USING ARTIFICIAL NEURAL NETWORK APPLICATION IN MODELLING THE MECHANICAL PROPERTIES OF LOADING POSITION AND STORAGE DURATION OF PEAR FRUIT

Elçin YEŞİLOĞLU CEVHER[1], Demet YILDIRIM[2], Gürkan Alp Kağan GÜRDİL[1]

[1]Department of Agricultural Machinery and Technologies Engineering, Faculty of Agriculture, Ondokuz Mayis University, Samsun, Türkiye
[2]Black Sea Agricultural Research Institute, Soil and Water Resources Department, Agricultural Irrigation and Land Reclamation, Samsun, Türkiye

Abstract
In the study, rupture energy values of Deveci and Abate Fetel pear fruits were predicted using Artificial Neural Network (ANN). The breaking energy of the pears was examined in terms of storage time and loading position, and the experiments were carried out in two stages with samples kept in cold storage immediately after harvest and 30 days later. Rupture energy values (output data) were estimated using four different single and multilayer ANN models. -Four different model results obtained using Levenberg - Marquardt, Scaled Conjugate Gradient and resilient backpropagation training algorithms were compared with the calculated values. Statistical parameters such as R^2, RMSE, MAE and MSE were used to evaluate the performance of the methods. Model 1 by ANN gave better results in network 5-1 the R^2 value is 0.90, the square of the root error is 0.018, and 0.093 in the MAE is obtained using three inputs.

Key words: *ANN, scaled conjugate gradient, rupture energy, prediction, Deveci, Abate Fetel.*

INTRODUCTION
Pear (Pyrus communis L.) is a type of fruit that was first grown in the Asian continent and spread all over the world. There are more than 5000 pear varieties in the world and about 640 of them are grown in Turkey (*Polatcı et al., 2020*). The determination of the physical and mechanical properties of the pear, which is widely produced in the world and has commercial importance, is important in the adoption and design of various unit operations. The fruit compression test simulates the static loading condition that the fruit can withstand during mechanical transport and storage (*Tabatabaekoloor, 2014*).
It is important in determining the physical, mechanical and quality characteristics of fruits under harvest and storage conditions. For this, various modeling studies are carried out. In recent years, especially soft calculation techniques have been used. Among these techniques, artificial neural networks (ANN) are widely used (*Wu et al., 2017*). The artificial neural network application is aimed to make high-accuracy predictions using a few inputs. Different input, network structure, training algorithm, number of iterations, etc. by creating different combinations, suitable ANN models were determined to be used to predict physical and mechanical properties. The ANN method was used to estimate the physiological characteristic change in pear, and it was determined that the ANN model made the best estimation based on real data (*Azadbakht et al., 2022*).
The aim of the study is to model the rupture energy of Deveci and Abate Fetel pear cultivars for loading location and storage time conditions using artificial neural network method. In the research, R^2, RMSE, MSE, MAE parameters were used as an acceptability indicator for the estimation of the rupture energy for pear.High accuracy predictions were made in the 4 ANN models created. Using these models according to the entered parameters, a high-accuracy estimation of rupture energy for pear can be made.

MATERIALS AND METHOD
Deveci and Abate Fetel pear varieties used in the research were harvested from SAMMEY fruit production farm in Samsun in October. Harvesting was done by hand. Pear varieties are divided into two groups for storage and room temperature conditions. Half of the separated pear cultivars were stored at 1˚C storage temperature and 90% relative humidity for 30 days. A refrigerator was used as a storage medium. Trials of the other half were carried out in a laboratory environment at 21±2˚C room temperature after harvest (*Yeşiloğlu et al., 2016*).

