Application of Simulated Neural Networks as Non-Linear Modular Modeling Method for Predicting Shelf Life of Processed Cheese

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Abstract

This paper presents the capability of simulated neural network (SNN) models for predicting the shelf life of processed cheese stored at ambient temperature 30° C. Processed cheese is a dairy product generally made from medium ripened Cheddar cheese. Elman and Linear Layer(Train) SNN models were developed. Body & texture, aroma & flavour, moisture, free fatty acids were used as input variables and sensory score as the output. Neurons in each hidden layers varied from 1 to 40. The network was trained with single as well as double hidden layers up to 100 epochs, and transfer function for hidden layer was tangent sigmoid while for the output layer, it was pure linear function. Mean square error, root mean square error, coefficient of determination and nash - sutcliffo coefficient performance measures were used for testing prediction potential of the developed models. Results showed a 4→20→1 topology was able to predict the shelf life of processed cheese exceedingly well with R^2 as 0.99992157. The corresponding RMSE for this topology was 0.003615359. From this study it is concluded that SNN models are excellent tool for predicting the shelf life of processed cheese.

Keywords: *SNN, Elman, Linear layer (train), Processed cheese, Shelf life prediction, Artificial intelligence, Artificial neural network*

1. INTRODUCTION

This paper highlights the importance of Simulated Neural Networks (SNN) for predicting the shelf life of processed cheese stored at ambient temperature 30° C. Processed cheese is one of the most popular varieties among the types of cheeses and is generally prepared by using medium ripened (up to 6 months old) grated Cheddar cheese by adding water, emulsifiers, salt, and preservatives by heating to 70ºC 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 min.) with a flattened ladle in order to get unique body & texture in the product.

1.1 Simulated Neural Network

SNNs are relatively new computational tools that have found extensive application in solving many complex real-world problems. The attractiveness of SNNs comes from their remarkable information processing characteristics pertinent mainly to nonlinearity, high parallelism, fault and noise tolerance, learning and generalization capabilities (Basheer and Hajmeer, 2000).

SNNs are inspired by the early models of sensory processing by the brain. An SNN can be created by simulating a network of model neurons in a computer. By applying algorithms that mimic the processes of real neurons, one can make the network 'learn' to solve many types of problems. A model neuron is referred to as a threshold unit. It receives input from a number of other units or external sources, weighs each input and adds them up. If the total input is above a threshold, the output of the unit is one; otherwise it is zero. Therefore, the output changes from 0 to 1 when the total weighted sum of inputs is equal to the threshold. The points in input space satisfying this condition define a so called hyperplane. In two dimensions, a hyperplane is a line, whereas in three dimensions, it is a normal plane. Points on one side of the hyperplane are classified as 0 and those on the other side as 1. Thus,

a classification problem can be solved by a threshold unit if the two classes can be separated by a hyperplane (Krogh, 2008).

1.2 Elman Simulated Neural Network (ESNN) Model

ESNN models 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 model to learn to recognize and generate temporal patterns, as well as spatial patterns. The ESNN model 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 model 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 (Demuth *et al., 2009).*

1.3 Linear Layer (Train)

Linear layers are single layers of linear neurons. They may be static with input delays of 0, or dynamic with input delays greater than 0. They can be trained on simple linear time series problems, but often used adaptively to continue learning while deployed, so they can adjust to changes in the relationship between inputs and outputs while being used (Mathworks Website, 2011).

1.4 Importance of Shelf Life

Martins *et al.* (2008) defined shelf life as the time that a product is acceptable and meets the consumer's expectations regarding food quality. It is the result of the conjunction of all services in production, distribution, and consumption. Shelf life dating is one of the most difficult tasks in food engineering. Market requirement has led to the implementation of shelf-life by sensory evaluation method, which is an expensive and long time consuming procedure, and also may not reflect the full quality spectra. 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. The food industry is facing the challenges to monitor, diagnose, and control the quality and safety of food products, but of late innovation of new technologies, *viz.,* nanotechnology, multivariate sensors, and computerized systems have made the task of shelf life estimation quite handy.

Artificial Neural Network (ANN) modeling and several mathematical models were applied to predict the moisture ratio in an apple drying process (Khoshhal *et al.,* 2010). Four drying mathematical models were fitted to the data obtained from eight drying runs and the most accurate model was selected. Two sets of ANN modeling were also performed. In the first set, the data obtained from each pilot were modeled individually to compare the ANN predictions with the best mathematical model. In the second set of ANN modeling, the simultaneous effect of all the four input parameters including air velocity, air temperature, the thickness of apple slices and drying time was investigated. The results showed that the ANN predictions were more accurate in comparison with the best fitted mathematical model. In addition, none of the mathematical models were able to predict the effect of the four input parameters simultaneously, while the developed ANN model predicted this effect with a good precision.

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.

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, 20ºC).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 obtained results demonstrated that both the approaches were effective in discriminating the 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 (Efstathios *et al.,* 2011).The performance of these was based on graphical plots and statistical indices (bias factor, accuracy factor and root mean square error).

