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INTELLIGENT ARTIFICIAL NEURAL NETWORK COMPUTING TECHNIQUES FOR SHELF LIFE DETERMINATION OF PROCESSED CHEESE

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Abstract

In this study feedforward and competitive artificial neural network models were developed for predicting shelf life of processed cheese stored at 30^o C. Processed cheese is a food product generally made from Cheddar cheese. Processed cheese has several advantages over unprocessed cheese, such as extended shelf-life, resistance to separation when cooked, and uniformity of product. Input parameters consisted of texture, aroma and flavour, moisture, free fatty acids, and sensory score was taken as output parameter. Backpropagation algorithm based on Bayesian regularization mechanism was selected for training the network. Neurons in each hidden layers varied from 1 to 50. The network was trained with 100 epochs 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. MSE, RMSE, R^2 and E^2 were used in order to compare the prediction potential of the developed ANN models. FANN with single hidden layer having twenty neurons exhibited the best results, hence regression equations based on these results were developed for predicting shelf life of the product, which came out as 28.32 days, which is comparable to experimental shelf life of 30 days.

Keywords: *Artificial Neural Network, Artificial Intelligence, Shelf Life, Feedforward, Competitive, Cheese*

1 INTRODUCTION

Processed cheese is a food product generally made from Cheddar cheese, plus emulsifiers, extra salt, food colorings. Many flavors, colors, and textures of processed cheese exist. Although processed cheese was first invented in 1911 by Walter Gerber of Thun, Switzerland, it was James L. Kraft who first applied for an American patent for his method in 1916. Kraft Foods also created the first commercially available sliced processed cheese, which was introduced in 1950. This form of sliced cheese and its derivatives have become commonplace in the United States, most notably used for cheeseburgers and grilled cheese sandwiches. The Laughing Cow is an example of European processed cheese. Processed cheese has several advantages over unprocessed cheese, such as extended shelf life, resistance to separation when cooked, and uniformity of product. Its production also enjoys significant economic advantages over traditional cheese making processes, most often through the ability to incorporate any of a wide variety of less expensive ingredients. The use of emulsifiers in processed cheese results in cheese that melts smoothly when cooked. With prolonged heating, unprocessed cheese will separate into a molten protein gel and liquid fat; processed cheese will not separate in this manner. The emulsifiers, typically sodium phosphate, potassium phosphate, tartrate, or citrate, reduce the tendency for tiny fat globules in the cheese to coalesce and pool on the surface of the molten cheese. Because processed cheese does not separate when melted, it is used as an ingredient in a variety of dishes. It is a popular addition to hamburgers, as it does not run off, nor does it change in texture or taste as it is heated [1].

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1.1 Artificial neural network (ANN)

An ANN is, in essence, an attempt to simulate the brain. Neural network theory revolves around the idea that certain key properties of biological neurons can be extracted and applied to simulations, thus creating a simulated (and very much simplified) brain. The first important thing to understand them is that the components of an artificial neural network are an attempt to recreate the computing potential of the brain. The second important thing to understand, however, is that no one has ever claimed to simulate anything as complex as an actual brain; whereas the human brain is estimated to have something of the order of ten to a hundred billion neurons. A typical ANN is not likely to have more than 1,000 artificial neurons [2].

1.2 Description of algorithm

Artificial neural networks (the ones that run on a computer as opposed to a brain) can be thought of as a model which approximates a function of multiple continuous inputs and outputs. The network consists of a topology graph of neurons, each of which computes a function (called an activation function) of the inputs carried on the in-edges and sends the output on its out-edges. The inputs and outputs are weighed by weights w_{ij} and shifted by bias factor specific to each neuron. It has been shown that for certain neural network topologies, any continuous function can be accurately approximated by some set of weights and biases [3].

1.3 Feedforward artificial neural network (FANN)

FANN consists of input, hidden and output layers. Backpropagation learning algorithm was used for learning these networks. During training this network, calculations were carried out from input layer of network toward output layer, and error values were then propagated to prior layers. Feedforward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors. The linear output layer lets the network produce values outside the range –1 to +1. On the other hand, outputs of a network such as between 0 and 1 are produced, then the output layer should use a sigmoid transfer function (logsig) [4].

1.4 Competitive artificial neural network (CANN)

Competitive learning is a rule based on the idea that only one neuron from a given iteration in a given layer will fire at a time. Weights are adjusted such a manner that only one neuron in a layer, for instance the output layer, fire. Competitive learning is useful for classification of input patterns into a discrete set of output classes. The “winner” of each iteration, element i*, is the element whose total weighted input is the largest [5].