Kern brand electronic precision scales were used for mass measurements of pear varieties. Dimension measurements of fruits were made with a digital caliper (*Mohsenin, 1980; Yeşiloğlu et al., 2016*). The water-soluble dry matter content was determined digital refractometers (0.1% Bx, Davras et al., 2019). A single column Universal Tester (Lloyd Instrument LRX Plus, Lloyd Instruments Ltd, An AMETEK Company, Hampshire, UK) attached to a Magness-Taylor probe (10 mm) was used to obtain the firmness values of the fruits. Force was applied to fruit varieties with a 100 N capacity load cell at a compression speed of 10 mm/min. Data were obtained with NEXYGEN Plus Material Test Software Version 2.1 (Lloyd Instrument Ltd, An AMETEK Company) and in the force-deformation graph provided by the software was taken as the Magness-Taylor force (*Yeşiloğlu et al. 2016; Abbott et al., 1992*). With the calculation of the area under the curve, rupture energy values were obtained (*Yurtlu and Yeşiloğlu, 2011*). Estimation of the repture energy value (RE) for single and double-layer neural structures using different input combinations of length (L), thickness (T), width (W), mass (M), water soluble dry matter (WSDM), Magness-Taylor force values were made with artificial neural networks (ANN). The layers used in the study; input layer, middle layers (hidden layer) and output layer that are shown in Figure 1.

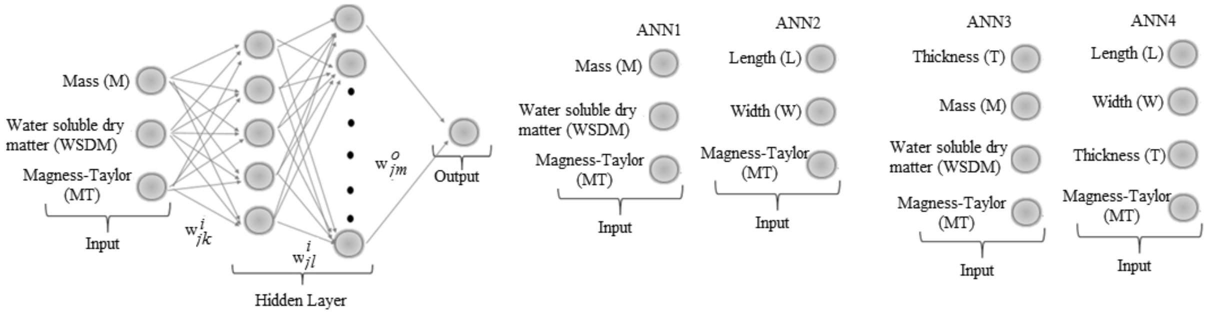

Fig. 1 Artificial neural network multi-layer structure with 3-5-8-1 and ANN models inputs

The ANN method requires adjusting the inter-network weight relationships and using a training pattern with appropriate output values. Necessary adjustments between the weights are made by adding rules to the training and thus a single information is obtained from the data. The model of a neural network is influenced by the network's topology, characteristics, and training algorithm (*Zhou and Si, 1998*) and (*Hagan and Menhaj, 1994; Parisi et al., 1996*). In this study, four different models were created with the inputs length, thickness, width, mass, and water soluble dry matterused in the study. The inputs used for the models (ANN1, ANN2, ANN3 and ANN4) are given in Fig. 1. For 4 models, estimations were made on single-layer networks as 5*1, 8*1, 10*1 and double-layer networks as 5*5*1, 5*8*1, 5*10*1. As an example, the model structure of ANN1 with 5*8*1 (double hidden layers) is shown in Figure 1. The results obtained by using three different training algorithms as Levenberg-Marquardt (LM), Scaled Conjugate Gradient (SCG) and Resilient Backpropagation (RP) were compared with the real values by performing 250-500-750 iterations. 174 (74%) of 274 data were used as training data and 60 (26%) as test data. The determination coefficient (R^2) of the data (*Azadbakht et al., 2017*), root mean square error (RMSE) (*Khoshnevisan et al., 2013; Azadbakht et al., 2018*), mean absolute error (MAE) (*Azadbakht et al., 2016*) and mean square error (MSE) (*Azadbakht et al., 2016*) values were calculated to choose the best model according to the highest R^2 and lowest RMSE, MSE, and MAE values. The aim of the study is to model the rupture energy of Deveci and Abate Fetel pear cultivars for loading location and storage time conditions using artificial neural network method. In the research, R2, RMSE, MSE, MAE parameters were used as an acceptability indicator for the estimation of the rupture energy for pear. High accuracy predictions were made in the 4 ANN models created. Using these models according to the entered parameters, a high-accuracy estimation of rupture energy for pear can be made.

