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Full Length Research Paper

Predicting shelf life of dairy product by using artificial neural networks (ANN) and statistical computerized methods

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Artificial neural networks (ANN) have been developed as generalizations of mathematical models of biological nervous systems. Generalized regression (GR) and multiple linear regression (MLR) models for shelf life prediction of dairy product were developed. Results of both the models were evaluated with three types of prediction performance measures *viz.*, mean square error, root mean square error and coefficient of determination R^2, and compared with each other. Based on these results, regression equations were developed. From the study, it is concluded that ANN and statistical computerized methods can be employed for predicting shelf life of dairy products.

Key words: Artificial neural networks (ANN), shelf life, dairy product, prediction, generalized regression, multiple linear regression.

INTRODUCTION

Milky bars are popular Indian sweet made out of solidified, sweetened milk and cottage cheese. It owes its origin to the milk-rich *Braj* area of western Uttar Pradesh, India. It is a very popular sweetmeat (Wikipedia website, 2011). The human brain provides proof of the existence of massive neural networks that can succeed at those cognitive, perceptual, and control tasks in which humans are successful. The brain is capable of computationally demanding perceptual acts (for example, recognition of faces and speech) and control activities (for example, body movements and body functions). The advantage of the brain is its effective use of massive parallelism, the highly parallel computing structure, and the imprecise information-processing capability. The human brain is a collection of more than 10 billion interconnected neurons. Treelike networks of nerve fibers called dendrites are connected to the cell body or soma, where the cell nucleus is located. Extending from the cell body is a single long fiber called the axon, which eventually branches into strands and substrands, and is connected to other neurons through synaptic terminals or synapses. The transmission of signals from one neuron to another at synapses is a complex chemical process in which specific transmitter substances are released from the sending end of the junction. The effect is to raise or lower the electrical potential inside the body of the receiving cell. If the potential reaches a threshold, a pulse is sent down the axon and the cell is 'fired'. Artificial neural networks (ANN) have been developed as generalizations of mathematical models of biological nervous systems. A first wave of interest in neural networks (also known as connectionist models or parallel distributed processing) emerged after the introduction of simplified neurons by McCulloch and Pitts (1943). The basic processing elements of neural networks are called artificial neurons or simply neurons or nodes. In a simplified mathematical model of the neuron, the effects of the synapses are represented by connection weights that modulate the effect of the associated input signals, and the nonlinear characteristic exhibited by neurons is represented by a transfer function. The neuron impulse is then computed as the weighted sum of the input signals, transformed by the transfer function. The learning capability of an artificial neuron is achieved by adjusting the weights in

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accordance to the chosen learning algorithm. A neural network has to be configured such that the application of a set of inputs produces the desired set of outputs. Various methods to set the strengths of the connections exist. One way is to set the weights explicitly, using a priori knowledge. Another way is to train the neural network by feeding it teaching patterns and letting it change its weights according to some learning rule. The learning situations in neural networks may be classified into three distinct sorts. These are supervised learning, unsupervised learning and reinforcement learning. In supervised learning, an input vector is presented at the inputs together with a set of desired responses, one for each node, at the output layer. A forward pass is done, and the errors or discrepancies between the desired and actual response for each node in the output layer are found. These are then used to determine weight changes in the net according to the prevailing learning rule. The term supervised originates from the fact that the desired signals on individual output nodes are provided by an external teacher (Softcomputing website, 2011).

Generalized regression (GR) model

GR models are a kind of radial basis network that is used for function approximation.
Syntax: net = newgrnn (P, T, spread)
net = newgrnn(P,T,spread) takes three inputs,
P: R-by-Q matrix of Q input vectors
T: S-by-Q matrix of Q target class vectors

Spread: Spread of radial basis functions (default = 1.0) and returns a new GR model. To fit data very closely, use a spread smaller than the typical distance between input vectors. To fit the data more smoothly, use a larger spread; the larger the spread, the smoother the function approximation. Newgrnn creates a two-layer neural network. The first layer has radbas neurons in it and calculates weighted inputs with dist and net input with netprod. The second layer has purelin neurons, which calculates weighted input with normprod, and net inputs with netsum. Only the first layer has biases. newgrnn sets, the first layer weights to *P*', and the first layer biases are all set to 0.8326/spread, resulting in radial basis functions that cross 0.5 at weighted inputs of +/- spread. The second layer weights *W2* are set to *T* (Mathworks. website, 2011).

