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Application of Artificial Neural Network to Predict Colour Change, Shrinkage and Texture of Osmotically Dehydrated Pumpkin

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Abstract. The objectives of this study were to use Artificial Neural Network (ANN) to predict colour change, shrinkage and texture of osmotically dehydrated pumpkin slices. The effects of process variables such as concentration of osmotic solution, immersion temperature and immersion time on the above mentioned physical properties were studied. The colour of the samples was measured using a colorimeter and the net colour difference changes, ΔE were determined. The texture was measured in terms of hardness by using a Texture Analyzer. As for the shrinkage, displacement of volume method was applied and percentage of shrinkage was obtained in terms of volume changes. A feed-forward backpropagation network with sigmoidal function was developed and best network configuration was chosen based on the highest correlation coefficients between the experimental values versus predicted values. As a comparison, Response Surface Methodology (RSM) statistical analysis was also employed. The performances of both RSM and ANN modelling were evaluated based on absolute average deviation (AAD), correlation of determination (R^2) and root mean square error (RMSE). The results showed that ANN has higher prediction capability as compared to RSM. The relative importance of the variables on the physical properties were also determined by using connection weight approach in ANN. It was found that solution concentration showed the highest influence on all three physical properties.

1.Introduction

Pumpkin (Cucurbita pepo L.) has been used for human consumption and animal feed [1]. It is a fruit that can be taken fresh or cooked, or made into various kind of food such as soups, pies and bread. However, pumpkin is still considered as underrated fruits in the food industry. Nowadays, the increase of public awareness for a healthy lifestyle leads to the consumption of high nutritional and health related food material including processed pumpkin. Pumpkin is a good source of carotenoids, contains mainly α- carotene and β-carotene as well as minerals e.g potassium, phosphorus, magnesium, iron and selenium. Besides, it is also a low caloric food [2] and contains phenolics, flavonoids, polysaccharides, vitamins, and other substances that are good for health [3]. However, fresh pumpkin is very sensitive to microbial spoilage, even at refrigerated conditions, hence, it must be processed to dried or frozen products [4].

Drying is the most widely applied method to preserve fruits and vegetables. However, high heat can cause excessive damage to the foods. Hence, osmotic dehydration (OD) is often used as a pre-treatment before drying process. Osmotic dehydration is a method to partially reduce the moisture content of fruits or vegetables, with the purpose to extend the shelf life of food materials [5]. Due to the mild condition used, it can reduce the damage of heat to the flavour and colours of fruits or vegetables, prevent spoilage and reduce energy consumption. It had been applied to fruits such as apple, banana, kiwi fruits, mango and etc [6–10].

Dehydration process leads to alteration of chemical properties, nutritional values and physical properties of food products such as colour, food shape (shrinkage) and texture [9]. Colour of a food product is the most important quality parameter considered by the consumers, and it has high influence in the acceptance of a product [11]. This quality may be altered during processing, depending on the water content in foods, particularly dried foods. Studies conducted on the colour changes of fruits during OD were reported. For example, Falade et al. [12] investigated the effects of OD on the colour change of watermelon. It was observed that the colour intensity increase with the osmotic solution concentration. Krokida et al. [13] studied the colour changes of apple and banana during OD. Osmotically treated samples show less browning than untreated sample and lightness L decreased slightly, while redness a, yellowness b increased slightly. Another physical change of food during OD is shrinkage. The volume and food shape of products will be altered during the dehydration process [14]. Among studies reported on the volumetric shrinkage during OD, include strawberries [15], mango [16] and tomatoes [17]. Texture is a multi-parameter attributes and also one of the sensory property [18]. Several studies investigated the effect of OD on texture of some fruits, such as pineapple [19], apple [20], cucumber [21], strawberry [22], guava, melon and papaya [23].

Artificial neural network (ANN) modelling is commonly utilized due to its capability of relating the input and output parameter by learning from examples through iteration, without requiring a prior knowledge on the relationships between the process variables [24]. ANN has been applied successfully in modelling of physical properties of foods. Zenoozian et al. [25] used ANN and image analysis to predict the colour intensity (DE), shrinkage percentage as well as Heywood shape factor of osmotically dehydrated and air-dried pumpkin pieces. Zenoozian and Devahastin [26] also applied wavelet transform coupled with ANN to predict physicochemical properties of osmotically dehydrated pumpkin. Chen et al. [27] used multi-layer ANN models with three inputs (concentration of osmotic solution, temperature, and contact time) to predict five outputs (drying time, colour, texture, rehydration ratio, and hardness) during osmo-convective drying of blueberries. Youssefi et al.[28] employed ANN with three inputs (carrier type, carrier concentration, and concentration of crystalline cellulose) to predict the quality parameter of spray-dried pomegranate juice with five outputs (drying yield, solubility, colour change, total anthocyanin content, and antioxidant activity).

