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Shelf Life Estimation of Processed Cheese by Artificial Neural Network Expert Systems

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Abstract

Time–delay artificial neural network (ANN) single layer and multilayer artificial models were developed for predicting the shelf life of processed cheese stored at 7-8o C. Soluble nitrogen, pH; standard plate count, yeast & mould count, and spore count were input variables, and sensory score was output variable. The results showed excellent agreement between training and validation data with high coefficient of determination and nash - sutcliffo coefficient, thus suggesting that the developed models are good for predicting the shelf life of processed cheese.

Keywords: *Artificial Intelligence, Artificial Neural Network, Processed Cheese, Shelf Life, Time – Delay.*

1 Introduction

Artificial neural networks (ANNs) are relatively new computational tools that have found extensive application in solving many complex problems. The peculiarity of ANNs comes from their unique information processing characteristics pertinent mainly to nonlinearity, high parallelism, fault and noise tolerance, and learning and generalization capabilities. Time -Delay Neural Networks are special ANNs which receive input over several time steps. It is an alternative neural network architecture whose primary purpose is to work on continuous data. The advantage of this architecture is to adapt the network online and hence helpful in many real time applications, like time series prediction, online spell check, continuous speech recognition, etc. The architecture has a continuous input that is delayed and sent as an input to the neural network [1, 2].

As an increasing number of new foods vie for space on supermarket shelves, the words “speed and innovation” have become the watchwords for food companies seeking to become “first to market” with successful products. That all important market share which goes to the pioneer of each successful new product keeps that company in an excellent competitive position. Total quality is of paramount importance to this competitive posture and needs to be built into the speed and innovation system. How the consumer perceives the product is the ultimate measure of total quality. Therefore, the quality built in during the development and production process must last through the distribution and consumption stages. Shelf life studies can provide important information to product developers enabling them to ensure that the consumer will see a high quality product for a significant period of time after production. Since long time taking shelf life studies do not fit with the speed requirement, hence new accelerated studies have been developed [3].

Processed cheese is very popular variety of cheese. Generally it is prepared from 4 to 6 months old ripened grated Cheddar cheese. Often a part of ripened cheese is replaced by fresh cheese. During its manufacture required amount of water, emulsifiers, extra salt, preservatives, food colorings and spices (optional) are added, and the mixture is heated to 70º C for 10-15 minutes with steam in a cleaned double jacketed stainless steel kettle (which is open, shallow and round-bottomed) with continuous gentle stirring (about 50-60 circular motions per minute) with a flattened ladle in order to get unique body & texture and desirable consistency in the product. The determination of shelf life of processed cheese in the laboratory is very costly affair and takes a very long time to give results. Therefore, it was felt that ANN technique, which is fully equipped to predict the shelf life of food products, be employed for processed cheese as well. Hence, the present study was planned with the aim to develop feedforward ANN single and multilayer intelligent models for predicting the shelf life of processed cheese stored at 7-8ºC.The results of this research would be very beneficial for consumers, dairy factories manufacturing processed cheese, wholesalers, retailers, food researchers, academicians and regulatory authorities.

2 Literature Review: Prediction Using ANNs

The literature search revealed that the artificial neural networks have been efficiently used for prediction in the food industry. The brief pertinent review is presented:

2.1 Honey samples

Seventy samples of honey of different geographical and botanical origin were analyzed with an electronic nose. The instrument, equipped with 10 Metal Oxide

Semiconductor Field Effect Transistors (MOSFET) and 12 Metal Oxide Semiconductor (MOS) sensors, was used to generate a pattern of the volatile compounds present in the honey samples. The sensor responses were evaluated by Principal Component Analysis (PCA) and ANN. Good results were obtained in the classification of honey samples by using a neural network model based on a multilayer perceptron that learned using a backpropagation algorithm. According to researchers methodology is simple, rapid and results proposed that the electronic nose could be a useful tool for the characterization and control of honey [4].

2.2 Production of egg

A study has been reported on neural network applications to data analysis in egg production. An ANN model with two hidden layers, trained with a backpropagation algorithm, successfully learned the relationship between the input (age of hen) and output (egg production) variables. High R^2 and T for ANN model revealed that ANN is an efficient method of predicting egg production for pullet and hen flocks. It was also estimated that ANN parameters a number of eggs on four data sets of individual hens. By increasing the summary intervals to 2 wk, 4 wk and then to 6 wk, ANN power was increased for prediction of egg production. The results suggested that the ANN model could provide an effective means of recognizing the patterns in data and accurately predicting the egg production of laying hens based on investigating their age [5].

