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Modeling and Estimation of Banana Slice Browning during Drying using Artificial Neural Network

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Abstract **– In this study two primary models were used for mathematical modeling and artificial neural networks were used for estimation of the browning behavior of banana. Comparing between the models was shown that the first-order model (R-square close to 0.98) had presented the browning behavior of banana slices better than the zero-order model. The feed-forward ANN with Levenbery-Marqwardt algorithms as learning role, tangent sigmoidal as transfer function, 20 neurons in first hidden layer and 10 neurons in second hidden layer had the best estimation due to R-square of 0.9813 and RMSE of 0.6403.**

Keywords **– Banana Slice, Artificial Neural Network (ANN), R-Square, RMSE.**

I. Introduction

Banana is a favourite fruit widely grown in the areas of tropical and subtropical climates. After harvesting, the quality of bananas deteriorates rapidly(Prachayawarakorn et al. , 2008). The moisture content is the most effective parameter on deterioration of banana and similar products. Due to dehydration process, dryingwas known as the oldest methods to protect foods and agricultural products.

During drying the color of the dried fruit changes due to the formation of browning, this has often been associated with the Maillard reaction (Baini and Langrish, 2009). Modeling and estimation of this change for controlling and reducing of this is one of the major aims of the food researchers.

At present, the artificial neural networks (ANNs) were known as one of the useful methods for the processes estimation. An artificial neural networkis a system imitating the operation of a biological neural network. It is composed of the set of basic elements (artificial neurons) that are mutually connected. In general, to describe the ANN operation at least three basic properties should be known namely a neuron model (transfer function), the network topology and the method of training (Tomczak and Kaminski, 2001).

Mousavi and Javan (2009), Movagharnejad and Nikzad (2007), Cakmak and Yildiz (2011) used ANNs for modeling and simulation of drying kinetics of apple, tomato and seedy grape, respectively. Moreover,Assidjo et al (2008) used artificial neural networks for modeling of an industrial drying process.

The major aims of this study were the mathematical modeling of the browning behavior of the dried banana slice and estimation of this behavior using artificial neural networks.

II. Material and Methods

Bananas were bought in a local market and were transmitted to laboratory of design and development at department of agricultural machinery engineering, University of Tehran. Any banana that was used in the experiment was sliced into 3 and 5 mm in thickness by meat slicer, the samples were then arranged upon the tray and the tray was placed into dryer at a set condition. Since ending of every experiment, the samples were placed into oven to exit remain moisture. The experiments were done at five air temperature levels of (50, 60, 70, 80, 90°C), three air velocity levels of (0.5, 1 and 1.5 m/s), and three thickness levels of (3, 5and 7 mm). These experiments were done using a thin layer dryer with a machine visionsystem.

2.1 Dryer

A thin-layer dryer was made based on computer vision for measuring the effects of drying on change of visual properties of products and relation between these properties and moisture content of products (Fig.1). The dryer consisted of a centrifugal fan (Damandeh, BEF-25/25F4T, 6300 m3/hr), air duct, four electrical heating elements (a 750W element in the centrifugal fan for preheating the airflow and 3×2000W elements in the air duct for heating the airflow), straightener, control unit, illumination and imaging chamber, a single point load cell, measurement sensors and drying chamber with one layer tray. Whole body of the dryer was thermally insulated with glass wool.

Fig.1. Experimental dryer: 1.fan; 2.preheating element; 3.heating elements; 4.straightener; 5.air velocity sensor; 6.relative humidity and temperature sensor; 7.temperature sensor; 8.digital color camera; 9.fluorescent lamps; 10.platform; 11.load cell; 12.control unit; 13.outside temperature sensor; 14.HMI; 15.computer; 16.monitor; 17.keyboard.

2.2 Browning

The total color difference as the most important parameter of the color variation was used to describe the browning behavior of banana slices. This parameter was defined in the following equation (Eq.1).

$$\Delta E = \sqrt{(L^* - L_0{}^*)^2 + (a^* - a_0{}^*)^2 + (b^* - b_0{}^*)^2} \qquad (1)$$

In this equation, L* is the luminance or lightness component, which ranges from 0 to 100, and parameters a* (from green to red) and b* (from blue to yellow) are the two chromatic components, which range from -120 to 120 (Papadakis et al, 2000; Segnini et al, 1999; Yam and Papadakis, 2004).

2.3 Mathematical Modeling

Traditional, mathematical approaches to system modeling have recently become particularly attractive due to rapid advancements in computer technology (Tomczak and Kaminski, 2001).