Response surface methodology (RSM) is a statistical technique used for experimental design, data analysis and modelling. It is widely used to investigate the relationship between process parameters and output, optimization of the operating conditions and responses in order to fulfil customer demands and target specifications [29]. There are numerous studies on the optimized conditions for osmotic dehydration process using RSM, such as papaya [30], diced green pepper [31], cantaloupe [32], pumpkin [33] and so on. However, only several studies on the prediction of physical properties of osmotic dehydration process have been published, such as potato [34] and Carrot [35].

2.Materials and Methods

2.1. Fresh Material

Pumpkins were purchased from a local market. The initial moisture content of the fresh pumpkin varied within 92 ± 0.2% (w.b.). Commercial sucrose and salt were also purchased from the local supermarket.

2.2. Experimental Procedure
At the beginning of each experiment, pumpkin was cleaned, peeled and cut into slab with dimensions of 60 mm x 15 mm x 5 mm. Osmotic solution with the desired concentration using commercial sucrose, sodium chloride solution and distilled water was prepared. The independent variables were sucrose concentration (30, 45 and 60°Brix), solution temperature (35, 50 and 65℃) and immersion time (90, 150 and 210 min). The range of process variables chosen were the typical range used in OD processes [9,36,37]. All osmotic solutions consist of 5%w/w sodium chloride. The concentration of osmotic solution was obtained using a refractometer. The experiment was conducted in a water bath (Memmert, WB 14) to maintain a constant temperature. The pumpkin to solution ratio was fixed at 1:10. The osmotic solution was agitated manually at every 30 minute interval to avoid localize dilution of sucrose solution. After the osmotic dehydration treatment, pumpkin slabs were removed from the osmotic solution and gently blotted with kitchen towel to remove excess sucrose solution, and kept in a sealed bag until experimental determinations. All the experiments were performed in triplicate, and the average value was used for the determination of colour changes, shrinkage and texture.

2.3. Determination of colour
Colour of pumpkin slabs were measured using Hunterlab Colorflex (Hunter Associates Laboratory Inc, Mumbai). The meter was calibrated using the manufacturer's standard white and black plate. The colour of L*a*b* values were obtained directly from the meter. The net colour difference (ΔE) was calculated with the equation 1 [38]:

$$\Delta E = \sqrt{(L_2^* - L_1^*)^2 + (a_2^* - a_1^*)^2 + (b_2^* - b_1^*)^2} \quad (1)$$

where L* represents lightness, a* represents redness and b* represents yellowness.

2.4. Shrinkage
To determine the shrinkage of osmotically dehydrated pumpkin slices, volume displacement method was used. Shrinkage is expressed in terms of the percentage change of the sample's volume as compared with its original volume [39].

$$\%S = \left(\frac{V_i - V_f}{V_i}\right) \times 100 \quad (2)$$

where V_i and V_f are the volumes of the samples at the starting and at the end of osmotic dehydration experiment.

2.5. Texture Profile Analysis (TPA)
For determination of sample's firmness, Texture Analyzer (TA.XT Plus, Stable Micro System Ltd, US) was used to measure the hardness of samples. All measurements were conducted at room temperature of 25℃. The maximum force measurement was carried out using a 5 kg loading cell and a knife blade probe (width 7 cm, thickness 3 mm). The test speed is 5.0 mm/s. The knife blade probe cut the samples placed on a mounted fixed table. The blade was lowered until almost contacted the surface of the plate. Each sample was cut one time and repeated 3 times with 3 samples for each condition.

2.6. Artificial Neural Network
In this study, Neural Network Toolbox 7.12.0 of MATLAB (Mathwork, 2011) software was used. A feed forward multi-layered ANN trained by back propagation (BP) algorithm was selected and trained with three input variables which were sucrose concentration, solution temperature and immersion time and colour changes, shrinkage and texture as the output of the model. The general scheme of the ANN network is shown in Fig1.