1.5 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 [6]. Goyal and Goyal compared radial basis and multiple linear regression for forecasting shelf life of instant coffee drink and reached to a conclusion that radial basis artificial neural model is better in forecasting shelf life of instant coffee drink [7]. Time-Delay and Linear Layer ANN models were developed for predicting shelf life of

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soft mouth melting milk cakes stored 6^o C, and it was concluded that the developed expert system computing models were good in predicting shelf life of soft mouth melting milk cakes stored at 6^o C [8]. Elman and self-organizing simulated neural network models predicted shelf life of soft cakes [9].Some other applications of ANN have been successfully applied for predicting shelf life of Brown Milk Cakes Decorated with Almonds [10], Kalakand [11], Cascade and Feedforward backpropagation ANN models predicted sensory quality of instant coffee flavoured sterilized drink [12].Till date there is no report on prediction of shelf life of processed cheese. The purpose of this study is to develop FANN and PANN models and to compare them with each other for predicting shelf life of processed cheese stored at 30^o C. This investigation will be very useful for researchers, academicians, and food industry.

2 MATERIAL AND METHODS

The experimental data on quality parameters, *viz.*, body and texture, aroma and flavour, moisture and free fatty acids for processed cheese stored at 30^o C were taken as input parameters. The sensory score was taken as output parameter for developing ANN models. Experimentally obtained 36 observations for each input and output parameters were taken for development of the models. The dataset was randomly divided into two disjoint subsets, namely, training set containing 30 observations and validation set consisting of 6 observations. Different combinations of internal parameters, *i.e.*, data preprocessing, data partitioning approaches, 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 [9]. Backpropagation algorithm based on Bayesian regularization mechanism was finally selected for training the FANN models, as it gave the best results. Neurons in each hidden layers varied from 1 to 50. The network was trained with 100 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. FANN and CANN models were trained with training set after getting optimum values for architectural parameters; the neural network models were simulated with the validation data in order to validate the models. MALTAB 7.0 software was used for performing experiments.

2.1 Performance prediction measures

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

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

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

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

where,

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$Q_{\exp}$ = 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 ANN models.

3 RESULTS AND DISCUSSION

FANN model performance matrices for predicting sensory scores are presented in Table 1.

Table 1: Performance of FANN model with single hidden layer for predicting sensory score

Neurons	MSE	RMSE	R^2	E^2
3	0.00178	0.04227335	0.9892777	0.9982129
5	0.00426	0.06530235	0.9744136	0.9957356
8	0.00029	0.01704180	0.9982574	0.9997095
10	0.00118	0.03435199	0.9929196	0.9988199
12	0.00046	0.02149566	0.9972276	0.9995379
15	0.00134	0.03670376	0.9919170	0.9986528
20	**6.07265**	**0.00246427**	**0.9999635**	**0.9999939**
23	0.00076	0.02766124	0.9954091	0.9992348
25	0.00110	0.03321384	0.9933810	0.9988968
30	0.00073	0.02719250	0.9955634	0.9992605
40	0.00017	0.01305800	0.9989769	0.9998294
50	0.00023	0.01529258	0.9985968	0.9997661

Table 2: Performance of FANN model with double hidden layer for predicting sensory score

Neurons	MSE	RMSE	R^2	E^2
3:3	0.0001367	0.01169	0.999179709	0.99986328
5:5	0.0009066	0.03011	0.994560294	0.99909338
7:7	0.0008068	0.00013	0.995158909	0.99999998
9:9	0.0004344	7.24133	0.997393122	0.99999999
11:11	2.28893E-	0.00478	0.999862664	0.99997711
13:13	2.00464E-	0.00447	0.999879722	0.99997995
15:15	5.60353E-	0.00748	0.999663788	0.99994396
18:18	**6.353E-06**	**0.00252**	**0.999961882**	**0.99999364**
20:20	0.0009816	0.03133	0.994110221	0.99901837

Table 3: Performance of CANN model for predicting sensory score

MSE	RMSE	R^2	E^2
0.000189224	**0.01375588**	**0.998864655**	**0.9998107**

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FANN and CANN models were developed for predicting processed cheese stored at 30^o C. The best results of FANN with single hidden layer having twenty neurons were (MSE: 6.07265E-06, RMSE: 0.002464275, R^2 : 0.999963564, E^2: 0.999993927) and with two hidden layers having eighteen neurons in the first and second layer were (MSE: 6.353E-06,RMSE: 0.002520516, R^2 : 0.999961882, E^2: 0.999993647). Results for CANN were (MSE: 0.000189224; RMSE: 0.01375588; R^2 : 0.998864655; E^2: 0.9998107).The best results of all the models were compared with each other and it was observed that FANN model with single hidden layer having twenty neurons was better than other models. The comparison of Actual Sensory Score (ASS) and Predicted Sensory Score (PSS) for FANN single and double hidden layer models with CANN model are illustrated in Fig.1, Fig.2 and Fig.3.

