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Using Artificial Neural Network Application in Modeling the Mechanical Properties of Loading Position and Storage Duration of Pear Fruit

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Abstract: In the study, rupture energy values of Deveci and Abate Fetel pear fruits were predicted using artificial neural network (ANN). This research aimed to develop a simple, accurate, rapid, and economic model for harvest/post-harvest loss of efficiently predicting rupture energy values of Deveci and Abate Fetel pear fruits. The breaking energy of the pears was examined in terms of storage time and loading position. The experiments were carried out in two stages, with samples kept in cold storage immediately after harvest and 30 days later. Rupture energy values were estimated using four different single and multi-layer 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. The best-performing model was obtained in network structure 5-1 that used three inputs: the highest R^2 value (0.90) and the lowest square of the root error (0.018), and the MAE (0.093).

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1. Introduction

Pear (*Pyrus communis* L.) is a type of fruit first grown in the Asian continent and spread worldwide. Pear fruit is the most grown fruit in the world after apples and grapes. There are more than 5000 pear varieties worldwide, and about 640 are grown in Turkey. Within the fresh pear are vitamins, phenolic compounds, organic acids, fatty acids, and a large amount of water [1]. Determining the physical and mechanical properties of pear, which is rich in nutritional value, widely produced worldwide, and has commercial importance, is important in the adoption and design of various unit operations. Fruits are susceptible to mechanical damage during harvest and post-harvest processes such as harvesting, sorting, packaging, and transportation. These damages are related to external forces such as splits, punctures, and bruises.

The biomechanical properties of fruits are important in designing and adopting various post-harvest systems. The fruit compression test simulates the static loading condition that fruit can withstand in mechanical transport and storage [2]. Fruit tissue is susceptible to mechanical effects. The biological yield point is the measure showing the first cell rupture in the whole fruit. The biological yield point is the region on the curve where the deformation increases or does not change. At this point, intracellular ruptures occur in the fruit. Before the biological yield point, the cell is not damaged. The energy (rupture energy) up to this point is the work required for the sample's rupture. The concept of rupture energy of the fruit is used in the design of cushioning materials for filling surfaces used for processing and transportation [3,4]. Fruit firmness varies according to the texture characteristics of the fruit, which is related to the maturity state of the fruit. Firmness can be an indicator of fruit maturity and is one of the important parameters affecting mechanical properties. In addition, the storage of fruits after harvest can cause significant changes in physical and mechanical properties [5,6]. Magness–Taylor tests are used to measure fruit firmness, which is an important parameter for post-harvest processes [7]. Another important parameter is the amount of water-soluble dry matter (WSDM), which determines the maturity and harvest time of fruits.

With the information obtained by determining the behavior of fruits against external forces, it will be possible to increase the product quality and contribute to its economic value. In addition, systems and designs for harvesting and post-harvest processes will be established or improved. Various methods are used to obtain data for this purpose. Mathematical modeling studies are carried out for different fruit species and varieties worldwide. It is essential in determining fruits' physical, mechanical, and quality properties under harvesting and storage conditions. For this, various modeling studies are carried out. In recent years, especially soft computing techniques have been used. Among these techniques, artificial neural network (ANN) is widely used. Many studies emphasize the accuracy of modeling and prediction, as ANN tends to explore relationships between input and output data without making any prior assumptions about physical data [8]. ANN architecture is a model inspired by biological neural networks. In recent years, there has been a significant increase in its field due to the development of computer technologies in different scientific applications. Thus, ANN started to be used in different scientific fields [9]. Du and Sun [10] stated that the artificial neural network method is used in food production classification, separation, estimation, and quality evaluation.