2.3 Beef

A series of partial least squares (PLS) models were employed to correlate spectral data from FTIR(Fourier transform infrared spectroscopy) analysis with beef fillet spoilage during aerobic storage at different temperatures (0,5,10,15,and20ºC).The performance of the PLS models was compared with a three - layer feedforward ANN developed using the same dataset. FTIR spectra were collected from the surface of meat samples in parallel with microbiological analyses to enumerate total viable counts. Sensory evaluation was based on a three-point hedonic scale classifying meat samples as fresh, semi-fresh, and spoiled. The purpose of the modelling approach employed in this work was to classify beef samples in the respective quality class as well as to predict their total viable counts directly from TIR spectra. The results obtained demonstrated that both approaches showed good performance in discriminating meat samples in one of the three predefined sensory classes. The PLS classification models showed performances ranging from72.0 to 98.2% using the training dataset, and from 63.1 to 94.7% using independent testing dataset. The ANN classification model performed equally well in discriminating meat samples, with correct classification rates from 98.2 to 100% and 63.1 to73.7% in the train and test sessions, respectively. PLS and ANN approaches were also applied to create models for the prediction of microbial counts. The performance of these was based on graphical plots and statistical indices (bias factor, accuracy factor and root mean square error) [6].

2.4 Fried potato chips

Quality of potatoes in chips industry is estimated from the intensity of darkening during frying. This is measured by a human jury, subject to numerous factors of variation. Gray level intensities were obtained for the apex, the center, and the basal parts of each chip using image analysis of frying assays. Feedforward ANN was designed and tested to associate these data with color categories. The developed ANN showed good performance, learning from a relatively small number of data values. The ANN model behaved better than multiple linear regression analysis. Predicted categories appear to reproduce the pattern of the experimental data issued from the jury, revealing nonlinear mapping, existence of sub regions and partial overlapping of categories. Moreover, the generalization capacities of the network allowed to simulate plausible predictions for the whole set of parameter combinations. Marique *et. al.* (2003) were of the opinion that this work is to be considered as a 1st step toward a practical ANN model that will be used for objective, precise, and accurate online prediction of chips quality [7].

2.5 Dairy products and sterilized drinks

In recent past attention has been focused on the application of neural networks for developing different models for various following dairy products and milk based sterilized drinks: Cakes [8]; soft cakes [9]; kalakand [10]; instant coffee drink [11]; instant coffee flavoured sterilized drink [12; 13]; milky white dessert jeweled with pistachio [14]; brown milk cakes [15]; soft mouth melting milk cakes [16]; post-harvest roasted coffee sterilized milk drink [17].

3 Method Material

The input variables used in the ANN were the experimental data of processed cheese relating to soluble nitrogen, pH; standard plate count, yeast & mould count, and spore count. The sensory score assigned by the trained panelists was taken as output variable for developing computing models (Fig.1). Experimentally obtained 36 observations for each input and output variables were used for developing the models. The dataset was randomly divided into two disjoint subsets, namely, training set having 30 observations (80% for training), and validation set 6 observations (20% for testing). 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 applied in order to compare the prediction ability of the developed models. *Bayesian regularization* mechanism was used for training neural networks, as it exhibited the best results. The network was trained up to 100 epochs, and neurons in each hidden layer varied from 1 to 20.

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

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

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

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

Where,

$Q_{\exp}$ = Observed value; Q_{cal} = Predicted value; $\overline{Q}_{\exp}$ =Mean predicted value; n = Number of observations in dataset.

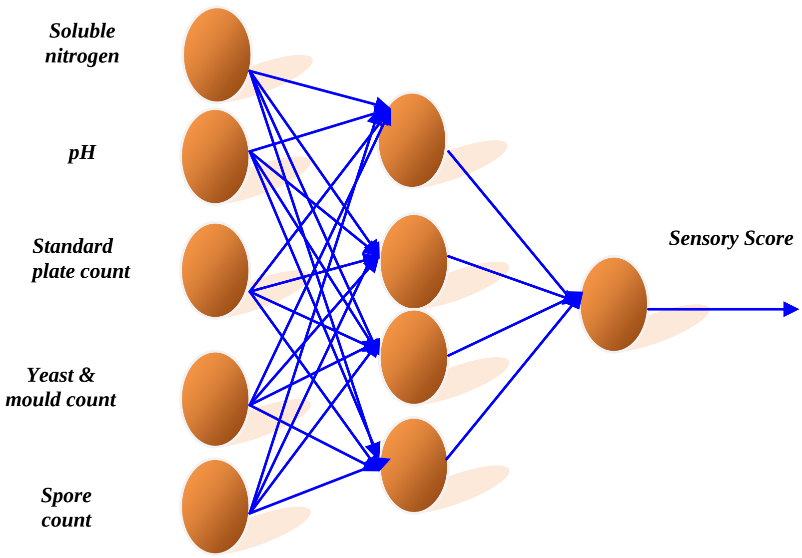

Figure1: Input and output parameters for ANN models

The ANN was trained with single as well as multiple hidden layers, and transfer function for hidden layer was *tangent sigmoid,* while for the output layer it was *pure linear* function. MALTAB software was used for performing experiments.

