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Monitoring the Osmotic Dehydration Process of Quince by the Novel Fusion Modular Neural Networks - Fuzzy Logic (FMNN-FL)

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Abstract

This paper presents a novel approach to monitor food process based on Modular Neural Networks (MNNs) and fuzzy inference system. The proposed MNN consists of three separate modules, each using different image features as input including: edge detection, wavelet transform, and Hough transform. The sugeno fuzzy inference system was used to combine the outputs from each of these modules to classify the images of quince during osmotic dehydration process. To test the method, for classification, database was made of 108 quince samples' images (12 classes). In experiments, the developed architecture achieved 91.6% recognition accuracy. Next step, solid gain, water loss and moisture content of quince samples were considered as MNNs outputs, whereas osmotic dehydration time and classified images were MNNs inputs. The minimum %MRE (18.153) with 89% prediction ability for water loss (WL) was obtained when applying two hidden layers with 6 neurons per each two layers. The lowest %MRE (35.5335) with 93% prediction ability for solid gain (SG) was obtained when using 6 and 8 neurons per first and second layer, respectively. And finally %MRE was at least (7.4759) with 96% prediction ability for moisture content (MC) by 6 and 5 neurons per first and second layer, respectively. The results show that this model could be commendably implemented for quantitative modeling and monitoring of food quality changes during osmotic dehydration process.

Keywords: Modular Neural Networks, Quince, Fuzzy Inference System, Osmotic Dehydration, Neural Networks

Introduction

Food monitoring is a very active area of study in many research institutes nowadays. Many methods have been developed for monitoring systems in food industry. Such systems usually look for some factors used in quality and process control. Among these methods, artificial neural networks, fuzzy logic, and image processing are new techniques to develop the monitoring systems in food technology. Computer vision is used for analyzing image to achieve information or to control food process (Pandit *et al*., 2005). It can also be a successful tool for classifying food products in different operations such as sorting, determination of ripeness, and grading

Computer vision has been used in many literatures for classifying. For example, Blasco *et al* (2009) classified and recognized 11 types of the most common external defects in citrus via computer vision systems. Near infrared reflectance and ultraviolet induced fluorescence of images were used as spectral information and they were combined with morphological estimations of defects in order to classify the fruits. A unified method was introduced to combine many features of images of fruits and vegetables to classify them with less training, this method was amenable to continuous learning, both when refining a learned model and also when adding new classes to be discriminated. The results presented that the solution reduced the classification error in up to 15 percent (Rocha *et al*, 2010). Different methods were utilized to classify the apple. Multilayer feed-forward artificial neural networks had the prediction ability of 97% and 99% for unripe and ripe categories, respectively (Alonso-salces *et al*.,

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2005). Crispiness of freeze-dried Durian was classified through imaging method and fuzzy logic. The physical changes of a freeze dried durian include the pores appearing in the images. Three physical features including (1) the diameters of pores (2) the ratio of the pore area and the remaining area and (3) the distribution of the pores are considered to contribute to the crispiness. The fuzzy logic was used for making the decision. The results showed that the accuracy of this method was 83.33 percent (Kanitthakun *et al*., 2007). Beans were classified by means of computer vision and artificial neural networks. The standard images were captured from beans and then images were coded in Matlab software for segmentation, morphological operation and colour quantification of the samples (Kılıç *et al*, 2007). For grading strawberries, machine-vision system was applied by Liming et al (2010), the features were shape, size and colour for grading. The results displayed that the error of size was not more than 5% and the preciseness of colour grading based on the a* channel was about 88.8% and the preciseness of shape sorting was over than 90%.

Also fuzzy set and neural network methods were useful to determine food process set points and classification. For example rice cake production was used as a model and its sensory characteristics were measured with a trained panel. New products were performed through the process set points and sensory characteristics of product matched the desirable sensory target values by less than 9% error. The results indicated the ability of fuzzy set idea and neural network method in sensory quality-based food process control (Kupongsak and Tan, 2006). The fuzzy method was studied for baby food and water quality estimation with an electronic tongue. The outcomes were displayed to the users similar to traffic light signal. Green light, red light and yellow light stand for good quality, bad quality and warning situation respectively (Iliev *et al*., 2006). A fuzzy traceability was applied to enhance the handling attributes in continuous production of liquid food. A real dairy line was used for demonstrating this method (Skoglund and Dejmek, 2007). Combining discriminate analysis and neural networks were used for corn variety identification. Five China corn varieties were identified according to their external features based on machine vision and pattern recognition. The classification accuracies were between 88 and 100% for different corn varieties (Chen *et al*., 2010).

