Prediction of Physical Parameters of Pumpkin Seeds Using Neural Network

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Abstract

The design of the machines and equipment used in harvest and post-harvest processing should be compatible with the physical, mechanical and rheological characteristics of the fruits and vegetables. In machine design for agricultural products, several characteristics of relevant products and seeds should be known ahead. Designers can either measure all these design parameters one by one, or they may use intelligent systems to estimate such parameters. Neural networks (NNs) are new computational tools that provide a quick and accurate means of physical properties prediction of agricultural materials, and have been shown to perform well in comparison with traditional methods. In this research, some physical properties of pumpkin (Cucurbita pepo L.) seeds, including linear dimensions, volume, surface and projected area, geometric mean diameter and sphericity were calculated tridimensional in lab conditions. Then, prediction of these parameters was carried out using NNs. The research was divided into two parts: experimental investigation and simulation analysis with NNs. Back Propagation Neural Network (BPNN) and Radial Basis Neural Network (RBNN) structures were employed to estimate physical parameters of the pumpkin seeds. The Root Mean Squared Error (RMSE) was 0.6875 for BPNN and 0.0025 for RBNN structures. The RBNN structure was superior in prediction and could be used as an alternative approach to conventional methods.

Keywords: agricultural products, computational system, Cucurbita pepo L., physical properties, prediction

Introduction

Pumpkin belongs to Cucurbitaceae family (Taylor and Brant, 2002; Cals, 2006). The majority of the species in this family are found in five genera. The genus Cucurbita includes five species: C. maxima, C. pepo, C. moschata, C. ficifolia, and C. turbaniformis in which C. pepo exhibits the widest variation (Gemrot et al., 2006; Ardabili et al., 2011).

Determination of the physical attributes of agricultural products is very significant for design of post-harvesting technologies and prediction of some essential parameters and characteristics correctly (Mohsenin, 1986). Physical attributes like geometric mean diameter, sphericity, grain trajectory, surface area, grain volumetric and specific weight, density, porosity and colour are used to design processes and equipment for product processing, transportation, screening, storage and drying-like processes (Tabatabaeefar and Rajabipour, 2005). In addition, determination of the physical attributes is used in terms of the final product quality evaluation and classification of different types (Taner et al., 2015). It also allows planning and controlling the above processes and gives a possibility of selecting parameters to functioning of devices and machines (Kalniniewicz et al., 2014). The information on the size and forms of farming components is essential to plan sizing, harvesting, separation, planting and handling devices (Sahay and Singh, 2004). Design of pneumatic separation devices requires surface and projected area (Bwade and Aliyu, 2012).

NNs have been used in various disciplines like hydrology (Aksoy and Mohammadi, 2016), renewable and sustainable energy (Ara, 2015), robotics and computer-integrated manufacturing (Chen and Wang, 2016), robotics and autonomous systems (Woodford et al., 2017). Some application areas in agriculture are data prediction (Šťastný et al., 2011), classification of agricultural products (Shahin et al., 2002; Khalesi et al., 2012; Doust et al., 2013; Reshadsedghi et al., 2014), food and crop analysis (El-Sanhoty et al., 2006; Monteiro et al., 2007), drying process (Khazaei et al., 2013), precise weed detection and weed seeds identification (Granitto et al., 2017).
In this investigation, feed forward neural network model was applied to estimate some physical parameters of pumpkin seeds. Fig. 2 presents schematic illustration of neural network predictor.

\[ jf = \sum w_{ij} \cdot f_i + b_j \]

where \( jf \) is the output of the \( j \)th neuron, \( w_{ij} \) is the weight of the relation between the input and hidden layer neurons, \( b_j \) is the bias of the \( j \)th neuron in the hidden layer. The function \( g(.) \) is named as the hidden layer transfer function. The network output signal can be described in the following design:

\[ y_k = g \left( \sum w_{kj} \cdot f_j + b_k \right) \]

where \( w_{kj} \) are the weights between \( j \)th neurons and \( k \)th neurons, \( b_k \) is the bias of the \( k \)th neurons in the output layer (Soylak et al., 2015). Two learning algorithms which are applied to predict parameters of pumpkin seeds, concisely depicted in the bellowing subdivisions. During the analysis, NeuralWorks Professional II/Plus software was used.

