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ORIGINAL ARTICLE

Prediction of Walnut Mass Based on Physical Attributes by Artificial Neural Network (ANN)

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Abstract
Several researchers have investigated the relationships among different physical attributes of the fruits. For proper design and operation of grading systems, important relationships among the mass and other properties of fruits such as length, width, thickness, arithmetic mean diameter, geometric mean diameter, sphericity, surface area, volume, projected area, shape index, aspect ratio and elongations must be known. Recent researches have focused on artificial neural network (ANN) approaches to predict hard-to-find attributes of the fruits from easily-determined and readily available values. In this study, Modular Neural Network (MNN) and Radial Basis Neural Network (RBNN) structures of Artificial Neural Network (ANN) were employed to predict walnut mass from the physical attributes of the walnuts. Root mean square errors (RMSE) of MNN structure ranged from 0.60 to 0.89, while RMSE of RBNN structure were found to be very low (0.0002) in all of walnut varieties. These results showed that RBNN structures of Artificial Neural Network could potentially be used to estimate mass of walnuts and various physical attributes of walnuts were sufficient to predict the mass characteristics of a walnut.

Keywords Artificial Neural Network (ANN) · mass estimation · sizing

Prognose des Fruchtgewichts von Walnüssen anhand physikalischer Fruchteigenschaften mittels Künstlicher Neuronaler Netze

Schlüsselwörter Artifizielles (Künstliches) Neuronales Netzwerk (ANN) · Fruchtgewicht · Walnuss

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Introduction

Walnuts (*Juglans regia* L.) are quite rich in several nutrients and thus cultivated in various parts of the world (Shah et al. 2018). Walnuts are the most popular nuts and used either as an individual foodstuff or as an ingredient in various food products (Eliseeva et al. 2017).

Turkey has an important position in the world in terms of walnut production. World annual production is 3,747,549 T and Chine is the leading producer with an annual production of 1,785,879 T corresponding to about 47% of world production. Chine is respectively followed by the USA (607,814 T), Iran (405,281 T) and Turkey (195,000 T) (FAO 2016).

Walnuts have quite high content and a rich nutritional composition (Altuntaş and Erkol 2010). Kernels are rich in proteins and lipids (corresponding about 85% of total kernel weight) (Sze-Tao and Sathe 2000). Besides proteins and lipids, walnut kernels are also rich in riboflavin, thiamine,

