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Simulated Neural Network Intelligent Computing Models for Predicting Shelf Life of Soft Cakes

By Sumit Goyal,Gyandera Kumar Goyal
National Dairy Research Institute, Karnal,India

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SIMULATEDNEURALNETWORKINTELLIGENTCOMPUTINGMODELSFORPRDICTINGSHELFLIFEOFSOFTCAKES

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Simulated Neural Network Intelligent Computing Models for Predicting Shelf Life of Soft Cakes

Sumit Goyal[α] ,Gyanendra Kumar Goyal[Ω]

Abstract - This paper highlights the potential of simulated neural networks for predicting shelf life of soft cakes stored at 10° C. Elman and self organizing simulated neural network models were developed. Moisture, titratable acidity, free fatty acids, tyrosine, and peroxide value were input parameters, and overall acceptability score was output parameter. Neurons in each hidden layers varied from 1 to 30. The network was trained with single as well as double hidden layers with 1500 epochs, and transfer function for hidden layer was tangent sigmoid while for the output layer, it was pure linear function. The shelf life predicted by simulated neural network model was 20.57 days, whereas as experimental shelf life was 21 days. From the study, it can be concluded that simulated neural networks are excellent tool in predicting shelf life of soft cakes.

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I. Introduction

This paper highlights the importance of simulated neural networks for predicting shelf life of soft cakes stored at 10° C. Soft cakes are exquisite sweetmeat cuisine made out of heat and acid thickened solidified sweetened milk. Soft cakes from water buffalo milk were prepared, milk was standardized to 6% fat. The cakes were manufactured in a double jacketed stainless steel kettle, and stored at 10°C. The study of Simulated Neural Networks (SNN) began in the decade before the field artificial intelligence research was founded, in the work of Walter Pitts and Warren McCullough. Other important early researchers were Frank Rosenblatt, who invented the perceptron and Paul Werbos who developed the backpropagation algorithm. The main categories of networks are acyclic or feedforward neural networks (where the signal passes in only one direction) and recurrent neural networks, which allow feedback. Among the most popular feedforward networks are perceptrons, multi-layer perceptrons. Among recurrent networks, the most popular is the Hopfield net, a form of attractor techniques as Hebbian Learning network, which was first described by John Hopfield in 1982. Neural networks can be applied to the problem of intelligent control (for robotics) or learning, using such and competitive learning [1].

Author α : Sr. Research Fellow, National Dairy Research Institute, Karnal-132001,India .(Telephone:+911842259244)
E-mail : thesumitgoyal@gmail.com
Author Ω: Emeritus Scientist, National Dairy Research Institute, Karnal-132001,India .(Telephone:+911842259244)
E-mail : gkg5878@yahoo.com

a) Elman Simulated Neural Network (ESNN)

ESNN are two layered backpropagation networks, with the addition of a feedback connection from the output of the hidden layer to its input. This feedback path allows ESNN to learn to recognize and generate temporal patterns, as well as spatial patterns. The ESNN has *tansig* neurons in its hidden (recurrent) layer, and *purelin* neurons in its output layer. This combination is special in that two-layered networks with these transfer functions can approximate any function (with a finite number of discontinuities) with arbitrary accuracy. The only requirement is that the hidden layer must have enough neurons. More hidden neurons are needed as the function being fitted increases in complexity. ESNN differs from conventional two-layer networks in that the first layer has a recurrent connection. The delay in this connection stores values from the previous time step, which can be used in the current time step. Therefore, even if two ESNN models, with the same weights and biases, are given identical inputs at a given time step, their outputs can be different because of different feedback states. Because the network can store information for future reference, it is able to learn temporal patterns as well as spatial patterns. The ESNN models can be trained to respond to, and to generate, both kinds of patterns [2]. The data samples for soft cakes used in this study, relate to overall acceptability score, evaluation at regular intervals by a panel of well trained judges and changes in physicochemical characteristics, viz., moisture, titratable Acidity (TA), Free Fatty Acids (FFA), Peroxide Value (PV) and Tyrosine as shown in (Fig.1).