Osmotic dehydration is widely used to remove part of the water content of fruit to achieve a product of intermediate moisture or as a pre-treatment before further processing (Lenart, 1996; Torreggiani & Bertolo, 2004). Osmotic dehydration is also used to treat fresh produce before further drying to improve sensory, functional and even nutritional properties. The shelf life quality of the final product is better than without such treatment due to the increase in sugar/acid ratio, the improvement in texture and the stability of the colour pigment during storage. Bchir (2009) studied osmotic dehydration of pomegranate seeds. Bchir (2009), Bui (2009), Abraão *et al* (2013), Abbasi Souraki *et al* (2013), da Silva *et al* (2014), Nowacka *et al* (2014), Silva *et al* (2014), Mauro *et al* (2015) and Derossi *et al* (2015) studied osmotic dehydration of pomegranate seeds, tomato slices, candied pumpkins, green bean, pineapple, kiwifruit, pineapple, cherry tomatoes and apple respectively in different osmotic solutions and conditions. Quince is a very ancient and delicious fruit. Iran is one of the leading growers of quince in the world. A few authors have been performed the quince dehydration. Koc *et al* (2007) worked to model the change of bulk density, porosity and shrinkage of quince during drying. Kaya *et al* (2007) illustrated the experimental study on the drying kinetics of quince. The objective of this research was to predict the solid gain, water loss, and moisture content of osmosed quince through the classified images and osmotic dehydration time as inputs of predictive module. The modular neural networks (MNNs) coupled with the fuzzy logic response integration (FLRI), as an effective tool, classified the images of osmosed quince before the predictive module. The hybrid application of MNN coupled with FLRI is firstly introduced in this paper to monitor the osmotic dehydration characteristics of quince.

Material and method

Class preparation

Quinces were washed and then cut into pieces with dimensions of 1.78 × 1.78 × 0.5 cm^3 as samples. We used the following three different osmotic solutions: 50%, 60%, and 70% (w/w) sucrose solution, (Merck, Darmstadt, Germany). Quince samples were put at two different temperatures, 25º C and 75º C. The ratio of osmotic solution to quince was maintained at 5:1 and 10:1 in volume in order not to dilute the osmotic solution by water removal from the sample during the experiments. The samples were kept in the osmotic solutions under the above mentioned conditions for 8 hours. And then they were left in equilibrium condition of osmotic dehydration for the next 16 hours.

Solid gain and water loss determination

Solid gain and water loss of quince samples (osmotically dehydrated into sucrose solutions) were calculated from the following equation:

$$\text{SG or WL} = \frac{m_0 x_0^i - m_t x_t^i}{m_0} \quad (1)$$

Where m_0 and X_0 are the initial mass of the sample and the initial mass fraction, respectively. m_t and X_t are the sample mass and the mass fraction at time t, respectively. Superscript i stand either for solid gain (for SG) or water loss (for WL) (Shafafi zenozian and Devahastin, 2009).

Image capturing System

An image acquisition system, consisting of four basic components; illuminating, camera, hardware, and software was used (Fig.1). A sample was illuminated using tube fluorescent lamp (Barmika, SCL-T9-32W., Taiwan) with the surface temperature of 65 °C and a colour reproduction index close to 95%. The tube lamp was installed on the ceiling of box to give an even uniform light intensity over the sample. Images of quince samples were captured directly by means of a digital camera (Olympyus, SP-565UZ, Vietnam) under dark background. The digital camera was set on top of the box (outside) and its distance from the samples was 3 cm. The dimensions of box were 53 × 55 × 19 cm^3. Images were captured at the resolution of 3648×2736 pixels.

Image Preprocessing

Preprocessing of image was performed to reduce the noise of images and clean the sides of main section of each image. This stage was done automatically before database creations for each ANN. Images dimension were 3648×2736 that we resized them to 2000×2000 pixels to reduce computing complexity. After resizing, first we used roicolor function in order to convert original images to binary format. It was created a predefined 2-D filter by fspecial function. It was applied the Laplacian 2-D Operator as the filter type, the Laplacian of an image highlights regions of rapid intensity change and is often used for edge detection and also it's used in order to reduce image's sensitivity to noise, so this filter provided the best results for our case study.

Finally, to select the region of interest, (ROI) roifilt2 (Filter Region of Interest) function was applied. In fact, the result of this reprocess is cleaning the noise and preparing the images to create the images database for each ANN. This approach was based on segmentation technique in which we can select the desired section of image. Database Creation

Database creation stage was really time consuming and sensitive. The inputs of this system were original images that could perform all necessary preprocesses for the modules and could provide inputs related to each artificial neural network. As mentioned before, original images had 2000×2000 pixels and after preprocessing, images were in gray scale and without any noise. Each module had specific database of images that was obtained from related feature selection.