Browning of fruits, such as banana, during drying process was occurred as a function of drying time. Therefore, the browning behavior of fruits is able for mathematical modeling. The zero-order and the first order model have been used to describe the non-enzymatic browning behavior (Ibaz et al, 1999, Masken, 2001, Demir et al, 2002). The mathematical functions of the models were given in Eq.2 and 3, respectively.

$$C = C_0 + k_0 t \tag{2}$$

$$C = (C_0 - C_\infty)\exp(k_1 t) + C_\infty \tag{3}$$

Where C is the variable content studied at time t, C_0 is the value at time zero, C_∞ is the value at time extreme, k_0 the zero order kinetic constant, and k_1 is the first order kinetic constant.

2.4 Structure of Neural Network

In order to estimate the browning behavior of banana, back-propagation feed forward neural network was chosen. Momentum and Levenbery-Marqwardtalgorithms were chosen as the network learning roles. Pure line, Logarithmic sigmoid and tangent sigmoid functions were used as activation functions. Mathematical model of the transfer functions were shown in Eqs.4, 5 and 6, respectively.

$$Purelin(n) = n \tag{4}$$

$$Logsig(n) = \frac{1}{1+\exp(-n)} \tag{5}$$

$$Tansig(n) = \frac{2}{(1+\exp(-2n))} - 1 \tag{6}$$

Where, n is number of inputs to the neuron.

In the selected structure of the applied neural network, the air velocity, drying time, slice thickness, drying temperature and moisture content of the slices were chosen as the network inputs and total browning was chosen as the network outputs (Fig.2). Therefore, the experiments were done at five levels of drying air temperature (50, 60, 70, 80 and 90°C); three levels of air flow velocity (0.5, 1 and 1.5 m/s) and three levels of the slice thickness (3, 5 and 7 mm).

Fig.2. The schematic of the selected structure of the applied neural network

The networks were trained for a fixed number of 1000 cycle. All trains were performed in the MATLAB environment. In this software environment, all experimental data were divided into three partitions. The data of the first part for network training, seconded part for network validation and third part for network testing were used. In order to avoid over fitting, two common methods were used. These were: (i) early stopping; and minimizing the number of hidden layer (Erenturk, 2007). Also, the statistical parameters of the mean square error (MSE) and the correlation coefficient (r) were used for selecting the best network topology.

III. Results and Discussion

The hunter color values (L*, a* and b*) of taken images were calculated using image processing technique in the MATLAB environment. Then, the total color difference was obtained by Eq.1. The model of change of the ΔE as function of drying time was given in Fig.3. According to the figure, the browning of banana slices was increased during drying process. This may be occurred due to pigment destruction, ascorbic acid browning and non-enzymatic Maillard browning (AbersandWrolstad, 1979; Ibarz et al., 1999; Skrede, 1985; Maskan, 2001). In addition, the browning kinetics of the slices was occurred as an exponential curve versus drying time (Fig.3). The rate of Maillard reaction decreases with decreasing of samples moisture content during dehydration process. Therefore, the browning rate of the slices was increased during drying time.

Fig.3. Variation modelof the ΔE during drying (air temp of 90°C, slice thick of 7mm, air velocity of 0.5 m/s)

Non-regression results of the browning modeling at the different drying conditions using zero and first-order models were shown in tables 1 and 2, respectively. In the zero- order model, the constant of K_0 represents the browning rate. According to the table.1, increasing of drying temperature was found to increase K_0, approximately. Therefore, increasing of drying temperature resulted in an approximate increase in the rate of browning due to Maillard reaction increase.

However, the both models had an acceptable presentation, but the statisticalresults show that the first-order model with a higher R value had presented the browning behavior of banana slices better than the zero-order model.

Table.1. Non-regression Results of modeling at the different drying conditions using zero-order model

Table.2. Non-regression Results of modeling at the different drying conditions using first-order model

The result of the network learning using Momentum and Levenbery-Marqwardtalgorithms were shown in fig.4. The performance of the Momentum algorithm for reducing the estimation error was observed close to 0.067. But the performance of Levenbery-Marqwardt algorithm was observed abut 2.38×10^{-5}. Therefore, Levenbery-Marqwardt algorithm was used to learning of the network.