RESULTS AND DISCUSSION

The descriptive statics properties of the mechanical properties measured for Deveci and Abate Fetel pear cultivars at storage and room conditions are shown in Table 2. Coefficient of variation (CV) measures the variation of an attribute. A CV ≤ 15% indicates a low variation, 16-35% a moderate variation, and a CV ≥ 36% high variation (*Wilding, 1985*). In the measured mechanical properties, CV values varied between 4.7%-39.3% in Deveci warehouse, 5.4%-37.6% in room conditions, and 3.4%-41.5% in

Abate Fetel warehouse conditions, 4.6%-41.9% in room conditions. The Skewness values for Deveci and Abate Fetel pear cultivars varied between 0 and 0.5 under storage and room conditions. It is accepted that the variables given in the table 1 show a normal distribution according to Skewness values.
In the study, 4 ANN models were created using different inputs. Using 3 inputs and 4 inputs, rupture energy was estimated for different model structures and the estimation results according to the training and testing datas, performance indicators are given in Table 2. 750 iterations were made in the SCG training algorithm, and better results were obtained than the LM and RP training algorithms. R^2 values were changed between 0.81 and 0.60 in LM and between 0.76 and 0.54 in RP for models and neural network. RMSE, MSE and MAE values higher results were obtained than the SCG training algorithms.

Tab 1 Descriptive statistical parameters for Deveci and Abate Fetel fruits

Variables		Max.	Min.	Mean	SD	CV	Skew-ness	Kur-tosis		Max.	Min.	Mean	SD	CV	Skew-ness	Kur-tosis
L	Deveci Stor-age	94.1	70.4	81.5	5.2	6.3	0.2	0.2	Abate Fetel Stor-age	130.5	117.2	122.9	4.2	3.4	0.3	-1.0
W		90.2	67.3	74.1	3.5	4.7	1.3	4.8		66.6	58.8	62.7	2.1	3.4	-0.2	0.1
T		87.8	61.4	71.2	4.0	5.6	0.4	2.7		63.8	53.5	58.7	2.8	4.8	-0.2	-0.1
M		317.5	181.8	214.6	20.6	9.6	1.3	5.6		227.1	182.3	206.2	13.8	6.7	-0.3	-1.0
WSDM		12.4	7.6	9.9	1.0	10.5	0.4	-0.1		15.3	12.9	13.9	0.7	4.8	0.5	0.0
MT		78.5	26.7	53.1	13.0	24.4	-0.2	-0.6		59.3	23.0	40.6	9.5	23.3	0.0	-0.4
RF		0.3	0.0	0.2	0.1	39.3	0.4	0.02		0.3	0.0	0.1	0.1	41.5	1.0	0.5
L	Deveci Har-vest-ing	92.2	61.2	79.3	6.5	8.1	-0.4	0.9	Abate Fetel Har-vest-ing	130.6	113.6	122.9	5.7	4.6	0.0	-1.3
W		94.0	75.4	86.2	4.8	5.5	-0.3	-0.7		66.5	53.7	58.1	3.3	5.7	1.5	2.6
T		94.8	72.7	82.9	4.4	5.4	0.1	0.8		65.1	50.1	59.2	4.3	7.2	-0.7	0.1
M		360.2	260.1	309.0	23.4	7.6	0.2	-0.5		234.9	175.7	207.8	18.3	8.8	-0.5	-0.8
WSDM		15.7	9.5	12.0	1.2	10.2	0.7	1.7		13.7	10.8	11.8	0.8	6.6	1.1	1.3
MT		67.7	20.3	40.9	10.1	24.6	0.3	-0.2		59.0	15.2	37.8	10.7	28.4	-0.3	-0.6
RF		0.3	0.0	0.1	0.0	37.6	0.6	1.1		0.3	0.0	0.1	0.1	41.9	0.2	-0.3