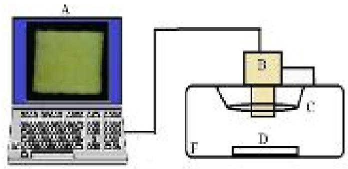

Fig. 1. Components of a computer vision system A: software and PC, B: digital camera, C: tube light, D: food sample, F: illumination box

After image preprocessing, dimension of each image change into 200×200 pixels. Fig. 2 depicts some databases of quince image's samples

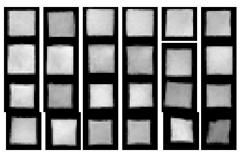

Fig. 2. Quince images from database

Modular neural networks

The designed system consisted of a modular neural networks occupied with three separate modules. Each module is given as input. The features extracted from different feature extraction techniques: edge detection, wavelet transform, and Hough transform. The responses were obtained from each module and then were combined by a sugeno fuzzy integral, i.e. this function determined the class to which the input image corresponds. Each image recognition system was developed by using modular neural networks (MNNs) conjugated with a sugeno fuzzy integral. As mentioned before, just an image was the input to recognize the class. In order to overcome some of the shortcomings of monolithic ANNs, several investigators have proposed modular approaches. MNNs were based on the general principle of divide-and-conquer, where one attempts to split a large problem into smaller sub-problems that are easier to analysis independently. Then these partial solutions are collected in order to achieve the comprehensive answer for the original problem (Beltran *et al*. 2009). In fact, only computed image features were extracted easily and underwent preprocessing, these features were: image edges, wavelet transform coefficients and the Hough transform matrix. The MNN was used to perform a very accurate discrimination of the input data applied in experimental tests. Therefore, it had been confirmed that a MNN system can solve difficult food recognition problems based on image processing by a simple set of image features. MNNs employed a parallel combination of several ANNs, and normally contained two main components: (1) local experts; and (2) an integrating unit. The basic architecture is seen in Fig.3. When using a modular network, a given task was dividing up among several local experts ANNs. The average load on each ANN was decreased in comparison with a single ANN that must learn the entire task, and thus the hybrid model might be able to overcome the weak points of a single ANN implementation. The output of a certain number of local experts (O_i) was mediated by an integration unit. The integration unit put the outputs together through estimated combination weights (g_i). The overall output Y was:

$$Y_i = \sum g_i o_i \tag{2}$$

The gating network used a softmax activation g_i of ith output unit given by Jordan and Jacobs (1994).

$$g_i = \frac{exp\,(u_i)}{\sum_j exp\,(u_i)} \tag{3}$$

Where u_i was the weighted sum of the inputs flowing to the ith output neuron of the gating network. Use of the softmax activation function in modular networks made a sort of "competitive" combining perspective because the ith local expert's output O_i with a minor activation u_i did not have a great impact on the overall output Y_i.

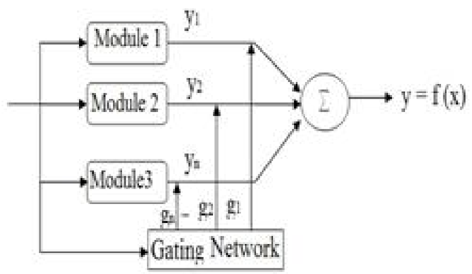

Fig. 3. Architecture of a modular network

Sugeno Fuzzy Integral

To integrate the results of the three features of an image, sugeno fuzzy integral was used to identify the class. Sugeno fuzzy integral is a nonlinear aggregation operator that can combine different sources of information. In order to replicate this process through an automatic system, a good model can be obtained via a fuzzy representation. The architecture of the fuzzy system used for this decision process has been displayed in Fig. 4.

Table 1 displays the complete set of fuzzy rules that has been used in the fuzzy system for image recognition. Three membership functions covered the range of its input for each feature selection. Sugeno fuzzy inference also had three constant values for the results; therefore, there are 27 rules made of output combination of these membership functions.

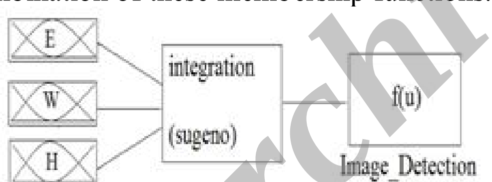

Fig. 4. Architecture of the Fuzzy system for quince image recognition E: Edge Detection, H: Hough Transform, W: Wavelet Transform

Feature extraction

In this research, three individual modules were used, and each received different image features extracted from the original image of quince samples. Mirzaei *et al* (2011) used edge detection, Curvelet transform and hough transform to offline signature recognition and Shafafi Zenoozian and Devahastin (2009) used wavelet transform to predict physicochemical properties of osmotically dehydrated pumpkin. We applied these ideas to extract image features in order to classify quince images during osmotic dehydration.