4 Results and Discussion

Table 1: Results of time - delay single layer ANN model

Neurons	**MSE**	**RMSE**	**R^2**	**E^2**
3	0.000353235	0.018794542	0.981205458	0.999646765
4	0.000467513	0.021622039	0.978377961	0.999532487
5	0.000287554	0.016957424	0.983042576	0.999712446
6	0.000384692	0.019613558	0.980386442	0.999615308
7	0.000493585	0.022216771	0.977783229	0.999506415
8	0.000634431	0.025187912	0.974812088	0.999365569
9	0.000215482	0.014679298	0.985320702	0.999784518
10	0.00025342	0.015919163	0.984080837	0.99974658
11	0.000181976	0.013489834	0.986510166	0.999818024
12	0.000564971	0.023769123	0.976230877	0.999435029
13	0.000234066	0.015299231	0.984700769	0.999765934
14	0.000546084	0.023368435	0.976631565	0.999453916
15	0.000998333	0.031596402	0.968403598	0.999001667
16	**2.52858E-06**	**0.001590152**	**0.998409848**	**0.999997471**
17	0.000268233	0.016377813	0.983622187	0.999731767
18	0.000283551	0.016838982	0.983161018	0.999716449
19	0.000484002	0.022000047	0.977999953	0.999515998
20	0.001019464	0.031929048	0.968070952	0.998980536

Table 2: Results of time - delay multilayer ANN model

Neurons	MSE	RMSE	R^2	E^2
3:3	0.000221891	0.014896022	0.985103978	0.999778109
4:4	1.30957E-05	0.003618793	0.996381207	0.999986904
5:5	1.50612E-07	0.000388088	0.999611912	0.999999849
6:6	9.45232E-08	0.000307446	0.999692554	0.999999905
7:7	4.97892E-09	7.05614E-05	0.999929439	0.999999995
8:8	0.00038687	0.019668999	0.980331001	0.99961313
9:9	0.000120447	0.010974823	0.989025177	0.999879553
10:10	1.1797E-06	0.001086142	0.998913858	0.99999882
11:11	**3.74383E-05**	**6.23972E-06**	**0.99999376**	**1**
12:12	0.000268646	0.016390413	0.983609587	0.999731354
13:13	0.000350493	0.01872146	0.98127854	0.999649507
14:14	9.17035E-05	0.009576194	0.990423806	0.999908296
15:15	9.17518E-05	0.009578715	0.990421285	0.999908248
16:16	0.000212019	0.014560856	0.985439144	0.999787981
17:17	0.000483115	0.021979886	0.978020114	0.999516885
18:18	3.50587E-06	0.001872398	0.998127602	0.999996494
19:19	0.000483337	0.021984926	0.978015074	0.999516663
20:20	0.000684907	0.026170731	0.973829269	0.999315093