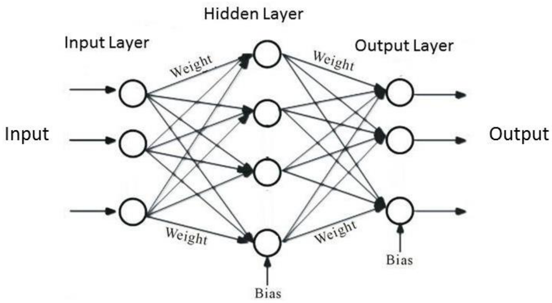

Figure 1. Structure of feed forward multi-layer ANN.

In this study, the tangent sigmoid transfer function (equation 3 and equation 4), and pure linear transfer function were applied at the hidden layer and output layer by trial and error method. The tangent sigmoid transfer function was selected as the activation function for both the hidden layer and the output layer, due to the lower calculated mean square error (MSE) when compared with linear function.

$$\mathrm{sig(x)} = \frac{1}{1+\mathrm{e}^{-\mathrm{x}}} \tag{3}$$

$$\tanh(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \tag{4}$$

In order to find the best networks, 27 sets of data were used for three different concentration, three temperatures and three immersion time. The data were randomly divided into three partitions, 70% in the training set, 15% in the validation set and 15% in the test set. The number of neurons varied from 3 to 12 were used in the hidden layer. The adopted learning function was “trainlm”. “Trainlm” is an iterative technique that updates the connection weight and bias values according to Levenberg-Marquardt (LM) algorithm. The training process was conducted for 1000 epochs. Both input and output variables were normalized between 0 to 1 for reduction of network error. The norrmalized equation applied is as follows:

$$Y_n = \frac{Y_a - Y_{min}}{Y_{max} - Y_{min}} \tag{5}$$

where Y_n, Y_a, Y_{min} and Y_{max} are normalized value, actual value, minimum value and maximum value, respectively. The evaluation of performance of the ANN was based on MSE and the highest correlation coefficients between the experimental values versus predicted values (R^2). This is to ensure the accuracy of the neural network to produce the output that are closer or equal to the experimental values.

2.7. Response Surface Methodology

A full factorial experimental design was generated with the Design-Expert 8.0.7.1 software. The same independent process variables were selected, i.e. sucrose concentration (X_1), solution temperature (X_2), and immersion time (X_3). A second order polynomial equation was used to fit experimental data and the quadratic model which includes the linear model can be described as:

$$Y = \beta_0 + \sum_{j=1}^{k} \beta_j x_j + \sum_{j=1}^{k} \beta_{jj} x_j^2 + \sum_{j=1}^{k} \beta_{ij} x_i x_j + e_i \tag{6}$$

where Y is the response; $\mathbf{x_i}$ and $\mathbf{x_j}$ are independent variables, $\boldsymbol{\beta_0}$, $\boldsymbol{\beta_i}$, $\boldsymbol{\beta_{ii}}$, $\boldsymbol{\beta_{ij}}$ are the regression coefficients for intercept, linear, quadratic and second-order terms, respectively; k is the number of parameters, and $\mathbf{e_i}$ is the error [40].

2.8. Comparison of RSM and ANN Performance

In order to evaluate the performance of RSM models and ANN models, error analysis was performed in terms of Root Mean Square Error (RMSE), Model Predictive Error (MPE), and Correlation of Determination (R^2) between predicted and experimental values.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(Y_{i,exp}-Y_{i,pred})^2}{n}} \quad (7)$$

$$\text{MPE}(\%) = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{(Y_{i,exp}-Y_{i,pred}}{Y_{i,pred}}\right| \quad (8)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_{i,pred}-Y_{i,exp})^2}{\sum_{i=1}^{n}(Y_{i,pred}-Y_{i,m})^2} \quad (9)$$

where $Y_{i,exp}$ was the experimental value of the *i*th experiment; $Y_{i,pred}$ was the predicted value of the *i*th experiment, n was the number of experiment and $Y_{i,m}$ was the average of the experimental value.