Studies are conducted to determine the physical, mechanical, and quality properties of fruits in different network structures for the artificial neural network. 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 characteristic physiological change in pear, and it was determined that the ANN model made the best estimation based on real data [11]. Ziaratban et al. [12] reported that estimating the fruit's volume and surface area can be better determined using an artificial neural network. Lu et al. [13], in their study on asparagus, used single hidden layer ANNs, and the number of neurons in the hidden layer were selected by trial and error. Artificial neural networks (ANNs) with backpropagation algorithms have been developed to predict the percentage loss of ascorbic acid, total phenols, flavonoids, and antioxidant activity in different segments of asparagus. In addition, optimized ANN models have been developed to predict nutrient losses in the bud, upper, middle, and lower parts of asparagus. The obtained results showed that the estimated values of the correlation coefficients between the experimental and ANN varied between 0.8166 and 0.9868. This study reveals the correct estimation of rupture energy parameters by the artificial neural network method under loading position and storage duration conditions of Deveci and Abate Fetel pear cultivars. Using the researcher's ANN model aims to reveal the most accurate model with various performance criteria among different inputs and network structures. The results obtained can be considered a useful tool to deal with harvest/post-harvest loss of pear fruit.

2. Materials and Methods

2.1. Determination of Mechanical Properties of the Samples

Deveci and Abate Fetel pear varieties used in the research were harvested from SAMMEY fruit production farm in Samsun in October. The harvest was conducted by hand. Before starting the trials, the materials were cleaned from foreign materials such as branches and leaves. Pear varieties were divided into groups according to storage and room temperature conditions. Half of the sorted pear varieties 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. The samples were kept at ambient temperature for 1 h before starting the trials [14].

Kern (Germany) brand electronic precision scales with a sensitivity of 0.01 g and a maximum measurement capacity of 2500 g were used for mass measurements of pear varieties. Dimension measurements of fruits were made with a digital caliper with a precision of 0.01 mm (Mitutoya brand, Absolute Digimatic model, Kawasaki, Japan) [3,14]. The water-soluble dry matter content was determined using the Atago Pocket (Japan) brand digital refractometers -. The Brix measurement range of the digital refractometer is 0.0–53%, and the resolution is 0.1% Bx [15]. 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 10 mm/min compression speed. Data were obtained with NEXYGEN Plus Material Test Software Version 2.1 (Lloyd Instrument Ltd., An AMETEK Company, Hampshire, UK). The maximum force in the force-deformation graph provided by the software was taken as the Magness–Taylor force [14,16]. Rupture energy values were obtained with the calculation of the area under the curve [17].

2.2. Artificial Neural Network (ANN)

ANN is a computer system developed to automatically realize the ability of the human brain to derive and discover new information through learning without any assistance. ANN is a learning algorithm that predicts outputs against inputs with adjusted weights and biases. In this algorithm, the importance and value of the information reaching the neurons are determined by weights. In the next step, biases are determined by numerical values. Artificial neurons come together to form an artificial neural network. The coming together of nerve cells is not random. In general, cells come together in 3 layers and in parallel in each layer to form the network. These layers are the input layer, middle layers (hidden layer), and output layer. The relations between the layers used in the study are seen in Figure 1.

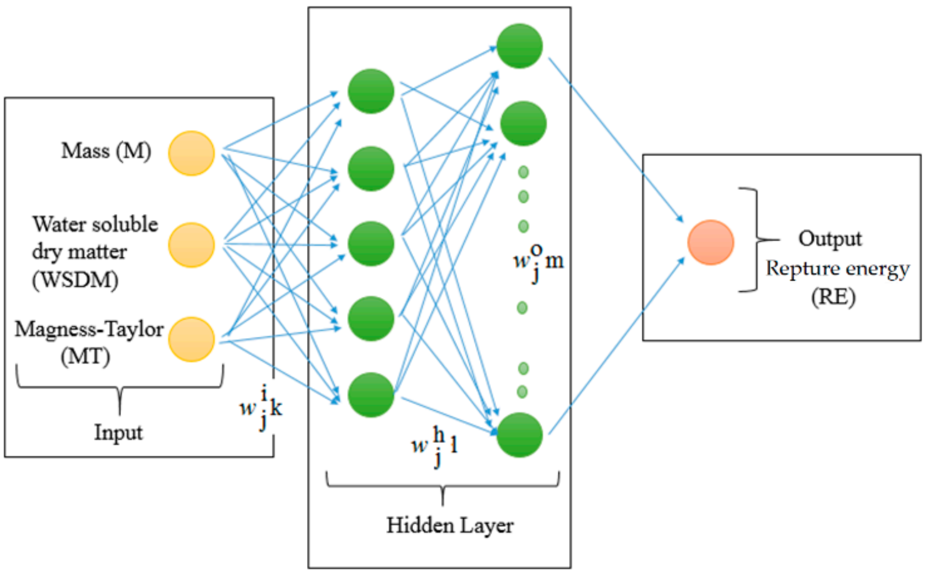


Figure 1. Artificial neural network multi-layer structure with 3-5-8-1 for rupture energy prediction.