ANNs have been successfully applied for predicting the shelf life of brown milk cakes decorated with kalakand (Goyal and Goyal, 2011a), milky white dessert jeweled with pistachio (Goyal and Goyal, 2011b), instant coffee flavoured sterilized drink (Goyal and Goyal, 2011c, d).Time-delay and linear layer ANN models were suggested for estimating the shelf life of soft mouth melting milk cakes

(Goyal and Goyal, 2011e). Elman and self-organizing models were used to predict shelf life of soft cakes (Goyal and Goyal, 2011f). Radial Basis models were applied for determining the shelf life of brown milk cakes decorated with almonds (Goyal and Goyal, 2011g). ANN models also predicted shelf life of milk based products (Goyal and Goyal, 2012 a, b, c) and processed cheese (Goyal and Goyal, 2012 d, e, f).

The review search revealed that till now the suitability of SNN models for predicting the shelf life of processed cheese stored at ambient temperature 30° C has not been investigated, hence the present study was planned. The outcome of this research would be very beneficial and relevant for dairy factories manufacturing the product, wholesalers, retailers, consumers, regulatory authorities, food researchers and academicians.

2. METHOD MATERIAL

2.1 Data Set

The experimental data concerning quality parameters, *viz.*, body & texture, aroma & flavour, moisture, and free fatty acids of processed cheese stored at ambient temperature 30° C were taken as input variables and sensory score assigned by the trained expert panel was taken as the output for developing the SNN models (Fig.1). The dataset used in the study consisted of 36 observations, which were randomly divided into two disjoint subsets, *viz.,* training set having 30 observations and validation set 6.
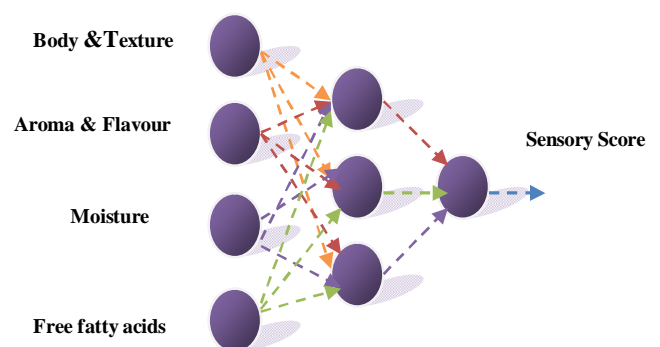

Figure1: Input and output parameters of SNN

Several approaches of internal parameters, *i.e.*, data preprocessing, data partitioning, number of hidden layers, number of neurons in each hidden layer, transfer function, error goal, *etc.*, were tried in order to optimize the prediction ability of the model. Different algorithms like Gradient Descent algorithm with adaptive learning rate, Polak Ribiére Update conjugate gradient algorithm, Fletcher Reeves update conjugate gradient algorithm, Levenberg Marquardt algorithm, Bayesian regularization were tried (Goyal and Goyal, 2011c). Bayesian regularization mechanism was selected for training the SNN models, as it gave the most promising results. Neurons in each hidden layer varied from 1 to 40. The network was trained up to 100 epochs. SNN was trained with single and double hidden layers. Transfer function for hidden layer was *tangent sigmoid,* and for the output layer it was *pure linear* function. MALTAB 7.0 software was used for performing the experiments.

2.2 Measures of 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.

3. RESULTS AND DISCUSSION

SNN model's performance matrices for predicting the sensory scores are presented in Table 1, Table 2, and Table 3, respectively.

Table 1: Performance of ESNN models with single hidden layer for predicting sensory score

Neurons	MSE	RMSE	R^2	E^2
3	2.99175E-05	0.005469686	0.99982049	0.99997008
6	3.18769E-05	0.005645962	0.99980873	0.99996812
7	3.23294E-05	0.005685896	0.99980602	0.99996767
9	3.30815E-05	0.005751653	0.99980151	0.99996691
11	3.37329E-05	0.005807999	0.99979760	0.99996626
13	0.000103962	0.010196179	0.99937622	0.99989603
15	0.001372968	0.037053579	0.99176219	0.99862703
17	0.000180204	0.013424025	0.99891877	0.99981979
20	**1.30708E-05**	**0.003615359**	**0.99992157**	**0.99998692**
25	0.000308126	0.017553523	0.99815124	0.99969187
33	0.001512566	0.038891717	0.99092460	0.99848743
40	8.32327E-05	0.009123197	0.99950060	0.99991676

Table 2: Performance of ESNN models with double hidden layer for predicting sensory score