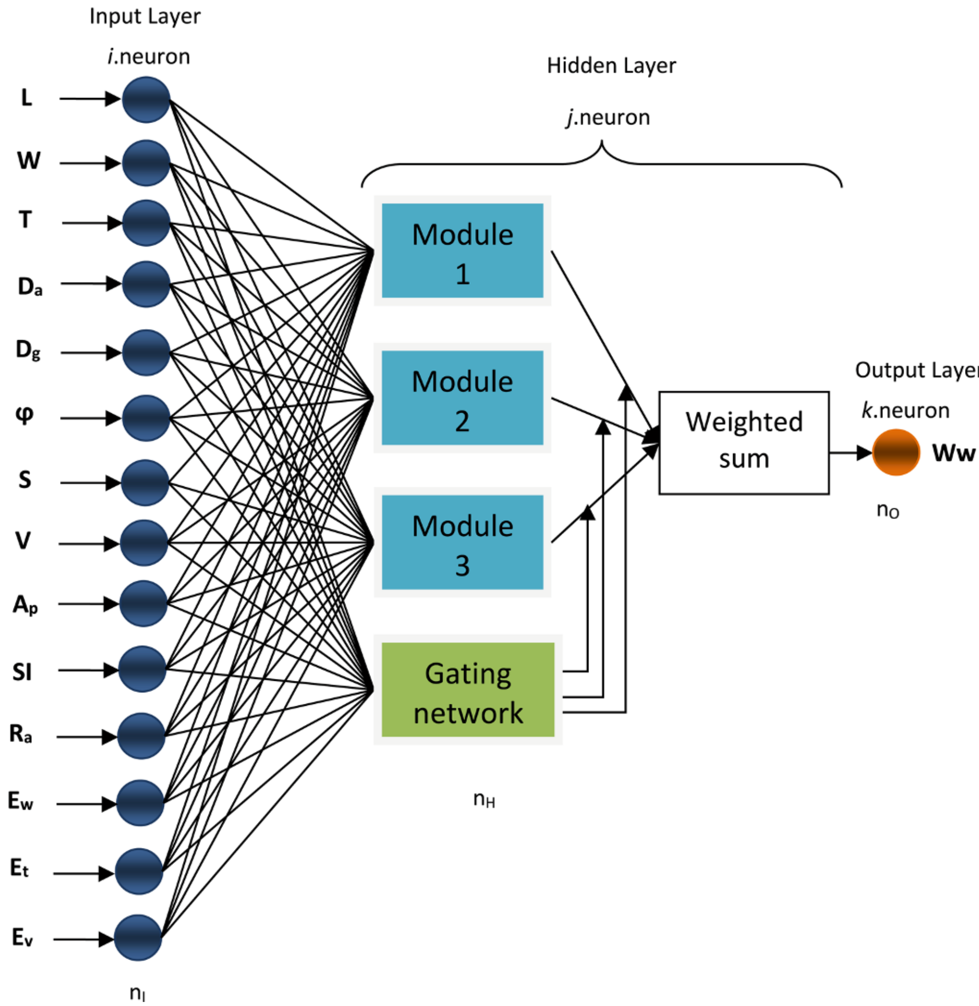


Fig. 1 Schematic illustration of the MNN predictor

niacin, vitamin B6 and E, folic acid, potassium, phosphorus, iron, magnesium (Wardlaw 1999). Therefore, they play significant roles in human nutrition and thus FAO listed walnuts among the priority plants (Gandev 2007; Taha and Al-wadaan 2011; Ikhsan et al. 2016).

Usually the fruits with the similar weight and uniform shape are preferred in markets (Naderi-Boldaji et al. 2008). Consumers also prefer the same fruits with equal size and shape (Rashidi and Keshavarzpour 2012). Fruit size classification based on fruit mass is a significant parameter used in packaging and processing of agricultural commodities (Ashtiani et al. 2014). Such sizing or size classifications require mechanical or electronic mechanisms. While electronic sizing mechanisms are quite expensive processes, mechanical sizing mechanisms are quite time-consuming slow processes. Thus, previous researchers indicated that some easily-determined geometric properties could be used to estimate fruit mass (Mohsenin 1986; Tabatabaeefar and Rajabipour 2005; Khoshnam et al. 2007; Hassan-Beygi et al. 2010).

Fruit sizing systems commonly employ physical dimensions, volume, mass, projected area and surface areas (Ashtiani et al. 2014). Fruit physical attributes and the relationships among them should be investigated for the design and optimization of post-harvest operations (transportation, sorting, packaging, classification, and etc.) (Ercisli et al. 2012; Ashtiani et al. 2014). Such relationships can also be used in machine design for post-harvest processes, especially to design mass-based sorting machines. Fruit physical dimensions and projected areas can be used to estimate fruit mass (Stroshine and Hamann 1994; Naderi-Boldaji et al. 2008; Ghabel et al. 2010).

Mass and volume estimations from easily-measured physical attributes enhance the design and operation of post-harvest sorting machines and processes (Gonzalez et al. 2017). Several researchers reported that artificial neural network (ANN) models yielded quite better outcomes than traditional methods (Moosavi and Sepaskha 2012; Demir et al. 2017; Kus et al. 2017; Shabani et al. 2017) in estimation of fruit characteristics.

Sabzi et al. (2013) employed ANFIS (Adaptive-Network-based Fuzzy Inference System) and linear regression models to predict the fruit mass from sphericity and projected areas. Rad et al. (2015) predicted the final fruit weight of melon plants by applying the Artificial Neural Network models. Schulze et al. (2015) applied three different models (SLR—Simple Linear Regression, MLR—Multiple Linear Regression and ANN—Artificial Neural Network) to estimate mango fruit mass from geometric dimensions and compared the quality of estimation and robustness of the models for calibration and validation. Javadikia et al. (2017) employed ANFIS method for mass modeling of three varieties of oranges based on fourteen physical attributes.

Walnut cultivars are distinguished by nut characteristics and fruit dimensions. Size, mass, color, and shape are the most significant physical attributes used in distinguishing the fruits from one another (Yarilgaç et al. 2001; Ercisli et al. 2012). A detailed study about mass predicting of walnut fruits with MNN and RBNN structures of ANN was not come across in literature. Therefore, this study was conducted to estimate fruit mass of walnuts from physical attributes with RBNN (Radial Basis Neural Network) structure of Artificial Neural Network (ANN) and RBNN structure was compared with MNN (Modular Neural Network) structure.

Material and Methods

In this study, 10 common Walnut (*Juglans regia* L.) cultivars ('Yalova-1', 'Bilecik', 'Fernor', 'Maraş-12', 'Maraş-18', 'Kaman-1', 'Fernette', 'Sunland', 'Yalova-3' and 'Şen-2') supplied from Eğirdir Fruit Research Institute in 2016 harvest season were used as the plant material.