2.3. Data Proceeding for ANN Models

Estimation of rupture energy value for single- and double-layer network structures using different input combinations of length (L), thickness (T), width (W), mass (M), water-soluble dry matter (WSDM), and Magness–Taylor force (MT) values were made with artificial neural networks (ANN).

Training an ANN construct makes backpropagation essential in the basic training construct. This 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; thus, a single piece of information is obtained from the data. The neural network model is influenced by the network's topology, characteristics, and training algorithm [18–20].

In these studies, the input variables must first be determined. Different input combinations were assessed to evaluate each variable's effect on the rapture energy values. Different input parameters used in prediction models directly affect the model's performance. In this study, suitable input combinations were determined by correlation analysis that evaluated different combinations of input variables. The Pearson correlation coefficient was a simple, reliable, and understandable method [21]. Therefore, four models were created. Four models were created with the inputs (length, thickness, width, mass, and water-soluble dry matter used in the study. The inputs used for the models are given in Table 1.

Table 1. Inputs are used in ANN models.

Model	ANN1	ANN2	ANN3	ANN4
L		√		√
W		√		√
T			√	√
M	√		√	
WSDM	√		√	
MT	√	√	√	√

L: Length (mm); W: Width (mm); T: Thickness (mm); M: Mass (g); WSDM: Water-Soluble Dry Matter (%); MT: Magness–Taylor (N).

Three different inputs were used in ANN1 and ANN2 models, and four different inputs were used in ANN3 and ANN4 models. For four 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, and 5*10*1. As an example, the model structure of ANN2 with 5*8*1 (double hidden layers) is shown in Figure 1. The number of neurons in the hidden layer was determined by using the trial-and-error approach that tested 5, 8, and 10 in the number of neurons to find optimal best results. The tangent sigmoid (tansig) and linear (purelin) activation functions were used in the input and output layers, respectively.

The results werevobtained by using three different training algorithms: Levenberg–Marquardt (LM), Scaled Conjugate Gradient (SCG), and Resilient Backpropagation (RP), which were compared with the real values by performing 250-500-750 iterations. In this study, we used a training-testing analysis design that allowed for estimating effect sizes in an unbiased way. Moreover, 174 (74%) of 274 data were used as training data and 60 (26%) as test data which were carried out for model selection. Modeling was created according to 174 data, and the remaining 60 data were used as test data.

2.4. Model Evaluation

As a result of the analysis, the determination coefficient (R^2) [22] of the data, root mean square error (RMSE) [23,24], mean absolute error (MAE) [25], and mean square error (MSE) [25] values were calculated in Equations (1)–(4), respectively. Using the equations given below, the best model was determined according to the highest R^2 value and lowest RMSE, MSE, and MAE values:

$$R^2 = \frac{\left[\sum_i^m (y_i - \overline{y})(O_i - \overline{O}\right]}{\sum_{i-1}^m (y_i - \overline{y})^2 \sum(O_i - \overline{O})^2} \tag{1}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i-1}^m (y_i - O_i)^2}{n}} \tag{2}$$

$$\mathrm{MAE} = \left| \frac{\sum_{i-1}^{n} (y_t\ - O_t)}{n} \right| \tag{3}$$

$$\mathrm{MSE} = \frac{\sum_{i-1}^{n} (y_i - O_i)^2}{n} \tag{4}$$

where n: total number of data; O_i: estimated data; y_i: actual (measured) data.

3. Results and Discussion

The descriptive statistics properties of the mechanical properties measured for Deveci and Abate Fetel pear cultivars at storage and room conditions are shown in Table 2. The coefficient of variation (CV) measures the variation of an attribute. A CV $\leq$ 15% indicates a low variation, 16–35% a moderate variation, and a CV $\geq$ 36% high variation [26,27].