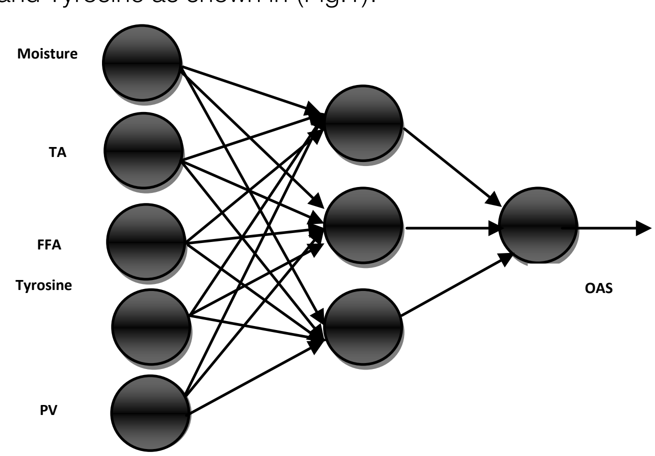

Fig.1 : Input and output parameters for SNN

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b) *Self-Organizing Simulated Neural Network (SOSNN)*

Self-organizing is one of the most interesting topics in the SNN field. These networks can learn to detect regularities and correlations in their input and adapt their future responses to that input accordingly. The neurons learn to recognize groups of similar input vectors. Self-organizing maps learn to recognize groups of similar input vectors in such a way that neurons physically near each other in the neuron layer respond to similar input vectors. Learning vector quantization (LVQ) is a method for training competitive layers in a supervised manner. A competitive layer automatically learns to classify input vectors. However, the classes that the competitive layer finds are dependent only on the distance between input vectors. If two input vectors are very similar, the competitive layer probably will put them in the same class. There is no mechanism in a strictly competitive layer design to say whether or not any two input vectors are in the same class or different classes. LVQ networks, on the other hand, learn to classify input vectors into target classes chosen by the user [2]

i. *Competitive Learning*

The || *dist* || box accepts the input vector *p* and the input weight matrix *I W1*, 1, and produces a vector having *S1* elements. The elements are the negative of the distances between the input vector and vectors *i IW1*, 1 formed from the rows of the input weight matrix as illustrated in Fig.2

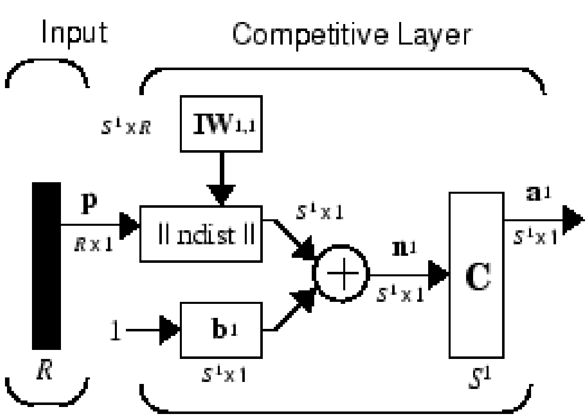

Fig.2 : Architecture of competitive model

The net input *n1* of a competitive layer is computed by finding the negative distance between input vector *p* and the weight vectors and adding the biases *b*. If all biases are zero, the maximum net input a neuron can have is 0. This occurs when the input vector *p* equals that neuron's weight vector. The competitive transfer function accepts a net input vector for a layer and returns neuron outputs of 0 for all neurons except for the winner, the neuron associated with the most positive element of net input *n1*. The winner's output is 1. If all biases are 0, then the neuron whose weight vector is closest to the input vector has the least negative net input and, therefore, wins the competition to output a 1 [3].