Neurons	MSE	RMSE	R^2	E^2
3:3	3.57853E-07	0.00059820	0.99999785	0.99999964
4:4	3.75352E-07	0.00061265	0.99999774	0.99999962
5:5	0.00035657	0.01888306	0.99786058	0.99964343
7:7	**1.56709E-05**	**0.00395865**	**0.99990597**	**0.99998432**
9:9	0.000390009	0.01974863	0.99765994	0.99960999
10:10	3.26855E-07	0.00057171	0.99999803	0.99999967
11:11	0.000370803	0.01925625	0.99777518	0.99962919
14:14	2.04387E-05	0.00452092	0.99987736	0.99997956
16:16	0.00020208	0.01421549	0.99878751	0.99979792
20:20	1.8226E-05	0.00426919	0.99989064	0.99998177

Table 3: Performance of linear layer (train) model for predicting sensory score

MSE	RMSE	R^2	E^2
0.000241726	0.015547539	0.998549644	0.999758274

The comparison of Actual Sensory Score (ASS) and Predicted Sensory Score (PSS) for ESNN single hidden layer, double hidden layer and Linear Layer (Train) models are illustrated in Fig.2, Fig.3 and Fig.4, respectively.
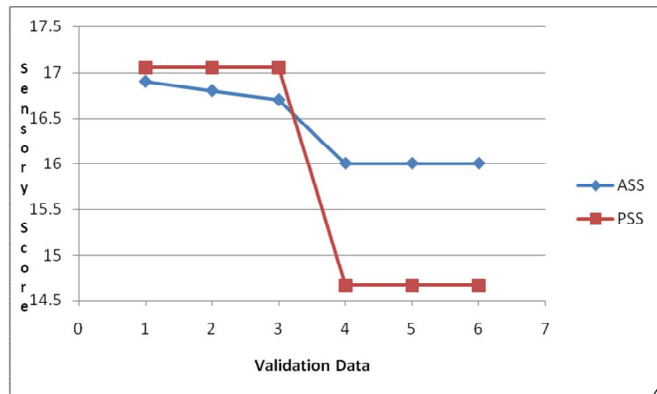

Figure 2: Comparison of ASS and PSS for single hidden layer ESNN model
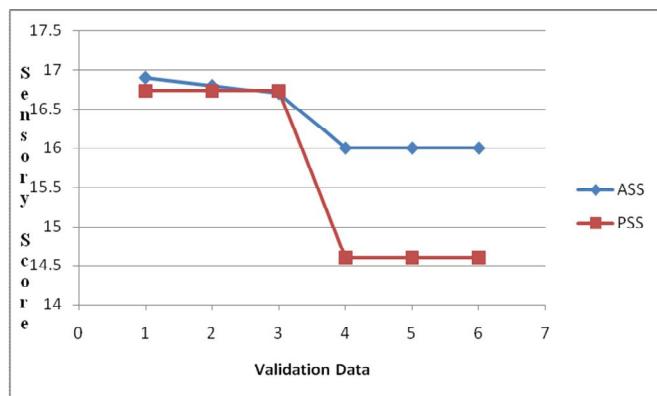

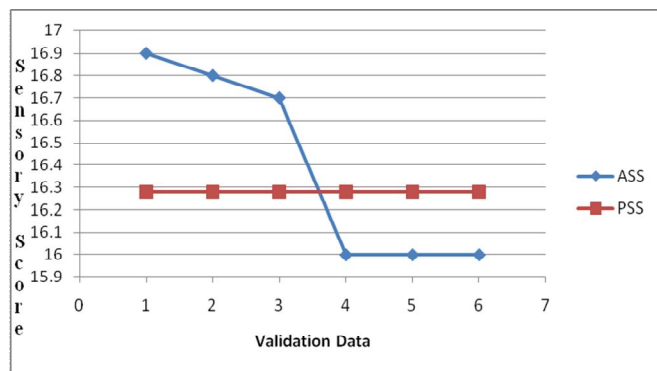Figure 3: Comparison of ASS and PSS for double hidden layer ESNN model

Figure 4: Comparison of ASS and PSS for Linear Layer (Train) model

ESNN models with single hidden layer and double hidden layer were developed for predicting shelf life of processed cheese. The best results of ESNN model with single hidden layer having 20 neurons were MSE: **1.30708E-05**, RMSE: **0.003615359**, R^2: **0.99992157**, E^2: **0.99998692** (Table 1); and with two hidden layers having 7 in the first and second layer MSE: **1.56709E-05**, RMSE: **0.00395865**, R^2: **0.99990597**, E^2: **0.999984329** (Table 2); and for Linear layer(Train) model MSE: **0.000241726**, RMSE**: 0.015547539**, R^2: **0.998549644**, E^2:**0.999758274** (Table 3).The best results of all the three models were compared with each other and it was observed that ESNN model with single hidden layer having 20 neurons gave the best fit.

4. 4. CONCLUSION

In this investigation Elman and linear layer(Train) simulated neural network (SNN) models were developed for predicting the shelf life of processed cheese stored at ambient temperature 30° C. The results showed that 4→20→1 topology was able to predict the shelf life of processed cheese exceedingly well with R^2 as 0.99992157. The corresponding RMSE for this topology was 0.003615359. From the study it is concluded that SNN models can be an effective alternative method for predicting the shelf life of processed cheese.

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