In the measured mechanical properties, CV values varied between 4.7–39.3% in the Deveci warehouse, 5.4–37.6% in room conditions, and 3.4–41.5% in the Abate Fetel warehouse, 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 show a normal distribution according to skewness values. The skewness value of the dataset is considered normal up to 0.5. When the skewness value is between 0.5 and 1, square root transformation is performed; however, logarithmic transformation is performed when it is greater than 1. The whole dataset for storage and room conditions values is given in Table 2. Average values of L, W, T, M, WSDM, MT, and RE are 92.0, 71.1, 68.0, 211.6, 10.9, 50.2, and 0.2 for storage conditions and 90.8, 78.8, 76.7, 282.4, 11.9, 40.1, and 0.1 for room conditions.

In the study, rupture energy was estimated for ANN models by using different combinations of length, thickness, width, mass, water-soluble dry matter, and Magness–Taylor force data. Four ANN models were created using different inputs. In total, 174 of 234 data were used as training data, and 60 were used as test data. Using three inputs and four inputs, rupture energy was estimated for different model structures, and the estimation results according to the training data and performance indicators are given in Table 3.

Estimation results and performance indicators according to test data are given in Table 4. According to the training and test data, 750 iterations were made in the SCG training algorithm, and better results were obtained than the LM and RP training algorithms presented in Tables 3 and 4. The test data results were obtained in the SCG training algorithm with the highest R^2 and performance comparison criteria.

In the SCG training algorithm using M, WSDM, and MT inputs, 750 iterations were made, with the highest R^2 value (0.94) and lowest RMSE (0.0152) in the 3-5-1 model with a 5*1 single-layer network structure. MSE (0.0002) and MAE (0.1397) values were obtained, and the model was determined as the best rupture energy estimation model (Table 3). The SCG training algorithm obtained a high deterministic coefficient (R^2) in the single- and double-layer other model structures. R^2 values were calculated as 0.91, 0.82, 0.88, 0.88, and 0.83 in 8-1, 10-1, 5-5-1, 5-8-1, 5-10-1 models, respectively. In the ANN2 model, where L, W, and MT values are used as inputs, the R^2 value was obtained as 0.83 in 8-1, 5-5-1, and 5-8-1 network structures in the SCG training algorithm. According to the performance criteria, the 5-5-1 model structure was determined as the best model according to the lowest RMSE values. In the ANN3 model, in which T, M, WSDM, and MT inputs are used, R^2 varies between 0.78 and 0.87 in single- and double-layer network structures. According to the highest R^2 and lowest performance criteria, the best rupture energy estimation was made in the 5-5-1 model structure. In the ANN4 model, L, T, W, and MT inputs were used, and the highest R^2 (0.85) and lowest RMSE (0.241), MSE (0.0006), and MAE (0.1394) values were calculated in the 5-5-1 network structure.

In ANN1, ANN2, ANN3, and ANN4 models, R^2 values in single- and double-layer network structures varied between 0.86 and 0.94. The highest R^2 and lowest RMSE, MSE, and MAE values were obtained in the network structures of 5-1 in the ANN1 model, 8-1 in the ANN2 model, and 5-5-1 in the ANN3 and ANN4 models (Table 4). Azadbakht et al. [11]

reported using a multi-layer perceptron featuring a hidden layer (MLP) artificial neural network of 5 and 10 neurons in each layer that forecasted amounts of the total phenol, antioxidants, and Vitamin C contents of the fruits. Considering all the data, rupture energy was estimated in the network structures selected according to the estimation models, and the distribution graphs are shown in Figure 2. Evaluating training, testing, and all data estimations, the most accurate rupture energy estimation was made using the SCG training algorithm with a single-layer 5-1 network structure in the ANN1 model, in which mass, water-soluble dry matter, and Magness–Taylor inputs were used.

Table 2. Descriptive statistical parameters for Deveci and Abate Fetel fruits and all datasets in environmental conditions.