Fig.4. Comparing between differentlearning role algorithms in order to reduce learning error

The statistical results of feed-forward ANN using Levenbery-Marqwardtlearning role for estimation of the browning behavior of banana were given in Table.3. However, the browning is a complex chemical process that is the results of several reactions. Nevertheless, the higher R-value and lower RMSE value confirm the ability of feed-forward ANN to estimate this thermal treatment. According to the table, the neural network structure with transfer function of tangent sigmoidal, 20 neurons in first hidden layer and 10 neurons in second hidden layer had the best estimation due to R-square of 0.9813 and RMSE of 0.6403.

Table.3. Statistical results of feed- forward ANN

Figure 1 represents a high correlation between experimental data and the neural network estimation. This figure shows ability of the ANN for estimation of the browning behavior of the dried banana slice. Therefore, using artificial neural network can be a useful method to predict the thermal reaction without doing experiment and spending extra time.Also, it is useable for controlling the experiment process.

Fig.5. Ability of the neural networks to estimate the browning behavior of banana slices

IV. Conclusion

The color of samples changed during drying process. Mathematical modeling is a useful method for processing of browning behavior of dried slices. Among, zero and first-order models are tow primary models. First- order model with R-square close to 0.98 presented the browning behavior of banana slices. Artificial neural networks can predict a process before occurring. In this study the feed-forward ANN with Levenbery-Marqwardt algorithms as learning role, tangent sigmoidal as transfer function, 20 neurons in first hidden layer and 10 neurons in second hidden layer had the best estimationof browning behavior of banana dried slices due to R-square of 0.9813 and RMSE of 0.6403.

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Table 1: Non-regression Results of modeling at the different drying conditions using zero-order model

Air Velocity	Air Temperature	Slice Thickness								
		3mm			5mm			7mm		
		K_0	C_0	R^2	K_0	C_0	R^2	K_0	C_0	R^2
0.5m/s	50°C	0.03	6.21	0.80	0.03	3.69	0.89	0.03	3.81	**0.92**
	60°C	0.038	9.24	0.82	0.04	6.96	0.86	0.028	3.85	**0.93**
	70°C	0.071	7.21	0.79	0.048	4.57	0.89	0.031	6.10	0.87
	80°C	0.023	7.65	0.42	0.067	6.77	**0.93**	0.061	2.85	**0.97**
	90°C	0.116	6.57	0.83	0.049	2.89	0.85	0.89	3.25	**0.95**
1.0m/s	50°C	0.041	5.97	0.72	0.022	7.19	0.80	0.029	3.87	**0.93**
	60°C	0.035	7.65	0.78	0.022	5.54	0.86	0.045	3.61	**0.93**
	70°C	0.075	2.44	0.87	0.051	9.69	0.81	0.028	2.62	**0.93**
	80°C	0.057	5.68	0.58	0.059	4.25	0.87	0.073	4.96	**0.91**
	90°C	0.083	6.16	0.75	0.078	5.89	0.805	0.094	3.69	0.88
1.5m/s	50°C	0.034	5.87	0.85	0.027	4.92	0.83	0.02	3.32	**0.94**
	60°C	0.054	0.79	0.79	0.050	5.87	0.88	0.051	7.64	0.86
	70°C	0.061	0.86	0.86	0.068	5.56	0.85	0.038	5.46	0.89
	80°C	0.068	5.96	0.83	0.075	7.55	0.82	0.062	4.70	0.88
	90°C	0.107	4.73	0.85	0.115	5.43	0.83	0.05	10.37	0.60

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Table.2. Non-regression Results of modeling at the different drying conditions using first-order model

