

SCIENTIFIC NOTE

Shelflife Prediction of Processed Cheese Using Artificial Intelligence ANN Technique

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Summary

Radial Basis (Fewer Neurons) and Multiple Linear Regression (MLR) models were developed and compared for predicting the shelf life of processed cheese stored at 30° C. Soluble nitrogen, pH, Standard plate count, yeast & mould count, and spore count were taken as input parameters, and sensory score as output parameter. Mean square error, Root mean square error, Coefficient of determination (R^2) and Nash - Sutcliffo coefficient (E^2) were applied in order to compare the prediction ability of the models. Results showed high correlation between the training and validation data with high R^2 and E^2 values; thus suggesting that the developed models are efficient for predicting the shelf life of processed cheese. From the study, it was revealed that Radial Basis (Fewer Neurons) model was superior over MLR model for predicting the shelf life of processed cheese.

Keywords: ANN; Artificial Intelligence; Radial Basis (Fewer Neurons); Multiple Linear Regression; Processed Cheese; Food and Shelf Life Prediction

Introduction

Processed cheese is very nutritious and generally manufactured from ripened Cheddar cheese, but often lesser quantity of fresh/less ripened cheese is also added. Its manufacturing technique includes addition of emulsifier, salt, water and selected spices (optional). The mixture is heated in double jacketed stainless steel vessel with continuous stirring with a flattened ladle in order to get homogeneous mass. Processed cheese has several advantages over raw and ripened Cheddar cheese, such as unique pleasing taste and longer shelf life. It is a protein rich food and comparable supplement to meat protein. Artificial Neural Network (ANN) has provided an exciting alternative method for solving a variety of problems in different fields of science and engineering. Human brain has many incredible characteristics such as massive parallelism, distributed representation and computation, learning ability, generalization ability, adaptively, which seems simple but is really complicated. Development of ANN models is an effort to apply the same method as human brain uses to solve perceptual problems. ANNs learn by updating network architecture and connection weights so that network can efficiently perform a task. There are two types of learning methods:

Supervised Learning – In this method correct answer is provided for the network for every input pattern; weights are adjusted regarding the correct answer.

Unsupervised Learning – This method does not need the correct output. The system itself recognizes the correlation and organizes patterns into categories accordingly (Courses Website, 2011).

A radial basis (fewer neurons) function network is an ANN that uses radial basis functions as activation functions. It is a linear combination of radial basis functions. They are used in function approximation, time series prediction, and control. Radial basis function network consists of one layer of input nodes, one hidden radial-basis function layer and one output

linear layer (Mateo *et al.*, 2009). Multiple linear regression is a technique that allows additional factors to enter the analysis separately so that the effect of each can be estimated. It is valuable for quantifying the impact of various simultaneous influences upon a single dependent variable (Law Website, 2011). Shelf life is the length of time given before a product is considered unsuitable for sale, use, or consumption. In most parts of the world, it is mandatory to write 'best before', 'use by' or freshness date on the packaged perishable foods.

ANNs have been successfully applied for predicting food quality (Xie and Xiong, 1999); shelf life of soya milk (Ko et al., 2000); sensory attributes of noodles (Tulbek et al., 2003); kiwifruit (Fathi et al., 2009); fruit juices (Rai et al., 2005a); apple juice (Raharitsifa and Ratti, 2010); grape juice (Mateo et al., 2009); mosambi juice (Rai et al., 2005b); and corn (Campbell et al., 1999). ANN models have also been applied successfully to problems concerning sales of food products, such as predicting the impact of promotional activities and consumer choice on the sales volumes at retail store (Agrawal and Schorling, 1996), and were found to perform better than linear models. Du and Sun (2006) reviewed the learning techniques used in computer vision for food quality evaluation. Vallejo-Cordoba et al. (1995) studied the usefulness of ANN models for prediction of shelf life of milk by multivariate interpretation of gas chromatographic profiles, and flavour related shelf life was evaluated and compared with Principal Components Regression (PCR). Ainscough and Aronson (1999) compared ANNs to linear regression for studying the same effects on yogurt. Ni and Gunasekaran (1998) observed that a three-layer ANN model is able to predict more accurately than regression equations for the rheological properties of Swiss type cheeses on the basis of their composition.

Artificial neural engineering and regression models for forecasting the shelf life of instant coffee drink have been developed, and compared with each other (Goyal and Goyal,

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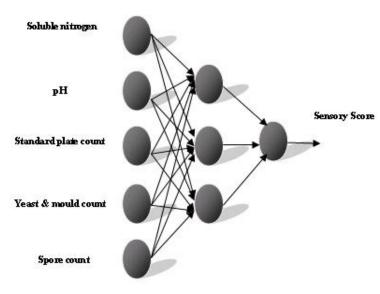


Figure 1. Input and output parameters for ANN models

2011a). ANN Generalized Regression and Linear Layer (Train) models successfully predicted the shelf life of milky white dessert jeweled with pistachio (Goyal and Goyal, 2011b). Elman and Self-Organizing Simulated Neural Networks (SNN) models detected shelf life of soft cakes, establishing that SNN can be used to predict the shelf life of soft cakes stored at 10°C (Goyal and Goyal, 2011c). Neuron based artificial intelligent scientific computer engineering models for predicting the shelf life of instant coffee sterilized drink have also been successfully applied (Goyal and Goyal, 2011d). Linear Layer (Design) and Time - Delay methods of intelligent computing expert system for shelf life detection of soft mouth melting milk cakes stored at 6°C were developed, and performances of the models were compared with each other. The study revealed that Linear Layer (Design) model exhibited better results (Goyal and Goyal, 2011e). Cascade artificial neural intelligence neurocomputing models predicted sensory quality of roasted coffee flavoured sterilized drink (Goyal and Goyal, 2012). Since no efforts have been made to develop ANN computerized models of Radial Basis (Fewer Neurons) and MLR for predicting the shelf life of processed cheese stored at 30° C, hence this study was planned.

