, 2012.

22. S. Goyal and G. Goyal, "Linear layer and generalized regression computational intelligence models for predicting shelf life of processed cheese," *Russian Journal of Agricultural and Socio-Economic Sciences*, vol. 3, no. 3, pp. 28-32, 2012.

23. S. Goyal and G. Goyal, "Estimating Processed Cheese Shelf Life with Artificial Neural Networks," *International Journal of Artificial Intelligence* (IJ-AI), vol. 1, no. 1, pp. 19-24, 2012.

24. S. Goyal and G. Goyal, "Smart Artificial Intelligence Computerized Models for Shelf Life Prediction of Processed Cheese," *International Journal of Engineering and Technology*, vol. 1, no. 3, pp. 281-289, 2012.

25. S. Goyal and G. Goyal, "Artificial Intelligence Elman Backpropagation Computing Models for Predicting Shelf Life of Processed Cheese," *Internetworking Indonesia Journal*, vol. 4, no. 1, pp. 3-7, 2012.

26. A. Motevali, S. Minaei, M. Khoshtaghaza, M. Kazemi, and A. Nikbakht, "Drying of Pomegranate Arils: Comparison of Predictions from Mathematical Models and Neural Networks," *International Journal of Food Engineering*, vol. 6, no. 3, pp. 1-19, 2010.