3.Result and Discussion

3.1. ANN modelling

The optimal number of neurons in the hidden layer of the neural network are examined by varying the number of neurons in the hidden layer using trial and error method. ANN optimization process need training to reduce the error function (MSE) by searching for a set of connection weights and bias that can enable the ANN to predict the more accurate outputs that are identical or closer to the experimental values. The error measures and correlation of determination (R^2) associated with different ANN configurations for estimations are presented in Table 1.

Table 1. Errors and correlation of determination (R^2) in prediction of net colour difference, shrinkage and texture using ANN with different numbers of neurons for osmotically dehydrated pumpkin slab.

No.	No. of neurons	Color Changes		Shrinkage		Texture	
		MSE	R^2	MSE	R^2	MSE	R^2
1	3	0.1977	0.9199	6.7322	0.9502	0.0066	0.9581
2	4	0.2210	0.9199	4.9030	0.9647	**0.0014**	**0.9926**
3	5	0.2033	0.9189	3.8146	0.9730	0.0025	0.9845
4	6	0.2916	0.8970	5.7380	0.9682	0.0142	0.9183
5	7	0.3276	0.8661	7.1610	0.9454	0.0020	0.9888
6	8	0.1406	0.9432	2.9180	0.9778	0.0041	0.9788
7	9	0.2371	0.9235	6.9280	0.9474	0.0023	0.9859
8	10	0.5140	0.8477	**2.6089**	**0.9804**	0.0074	0.9626
9	11	**0.1322**	**0.9457**	2.9397	0.9780	0.0052	0.9679
10	12	0.3448	0.8583	6.4621	0.9522	0.0120	0.9302

After several repetitions, it is found that a network with 11 hidden layers (colour changes), 10 hidden layers (shrinkage) and 4 hidden layers (texture) produce the best performance. The correlation of determination (R^2) for estimation of colour changes, shrinkage and texture (0.9457, 0.9804, and 0.9926, respectively) were revealed good agreement between predicted and experimental values.

The neural net weight matrix can be used to evaluate the relative importance of the input variables on the output variables. Garson et al. [41] proposed an equation based on the partitioning of connection weights:

$$I_j = \frac{\sum_{m=1}^{m=N_h}\left(\left(\left|W_{jm}^{ih}\right|/\sum_{k=1}^{N_i}\left|W_{km}^{ih}\right|\right)\times\left|W_{mn}^{ho}\right|\right)}{\sum_{k=1}^{k=N_i}\left\{\sum_{m=1}^{m=N_h}\left(\left|W_{km}^{ih}\right|/\sum_{k=1}^{N_i}\left|W_{km}^{ih}\right|\right)\times\left|W_{mn}^{ho}\right|\right\}} \quad (10)$$

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where I_j is the relative importance of the j^{th} input variable on the output variable, N_i and N_h are the numbers of input and hidden neurons, respectively, W is the connection weight, the superscripts "k", "m" and "n" refer to input, hidden and output neurons, respectively. The relative importance of the three input variables is shown in Table 2.

Table 2. Relative importance of input variables

Output Variable	Colour Changes	Shrinkage	Texture
Input Variable	Importance (%)	Importance (%)	Importance (%)
Concentration	41.47	36.06	48.88
Temperature	33.46	28.04	47.08
Time	25.07	35.90	4.04
Total	100	100	100

It can be seen that concentration has significantly affected the colour change of the samples compared to immersion temperature and time. For shrinkage, concentration and immersion time showed almost equal relative importance. As for the case of texture, concentration and temperature dominantly influence the property with immersion time showing only minimal effect.

3.2. RSM modelling

A quadratic polynomial equation was fitted with the experimental results obtained and the resulting RSM model equation is following:

$$\text{Colour} = 9.48974 - 0.1747 \text{ x } X_1 + 0.060052 \text{ x } X_2 - 9.88215 \text{ x } 10^{-3} \text{ x } X_3 + 2.01177 \text{ x } 10^{-3} \text{ x } X_1X_2 + 7.95101 \text{ x } 10^{-4} \text{ x } X_1X_3 + 2.86333 \text{ x } 10^{-4} \text{ x } X_2X_3 - 1.44471 \text{ x } 10^{-4} \text{ x } X_1^2 - 1.16503 \text{ x} 10^{-4} \text{ x } X_2^2 - 9.29399 \text{ x } 10^{-5} \text{ x } X_3^2 \quad (11)$$