All measurements were performed in accordance with the UPOV (2015) descriptors established for physical properties of walnuts as the quality criteria. The mass of each walnut fruit (W_W) was measured using a digital balance (±0.001 g). Three linear dimensions (Length—L, Width—W and Thickness—T) were measured by using a digital caliper (±0.001 mm).

The arithmetic mean diameter (D_a, mm), geometric mean diameter (D_g, mm) and sphericity (ϕ, %) were calculated using the following equations (Mohsenin 1986):

$$D_a = \frac{L + W + T}{3}$$

$$D_g = (LWT)^{1/3}$$

$$\phi = \left(\frac{D_g}{L}\right) \times 100$$

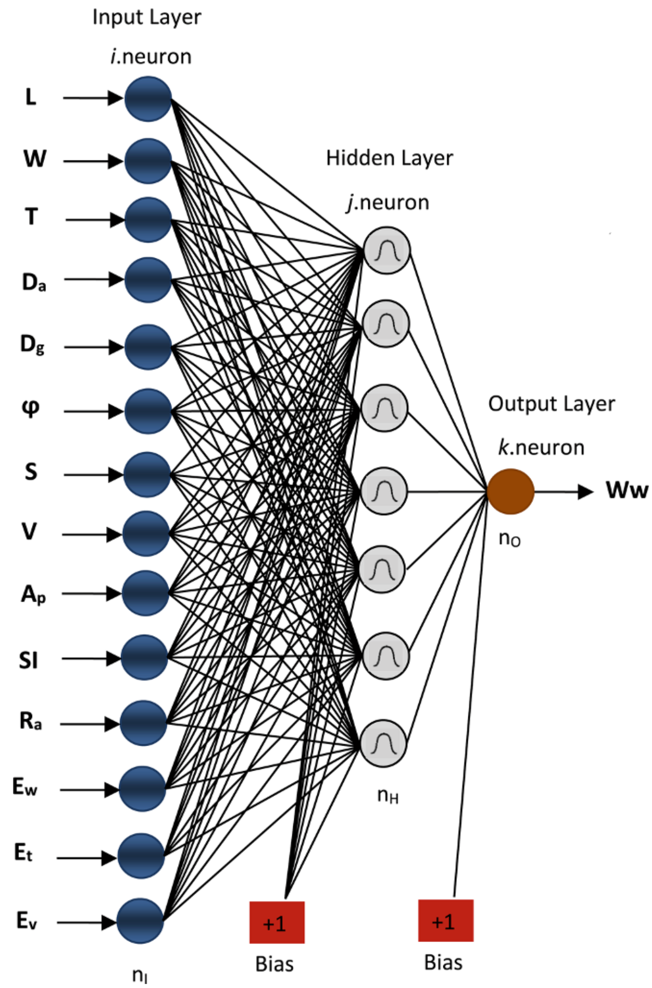


Fig. 2 Schematic illustration of the RBNN predictor

The surface area (S, mm^2) was calculated from the following equation (McCabe et al. 1986):

$$S = \pi D_g^2$$

The volume (V, mm^3) was calculated from the following equation (Ercisli et al. 2012):

$$V = \left(\frac{\pi}{6}\right) \times D_g^3$$

The projected area (A_p, mm^2) was calculated by using the following equation (Afonso Junior et al. 2007):

$$A_p = \left(\frac{\pi}{4}\right) \times D_g^2$$

The shape index (SI) was calculated with the following equation (Ozkan and Koyuncu 2005):

$$SI = \frac{2L}{(W + T)}$$

Table 1 Neural network parameters of the Modular Neural Network (MNN) and Radial Basis Neural Network (RBNN) structure

NN Type	η	α	*N*	n_I	n_H	n_O	g(.)	RMSEs	
MNN	0.25	0.3	10,000,000	14	7	1	Sigmoid	Yalova-1	0.73
								Bilecik	0.82
								Fernor	0.86
								Maraş-12	0.65
								Maraş-18	0.60
								Kaman-1	0.76
								Fernette	0.88
								Sunland	0.86
								Yalova-3	0.89
								Şen-2	0.87
RBNN	0.25	0.3	10,000,000	14	7	1	Sigmoid	Yalova-1	0.0002
								Bilecik	0.0002
								Fernor	0.0002
								Maraş-12	0.0002
								Maraş-18	0.0002
								Kaman-1	0.0002
								Fernette	0.0002
								Sunland	0.0002
								Yalova-3	0.0002
								Şen-2	0.0002

η Learning rate, α Momentum term, *N* Iteration number, n_I Number of the neuron in the input layer, n_H Number of the neuron in the hidden layer, n_O Number of the neuron in the output layer, *g(.)* Activation function, *RMSEs* Root Mean Square Errors