SD: Standard Deviation, CV: Coefficient of Variation

In ANN1, ANN2, ANN3, and ANN4 models, R^2 values in single and double-layer network structures varied between 0.86 and 0.94 and the distribution graphs are shown in Figure 2. By evaluating all data estimations, the most accurate rupture energy estimation was made using the SCG training algorithm with a single layer in the ANN1 (3*5*1) model for determining Deveci and Abate Fetel pear cultivars under storage and room conditions. Distribution and scatter graphs for rupture energy estimated storage and room conditions of Deveci and Abate Fetel pear varieties are presented in Figure 3. With the evaluation of the results, rupture energy estimation was made using the M, WSDM, and MT (ANN1) inputs. When there is missing data from the input parameters used in the study, accurate predictions can be made using the other 3 models (ANN2, ANN3, and ANN4). *Ziaratban et al., (2016)* used mathematical modeling of volume and surface area and feed-forward artificial neural network methods in Golden Delicious apples and using different training algorithms (GD, CGF, LM) 5, 10, 15 neuron structures, they predicted with high accuracy (R^2 0.99) for 15 neuron structures in the LM training algorithm. In the studies, different network neuron structures were modeled using 5, 10 (*Azadbakht et al., 2022*), between 2 and 20 neurons (*Vasighi-Shojae et al., 2020*) the and LM training algorithm (*Azadbakht et al., 2022*).

Tab. 2 Statistical results between calculated and predicted rupture energy in training and testing data

		SCG							
		Training Data				Testing Data			
Model	Model structure	R^2	RMSE	MSE	MAE	R^2	RMSE	MSE	MAE
ANN1	3-5-1	**0.94**	**0.0152**	**0.0002**	**0.1397**	**0.86**	**0.0256**	**0.0007**	**0.7853**
	3-8-1	0.91	0.0191	0.0004	0.1396	0.85	0.0270	0.0007	0.7843
	3-10-1	0.82	0.0295	0.0009	0.1391	0.80	0.0320	0.0010	0.7803
	3-5-5-1	0.88	0.0234	0.0005	0.1394	0.81	0.0259	0.0007	0.7829
	3-5-8-1	0.88	0.0238	0.0006	0.1394	0.75	0.0386	0.0015	0.7808
	3-5-10-1	0.83	0.0354	0.0013	0.1387	0.76	0.0326	0.0013	0.7784
ANN2	3-5-1	0.81	0.0287	0.0228	0.1391	0.80	0.0246	0.1061	0.7807
	3-8-1	**0.83**	**0.0266**	**0.0228**	**0.1392**	**0.91**	**0.0173**	**0.1057**	**0.7814**
	3-10-1	0.80	0.0367	0.0227	0.1386	0.87	0.0265	0.1056	0.7783
	3-5-5-1	0.83	0.0263	0.0229	0.1392	0.78	0.0434	0.1075	0.7800
	3-5-8-1	0.83	0.0273	0.0228	0.1392	0.79	0.0411	0.1072	0.7799
	3-5-10-1	0.79	0.0378	0.0227	0.1385	0.86	0.0202	0.1052	0.7782

ANN3	4-5-1	0.85	0.0268	0.0007	0.1392	0.92	0.0170	0.0035	0.7777
	4-8-1	0.80	0.0330	0.0011	0.1388	0.88	0.0244	0.0050	0.7783
	4-10-1	0.82	0.0261	0.0007	0.1392	0.82	0.0241	0.0038	0.7745
	4-5-5-1	**0.87**	**0.0250**	**0.0006**	**0.1393**	**0.94**	**0.0155**	**0.0029**	**0.7790**
	4-5-8-1	0.82	0.0282	0.0008	0.1391	0.87	0.0220	0.0043	0.7737
	4-5-10-1	0.78	0.0358	0.0013	0.1387	0.73	0.0236	0.0062	0.7763
ANN4	4-5-1	0.79	0.0291	0.0008	0.1391	0.81	0.0249	0.0045	0.7788
	4-8-1	0.81	0.0278	0.0008	0.1392	**0.90**	**0.0189**	**0.0040**	**0.7773**
	4-10-1	0.77	0.0365	0.0013	0.1386	0.84	0.0343	0.0078	0.7785
	4-5-5-1	**0.85**	**0.0241**	**0.0006**	**0.1394**	0.87	0.0238	0.0033	0.7793
	4-5-8-1	0.79	0.0409	0.0017	0.1383	0.85	0.0342	0.0086	0.7780
	4-5-10-1	0.78	0.0334	0.0011	0.1388	0.82	0.0236	0.0060	0.7761