c) *Significance of Shelf Life*

Shelf life is the recommendation of time that products can be stored, during which the defined quality of a specified proportion of the goods remains acceptable under expected (or specified) conditions of distribution, storage and display. Most shelf life labels or listed expiry dates are used as guidelines based on normal handling of products. Use prior to the expiration date guarantees the safety of a food product, and a product is dangerous and ineffective after the expiration date. For some foods, the shelf life is an important factor to health. Bacterial contaminants are ubiquitous, and foods left unused too long will often acquire substantial amounts of bacterial colonies and become dangerous to eat, leading to food poisoning[3]. Shelf life can be estimated by sensory evaluation, but it is expensive, very time consuming and does not fit well with the dairy factories manufacturing it. Sensory analyses may not reflect the full quality spectra of the product. Moreover, traditional methods for shelf life dating and small scale distribution chain tests cannot reproduce in a laboratory the real conditions of storage, distribution, and consumption on food quality. In the present era, food researchers are facing the challenges to monitor, diagnose, and control the quality and safety of food products. The consumer demands foods, under the legal standards, at low cost, high standards of nutritional, sensory, and health benefits. Goyal and Goyal [4] developed artificial neural engineering and regressions models for forecasting shelf life of instant coffee drink. They developed radial basis and multiple linear regression models to study their prediction capability for instant coffee drink. Goyal and Goyal [5] applied linear layer (design) and time - delay methods of intelligent computing expert system for shelf life prediction of soft mouth melting milk cakes. Neuron based artificial intelligent scientific computer engineering models for estimating shelf life of instant coffee sterilized drink were implemented by Goyal and Goyal [6]. Till now no SNN models have been developed for predicting shelf life of soft cakes and this system would be very much beneficial and relevant for food researchers, consumers and store owners. The purpose of this study is to develop simulated neural network models that would predict the shelf life of soft cakes stored at 10° C easily, at low cost and in less time.

II. Material and Methods

a) *Dataset*

The experimental data on quality parameters, *viz.*, moisture, titratable acidity, free fatty acids, tyrosine, and peroxide value of soft cakes stored at 10° C were taken as input parameters. The overall acceptability score was taken as output parameter for SNN models. Experimentally developed 60 observations for each input and output parameters were taken for development of the model. The dataset was randomly divided into two disjoint subsets, namely, training set containing 48 observations (80% of total observations) and validation set consisting of 10 observations (20% of total observations).

b) Experiments

Several combinations of internal parameters, *i.e.,* data preprocessing, data partitioning approaches [80:20, 70:30, 60:40] , number of hidden layers, number of neurons in each hidden layer, transfer function, error goal, *etc*., were explored in order to optimize the prediction ability of the model. Different algorithms were tried like Polak Ribiére Update conjugate gradient algorithm, Fletcher Reeves update conjugate gradient algorithm, Levenberg Marquardt algorithm, Gradient Descent algorithm with adaptive learning rate, Bayesian regularization, Powell Beale restarts conjugate gradient algorithm and BFG quasi-Newton algorithm. Backpropagation algorithm based on Levenberg Marquardt mechanism was finally selected for training the SNN, as it gave the optimum results. Neurons in each hidden layers varied from 1 to 30. The SNN was trained with 1500 epochs. The network was trained with single as well as double hidden layers and transfer function for hidden layer was tangent sigmoid, while for the output layer it was pure linear function. SNN models were trained with training set after getting optimum values for architectural parameters. The SNN models were simulated with the validation dataset in order to validate the models. MALTAB 7.0 software was used for performing experiments.

c) Measures for Prediction performance

$$MSE = \left[\sum_{1}^{N} \left(\frac{Q_{exp} - Q_{cal}}{n} \right)^2 \right] \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n} \left[\sum_{1}^{N} \left(\frac{Q_{exp} - Q_{cal}}{Q_{exp}} \right)^2 \right]} \quad (2)$$

$$R^2 = 1 - \left[\sum_{1}^{N} \left(\frac{Q_{exp} - Q_{cal}}{Q_{exp}^{\,2}} \right)^2 \right] \quad (3)$$

$$E^2 = 1 - \left[\sum_{1}^{N} \left(\frac{Q_{exp} - Q_{cal}}{Q_{exp} - \overline{Q}_{exp}} \right)^2 \right] \quad (4)$$

Where,

Q_{exp} = Observed value;

Q_{cal} = Predicted value;

$\overline{Q}_{exp}$ =Mean predicted value;

n = Number of observations in dataset. MSE (1), RMSE (2), R^2 (3) and E^2 (4) were used in order to compare the prediction potential of the developed SNN models.