Air Velocity	**Air Temp**	**Slice Thickness**											
		3mm				**5mm**				**7mm**			
		K_1	C_0	C_∞	R^2	K_1	C_0	C_∞	R^2	K_1	C_0	C_∞	R^2
0.5m/s	50°C	0.0051	3.47	18.83	0.86	0.0038	0.046	20.68	**0.96**	0.0022	1.16	27.43	**0.95**
	60°C	0.0071	3.62	24.03	**0.96**	0.0046	2.62	26.16	**0.94**	0.0027	1.16	22.94	**0.97**
	70°C	0.0115	3.15	21.65	0.89	0.0024	3.34	32.86	**0.91**	0.0061	3.17	17.91	**0.95**
	80°C	0.0410	0.05	11.89	0.76	0.0048	4.50	30.54	**0.95**	0.0029	1.24	33.5	**0.98**
	90°C	0.0215	1.85	20.79	**0.95**	0.0104	0.72	13.17	**0.91**	0.0059	0.86	28.87	**0.98**
1.0m/s	50°C	0.012	2.41	15.05	0.85	0.0049	2.92	19.29	**0.93**	0.0029	0.91	23.50	**0.98**
	60°C	0.104	1.83	18.74	**0.95**	0.0031	2.70	20.56	**0.92**	0.0034	-0.46	28.86	**0.98**
	70°C	0.012	0.40	14.74	**0.93**	0.0093	2.48	25.88	**0.97**	0.0025	1.53	20.31	**0.95**
	80°C	0.030	2.57	11.85	0.73	0.0067	1.78	20.97	**0.91**	0.0070	1.17	25.98	**0.98**
	90°C	0.022	2.17	16.50	0.89	0.017	0.47	18.81	**0.97**	0.0087	-1.68	27.5	**0.96**
1.5m/s	50°C	0.0068	1.35	19.08	**0.97**	0.0059	1.39	16.36	**0.94**	0.0021	1.66	19.97	**0.96**
	60°C	0.0135	-0.1	14.26	**0.93**	0.0061	0.89	24.89	**0.97**	0.0085	3.16	22.5	**0.96**
	70°C	0.0112	1.62	16.02	**0.93**	0.009	-0.51	24.49	**0.97**	0.0056	1.91	20.52	**0.96**
	80°C	0.0153	1.58	17.97	**0.96**	0.0106	0.22	27.08	**0.97**	0.0073	-0.69	24.84	**0.98**
	90°C	0.017	0.46	20.13	**0.96**	0.016	0.31	22.85	**0.95**	0.0190	-0.36	21.99	**0.93**

Table 3: Statistical results of feed- forward ANN

Hidden Layer		Transfer function			
		Tansig		Logsig	
Neuron in first hidden layer	Neuron in second hidden layer	R^2	RMSE	R^2	RMSE
2	-	0. 7946	2. 13307	0. 8558	1. 78606
4	-	0. 8069	2. 06640	0. 7220	2. 48193
6	-	0. 8891	1. 56525	0. 8381	1. 89209
8	-	**0. 9180**	**1. 34536**	**0. 9649**	**0. 87750**
10	-	**0. 9702**	**0. 80623**	**0. 9471**	**1. 07703**
12	-	**0. 9291**	**1. 24900**	**0. 9730**	**0. 76811**
14	-	**0. 9637**	**0. 86603**	**0. 9661**	**0. 86603**
16	-	**0. 9722**	**0. 78102**	**0. 9756**	**0. 73485**
18	-	**0. 9688**	**0. 82462**	**0. 9763**	**0. 72111**
20	-	**0. 9771**	**0. 70711**	**0. 9295**	**1. 24900**
2	1	0. 8647	1. 72916	0. 3116	3. 90512
4	2	0. 7639	2. 28473	0. 7864	2. 17486
6	3	0. 8836	1. 59687	0. 6815	2. 65518
8	4	**0. 9718**	**0. 79120**	**0. 9428**	**1. 12250**
10	5	**0. 9247**	**1. 29228**	**0. 9675**	**0. 84853**
12	6	**0. 9765**	**0. 72111**	0. 8554	1. 78885
14	7	**0. 9239**	**1. 29615**	0. 4516	3. 48569
16	8	0. 6512	2. 77489	0. 6322	2. 85482
18	9	0. 4746	3. 41306	**0. 9797**	**0. 67007**
20	10	***0. 9813***	***0. 64031***	**0. 9415**	**1. 13578**