Table 1. Results of Radial Basis (Fewer Neurons) Model

Spread Constant	MSE	RMSE	R ²	E ²
8	0.02673614	0.163511895	0.836488105	0.97326386
21	2.0659E-06	0.001437324	0.998562676	0.999997934
34	9.49614E-05	0.009744814	0.990255186	0.999905039
50	0.000472988	0.02174828	0.97825172	0.999527012
60	0.000649625	0.025487738	0.974512262	0.999350375
75	0.000844794	0.029065346	0.970934654	0.999155206
90	0.000951457	0.030845695	0.969154305	0.999048543
100	0.000985283	0.031389221	0.968610779	0.999014717
130	0.000991663	0.031490679	0.968509321	0.999008337
150	0.000964166	0.031051027	0.968948973	0.999035834

Material and Methods

Sample Preparation

In this investigation the data consisted of 36 observations, which were divided into two subsets, *i.e.*, 30 for training and 6 for validating the ANN network. Soluble nitrogen, pH, standard plate count (SPC), yeast & mould (Y&M) count, and spore count were taken as input parameters, and sensory score as output parameter for developing Radial Basis (Fewer Neurons) and MLR models (Fig.1).

Mean Square Error: MSE (1), Root Mean Square Error: RMSE (2), Coefficient of Determination: R^2 (3) and Nash - Sutcliffo Coefficient: E^2 (4) were used in order to compare the prediction ability of the developed models, where Q_{exp} = Observed value; Q_{cal} = Predicted value;

 $\overline{Q_{\rm exp}}$ = Mean predicted value; n = Number of observations in dataset

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

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

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

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

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

Neural Network Toolbox under MATLAB software was used for developing the models.

Results and Discussion

Performance matrices of Radial Basis (Fewer Neurons) and MLR models are presented in Table 1 and 2 respectively.

Actual Sensory Score (ASS) and Predicted Sensory Score (PSS) for Radial Basis (Fewer Neurons) and MLR models are illustrated in Fig.2 and Fig.3, respectively.

Radial Basis (Fewer Neurons) and MLR models were developed to study their shelf life prediction ability for processed cheese. Many experiments were performed



Table 2: Results of MLR Model

MSE	RMSE	R ²	E^2
8.67285E-05	0.009312816	0.990687184	0.999913271

and it was observed that Radial Basis (Fewer Neurons) model with spread constant as 21 (MSE: 2.0659E-06; RMSE: 0.001437324; R²: 0.998562676; E²: 0.999997934) gave better results than MLR model (MSE: 8.67285E-05; RMSE: 0.009312816; R²: 0.990687184; E²: 0.999913271) suggesting that Radial Basis (Fewer Neurons) ANN models are good in predicting the shelf of processed cheese. However, Goyal and Goyal (2011a) observed that MLR model was superior to Radial Basis (Fewer Neurons) for predicting the shelf life of instant coffee drink.

Figure 2. Comparison of ASS and PSS Radial Basis(Fewer Neurons) model

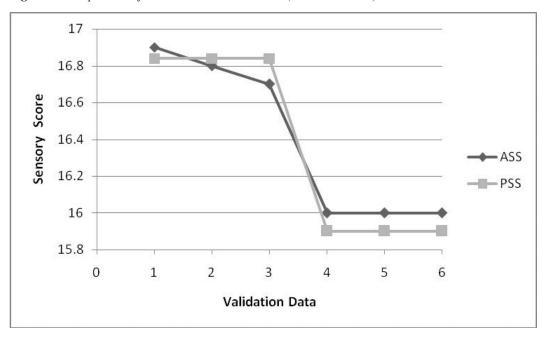
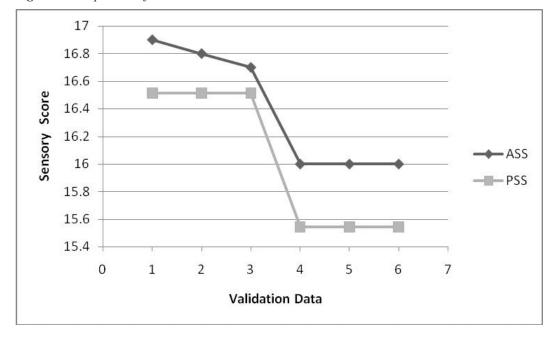


Figure 3. Comparison of ASS and PSS MLR model



Conclusion

Radial Basis (Fewer Neurons) and MLR models were developed and compared with each other for predicting the shelf life of processed cheese stored at 30° C. Soluble nitrogen, pH, SPC, Y&M and spore count

were input parameters, and sensory score was taken as output parameter. MSE; RMSE; R² and E² were used in order to compare the prediction ability of the developed models. The experiments revealed that the Radial Basis (Fewer Neurons) ANN model was slightly better than MLR model. Very good correlation was observed between the actual sensory score and predicted sensory score with a high R² and E², establishing that the developed ANN models were able to analyze non-linear multivariate data with brilliant performance. From the study

it is concluded that the developed Radial Basis (Fewer

Neurons) ANN model is good for estimating the shelf life of processed cheese.

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