III. Results and Discussion

Table 1 : Results of ESSN with double hidden layers

Neurons	MSE	RMSE	R^2	E^2
3	0.0022	0.04711	0.97336	0.99778
5	0.0027	0.05269	0.96667	0.99722
7	0.0031	0.05570	0.96276	0.99689
8	0.0067	0.08210	0.91910	0.99325
10	0.0010	0.03175	0.98781	0.99899
12	0.0007	0.0272	0.9910	0.9992
15	0.0008	0.02848	0.99026	0.99918
18	0.0007	0.02743	0.99096	0.99924
20	0.0004	0.02060	0.99490	0.99957
23	0.0094	0.09716	0.88671	0.99055
25	0.0121	0.11016	0.85436	0.98786
28	0.0071	0.08448	0.91435	0.99286
30	0.0033	0.05752	0.96028	0.99669

Table 2 : Results of ESSN with double hidden layers

Neurons	MSE	RMSE	R^2	E^2
2:2	0.0258	0.1608	0.6893	0.9741
3:3	0.0167	0.1292	0.7995	0.9832
5:5	0.0017	0.0421	0.9786	0.9982
7:7	0.0012	0.0352	0.9850	0.9987
8:8	0.0058	0.0764	0.9298	0.9941
10:10	0.0007	0.0278	0.9906	0.9992
12:12	0.0021	0.0462	0.9743	0.9978
14:14	0.0002	0.0160	0.9969	0.9997
15:15	0.0015	0.0399	0.9808	0.9984
16:16	0.0025	0.0509	0.9688	0.9974
18:18	0.0049	0.0706	0.9401	0.9950
19:19	0.0029	0.0543	0.9645	0.9970
20:20	0.0014	0.0384	0.9822	0.9985

Table 3 : Performance of SOSNN

MSE	RMSE	R^2	E^2
0.0009	0.0313	0.9882	0.9990

ESSN and SOSNN models were developed for predicting shelf life soft cakes stored at 10° C. The best results of ESSN with single hidden layer having twelve neurons were (MSE: 0.000744207,RMSE:0.027280165, R2 : 0.991069511, E2: 0.999255793) and with two hidden layers having fourteen neurons in the first and second layer were (MSE: 0.000257956,RMSE: 0.016061008, R2 : 0.996904528, E2: 0.999742044).

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Results for SOSNN were (MSE: 0.031316629; RMSE: 0.031316629; R2 : 0.988231225; 0.999019269).The best results of all the models were compared with each other and it was observed that ESSN model with double hidden layer was better. The comparison of Actual Overall Acceptability Score (AOAS) and Predicted Overall Acceptability Score (POAS) for ESSN single and double hidden layer models with SOSNN model are illustrated in Fig.3, Fig.4 and Fig.5.