Table1. Fuzzy rule base for quince image recognition

Rule	Edge	Wavelet	Hough	Decision
1	A	A	A	A
2	A	A	B	A
3	A	A	C	A
4	A	B	A	A
5	A	B	B	B
6	A	B	C	B
7	A	C	A	A
8	A	C	B	C
9	A	C	C	C
10	B	A	A	A
11	B	A	B	B
12	B	A	C	A
13	B	B	A	B
14	B	B	B	B
15	B	B	C	B
16	B	C	A	C
17	B	C	B	B
18	B	C	C	C
19	C	A	A	A
20	C	A	B	A
21	C	A	C	C
22	C	B	A	B
23	C	B	B	B
24	C	B	C	C
25	C	C	A	C
26	C	C	B	C
27	C	C	C	C

A, B and C are the output value of each module

(Here three neural network modules and a Sugeno Fuzzy Integral were used to predict the results. Output of each neural network sends to Sugeno Fuzzy Integral as a Membership Function. Each membership function values are between 0 and 1. Set of fuzzy rules are needed for Sugeno Fuzzy Integral in order to make decision and finally predict the results base on values of membership function. Because in definition of fuzzy rules the value is not important and just being equal or not equal of output values of membership function is the matter, here the values are shown as A, B and C.)

Edge detection

For images of quince sample, the edges could capture lots of the internal structures. Hence, Canny edge detector was used for each image generating a binary image of edge pixels. Fig. 5 exhibits the original image of quince sample and image edges obtained via edge detection.

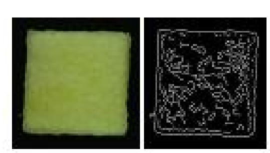

Fig. 5. (a) Original image and (b) Image edges of quince sample

Wavelet transform

The wavelet transform decomposes a signal through a family of orthogonal functions, it accounts for both the frequency and the spatial location at each point. The discrete wavelet transform (DWT) was used by a Haar wavelet. The DWT produces a matrix of wavelet coefficients that allows predicting the food properties (Shafafi Zenoozian and Devahastin, 2009)

Hough transform

The Hough transform matrix was applied as image features through the third module. The Hough transform could extract line segments from the image. Fig. 6 displays the Hough transform matrix for quince sample. In order to reduce the size of the matrix, and the size of the corresponding ANN, the information of the Hough matrix was reduced in size by resizing each image to 10% of its original size. Under these circumstances we have the small matrix with useful data. Thus, the computational burden decreased (Ballard, 1981).

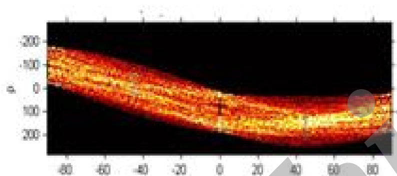

Fig. 6. Hough transform matrix for quince sample

Determination of Colour changes (ΔE)

The colour changes of the quince samples were monitored in terms of the total colour change (*ΔE*), which was calculated by:

$$\Delta E = [(\Delta L)^2 + (\Delta a)^2 + (\Delta b)^2]^{1/2} \qquad (4)$$

Where $\Delta L=L_0-L$, $\Delta a=a_0-a$, $\Delta b=b_0-b$. L, a, b corresponds to the color values of quince samples at the end of osmotic dehydration whereas L_0, a_0, b_0 are related to the quince samples before osmotic dehydration.

All algorithms for preprocessing of full images, segmentation of background and colour analysis were written by Matlab™ (version7.8.0.347)

Experimental Setup

There were three parameters including; temperature of 25 and 75º C, ratio of 1:5 and 1:10 and three sucrose solutions of 50, 60 and 70% w/w. Therefore, there were twelve classes. For each class, there were nine image samples. Eight images were related to first eight hours of osmotic dehydration and the ninth one was captured after 16 hours in equilibrium condition of osmotic dehydration. 108 images were available for all classes, from which 84 images, equal to 78% of total, were randomly selected for training and the remaining, 22% of total images, were considered for the test. Each input image was of 200×200 dimensions after preprocessing. Each monolithic neural network had these elements: 1- It was applied 100 neurons to the 1st layer; i. e. Input layer 2-There were 80 neurons at the 2nd layer; i. e. Hidden layer. 3- The output layer was left with 12 neurons occupied with TANSIG transfer functions. The training function updates weight and bias values according to the scaled conjugate gradient method (TRAINSCG) and adaptation learning function was gradient descent with momentum (TRAINGDM). One of the methods used for input vectors was Max-Min normalization method. This method mapped the range of original input to new range.

The designed system consisted of a modular neural network including three separate modules. Each module is given as input the features extracted from different feature extraction techniques: edge detection, wavelet transform and Hough transform. The responses were obtained from each module then they were combined through a sugeno fuzzy integral, i.e. this function determined the class to which was belonged to the input image corresponds. Therefore, it would have 27 rules that they can be constructed from combination of output of these membership functions. After recognition, the predictive module was conjugated. A general schematic of architecture is depicted in Figure 7.