Multiple linear regressions (MLR)

Regression reveals average relationship between two variables and makes possible to predict the yield. In mathematics, Y is called a function of X, but in statistics it is termed as regression which describes relationship. Hence, regression is the study of functional relationship between two variables of which one is dependent (Y) and other is independent (X). Regression analysis provides an estimate of values of the dependent variable from values of the independent variable. This estimation procedure is called the regression line. Regression analysis gives a measure of the error. With the help of regression coefficients, we can find the value of correlation coefficient. The multiple regression analysis gives the best linear prediction equation involving several independent variables. It also helps in finding the subset that gives the best prediction values of Y. The multiple regression equation describes the average relationship between dependent and independent variables which is used to predict the dependent variable. If Y depends partly on X1 and partly on X2, then the population regression equation is written as:

$$Y_R = \alpha - \beta_1 X_1 + \beta_2 X_2, \qquad (1)$$

β_1 measures the average change in Y when X_1 increases by 1 unit, X_2 remaining unchanged is called the partial regression coefficient of Y on X_1 and β_2 the partial regression coefficient of Y on X_2 which measures the average change in Y when X_2 increases by 1 unit, X_1 remaining unchanged. Thus, the regression model is:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \varepsilon, \qquad (2)$$

Where, $\varepsilon = N(0, \sigma^2)$ (Agarwal, 2010).

Goyal and Goyal (2011a) successfully applied artificial neural engineering and regressions models for forecasting shelf life of instant coffee drink. Goyal and Goyal (2011b) developed linear layer (design) and time-delay methods of intelligent computing expert system for shelf life prediction of soft mouth melting milk cakes and Kalakand (Goyal and Goyal, 2011c). Prediction of shelf life is important in order to achieve good quality of food products. As per government norms, it is mandatory to state expiry date on the package of food products. Factory owners, shopkeepers and restaurants do not have the facility of testing shelf life. So, they pay huge amount of money to the organizations that have the facility of testing shelf life in laboratory. Testing of shelf life in laboratory is a very time consuming activity. Hence, it would be relevant to develop such a model that could predict shelf life of milky bars at low cost and in less time.

METHODOLOGY

The models were tyrosine, moisture, free fatty acids, titratable acidity and peroxide value; and sensory score was output parameter, as shown in Figure 1. The dataset consisted of 60 live observations. Further, the dataset was divided into two subsets, that is, 48 data observations (80% of data observations) were used for training the network and 12 for testing (20% of data observations) the network. GR and MLR models were developed and compared with each other for shelf life prediction of milky bars. The network was trained with 100 epochs and number of neurons in single and double hidden layers varied from 1 to 30. Different

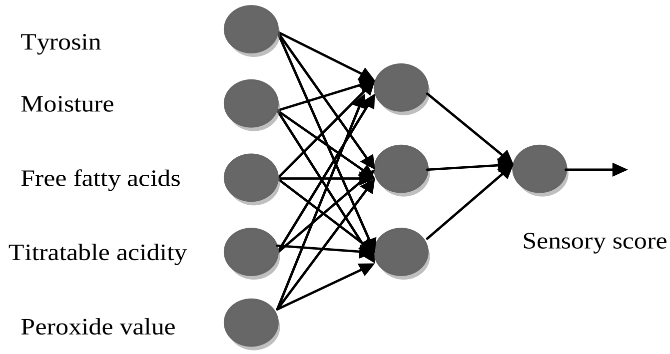

Figure 1. Design of neural network.

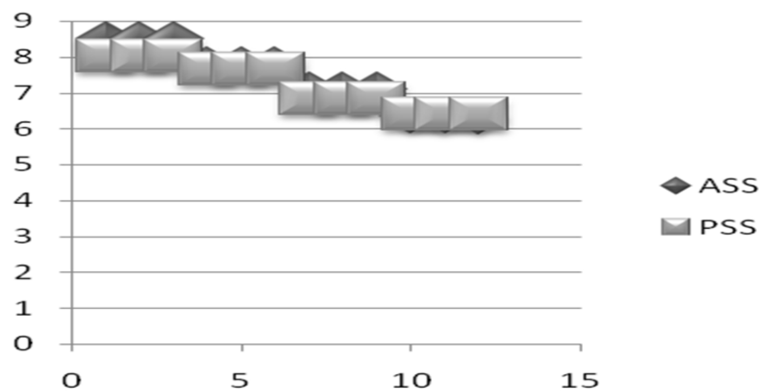

Figure 2. Graphical representation of actual and predicted sensory score for GR model.

combinations were tried and tested, as there is no predefined rule of achieving good results other than hit and trial method. The number of neurons increased as the training time. Two problems that were kept in mind while training the network were problem of overfitting and problem of underfitting. Overfitting means that the size of neurons used in training the network should not be large, as it is difficult for the network to train and underfitting means neurons should not be less as it is difficult for a neural network to get properly trained. Hence, balance must be maintained, while training the neural network. The neural network toolbox under MATLAB 7.0 software was used for development of artificial intelligence computing models.

Performance measures for prediction

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

$$RMSE = \sqrt{\frac{1}{n} \left[\sum_{1}^{N} \left(\frac{Q_{\exp} - Q_{cal}}{Q_{\exp}} \right)^2 \right]} \quad . \quad (4)$$

$$R^2 = 1 - \left[\sum_{1}^{N} \left(\frac{Q_{\exp} - Q_{cal}}{Q_{\exp}^{\ 2}} \right)^2 \right] \quad (5)$$

$Q_{\exp}$ = Observed value; Q_{cal} = predicted value; n = number of observations in dataset.