**Back Propagation Neural Network**

The BPNN is a type of multi-layered feed forward network. The BPNN is composed of at least three layers every time: input layer, hidden layer/layers and output layer. The BPNN is generally employed to revise the weights of the BPNN. The weights between input and hidden layers are revised as follows:

\[ \Delta w_{ij}(t) = -\eta \frac{\partial E(t)}{\partial w_{ij}(t)} + \alpha \Delta w_{ij}(t-1) \]

The weights between the hidden and output layer are revised in the following function:

\[ \Delta w_{kj}(t) = -\eta \frac{\partial E(t)}{\partial w_{kj}(t)} + \alpha \Delta w_{kj}(t-1) \]

where \( \eta \) is the learning coefficient, and \( \alpha \) is the momentum coefficient, \( E_j(t) \) is the propagation error and \( E_j(t) \) is the error between calculated and BPNN output signals.
Radial Basis Function Neural Network

RBNN with a hidden layer are able to perform universal approximation. The hidden layer consists of Gaussian equation modules. The Gaussian equation, \( \psi_i \), is determined as the following function (Yıldırım et al., 2013):

\[
\psi_i = \exp\left( -\frac{\|x - c_i\|^2}{\sigma_i^2} \right)
\]

where \( x \) is the vector of an input sample, \( c_i \) is the vector of the centre of the \( i \)-th module and \( \sigma_i^2 \) is the variance of the \( i \)-th module. The output layer integrates the Gaussian domains produced by the hidden modules. The output signal of the \( m \)-th module, \( r_m \), is determined with the following function:

\[
r_m = \sum_{i} w_{im} \psi_i
\]

where \( w_{im} \) is the weight from the \( i \)-th module to the \( m \)-th output module.

Results and Discussion

Results of the BPNN structure used in prediction of the average geometric diameter and sphericity of the pumpkin seeds are presented in Fig. 3. The error values of the BPNN predictor were quite high. Results of the BPNN structure used in prediction of the shape index and surface area of the pumpkin seeds are provided in Fig. 4. The results of the predictor were not good enough. The last physical properties for which the BPNN structure used as a predictor were volume and projected area (see Fig. 5). As seen in Fig. 3, 4 and 5, the BPNN algorithm was not a useful tool to predict the physical parameters of pumpkin seeds. BPNN structure has a quite slow learning ability. Since this NN structure try to reduce the errors from output to input, the learning is quite slow due to the back propagation. BPNN structure usually found to be insufficient in estimation of seed physical parameters for the same iteration period. Therefore RBNN structure with a different learning algorithm was employed to estimate relevant parameters.

Results for geometric mean diameter and sphericity prediction for this algorithm are given in Fig. 6. As seen in Fig. 6, results of the RBNN predictor were pretty good. Results for the shape index and surface area prediction for this algorithm are given in Fig. 7, volume and projected area in Fig. 8. According to the simulation results, it is obvious that in prediction of the related physical parameters, the RBNN structure was more successful than the BPNN structure (see Table 1). RBNN structure has some superiority over the other NN structures such as faster convergence, smaller extrapolation errors, and higher reliabilities. RBNN is a class of single hidden layer feedforward networks where the activation functions for hidden units are defined as radially symmetric basis functions such as the Gaussian function. Thus, the RBNN can be used in prediction of such physical parameters of agricultural production.

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Fig. 4. (a) Experimental and prediction results of shape index parameter using the BPNN structure; (b) Experimental and prediction results of surface area parameter using the BPNN structure

Fig. 5. (a) Experimental and prediction results of volume parameter using the BPNN structure; (b) Experimental and prediction results of projected area parameter using the BPNN structure

Fig. 6. (a) Experimental and prediction results of geometric mean diameter parameter using the RBNN structure; (b) Experimental and prediction results of sphericity parameter using the RBNN structure

Fig. 7. (a) Experimental and prediction results of shape index parameter using the RBNN structure; (b) Experimental and prediction results of surface area parameter using the RBNN structure
Similar to the results of the present research, the high performance of different NN structures in prediction or estimation of agricultural objectives was reported by Alvarez (2009), Dai X et al. (2011), Khoshnevisan et al. (2014), Rad et al. (2015), Taner et al. (2015), Shafaei et al. (2016).

**Conclusions**

Working with too many samples is both a time-consuming and a costly process. It also brings together various measurement errors. Right at this point, NNs can provide a great alternative to overcome such time-consuming, costly and erroneous processes. Therefore, NN structures were employed to estimate physical characteristics of pumpkin seeds from easily identified characteristics. In this study, some physical parameters of pumpkin seeds were predicted by two different NN structures. The RBNN had superior performance to predict different physical parameters of the pumpkin seeds. RBNN have some advantages also as of: they minimize the possibility of error and hence the hypothesis of linear behaviour is no longer required. RBNN structure of the present study provided high-accuracy outcomes and also great time and cost savings. For that reason, the RBNN could be employed to predict such physical parameters in agricultural applications.

**References**