	Variables	Maximum	Minimum	Mean	SD	CV	Skewness	Kurtosis
Deveci Storage	L	94.1	70.4	81.5	5.2	6.3	0.2	0.2
	W	90.2	67.3	74.1	3.5	4.7	1.3	4.8
	T	87.8	61.4	71.2	4.0	5.6	0.4	2.7
	M	317.5	181.8	214.6	20.6	9.6	1.3	5.6
	WSDM	12.4	7.6	9.9	1.0	10.5	0.4	−0.1
	MT	78.5	26.7	53.1	13.0	24.4	−0.2	−0.6
	RE	0.3	0.0	0.2	0.1	39.3	0.4	0.02
Deveci Room Conditions	L	92.2	61.2	79.3	6.5	8.1	−0.4	0.9
	W	94.0	75.4	86.2	4.8	5.5	−0.3	−0.7
	T	94.8	72.7	82.9	4.4	5.4	0.1	0.8
	M	360.2	260.1	309.0	23.4	7.6	0.2	−0.5
	WSDM	15.7	9.5	12.0	1.2	10.2	0.7	1.7
	MT	67.7	20.3	40.9	10.1	24.6	0.3	−0.2
	RE	0.3	0.0	0.1	0.0	37.6	0.6	1.1
Abate Fetel Storage	L	130.5	117.2	122.9	4.2	3.4	0.3	−1.0
	W	66.6	58.8	62.7	2.1	3.4	−0.2	0.1
	T	63.8	53.5	58.7	2.8	4.8	−0.2	−0.1
	M	227.1	182.3	206.2	13.8	6.7	−0.3	−1.0
	WSDM	15.3	12.9	13.9	0.7	4.8	0.5	0.0
	MT	59.3	23.0	40.6	9.5	23.3	0.0	−0.4
	RE	0.3	0.0	0.1	0.1	41.5	1.0	0.5
Abate Fetel Room Conditions	L	130.6	113.6	122.9	5.7	4.6	0.0	−1.3
	W	66.5	53.7	58.1	3.3	5.7	1.5	2.6
	T	65.1	50.1	59.2	4.3	7.2	−0.7	0.1
	M	234.9	175.7	207.8	18.3	8.8	−0.5	−0.8
	WSDM	13.7	10.8	11.8	0.8	6.6	1.1.	1.3
	MT	59.0	15.2	37.8	10.7	28.4	−0.3	−0.6
	RE	0.3	0.0	0.1	0.1	41.9	0.2	−0.3
All Dataset Storage	L	130.5	70.4	92.0	18.6	20.2	1.0	−0.6
	W	82.6	58.8	71.1	5.6	7.9	−0.5	−0.5
	T	78.5	53.5	68.0	6.4	9.4	−0.6	−0.6
	M	246.8	181.8	211.6	16.9	8.0	0.0	−0.7
	WSDM	15.3	7.6	10.9	2.0	18.2	0.7	−0.8
	MT	78.5	23.0	50.2	13.3	26.4	0.0	−0.6
	RE	0.3	0.0	0.2	0.1	40.9	0.5	0.0
All Dataset Room Conditions	L	130.6	61.2	90.8	20.3	22.3	0.9	−0.7
	W	94.0	53.7	78.8	13.2	16.8	−0.8	−0.9
	T	94.8	50.1	76.7	11.4	14.8	−0.8	−0.5
	M	360.2	175.7	282.4	49.9	17.7	−0.7	−0.7
	WSDM	15.7	9.5	11.9	1.1	9.4	0.8	2.1
	MT	67.7	67.7	40.1	10.3	25.7	0.1	−0.2
	RE	0.3	0.3	0.1	0.0	39.5	0.5	0.6

L: Length (mm); W: Width (mm); T: Thickness (mm); M: Mass (g); WSDM: Water-Soluble Dry Matter (%); MT: Magness–Taylor Force (N); RE: Rupture Energy (J); SD: Standard Deviation; CV: Coefficient of Variation.

Table 3. Statistical results between calculated and predicted rupture energy in training data by the developed ANN models.