$$\text{Shrinkage} = -46.9656 + 0.83909 \text{ x } X_1 + 1.90649 \text{ x } X_2 + 0.18509 \text{ x } X_3 + 5.5811 \text{ x } 10^{-3} \text{ x } X_1X_2 + 1.50907 \text{ x } 10^{-3} \text{ x } X_1X_3 - 4.74356 \text{ x } 10^{-4} \text{ x } X_2X_3 - 6.16985 \text{ x } 10^{-3} \text{ x } X_1^2 - 0.019982 X_2^2 - 4.31191 \text{ x } 10^{-4} \text{ x } X_3^2 \quad (12)$$

$$\text{Texture} = 2.46958 - 0.0178 \text{ x } X_1 - 0.026628 \text{ x } X_2 + 3.88043 \text{ x } 10^{-3} \text{ x } X_3 + 4.76255 \text{ x } 10^{-4} \text{ x } X_1X_2 + 1.26218 \text{ x } 10^{-4} \text{ x } X_1X_3 - 8.85556 \text{ x } 10^{-5} \text{ x } X_2X_3 - 7.85213 \text{ x } 10^{-5} \text{ x } X_1^2 - 1.74842 \text{ x } 10^{-5} \text{ x } X_2^2 - 5.38906 \text{ x } 10^{-6} \text{ x } X_3^2 \quad (13)$$

Table 3. ANOVA for the experimental results of the RSM modeling

Source	DF	Colour Changes			Shrinkage (%)			Texture (kg)		
		CE	SS	P value	CE	SS	P value	CE	SS	P value
Model	9	9.89	48.56	0.0012	60.92	3391.77	<0.0001	1.85	4.13	<0.0001
X_1	1	0.48	4.19	0.0526	11.84	2522.59	<0.0001	0.27	1.29	<0.0001
X_2	1	1.16	24.03	0.0001	1.32	31.59	0.0634	-0.30	1.66	<0.0001
X_3	1	0.74	9.85	0.0053	6	647.05	<0.0001	0.21	0.80	<0.0001
X_1X_2	1	0.45	2.46	0.1288	1.26	18.92	0.1426	0.11	0.14	0.0013
X_1X_3	1	0.72	6.14	0.0218	1.36	22.14	0.1147	0.11	0.15	0.0008
X_2X_3	1	0.26	0.8	0.3761	-0.43	2.19	0.6080	-0.080	0.076	0.0111
X_1^2	1	-0.033	6.34E-03	0.9363	-1.39	11.56	0.2459	-0.018	1.873E-03	0.6607
X_2^2	1	-0.26	0.41	0.5220	-4.5	121.28	0.0012	-3.934E-03	9.286E-05	0.9219
X_3^2	1	-0.33	0.67	0.4156	-1.55	14.46	0.1967	-0.019	2.258E-03	0.6300
Std. Dev		0.98			2.83			0.097		
Mean		9.47			55.96			1.83		
CV%		10.37			5.06			5.30		
PRESS		41.34			392.95			0.40		
Adeq.Prec		10.252			23.612			26.550		
R^2		0.7476			0.9614			0.9628		
Adj R^2		0.6140			0.9410			0.9431		
Pred R^2		0.3636			0.8886			0.9059		

DF – degree of freedom; CE – coefficient; SS – sum of square

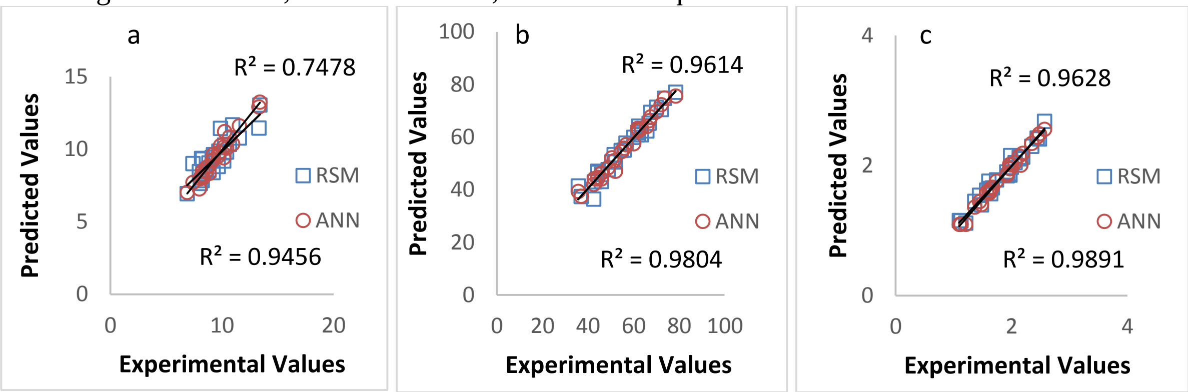

Figure 2. Experimental vs. predicted values for (a) colour change, (b) shrinkage percentage, (c) texture, by optimum RSM and ANN configuration respectively.