The aspect ratio (R_a) was calculated using the following equation (Mohsenin 1986):

$$R_a = \left(\frac{W}{L}\right) \times 100$$

The elongation was calculated for three orientations from the following equations (Fıratlıgil-Durmuş et al. 2010):

- Elongation at the width orientation (E_w):

$$E_w = \frac{L}{W}$$

- Elongation at the thickness orientation (E_t):

$$E_t = \frac{L}{T}$$

- Elongation at the vertical orientation (E_v):

$$E_v = \frac{W}{T}$$

Artificial Neural Networks

In this experimental and simulation study, feed forward neural network type was used to predict the walnut weights. Figs. 1 and 2 shows the schematic representation of neural network estimator. Two learning algorithms which are employed to estimate the walnuts weights, concisely depicted in the bellowing subdivisions.

Modular Neural Network (MNN)

MNN refer to the adaptive mixtures of local networks. Each local network receives the same input vector applied to the network. A gating network determines the contribution of each local network to the total output as well as what range of the input space each network should learn. The outputs of the local networks are combined to give the network output such that:

$$y_k = \sum_{j=1}^{14} g_j y_j \tag{1}$$

where y_j are the output of the j^{th} local network and y_j are the normalized output vector elements of the gating network given by:

$$g_j = \frac{e^{u_n}}{\sum_{j=1}^{14} e^{u_j}} \tag{2}$$

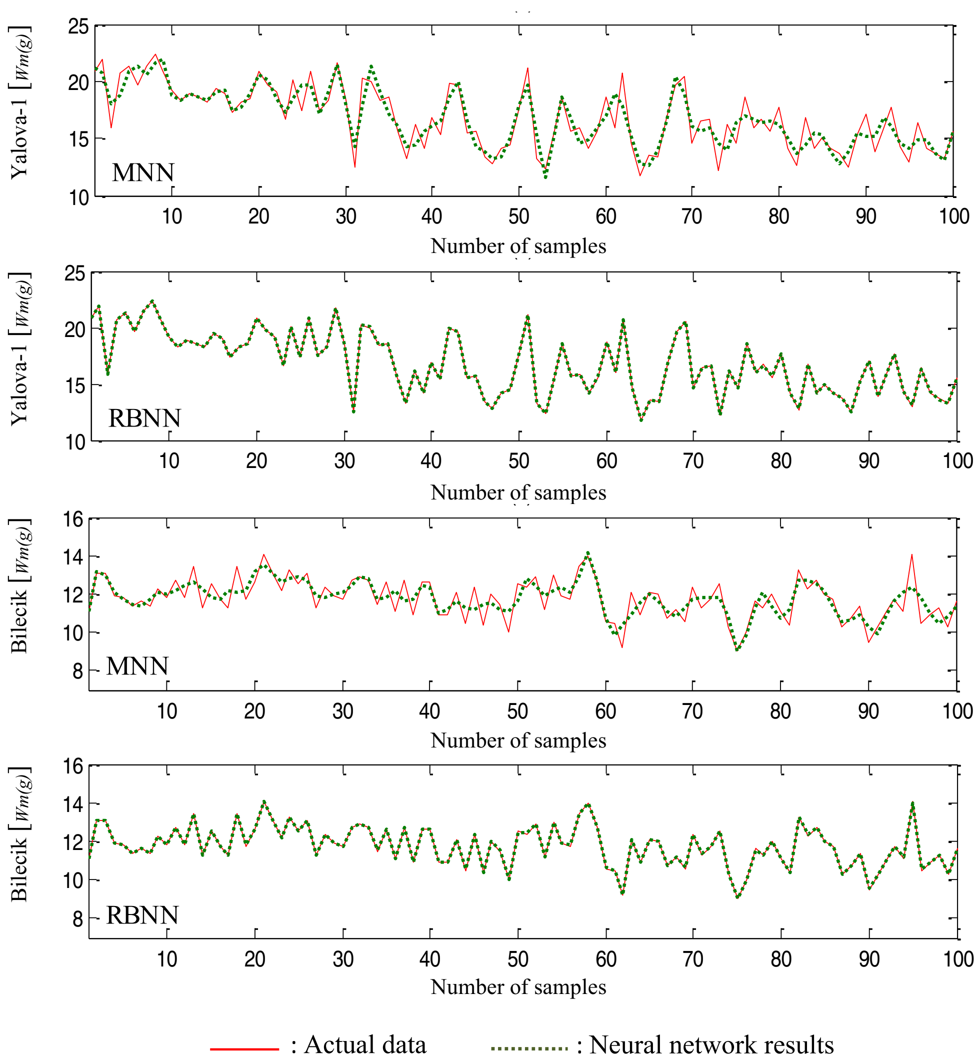


Fig. 3 Prediction results for 'Yalova-1' and 'Bilecik' walnuts using MNN and RBNN structures

where u_j are the weighted input received by the j^{th} output unit of the gating network. In Eq. 1, $\sum y_k = 1$ and $0 \leq y_j \leq 1$.