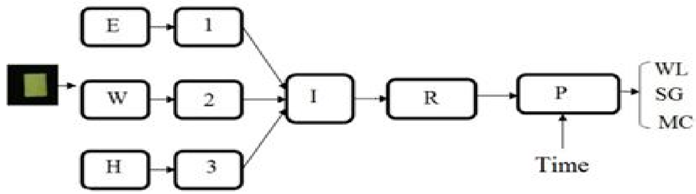

Fig. 7. General architecture of the proposed Modular Neural Network for image recognition and estimating parameters, E: Edge detection, H: Hough transform, I: Integrate or SFI, R: Recognition, P: Prediction Module, W: Wavelet transform, 1, 2 and 3 are modules.

The prediction module was developed by Matlab TM (version7.8.0.347) through the Neural Network Toolbox 4. As can be seen from Figure 3, the artificial neural network was simulated based on a multi-layer feed-forward algorithm. The classified images and drying time were applied as the ANN inputs, whereas the three factors (solid gain, water loss and moisture ratio) were the ANN outputs. Data sets of inputs and outputs consisted of sucrose solution (108 classes). Data set was subtracted into three groups, consisting of 58% for training, 22% for testing and 20% for validation. The number of neurons in the first hidden layer was fluctuated from 5 to 30. Also, the number of neurons in the second hidden layer was altered from 5 to 20. To realize the combination of hidden layers and neurons that produced the minimum error, a hyperbolic tangent (tansig) was used as the transfer function in each hidden layer while a linear transfer function (purelin) was applied in the output layer. The training procedure was the back-propagation technique. The input neurons were given the input data and the network gave its outputs. If the latter were not equal to the predicted outputs, the procedure calculated the differences (mean square error) between the two values and changed the weights in order to minimize them. These operations were repeated for each input pattern until the error was minimized. Minimization of error was done via the Levenberg– Marquardt algorithm (Bazaraa *et al*., 2006). Training was ended when the mean square error (MSE) converged and was less than 0.001. If the MSE did not go below 0.001, training was finished after 1000 epochs, where an epoch represents one complete sweep through all the data in the training set. The optimized configurations based on the training of each neuron were selected from thirty trial configurations based on the neural network performance, which introduced the minimum error from the training process. The percentage of relative mean square error (%MRE) was used to compare the performance of different ANN models as:

$$\%MRE = \left(\frac{1}{n}\sum_{i=1}^{N}\Delta P_R\right) \times 100 \qquad (5)$$

Where $\Delta P_R = |(Pp - P_E)/P_E|$, Pp is the predicted output for solid gain, moisture content and water loss and P_E is the experimentally measured outputs.

Result and discussion

Monolithic ANNs

The results for monolithic ANNs (Edge detection, wavelet and Hough features) are summarized in Table 2. This table depicts a corresponding identification number for each training case, the total epochs required to reach the goal error and the neurons in each hidden layer. Recognition performance is displayed with the correct number .Recognitions was acquired by 24 testing images, and the corresponding accuracy score. In this case, the best performance was accomplished in the seventh training run where the algorithm required 76 epochs, and the ANN exactly classified 17 of the quince testing images. The second monolithic ANN used the wavelet features as input. In this case the superlative performance was obtained in the eighth training run, through a total of 83 epochs, and 21 correctly classified images. It was noticeable that wavelet features gave an excellent discriminative description of the quince images that it was tested. The third monolithic ANN applied the Hough transform matrix and the consequence results are seen in Table 2. The best performance was achieved in the ninth training run, by means of total of 82 epochs and 20 correctly classified images. It is important to note that in all three cases, the monolithic methods did provide valuable results. The best performance was achieved via the wavelet features. The Hough transform matrix also led to acceptable results. On the other hand, the simple edge features yielded a less accurate recognition than the other two approaches. Beltran *et al* (2009) reported the same results i.e. accurate recognition at 87, 96 and 94% for edge detection, wavelet features and Hough transform in signature recognition, respectively. And Mirzaei *et al* (2011) reported accurate recognition at 83.3, 93.3 and 90% for edge detection, curvelet transform and Hough transform in signature recognition, respectively.

Modular neural network - sugeno fuzzy integral

The final experimental results correspond to the comprehensive MNN depicted in Fig. 4. Table 3 summarizes the results of ten independent training runs. With a brief glance, it can be clearly realized that Modular Neural Network achieves 91.66% accuracy and 22 corrected classified images 100-80 neurons. Having considered the information in Table 3, it can be easily inferred that when the neuron numbers were increased the accuracy was reduced significantly. Beltran *et al* (2009) and Mirzaei *et al* (2011) reported that using modular neural network lead to better accuracy in signature recognition in compare with Monolithic ANNs.