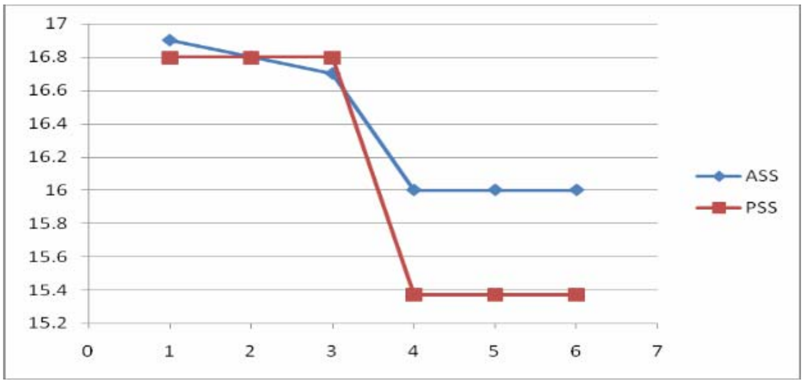

Fig. 1. Comparison of ASS and PSS for FANN single hidden layer model

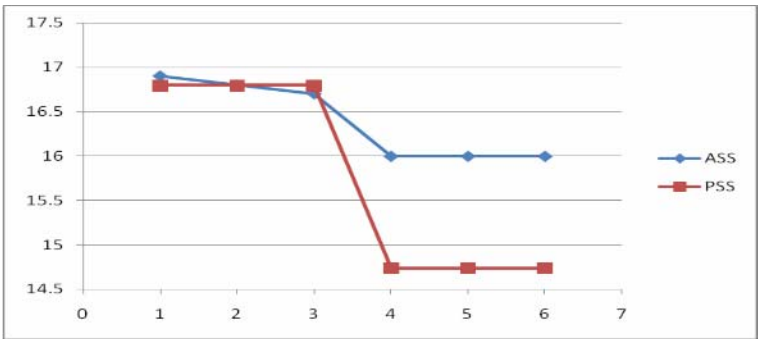

Fig. 2. Comparison of ASS and PSS for FANN double hidden layer model

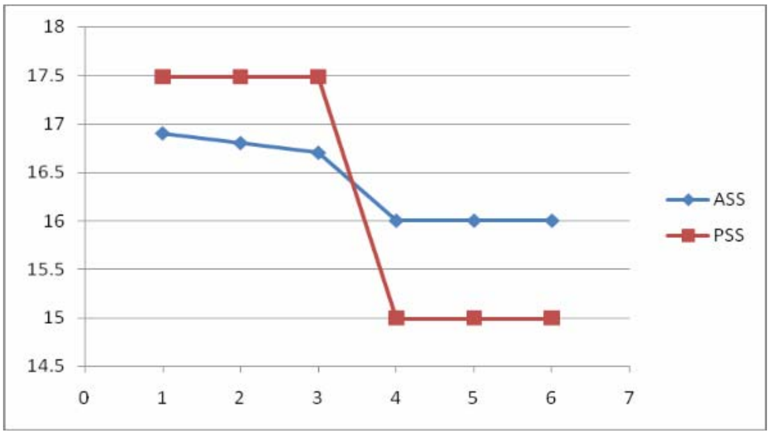

Fig.3. Comparison of ASS and PSS for CANN Model

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3.1 Prediction of shelf life

Regression equations were developed to predict shelf life of processed cheese, *i.e.*, in days for which product has been in the shelf, based on sensory score. The processed cheese was stored at 30°C taking storage intervals (in days) as dependent variable and sensory score as independent variable. R^2 was found to be 0.66 percent of the total variation as explained by sensory scores. Time period (in days) for which the product has been in the shelf can be predicted based on sensory score for processed cheese stored at 30° C. (Fig. 4).