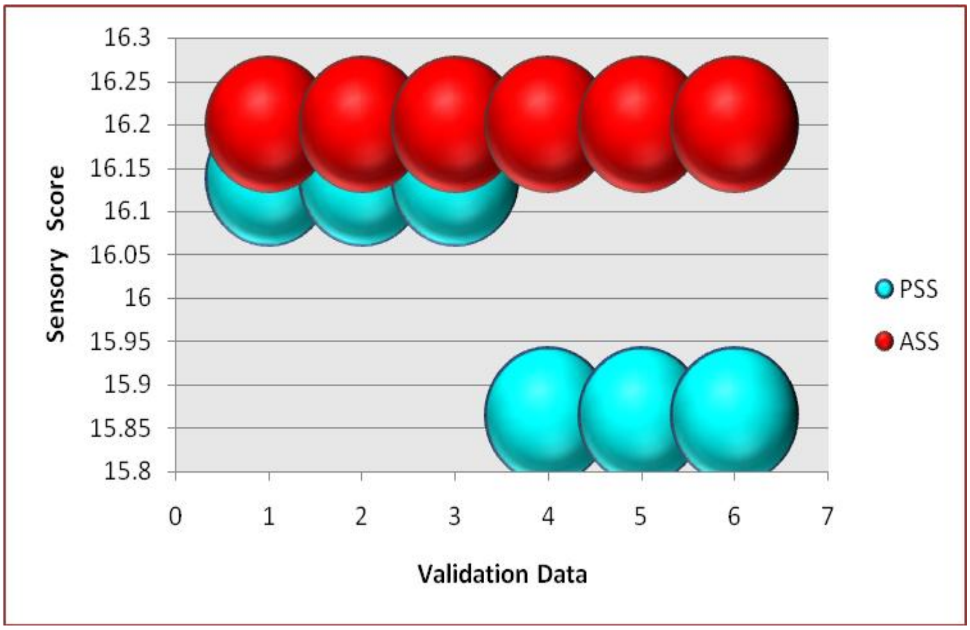

Figure 2: Comparasion of ASS and PSS for single layer time-delay model

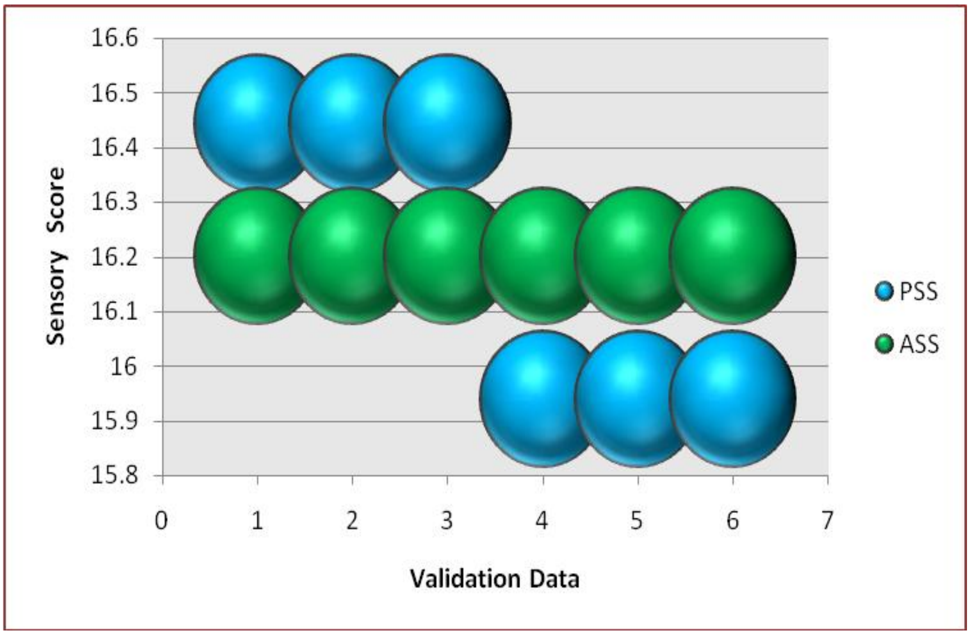

Figure 3: Comparasion of ASS and PSS for multilayer time-delay model

The comparison of Actual Sensory Score (ASS) and Predicted Sensory Score (PSS) for ANN models are illustrated in Fig.2 and Fig.3, respectively. Single layer model with 5→16→1 combination (**MSE**: **2.52858E-06**; **RMSE**: **0.001590152**; **R^2** : **0.998409848**; **E^2**: **0.999997471**) gave the best result among single layer experiments (Table 1); and for time – delay multilayer ANN models, the best result was for 5→11→11→1 combination (**MSE**: **3.74383E-05**; **RMSE**: **6.23972E-06**; **R^2** : **0.99999376**; **E^2** : **1**) (Table 2). These results show that time – delay model with single and multilayer got simulated exceedingly well with the experimental data, and thus could be used for predicting the shelf life of processed cheese stored at 7-8^o C. These proposed models are simple, convenient and less time consuming as compared to shelf life determination in the laboratory.

5 Conclusion

Time-delay single layer and multilayer ANN models were developed for predicting the shelf life of processed cheese stored at 7-8^o C. The inputs parameters of the ANN consisted of soluble nitrogen, pH; standard plate count, yeast & mould count, and spore count. The output parameter was sensory score. The results of the experiments showed excellent correlation between the training data and the validation data, with a high nash - sutcliffo coefficient and determination coefficient, suggesting that the developed time-delay models are able to analyze non-linear multivariate data with excellent performance, fewer parameters, and shorter calculation time. From the study it is concluded that time-delay ANN models are very good for predicting the shelf life of processed cheese.

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