		Training Data											
		LM				SCG				RP			
Model	**Model Structure**	**R^2**	**RMSE**	**MSE**	**MAE**	**R^2**	**RMSE**	**MSE**	**MAE**	**R^2**	**RMSE**	**MSE**	**MAE**
ANN1	3-5-1	**0.85**	**0.0263**	**0.0007**	**0.1392**	**0.94**	**0.0152**	**0.0002**	**0.1397**	**0.77**	**0.0312**	**0.0010**	**0.1390**
	3-8-1	0.72	0.0374	0.0014	0.1385	0.91	0.0191	0.0004	0.1396	0.70	0.0349	0.0012	0.1387
	3-10-1	0.70	0.0370	0.0014	0.1386	0.82	0.0295	0.0009	0.1391	0.53	0.0496	0.0025	0.1375
	3-5-5-1	0.75	0.0321	0.0010	0.1389	0.88	0.0234	0.0005	0.1394	0.61	0.0455	0.0021	0.1379
	3-5-8-1	0.68	0.0409	0.0017	0.1383	0.88	0.0238	0.0006	0.1394	0.70	0.0652	0.0042	0.1357
	3-5-10-1	0.71	0.0380	0.0014	0.1385	0.83	0.0354	0.0013	0.1387	0.69	0.0429	0.0018	0.1381
ANN2	3-5-1	0.65	0.1422	0.0186	0.1197	0.81	0.0287	0.0228	0.1391	0.64	0.0425	0.1381	0.1381
	3-8-1	0.59	0.0678	0.0218	0.1353	**0.83**	**0.0266**	**0.0228**	0.1392	0.61	0.0674	0.1354	0.1354
	3-10-1	0.69	0.0399	0.0225	0.1383	0.80	0.0367	0.0227	0.1386	0.70	0.0392	0.1384	0.1384
	3-5-5-1	**0.71**	**0.0368**	**0.0226**	**0.1386**	0.83	0.0263	0.0229	**0.1392**	0.72	0.0370	0.1386	0.1386
	3-5-8-1	0.68	0.1418	0.0186	0.1198	0.83	0.0273	0.0228	0.1392	**0.77**	**0.0325**	**0.1389**	**0.1389**
	3-5-10-1	0.66	0.1417	0.0187	0.1199	0.79	0.0378	0.0227	0.1385	0.64	0.0427	0.1381	0.1381
ANN3	4-5-1	0.65	0.0474	0.0022	0.1377	0.85	0.0268	0.0007	0.1392	0.71	0.0406	0.0016	0.1383
	4-8-1	0.73	0.0359	0.0013	0.1386	0.80	0.0330	0.0011	0.1388	0.67	0.0440	0.0019	0.1380
	4-10-1	0.68	0.0437	0.0019	0.1380	0.82	0.0261	0.0007	0.1392	0.64	0.0402	0.0016	0.1383
	4-5-5-1	**0.76**	**0.0312**	**0.0010**	**0.1390**	**0.87**	**0.0250**	**0.0006**	**0.1393**	0.68	0.0387	0.0015	0.1384
	4-5-8-1	0.59	0.0433	0.0019	0.1381	0.82	0.0282	0.0008	0.1391	0.71	0.0354	0.0013	0.1387
	4-5-10-1	0.68	0.0387	0.0015	0.1384	0.78	0.0358	0.0013	0.1387	**0.72**	**0.0405**	**0.0016**	**0.1383**
ANN4	4-5-1	0.65	0.0410	0.0017	0.1383	0.79	0.0291	0.0008	0.1391	0.68	0.0357	0.0013	0.1387
	4-8-1	**0.69**	**0.0953**	**0.0091**	**0.1308**	0.81	0.0278	0.0008	0.1392	**0.72**	**0.0359**	**0.0013**	**0.1386**
	4-10-1	0.65	0.0551	0.0030	0.1369	0.77	0.0365	0.0013	0.1386	0.65	0.0422	0.0018	0.1382
	4-5-5-1	0.53	0.0542	0.0029	0.1370	**0.85**	**0.0241**	**0.0006**	**0.1394**	0.69	0.0372	0.0014	0.1385
	4-5-8-1	0.55	0.0434	0.0019	0.1380	0.79	0.0409	0.0017	0.1383	0.68	0.0522	0.0027	0.1372
	4-5-10-1	0.60	0.1815	0.0330	0.1070	0.78	0.0334	0.0011	0.1388	0.63	0.0455	0.0021	0.1379

ANN: Artificial neural network, R^2: Determination coefficient, RMSE: Root mean square error, MSE: Mean square error, MAE: Mean absolute error, LM: Levenberg–Marquardt, SCG: Scaled conjugate gradient, RP = Resilient backpropagation. (The bold font represents the best results in table).