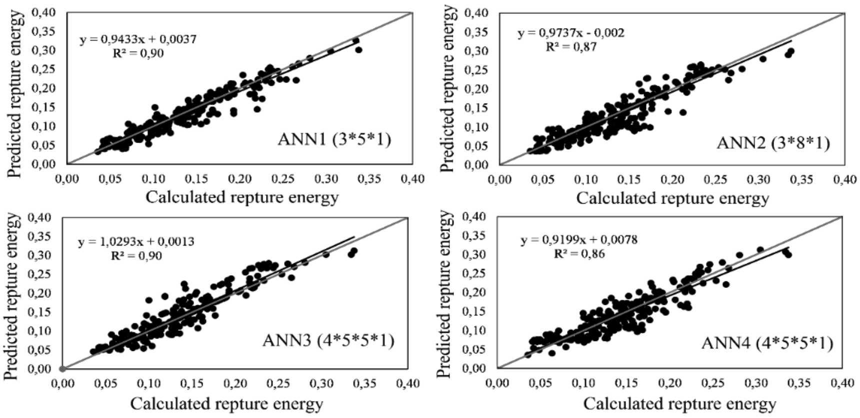

Fig. 2 Rupture energy results for all data by the best ANN models

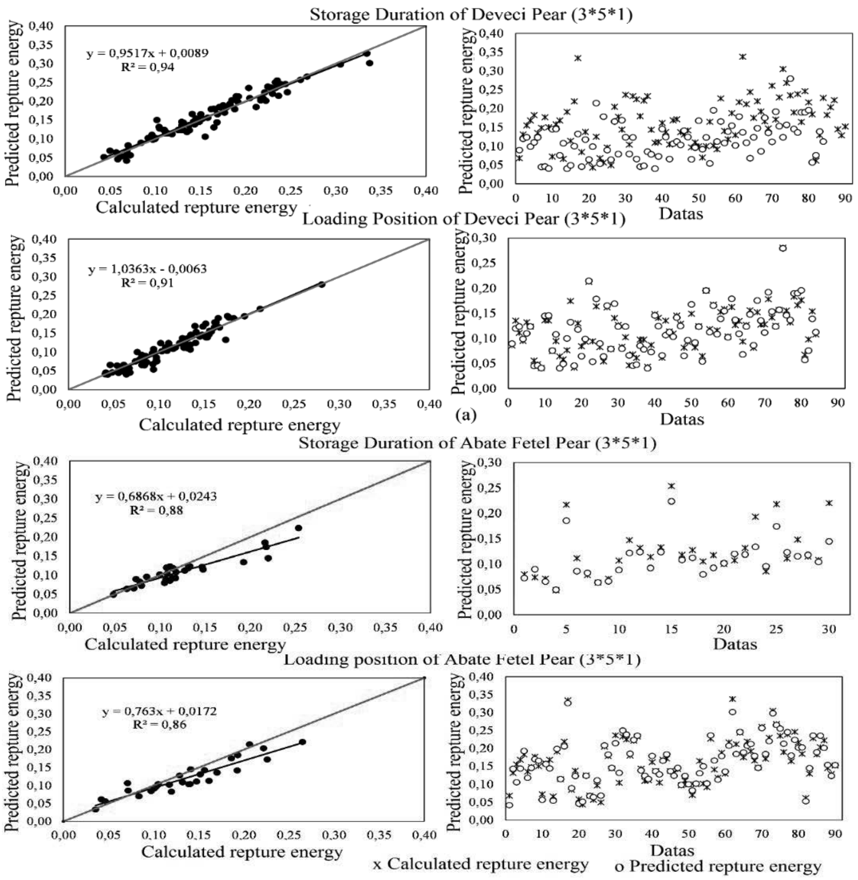

Fig. 3 Scatter plots between calculated and predicted rupture energy results by ANN1 a) storage duration and loading position of Deveci pear b) storage duration and loading position of Abate Fetel pear

Gorzelany et al., (2022) were reported to predict of mechanical properties of fresh and stored fruit of large cranberry by used artificial neural network. *Zarifneshat et al., (2012)* estimated the volume of apple fruit crunches using an artificial neural network. In the study, they concluded that the ANN model is more accurate than the regression model. The R^2 value was calculated as 0.994 for the ANN model and 0.969 for the regression model.