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Table 2. The best performance for monolithic ANN using edge, wavelet and Hough features

monolithic ANN	Neurons	Epochs	Time	Correct/Total	Accuracy (%)
Edge detection	100_80	76	00:02:11	17/24	70.83
Wavelet features	100_80	83	00:00:04	21/24	87.5
Hough transform	90_90	82	00:01:52	20/24	83.33

Table 3. Results for the modular neural network

No	Neurons	Correct/Total	Accuracy (%)
1	100_100	13/24	54.16
2	100_100	16/24	66.66
3	100_100	18/24	75
4	100_90	17/24	70.83
5	100_90	15/24	62.5
6	100_80	20/24	83.33
7	100_80	17/24	70.83
8	**100_80**	**22/24**	**91.66**
9	90_90	15/24	62.5
10	80_80	15/24	62.5

Solid gain and water loss

Water loss and solid gain of quince samples undergoing different osmotic condition are shown in Table 4. The osmotic pretreatments resulted in approximate maximum water loss and solid gain of 0.607 and 0.313 respectively. With a brief glance, it can vividly perceive that water loss and solid gain reveal an escalating trend when temperature and concentration of osmotic solution are accelerated. The increasing of water loss and solid gain with increasing in temperature and concentration of osmotic solution is resulted from the increase in the mass transfer throughout the osmotic solution. Irani *et al* (2010), Shafafi Zenoozian and Devahastin (2009) and Bui *et al* (2009) reported similar results for quince, pumpkins and tomatoes, respectively, immersing in sucrose solution

Moisture content(MC)

Table 4 indicates the final quince moisture contents. Regarding Table 4, it can be clearly realized that the moisture content of quince altered from 0.364 (T2R2S3) to 0.721 (T1R1S1) for each osmotic solution. When the sucrose concentration and temperature is increased, moisture content shows a reducing rate significantly. The similar outcomes were published by Shafafi-Zenoozian *et al* (2009) for osmotic dehydration of pumpkin in different osmotic solutions.

Colour change (ΔE)

The various ΔE values of quince samples are listed in Table 6. Having considered Table 4, it can be easily inferred that colour change values had fluctuating trend during osmotic dehydration through different conditions. Many reactions could be affected colour changes undergoing dehydration. Sucrose could contribute to colour change reactions. Chemical nature of the infused solute could be more important than for example, glass transition temperature in preventing colour changes. As far as, Table 4 is regarded the colour changes had not significant correlation with temperature and sucrose concentration. However, colour changes altered from 3.897 (T1R1S2) to 33.857 (T2R2S3). It can be supposed that assumed that polyphenol quince components might be affected the quince image colour changes for the duration of osmotic dehydration. These conclusions are confirmed by results of other researchers (Fathi *et al*., 2009).

Perdictive module

The results illustrated that the numbers of hidden layers and the number of neurons per hidden layer that gave minimum errors were distinctive for different osmotic solutions (Tables 5). As can be seen, the Table 5 shows the errors in the prediction of water loss with different neurons per layer. As far as, the Table 5 is regarded the minimum %MRE (18.153) for quince osmotically dehydrated was achieved when applying two hidden layers with 6 neurons per two each layers, correspondingly. Table 5 reveals the errors in the forecast of solid gain through different neurons per layer. Having surveyed in Table5, the lowest %MRE (35.5335) for solid gain was noticed when using 6 and 8 neurons per first and second layer, congruently.

Table 5 depicts the errors in the prediction of moisture content by different neurons per layer. It can be stated that minimum %MRE (7.4759) and maximum R^2 (0.96) for moisture content was obtained by 6 and 5 neurons per first and second layer, respectively. Also, the %MRE value shows reducing trend drastically when the neuron number is increased. On the other hand, the data for errors in the estimating of water loss had the greatest error (%MRE = 36.733) and lowest R^2 = 0.58 for water loss by 15 neuron at first layer. With a short glance in Table5, it can be vividly perceive that the highest %MRE (96.9622) and the lowest R^2 = 0.8 in support of solid gain was indicated when applying 20 and 15 neurons per first and second layer, correspondingly. As well as, the maximum %MRE was 49.5892 and lowest R^2 = 0.85 for moisture content. This value related to 10 and 10 neurons for each layers.