In the estimation of all data, R^2 was calculated as 0.90, RMSE as 0.018, MSE as 0.0003, and MAE as 0.093. For ANN2, ANN3, and ANN4 models, R^2 was calculated as 0.87, 0.90 and 0.86, RMSE 0.025, 0.023, 0.024, MSE 0.0006, 0.0005, 0.0006, MAE 0.931, 0.930, 0.932, respectively, in other model structures. Ziaratban et al. [12] used mathematical modeling of volume, surface area, and feed-forward artificial neural network methods in Golden Delicious apples. In this study, using different training algorithms (GD, CGF, LM) 5, 10, and 15 neuron structures, they predicted 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 [11], between 2 and 20 neurons [28], and the LM training algorithm [11].

The study estimated rupture energy using the mechanical properties of Deveci and Abate Fetel pear cultivars measured under storage and room conditions. In this study, the best-performing model was determined to estimate the rupture energy used in the 3-5-1 model network structure.

The estimation values were made in a single-layer 5-1 network structure by using M, WSDM, and MT inputs. Distribution and scatter graphs for rupture energy estimated storage and room conditions of Deveci and Abate Fetel pear varieties that are presented in Figure 3. The R^2 values of the Deveci pear cultivar were calculated as 0.94 and 0.91 in storage and room conditions, respectively, and 0.88 and 0.86 in storage and room conditions for Abate Fetel pear in the rupture energy estimation in the 3-5-1 network structure (ANN1 model). Vahedi Torshizi et al. [29] utilized the artificial neural network method to estimate weight, volume, and density parameters for kiwi and found loading force, storage period, loading direction, equivalent diameter, geometric diameter, arithmetic diameter, spherical coefficient, rounding coefficient, and aspect ratio. The coefficient was estimated with high accuracy R^2 of 0.9992, 0.9984, and 0.9970 using different input combinations.

The artificial neural network application is aimed at making high-accuracy predictions using a few inputs. In the study, different inputs were used for a total of four models. In addition, estimation results were evaluated according to LM, SCG, and RP training algorithms in six different network structures (5-1, 8-1, 10-1, 5-5-1, 5-8-1, and 5-10-1). According to the network structures used, high-accuracy predictions were made in the SCG training algorithm. With the evaluation of the results, high-accuracy rupture energy estimation was made in the 5-1 network structure using the M, WSDM, and MT (ANN1) inputs. When missing data from the input parameters used in the study, accurate predictions can be made using the other three models (ANN2, ANN3, and ANN4). There are many studies similar to this study.

Table 4. Statistical results between calculated and predicted rupture energy in testing data by the developed ANN models.