Radial Basis Neural Network (RBNN)

The RBNN which model functions y (x) mapping $x \in R^n$ to y $\in R$ have a single hidden layer so that the model,

$$\mathbf{f(x)} = \sum_{j=1}^{m} \boldsymbol{w_j h_j}\,\mathbf{(x)} \tag{3}$$

is linear in the hidden layer to output weight $(w_j)_{j=1}^{m}$. The characteristic feature of RBNN is the radial nature of the hidden unit transfer functions, $(h_j)_{j=1}^{m}$, which depend only on the distance between the input x and the center c_j of each hidden unit, scaled by a metric R_j,

$$h_j(x) = \varphi\left[(x-c_j)^T R_j^{-1}(x-c_j)\right]$$

where φ is some function which is monotonic for non-negative numbers. Gaussian basis function so that the transfer functions can be written as:

$$\boldsymbol{h_j}\,\mathbf{(x)} = \mathbf{exp}\Big(-\sum_{k=1}^{n}\frac{(\boldsymbol{x_k}-\boldsymbol{c_{jk}})^2}{\boldsymbol{r_{jk}^2}}\Big) \tag{4}$$

Experimental and Simulation Results

In this study, main dimensions (length, width, thickness) of walnut cultivars ('Yalova-1', 'Bilecik', 'Fernor', 'Maraş-12', 'Maraş-18', 'Kaman-1', 'Fernette', 'Sunland', 'Yalova-

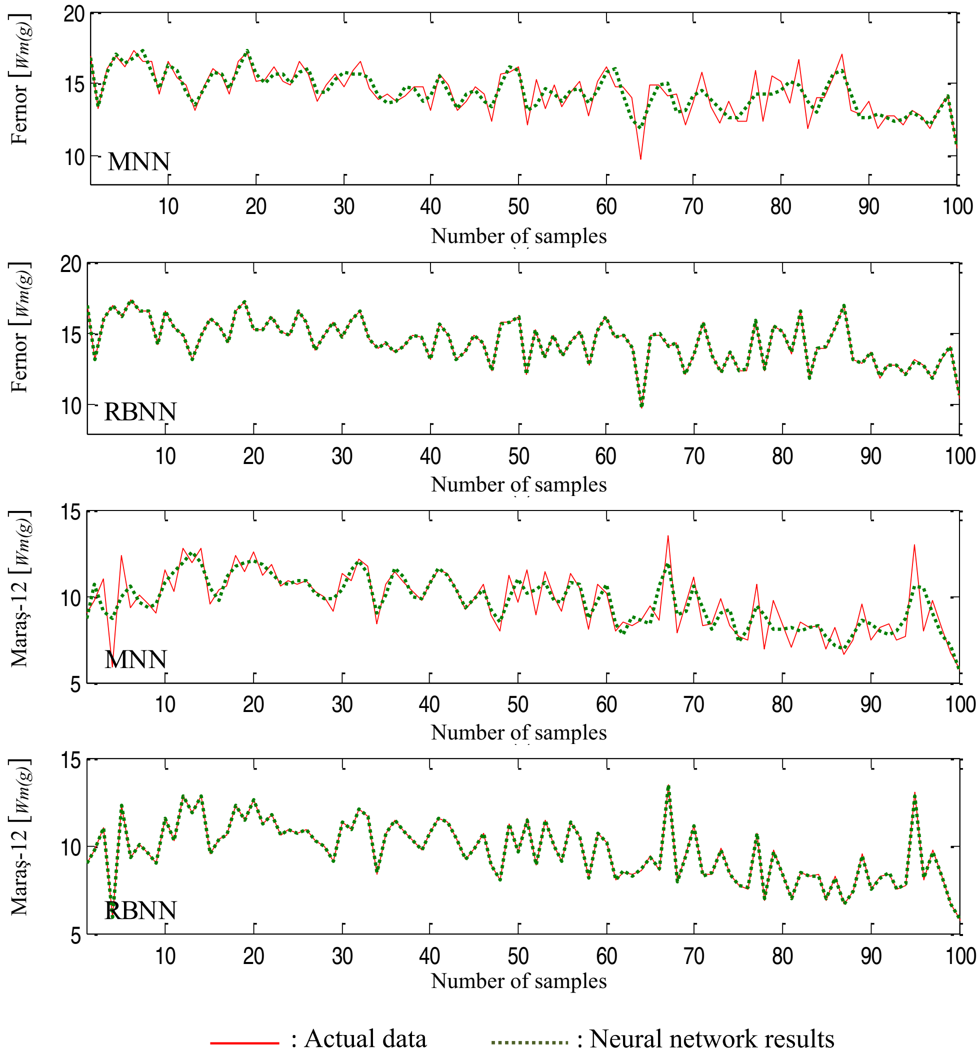


Fig. 4 Prediction results for 'Fernor' and 'Maraş-12' walnuts using MNN and RBNN structures