From equation 11, it can be seen that sucrose concentration and immersion time have negative effect on the colour changes while solution temperature has positive effect on colour changes of osmotically pumpkin slabs. From equation 12, both the three process variables have positive effect on the shrinkage percentage. However, from equation 13, sucrose concentration and solution temperature show negative effect, while immersion time shows positive effect on texture.

Table 3 shows the results of the second order polynomial model in the form of Analysis of Variance (ANOVA) and the equation indicated adequately relationship between the independent variables and the output variables. The ANOVA result for the color changes, shrinkage and texture indicates F-value of 5.59, 47.07 and 48.86 which proves that the model is significant. Coefficient of determination (R^2) was calculated to check the significance of the model and the values of R^2 were obtained to be 0.7476, 0.9614 and 0.9628 for color changes, shrinkage and texture respectively which imply the model is highly significant. In addition, p-value was obtained to be 0.0012 for colour changes, <0.0001 for shrinkage and texture, which indicates the proper fitting for the model. The coefficient of variation (CV%) measures the dispersion of the experiments values from the predictions values of the quadratic polynomial models [42].The values of CV are 10.37, 5.06 and 5.3 and these indicate the low deviation between the experimental and predicted values. Adequate precision (AP) refers to measures of the experimental signal to-noise ratio and AP exceeds 4 is desirable [43]. In this study, AP is found to be greater than 10, which implies good prediction of the model. Linear regression analysis was performed between the output variables (colour changes, shrinkage percentage and texture) values estimated by both RSM and ANN with their experimental values as shown in Figure 2.

3.3. Comparison of ANN and RSM models

The comparative values of RMSE, MPE (%) and R^2 of ANN and RSM has been calculated and listed in Table 4. The root mean square error (RMSE) for colour change by RSM and ANN is 0.779 and 0.364, the Model Predictive Error (MPE) is 6.319% and 2.874%, and the coefficient of determination (R^2) is 0.745 and 0.946. The RMSE for shrinkage by RSM and ANN is 2.245 and 1.615, the MPE is 3.360% and 2.092%, and the coefficient of determination (R^2) is 0.961 and 0.980. The RMSE for texture by RSM and ANN is 0.078 and 0.038, the Model Predictive Error (MPE) is 3.796% and 1.569%, the coefficient of determination (R^2) is 0.963 and 0.992. The results when compared with RSM showed that ANN has much better performance in correlating non-linear relationships. The same observation was also reported by Youssefi et al. [28].

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Table 4. Comparison between RSM and ANN

Statistical parameters	Color Changes		Shrinkage		Texture	
	RSM	ANN	RSM	ANN	RSM	ANN
RMSE	0.779	0.364	2.245	1.615	0.078	0.038
MPE (%)	6.319	2.874	3.360	2.092	3.796	1.569
R^2	0.745	0.946	0.961	0.980	0.963	0.992

The results of error prediction by RSM are larger than ANN, indicating that the ANN model has higher modelling and predictive ability than RSM. The higher predictive accuracy of ANN can be attributed to its universal ability to model non-linear system, while RSM only restricted to quadratic polynomial. RSM also requires a standard experimental design in order to construct the model. However, ANN model may require a greater number of experimental data and higher computation time than RSM [29,44].

4.Conclusion

This study compares the performance of RSM and ANN for their prediction capabilities using the experimental data of osmotically dehydrated pumpkin. The ANN models was found to have better predictive capabilities in color changes, shrinkage and texture after comparing RMSE, MPE and R^2 of both models. The structured nature of RSM provides the predicted quadratic equation to exhibit the factors contributions from the coefficient regression of the models. This ability is robust in identifying the significant and insignificant terms in the model and hence can reduce the complexity of the models. However, the ANN presents a better alternative in modelling and prediction.

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