CONCLUSIONS

In the study, mechanical properties of rupture energy for loading position and storage time conditions of Deveci and Abate Fetel pear cultivars were modeled using artificial neural network method.
In this study, the best model (3-5-1 model structure) determined in the study was used in the estimation of the Rupture energy value. High accuracy predictions were made in the created 4 ANN models. According to the input parameters, using these models, rupture energy estimations for pear can be made with high accuracy. According to the purpose of the ANN method, it is important to obtain highly accurate predictions using how little data. Based on this and evaluating the model results in the study, a high accuracy (R^2, 0.90) estimation was made in the 3*5*1 network structure according to the highest R^2 and lowest RMSE, MSE and MAE indicators. It is thought that the results of the study will be useful in estimating the breaking energy from the mechanical properties of the fruit by using the artificial neural network method and in the development of more powerful models. The study will also enable the development of models to be used to determine the mechanical and physical properties of different fruits grown in different regions.

REFERENCES

1. Abbott, J. A., Affeldt, H. A., & Liljedahl, L. A. (1992). Firmness Measurement of Stored-Delicious' Apples by Sensory Methods, Magness-Taylor, and Sonic Transmission. *Journal of the American Society for Horticultural Science*, *117*(4), 590-595.
2. Azadbakht, M., M. Vahedi Torshizi, A. Ziaratban, and E. Ghajarjazi. (2016). Application of artificial neural network (ANN) in predicting mechanical properties of canola stem under shear loading. Agric. Eng. Int. CIGR 182:413-425.
3. Azadbakht, M., H. Aghili, A. Ziaratban, and M. Vahedi Torshizi. (2017). Application of artificial neural network method to exergy and energy analyses of fluidized bed dryer for potato cubes. Energy 120:947–958. doi: 10.1016/j.
4. Azadbakht, M., M. Vahedi Torshizi, F. Noshad, and A. Rokhbin. (2018). Application of artificial neural network method for prediction of osmotic pretreatment based on the energy and exergy analyses in microwave drying of orange slices. Energy 165:836–845. doi: 10.1016/j.energy.2018.10.017.
5. Azadbakht, M., Mahmoodi, M.J., & Abbaszadeh-Mayvan, A. (2022). Prediction of physiological characteristic changes in pears subject to dynamic loading using artificial neural network (ANN). *International Journal of Horticultural Science and Technology*, *9*(3), 275-289.
6. Neural Network (ANN). *International Journal of Horticultural Science and Technology*, *9*(3), 275-289.
7. *School of Sciences. Department of Agricultural Machinery and Technologies Engineering*. Samsun, Türkiye.
8. Davras, İ., Koyuncu, M. A., & Erbaş, D. (2019). Reducing quality losses by salicylic acid treatment in tomato during cold storage. *Uluslararasi Tarim ve Yaban Hayati Bilimleri Dergisi*, *5*(2), 176-186.
9. Du, C. J., & Sun, D. W. (2006). Learning techniques used in computer vision for food quality evaluation: a review. *Journal of food engineering*, *72*(1), 39-55.
10. Gorzelany, J., Belcar, J., Kuźniar, P., Niedbała, G., & Pentoś, K. (2022). Modelling of mechanical properties of fresh and stored fruit of large cranberry using multiple linear regression and machine learning. *Agriculture*, *12*(2), 200.
11. Hagan, M. T., & Menhaj, M. B. (1994). Training feedforward networks with the Marquardt algorithm. *IEEE transactions on Neural Networks*, *5*(6), 989-993.
12. Khoshnevisan, B., S. Rafiee, and M. Omid. (2013). Prediction of environmental indices of Iran wheat production using artificial neural networks. Int. J. Energy Environ. 42:339–348.