3' and 'Şen-2') were measured under laboratory conditions. Then, some physical properties (arithmetic mean diameter, geometric mean diameter, sphericity, surface area, volume, projected area, shape index, aspect ratio and elongation) were calculated. One last physical property (walnut weight) was independently measured and these parameters of walnut cultivars were used in the training process of neural network structures. At last, walnut weights were predicted by using neural networks (see Table 1).

Fig. 3 shows actual weights and ANN estimation results of the 'Yalova-1' and 'Bilecik' walnut cultivars. The best results for both walnuts cultivars were obtained from RBNN approach. The results of MNN and RBNN structures used for weight estimation for 'Fernor' and 'Maraş-12' walnut cultivars are given in Fig. 4. As seen in Fig. 5, where the weight estimation results for 'Maraş-18' and 'Kaman-1' walnut species were presented, Radial-based ANN structure yielded the best estimations. As it can be seen in Fig. 6, which contained the results of 'Fernette' and 'Sunland' walnut cultivars, MNN yielded worse estimations than RBNN structure. When the weight estimation results for 'Yalova-3' and 'Şen-2' walnut varieties in Fig. 7 were analyzed, it was observed that RBNN structure yielded better estimations than MNN structure. Simulation results revealed that RBNN approach was more suitable for weight estimations.

Figs. 3, 4, 5, 6 and 7 present the trends in actual and predicted values. The curves generated by the RBNN structure of ANN approximately have the same shape of the curves created with the actual data. The RBNN had superior performance to estimate the weights of different walnut cultivars. The RBNN have some advantages: they minimize the probability of error and hence the hypothesis of local linear behavior is no longer needed. Another advantage of the RBNN training is very fast, without increasing the computational cost of standard local learning algorithm. Thus; the RBNN could be applied to estimate the mass of all fruit species.