Plots of experimentally determined water loss, solid gain and moisture content against module predicted values are shown in Figures 8. Figure 8 depicts the water loss estimated results against water loss experimental data for test database of quince. Regarding the figure 8, it can be clearly realized that the data had good correlation, R^2 = 0.8945, for predicted water loss. Therefore, there were good agreements between the predicted and experimental values in all experiments. It was desirable to introduce a novel modeling method to estimate the quality parameters from the osmotic processing conditions. Figure 8 shows the comparison between the predicted and experimental solid gain of the optimum neural network module. Plotted points represent predicted versus experimental values, while solid line indicates a perfect fit between predicted versus experimental values. Hence, the predicted values were very close to the desired values in most cases (R^2= 0.933). Thus, this neural network model could be used to predict the solid gain of the product under the osmotic dehydration system. Figure 8 also shows that estimated moisture content depicted excellent relationship with experimental data (R^2= 0.9674). The proposed neural network had a good generalization in predicting the moisture content of the osmosed quince from the drying process. Also we used the method proposed by Haykin (1994) to detect overtraining involves monitoring the validation data set, and noting when the classification performance fails to improve by a user specified amount (e.g., 0.5 percent).

Conclusion

This paper stated that modular neural networks with fuzzy logic response integration can be used to monitor the physico-chemical properties of quince undergoing osmotic dehydration techniques in term of only quince image. This Model was found to produce excellent classification for monitoring of quince osmotic dehydration. Drying time and classified images extracted by modular neural network conjugated with sugeno fuzzy integral could be used as input variables for predicting some physicochemical properties of osmosed quince. A modular system was introduced through ANNs and three types of image features: edges, wavelet coefficients, and the Hough transform matrix. It is confirmed that the modular approach always outperforms, with varying degrees, the monolithic ANNs. If the recognition problem is made more difficult, the modular architecture will more clearly show a better overall performance than the monolithic ANNs.

The results of model also depicts that even with the simple image features utilized in this study, each of the ANN modules is capable of discriminating functions that can correctly differentiate between our set of quince images. Therefore, it can be concluded that modular architectures and more specifically developed system can present a suitable technique to provide an osmotic dehydration classification method. Generally, model results were in a good agreement with experimental data. It can be concluded that the optimized models could estimate moisture content, solid gain and water loss by R^2 values greater than 0.894 in all cases. As the final analysis, it can be inferred that proposed model was developed for prediction of characteristics of osmotically dehydrated quince for a broad collection of experimental conditions. All in all, this technique is user-friendly apply to control and automation of osmotic dehydration processes.

The results develop several possible extensions for future investigation. First, different integration systems can be conjugated with the MNN architecture illustrated here; e.g., fuzzy inference system.

Table. 4. Values of quince properties during different osmotic dehydration conditions. T: Temperature (T1=25°c, T2 =75°c), R: Ratio (R1=5:1, R2 =10:1), S: Sucrose Solution (S1 = 50, S2 = 60, S3 =70% (w/w))

Treatment	WL	SG	ΔE	MC
T1 R1 S1	0.309	0.110	8.372	0.721
T1 R1 S2	0.256	0.103	3.897	0.743
T1 R1 S3	0.378	0.125	6.855	0.681
T1 R2 S1	0.267	0.119	5.572	0.727
T1 R2 S2	0.326	0.114	22.168	0.711
T1 R2 S3	0.455	0.133	19.325	0.635
T2 R1 S1	0.405	0.236	11.775	0.581
T2 R1 S2	0.517	0.278	25.443	0.466
T2 R1 S3	0.553	0.294	8.542	0.455
T2 R2 S1	0.330	0.261	31.664	0.598
T2 R2 S2	0.511	0.293	21.416	0.472
T2 R2 S3	0.607	0.313	33.857	0.364

Table. 5. Errors in the prediction of water loss, solid gain and moisture content with different neurons per layer.

Number of neuron	Water Loss		Solid Gain		Moisture Content	
	% MRE	R^2	% MRE	R^2	% MRE	R^2
5	23.587	0.83	44.6252	0.89	31.1904	0.89
10	23.427	0.77	41.8083	0.90	31.7231	0.87
15	36.733	0.58	51.6627	0.93	21.6747	0.90
20	28.762	0.75	64.8402	0.90	33.6	0.82
30	18.432	0.75	66.5014	0.89	21.446	0.91
5,5	19.271	0.87	40.3239	0.88	32.269	0.90
6,5	21.134	0.88	67.8637	0.91	7.4759	0.96
6,6	18.153	0.894	37.7965	0.92	12.5957	0.94
6,8	21.372	0.84	35.5335	0.93	12.4182	0.90
7,7	25.505	0.84	66.4809	0.92	35.8878	0.94
7,10	24.111	0.86	60.8171	0.90	11.3447	0.95
10,10	21.625	0.75	38.7185	0.91	49.5892	0.85
10,15	23.613	0.83	58.0818	0.90	30.9929	0.85
10,20	21.145	0.84	96.6286	0.87	18.6132	0.95
15,10	21.412	0.58	82.4477	0.92	31.2878	0.89
15,15	28.026	0.81	77.0235	0.88	29.2697	0.94
15,20	25.233	0.79	48.9053	0.90	22.3799	0.92
20,10	25.236	0.84	40.1583	0.91	25.3514	0.93
20,15			96.9622	0.80	48.5492	0.64
20,20			115.035	0.86	26.2759	0.94

Second, it might be used to solve a closely related task, such as food image verification which uses a more difficult classification process. Finally, this system can be examined through a complicated image database, by using food dehydration images and a lower set of training food samples, in order to verify the robustness of technique.