13. Landeras, G., Ortiz-Barredo, A., & López, J. J. (2008). Comparison of artificial neural network models and empirical and semi-empirical equations for daily reference evapotranspiration estimation in the Basque Country (Northern Spain). *Agricultural water management*, *95*(5), 553-565.
14. Lu, H., Zheng, H., Lou, H., Jiang, L., Chen, Y., & Fang, S. (2010). Using neural networks to estimate the losses of ascorbic acid, total phenols, flavonoid, and antioxidant activity in asparagus during thermal treatments. *Journal of Agricultural and Food Chemistry*, *58*(5), 2995-3001.
15. Meisami-asl, E., and S. Rafiee. (2012). Modeling of physical properties of apple slices Golab variety using artificial neural networks. Agric. Eng. Int. CIGR J. 143:175–178.
16. Parisi, R., Di Claudio, E. D., Orlandi, G., & Rao, B. D. (1996). A generalized learning paradigm exploiting the structure of feedforward neural networks. *IEEE Transactions on Neural networks*, *7*(6), 1450-1460.
17. Polatci, H., Taşova, M., & Saraçoğlu, O. (2020). Armut (Pirus communis L.) Posasının Bazı Kalite Değerleri Açısından Uygun Kurutma Sıcaklığının Belirlenmesi. *Academic Platform Journal of Engineering and Science*, *8*(3), 540-546.
18. Tabatabaekoloor, R. (2014). Bio-mechanical behavior of kiwifruit as affected by fruit orientation and storage conditions. In *Proceedings International Conference of Agricultural Engineering* (pp. 06-10).
19. Vasighi-Shojae, H., Gholami-Parashkouhi, M., Mohammadzamani, D., & Soheili, A. (2020). Predicting mechanical properties of golden delicious apple using ultrasound technique and Artificial Neural Network. *Food Analytical Methods*, *13*(3), 699-705.
20. Wilding, L. P. (1985). Spatial variability: its documentation, accomodation and implication to soil surveys. In *Soil spatial variability, Las Vegas NV, 30 November-1 December 1984* (pp. 166-194).
21. Wu, S. W., Zhou, X. G., Cao, G. M., Liu, Z. Y., & Wang, G. D. (2017). The improvement on constitutive modeling of Nb-Ti micro alloyed steel by using intelligent algorithms. *Materials&Design*, *116*, 676-685.
22. Yurtlu, Y. B., & Yeşiloğlu, E. (2011).. Mechanical Behaviour and Split Resistance of Chestnut under Compressive Loading. *Journal of Agricultural Science* 17(4):337-34
23. Yeşiloğlu, E., Yıldırım, D., & Öztekin Y. B. (2016). Effect Of Loading Position And Storage Duration On The Mechanical Properties Of Abate Fetel Pear Variety. *6th International Conference on Trends in Agricultural Engineering (TAE)*. pp.714-718
24. Zarifneshat, S., Rohani, A., Ghassemzadeh, H. R., Sadeghi, M., Ahmadi, E., & Zarifneshat, M. (2012). Predictions of apple bruise volume using artificial neural network. *Computers and electronics in agriculture*, *82*, 75-86.
25. Ziaratban, A., Azadbakht, M., & Ghasemnezhad, A. 2017. Modeling of volume and surface area of apple from their geometric characteristics and artificial neural network. *International Journal of Food Properties*, *20*(4), 762-768.
26. Zhou, G., Si, J. 1998. Advanced Neural-Network Training Algorithm with Reduced Complexity Based on Jacobian Deficiency. *IEEE Transactions on Neural Networks*, *9*(3), 448-453.
27. Zarifneshat, S., Rohani, A., Ghassemzadeh, H. R., Sadeghi, M., Ahmadi, E., & Zarifneshat, M. (2012). Predictions of apple bruise volume using artificial neural network. *Computers and electronics in agriculture*, *82*, 75-86.
28. Ziaratban A., Azadbakht M., Ghasemnezhad A. 2016. Modeling of volume and surface area of apple from their geometric characteristics and artificial neural network. International *Journal of Food Properties*. ISSN: 1094-2912 (Print) 1532-2386.

Corresponding author:
Elçin YEŞİLOĞLU CEVHER, Ph.D., Department of Agricultural Machinery and Technologies Engineering, Faculty of Agriculture, Ondokuz Mayis University, Samsun, Türkiye, phone: +90 3623121919/1258, e-mail: elciny@omu.edu.tr