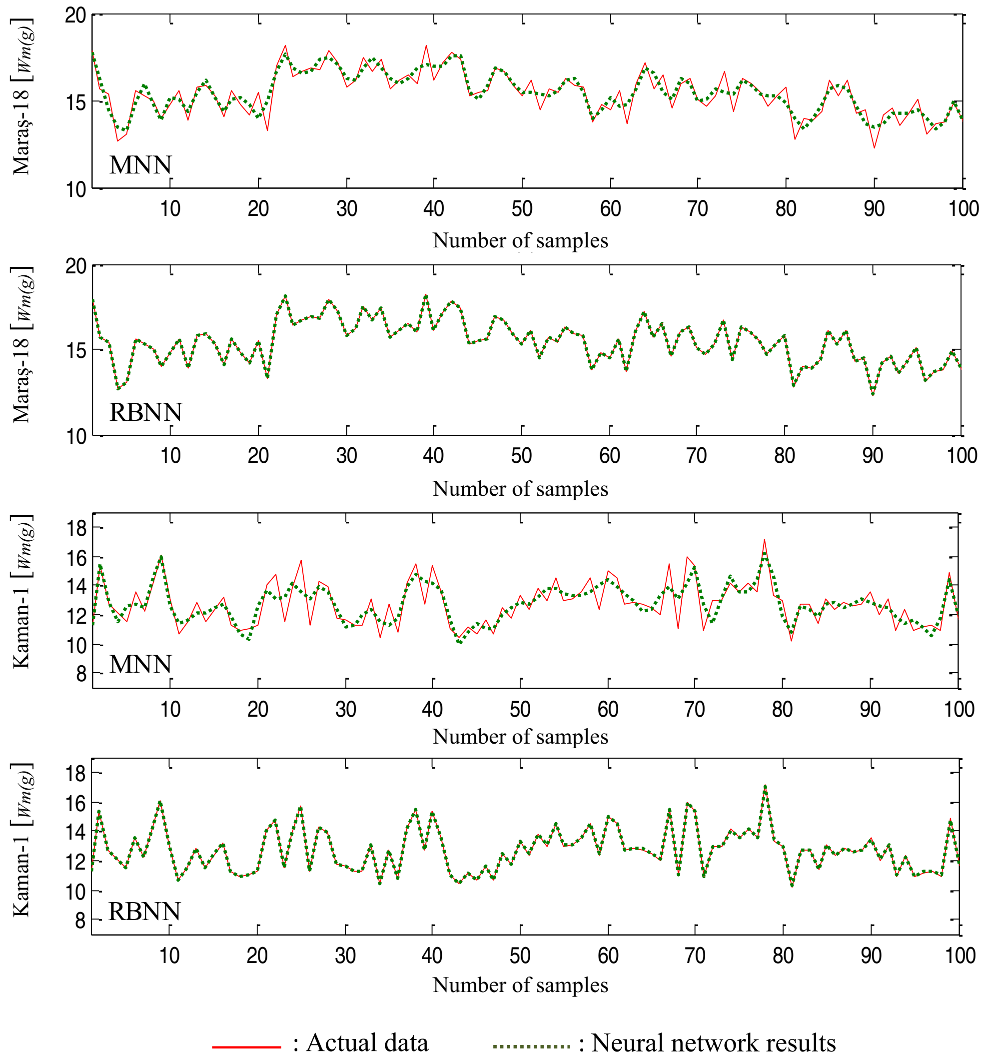


Fig. 5 Prediction results for 'Maraş-18' and 'Kaman-1' walnuts using MNN and RBNN structures

Present findings comply with the results of Soares et al. (2013), Rad et al. (2015) and Rad et al. (2017). Soares et al. (2013) proposed a methodology for predicting the bunch weights of bananas with artificial neural networks and reported that ANN produced an efficient prediction of the production. Rad et al. (2015) suggested a process to estimate the fruit weight of melon plants by applying the Artificial Neural Network models. The ANN models applied in this case predicted the final fruit weight of melons with high accuracy. Rad et al. (2017) developed and tested an ANN model to predict individual fruit weight of eggplants by a method not previously used to determine traits that could be important for increasing fruit weight and obtained a high accuracy for the ANN model.