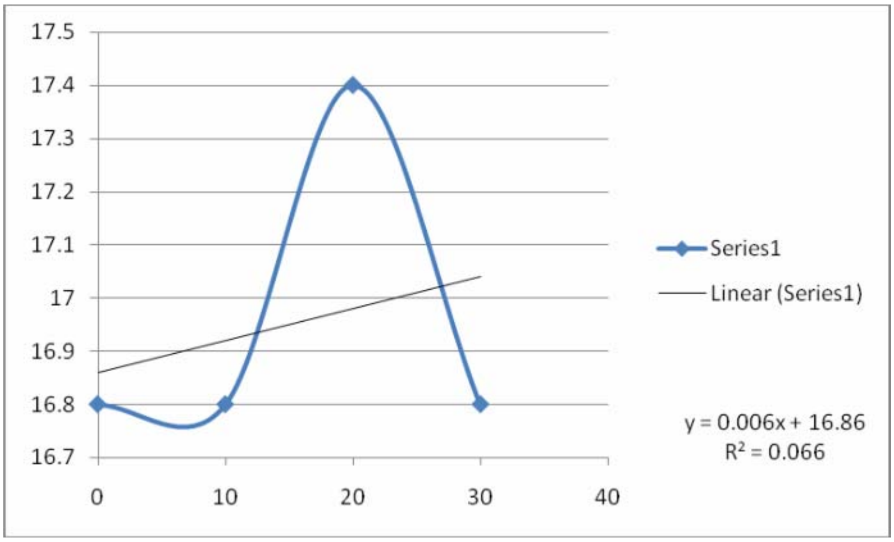

Fig.4. Shelf life prediction of processed cheese

The shelf life is calculated by subtracting the obtained value of days from experimentally determined shelf life, which was found to be 28.32 days. The predicted value is within the experimentally obtained shelf life of 30 days; therefore, the product is acceptable.

4. CONCLUSION

Feedforward and Competitive artificial neural networks models were developed for prediction of shelf life of processed cheese stored at 30° C. The performances of the two developed models were compared with each other. FANN model with single hidden layer having twenty neurons exhibited best results, and based on these results regression equations were developed for predicting the shelf life of the product. The shelf life predicted 28.32 days is very close to the experimentally obtained shelf life of 30 days. From the study, it can be concluded that ANN models can be used for predicting shelf life of processed chesses.

5. REFERENCES

1. Wikipedia Website: (accessed on 30.8.2011) http://en.wikipedia.org/wiki/Processed_cheese
2. Psych Website : (accessed on 21.8.2011)
   http://www.psych.utoronto.ca/users/reingold/courses/ai/nn.html
3. Emilstefanov Website : (accessed on 26.8.2011)
   http://www.emilstefanov.net/Projects/NeuralNetworks.aspx
4. H. Demuth, M. Beale and M. Hagan, Neural Network Toolbox User's Guide. The MathWorks, Inc., Natrick, USA, 2009.
5. Wikibooks Website: (accessed on 21.8.2011)
   http://en.wikibooks.org/wiki/Artificial_Neural_Networks/Competitive_Learning
6. Wikipedia Website: (accessed on 19.8.2011)
7. http://en.wikipedia.org/wiki/Shelf_life

ISSN 1512-1232
8. Sumit Goyal and G.K.Goyal," Application of artificial neural engineering and regression models for forecasting shelf life of instant coffee drink", International Journal of Computer Science Issues, vol.8(4), no 1, pp.320-324,2011.
9. Sumit Goyal and G.K.Goyal," Development of intelligent computing expert system models for shelf life prediction of soft mouth melting milk cakes", International Journal of Computer Applications, vol.25, no.9, pp.41-44,2011.
10. Sumit Goyal and G.K.Goyal," Simulated neural network intelligent computing models for predicting shelf life of soft cakes", Global Journal of Computer Science and Technology, vol.11, no.14, version 1.0, pp. 29-33,2011.
11. Sumit Goyal and G.K.Goyal, "Radial basis artificial neural network computer engineering approach for predicting shelf life of brown milk cakes decorated with almonds", International Journal of Latest Trends in Computing, vol.2, no.3, pp. 434-438,2011.
12. Sumit Goyal and G.K.Goyal, "Advanced computing research on cascade single and double hidden layers for detecting shelf life of kalakand: an artificial neural network approach", International Journal of Computer Science & Emerging Technologies,vol.2,no.5, pp.292-295, 2011.
13. Sumit Goyal and G.K.Goyal," Cascade and feedforward backpropagation artificial neural networks models for prediction of sensory quality of instant coffee flavoured sterilized drink", Canadian Journal on Artificial Intelligence, Machine Learning and Pattern Recognition, vol.2, no.6, pp.78-82,2011.

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