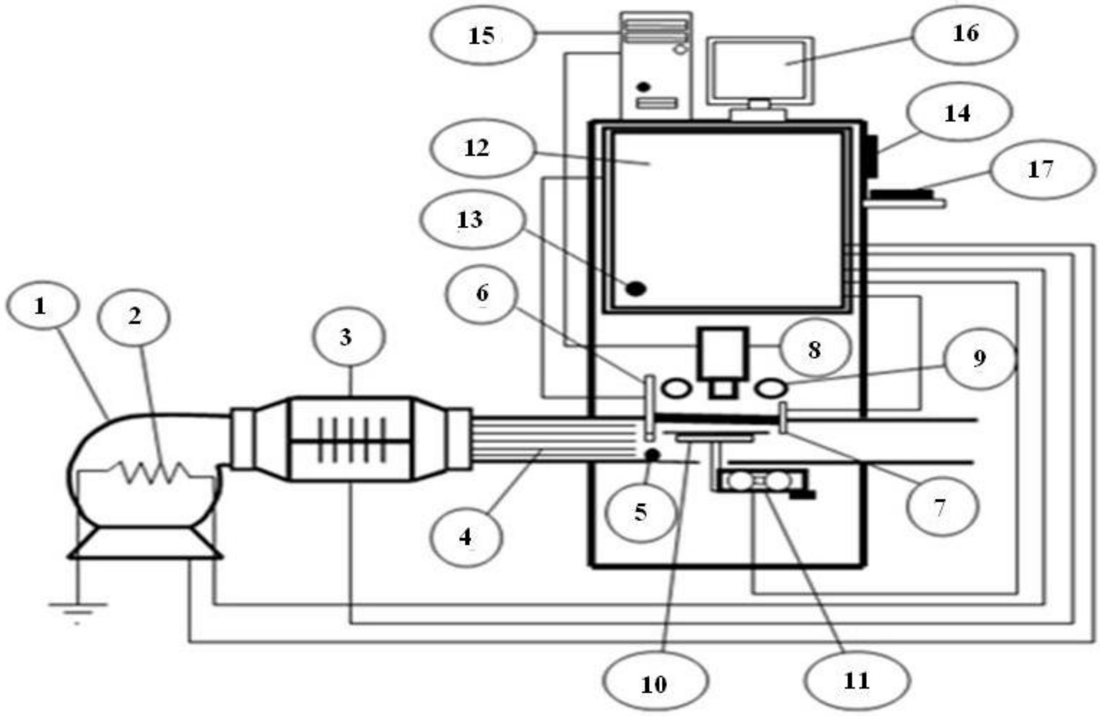

Fig.1. Experimental dryer: 1.fan; 2.preheating element; 3.heating elements; 4.straightener; 5.air velocity sensor; 6.relative humidity and temperature sensor; 7.temperature sensor; 8.digital color camera; 9.fluorescent lamps; 10.platform; 11.load cell; 12.control unit; 13.outside temperature sensor; 14.HMI; 15.computer; 16.monitor; 17.keyboard.