RESULTS AND DISCUSSION

The comparison of actual and predicted sensory score for ann models are illustrated in Figure 2 and Figure 3, respectively. Several experiments were carried out with GR and MLR models. Different combinations were tried, tested and compared with each other as shown in Tables 1 and Table 2. GR models best results with spread constant as 2 are MSE 0.001152787; RMSE: 0.033952711; R^2: 0.986166561. Statistical model of MLR was developed to compare the performance of artificial intelligence neural computing models. It displayed better results than GR model (MSE 0.000144005; RMSE:

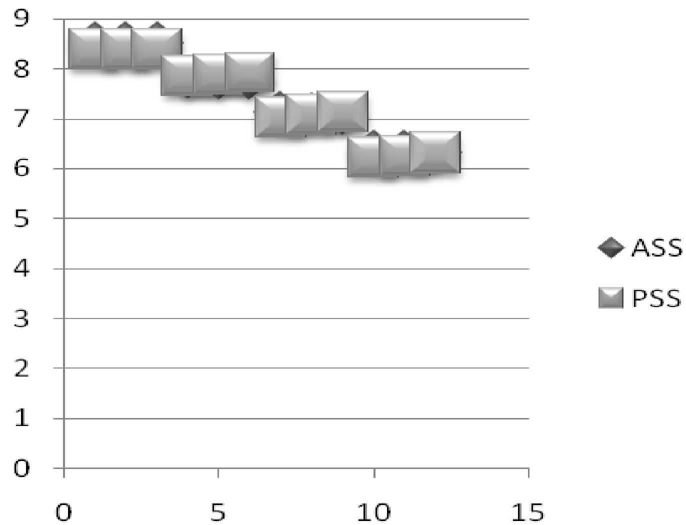

Figure 3. Graphical representation of actual and predicted sensory score for MLR model.

Table 1. Results of experiments for GR model.

Spread constant	MSE	RMSE	R^2
2	*0.001152787*	0.033952711	0.986166561
3	0.002836909	0.053262638	0.965957096
4	0.005046995	0.071042204	0.939436063
5	0.006850000	0.082764727	0.917799999
6	0.008135249	0.090195614	0.902377015
7	0.009032628	0.095040137	0.891608467
8	*0.009667907*	0.098325516	0.883985114
9	0.010129284	0.100644342	0.878448597
10	0.010471581	0.102330745	0.874341023
25	0.011789805	0.108580870	0.858522335
40	0.011952980	0.109329685	0.856564239

Table 2. Result of regression model.

Regression model	MSE	RMSE	R^2
MLR	*0.000144005*	0.0120002	0.998271839

0.0120002; R^2: 0.998271839) (Table 3). Our results are in agreement with the earlier findings of Goyal and Goyal (2011a). They developed artificial neural engineering and regression models for forecasting shelf life of instant coffee drink and concluded that MLR models are better than artificial neural engineering models in predicting shelf life instant coffee drink.

Based on the results, MLR model was selected for predicting shelf life of milky bars by building regressions equations based on sensory scores and constant came out as 8.516, regression coefficient as -0.041 and R^2 was found to be 99% as shown in Figure 4; after solving them 1.35 came as the output which was subtracted from the actual shelf life of the product *that is*, days. Hence, it was found 38.65 days.

Conclusion

The possibility of artificial intelligence neural network and statistical computing approach was investigated to predict shelf life of milky bars. GR model and statistical model of

Table 3. Displaying best results of different models.

Model	Best results
GR model	MSE 0.001152787; RMSE: 0.033952711; R^2: 0.986166561
MLR model	MSE 0.000144005; RMSE: 0.0120002; R^2: 0.998271839

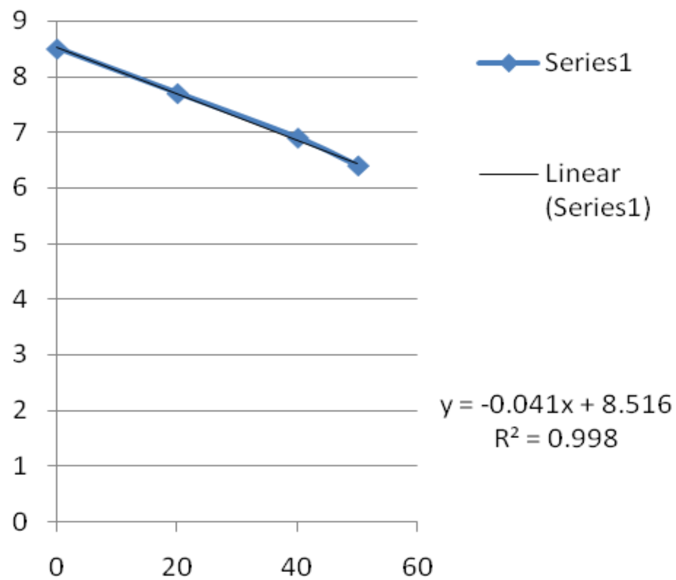

Figure 4. Displaying regression equations.

MLR was developed. From the results, it can be concluded that statistical computing model of MLR is superior over GR model in predicting shelf of milky bars stored at 6°C.

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