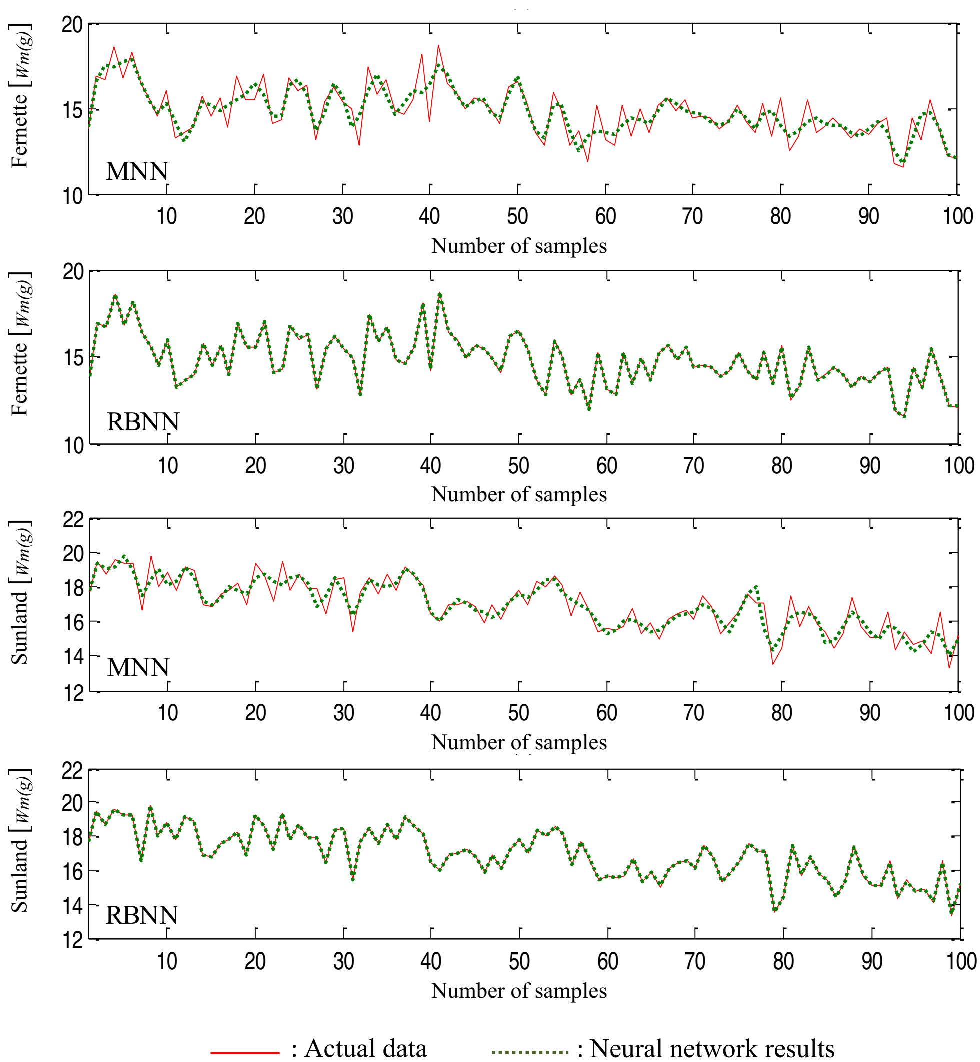
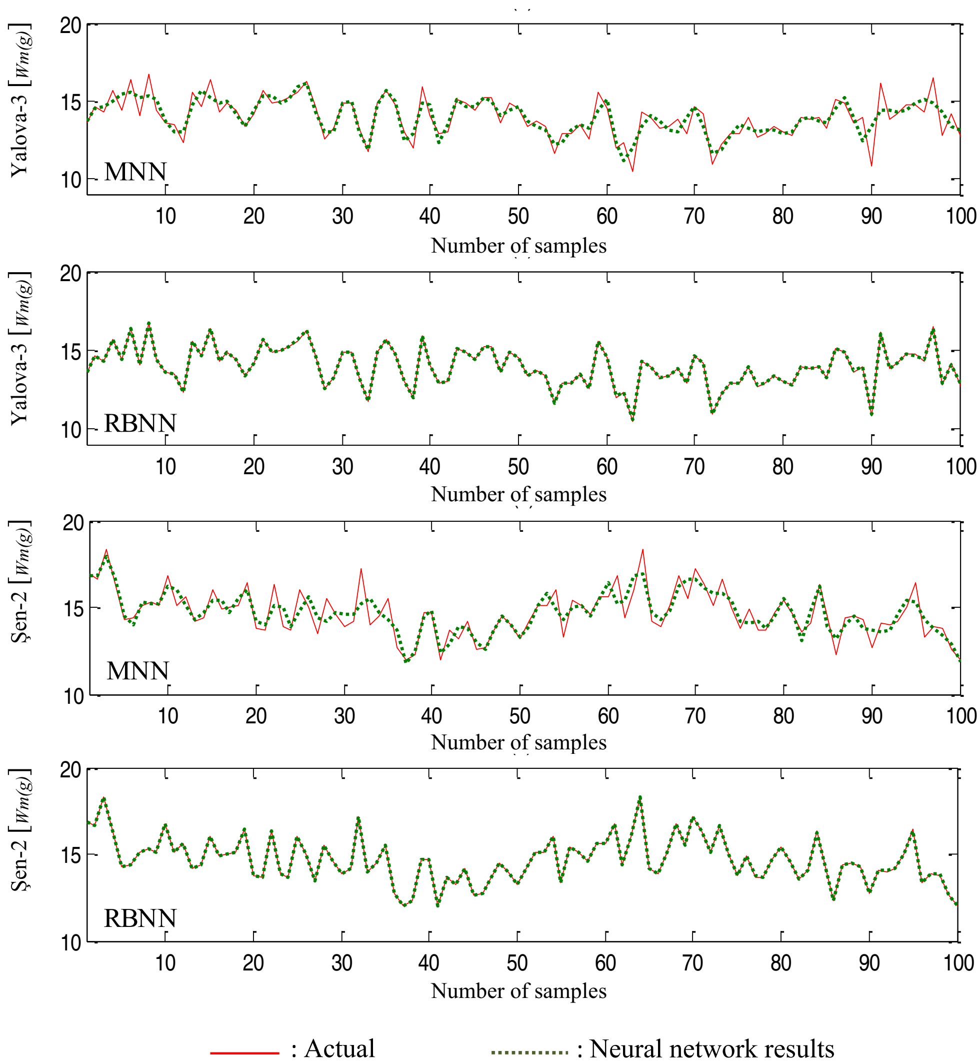


Fig. 6 Prediction results for 'Fernette' and 'Sunland' walnuts using MNN and RBNN structures

Fig. 7 Prediction results for 'Yalova-3' and 'Şen-2' walnuts using MNN and RBNN structures



Conclusion

The measurements and quantitative descriptions of the walnut mass are difficult and time-consuming. Post-harvest fruit mass can be estimated from indirectly calculated data. It was proved in this study that several physical properties of walnuts cultivars were sufficient to predict the weight characteristics of a walnut. The robustness and sensitivity of ANN models were determined by examining and comparing outputs produced with calculated values. These results demonstrated that ANN could be used as a useful tool for simulating and optimizing individual walnut mass.

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Conflict of interest B. Demir, İ. Eski, F. Gürbüz, Z.A. Kuş, Y. Sesli and S. Ercişli declare that they have no competing interests.

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