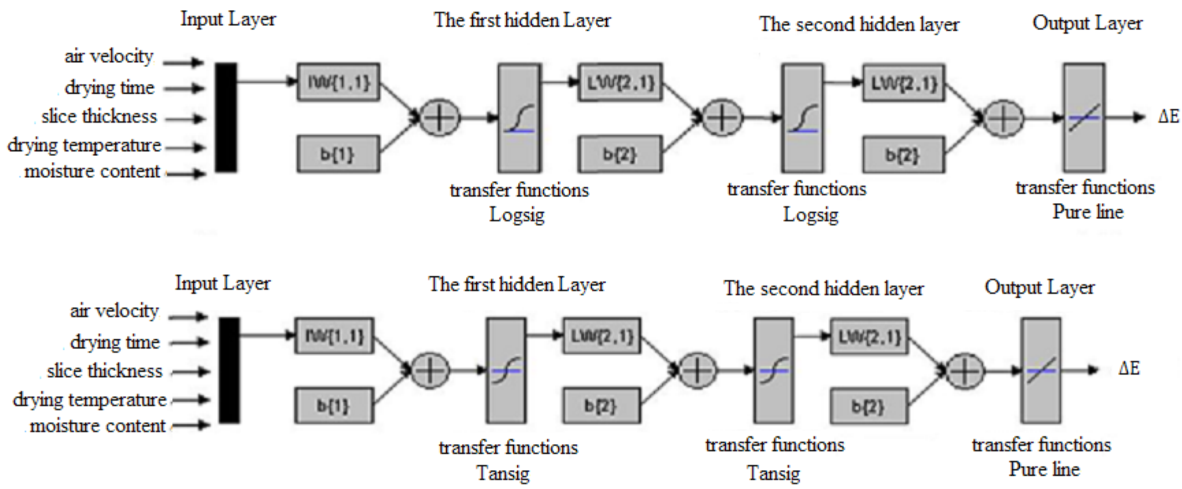

Fig.2. The schematic of the selected structure of the applied neural network

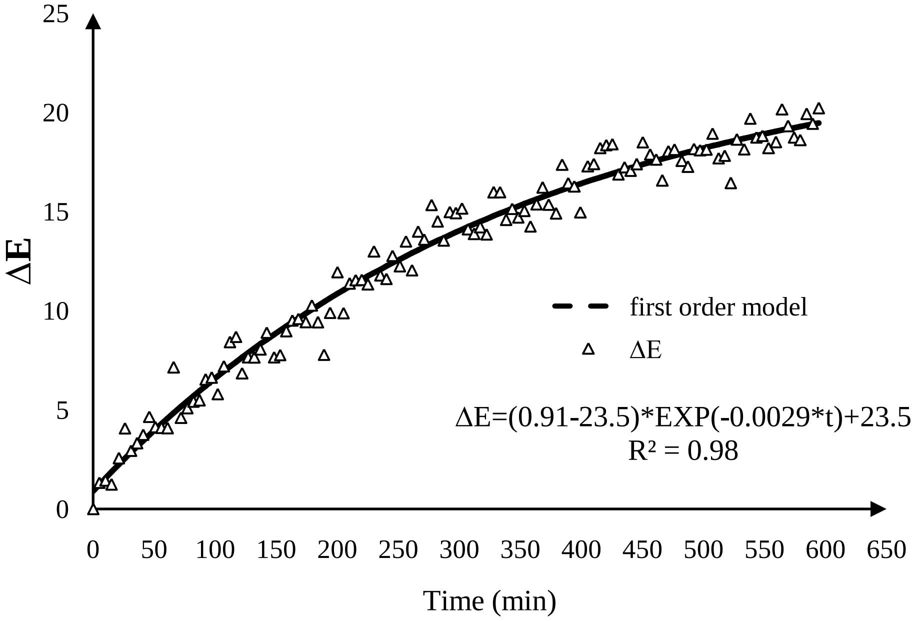

Fig.3. The model of change of the ΔE during drying time (air temp of 90°C, slice thick of 7mm, air velocity of 0.5 m/s)

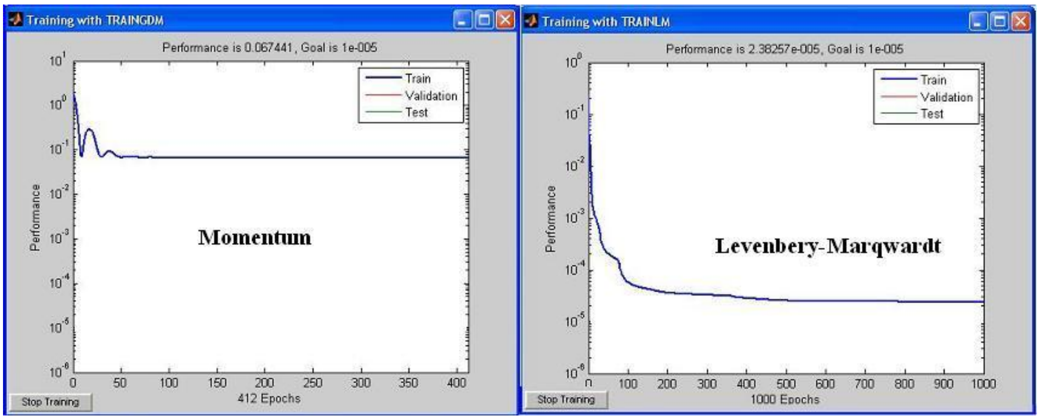

Fig.1. Comparing between learning role algorithms to reduce learning error

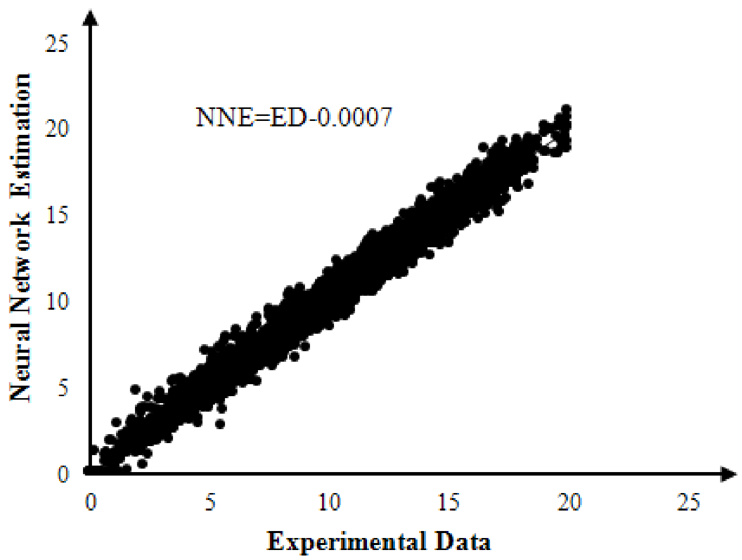

Fig.5. Ability of the neural networks to estimate the browning behavior of banana slices