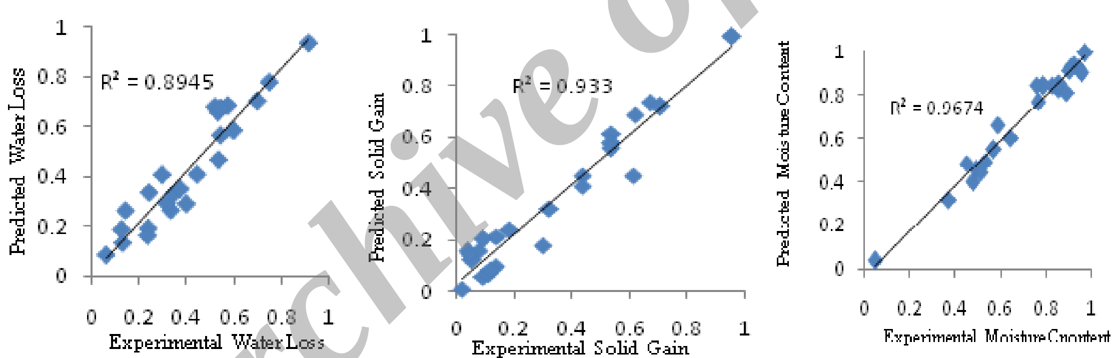

Fig.8. Experimental versus predicted values for water loss, solid gain and moisture content of osmotically dehydrated quince by optimum module.

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نشریه پژوهشهای علوم و صنایع غذایی ایران
جلد ۱۱، شماره ۳، مرداد - شهریور ۱۳۹۴، ص. ۲۵۹-۲۴۷

پایش فرآیند آبگیری اسمزی میوه به توسط روش ابداعی ترکیب مدول های شبکه عصبی- منطق فازی (FMNN-FL)

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چکیده

این مقاله روش جدیدی را بر پایه مودول های شبکه عصبی (MNNs) و سیستم استنتاج فازی جهت مونیتور کردن و کنترل فرآیند غذایی ارائه میدهد. MNN پیشنهاد شده متشکل از سه مودول است، هر یک از آنها مشخصه های مختلف تصویر را جهت ورددی استفاده میکنند، که شامل: edge detection، wavelet transform و Hough transform هستند. جهت ترکیب خروجی های مدول های شبکه عصبی در رابطه با طبقه بندی تصاویر میوه به در طی فرآیند آبگیری اسمزی از سیستم استنتاج فازی sugeno استفاده شد. جهت تست این روش، برای طبقه بندی، پایگاه داده از ۱۰۸ تصویر میوه به (۱۲ طبقه بندی یا کلاس) تشکیل شد. در آزمایشات صورت گرفته این روش توسعه یافته، طبقه بندی تصاویر را با دقت ۹۱/۶٪ تشخیص داد. در مرحله بعد، مقادیر جذب ماده جامد (SG)، میزان دفع آب (WL) و محتوای رطوبتی (MC) بعنوان خروجی مودول های شبکه عصبی در نظر گرفته شدند، در جاییکه زمان فرآیند آبگیری اسمزی و تصویر طبقه بندی شده بعنوان ورودی های شبکه عصبی در نظر گرفته شدند. حداقل MRE٪ (۱۸/۱۵۳) به همراه توانایی پیشگویی ۸۹٪ برای میزان دفع آب (WL) زمانیکه از دو لایه مخفی و در هر لایه ۶ نرون استفاده شد، بدست آمد. کمترین میزان MRE٪ (۳۵/۳۵۳۵) به همراه توانایی پیشگویی ۹۳٪ برای میزان جذب ماده جامد (SG) زمانیکه از از دولایه مخفی به نحوی که در لایه اول ۶ و در لایه دوم ۸ نرون استفاده شد، بدست آمد. و در نهایت برای محتوای رطوبتی (MC) حداقل MRE٪ (۷/۴۷۵۹) به همراه توانایی پیشگویی ۹۶٪ در استفاده از ۶ و ۵ نرون به ترتیب در لایه مخفی اول و دوم بدست آمد. نتایج نشان دادند که این روش بطور ستونی میتواند در جهت مدل سازی کیفی و مونیتور کردن تغیرات کیفی مواد غذایی در حین فرآیند آبگیری اسمزی مورد استفاده قرار بگیرد.

واژه‌های کلیدی: مودول های شبکه عصبی، میوه به، سیستم استنتاج فازی، آبگیری اسمزی، شبکه های عصبی

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