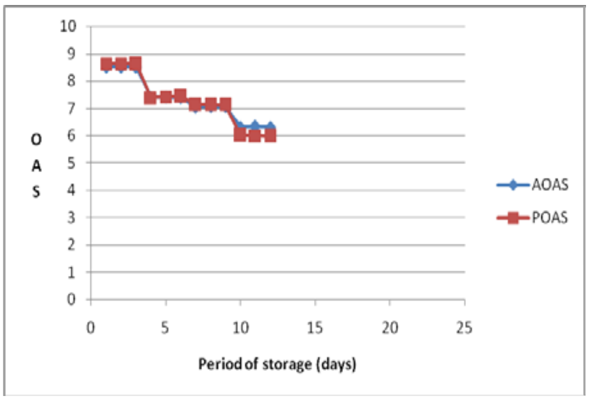

Fig.3 : Comparison of AOAS and POAS for ESSN single layer model

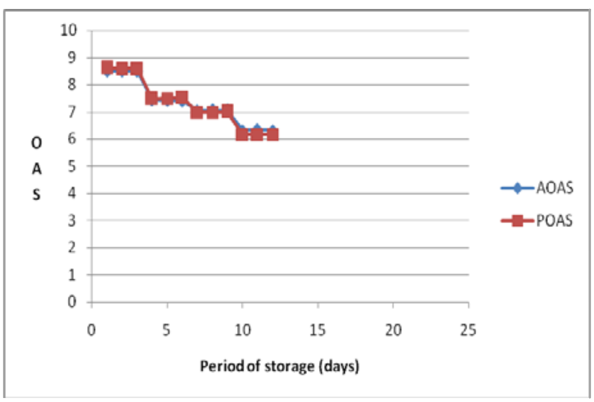

Fig.4: Comparison of AOAS and POAS for ESSN double layer model

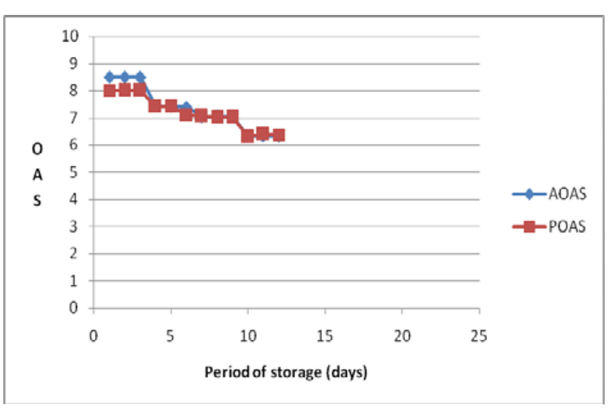

Fig.5. Comparison of AOAS and POAS for SOSNN model

a) Shelf Life Prediction

The regression equations were developed to predict shelf life of soft cakes, *i.e.*, in days for which product has been in the shelf, based on overall acceptability score. The soft cakes were stored at 10°C taking storage intervals (in days) as dependent variable and overall acceptability score as independent variable. R^2 was found to be 0.99 percent of the total variation as explained by overall acceptability scores. Time period (in days) for which the product has been in the shelf can be predicted based on overall acceptability score for soft cakes stored at 10°C. (Fig. 6).

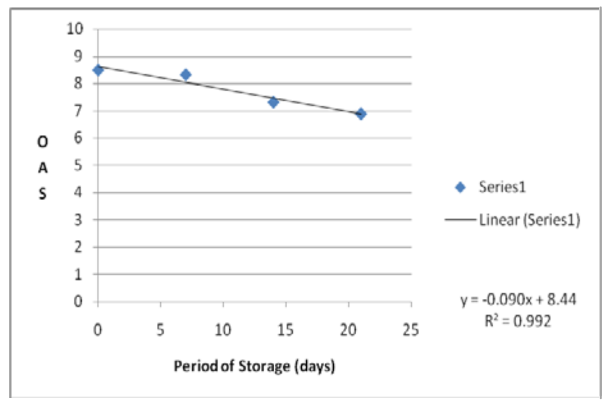

Fig.6 : Shelf life prediction of soft cakes

The shelf life is calculated by subtracting the obtained value of days from experimentally determined shelf life, which was found to be 20.57 days. The predicted value is within the experimentally obtained shelf life of 21 days, hence the product is acceptable.

IV. Conclusion

In the present era of high competition and marketing, for food manufactures, it is important that food products retain high nutritious quality before reaching to the consumer. Hence, keeping this in mind, simulated neural network based models were developed for predicting shelf life of soft cakes stored at 10° C. The shelf life predicted by simulated neural networks was 20.57 days, whereas experimental shelf life was 21 days. Therefore, it is evident from the study that simulated neural networks can be used to predict shelf life of soft cakes.

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