		Testing Data											
		LM				SCG				RP			
Model	**Model Structure**	**R^2**	**RMSE**	**MSE**	**MAE**	**R^2**	**RMSE**	**MSE**	**MAE**	**R^2**	**RMSE**	**MSE**	**MAE**
ANN1	3-5-1	0.72	0.0346	0.0012	0.7805	**0.86**	**0.0256**	**0.0007**	**0.7853**	**0.74**	**0.0454**	**0.0021**	**0.7786**
	3-8-1	0.70	0.0297	0.0009	0.7761	0.85	0.0270	0.0007	0.7843	0.68	0.0301	0.0009	0.7772
	3-10-1	**0.73**	**0.0293**	**0.0009**	**0.7774**	0.80	0.0320	0.0010	0.7803	0.72	0.0318	0.0010	0.7712
	3-5-5-1	0.70	0.0328	0.0011	0.7785	0.81	0.0259	0.0007	0.7829	0.68	0.0365	0.0013	0.7736
	3-5-8-1	0.72	0.0351	0.0012	0.7763	0.75	0.0386	0.0015	0.7808	0.68	0.0344	0.0012	0.7628
	3-5-10-1	0.70	0.0356	0.0013	0.7766	0.76	0.0326	0.0013	0.7784	0.62	0.0340	0.0012	0.7739
ANN2	3-5-1	**0.72**	**0.0332**	**0.0873**	**0.6911**	0.80	0.0246	0.1061	0.7807	0.57	0.0691	0.1083	0.7716
	3-8-1	0.70	0.0374	0.1016	0.7598	**0.91**	**0.0173**	**0.1057**	**0.7814**	**0.73**	**0.0278**	**0.1017**	**0.7624**
	3-10-1	0.68	0.0648	0.1082	0.7733	0.87	0.0265	0.1056	0.7783	0.68	0.0578	0.1074	0.7744
	3-5-5-1	0.71	0.0560	0.1075	0.7754	0.78	0.0434	0.1075	0.7800	0.69	0.0602	0.1079	0.7746
	3-5-8-1	0.65	0.0633	0.0903	0.6884	0.79	0.0411	0.1072	0.7799	0.54	0.1179	0.1188	0.7664
	3-5-10-1	0.53	0.1139	0.0994	0.6798	0.86	0.0202	0.1052	0.7782	0.65	0.0561	0.1067	0.7732
ANN3	4-5-1	**0.81**	**0.0312**	**0.0110**	**0.7698**	0.92	0.0170	0.0035	0.7777	0.72	0.0357	0.0085	0.7757
	4-8-1	0.74	0.0367	0.0071	0.7379	0.88	0.0244	0.0050	0.7783	**0.76**	**0.0301**	**0.0096**	**0.7757**
	4-10-1	0.69	0.0438	0.0098	0.7683	0.82	0.0241	0.0038	0.7745	0.70	0.0492	0.0099	0.7736
	4-5-5-1	0.75	0.0329	0.0055	0.7660	**0.94**	**0.0155**	**0.0029**	**0.7790**	0.73	0.0331	0.0084	0.7721
	4-5-8-1	0.67	0.0442	0.0108	0.7719	0.87	0.0220	0.0043	0.7737	0.71	0.0315	0.0067	0.7698
	4-5-10-1	0.73	0.0346	0.0085	0.6287	0.73	0.0236	0.0062	0.7763	0.71	0.0334	0.0079	0.7690
ANN4	4-5-1	0.60	0.0670	0.0125	0.7713	0.81	0.0249	0.0045	0.7788	0.74	0.0287	0.0066	0.7737
	4-8-1	0.72	0.0284	0.0444	0.7752	**0.90**	**0.0189**	**0.0040**	**0.7773**	**0.76**	**0.0267**	**0.0066**	**0.7726**
	4-10-1	0.73	0.0416	0.0140	0.7725	0.84	0.0343	0.0078	0.7785	0.71	0.0364	0.0087	0.7724
	4-5-5-1	0.72	0.0367	0.0163	0.7768	0.87	0.0238	0.0033	0.7793	0.70	0.0606	0.0102	0.7739
	4-5-8-1	**0.74**	**0.0370**	**0.0104**	**0.7715**	0.85	0.0342	0.0086	0.7780	0.75	0.0329	0.0124	0.7756
	4-5-10-1	0.72	0.0645	0.1536	0.7738	0.82	0.0236	0.0060	0.7761	0.71	0.0569	0.0133	0.7744

ANN: Artificial neural network, R^2: Determination coefficient, RMSE: Root mean square error, MSE: Mean square error, MAE: Mean absolute error, LM: Levenberg-Marquardt, SCG: Scaled conjugate gradient, RP: Resilient backpropagation. (The bold font represents the best results in table).

Saiedirad et al. [30] used an artificial neural network to determine the mechanical properties of cumin seeds. In order to estimate the rupture energy value, 13 models were created in single and multi-layered network structures, and lower RMS (root mean functional error) values were obtained from the results of the single-layer model compared to the results of the multi-layered model. It is seen that the 6-1 structure has the lowest RMS percentage and was chosen as the best ANN model for the estimation of the force required to break the cumin seed. Zarifneshat et al. [31] estimated the volume of apple fruit crunches using an artificial neural network. The study 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.

Azadbakht et al. [11] used an artificial neural network to estimate total pear phenol, antioxidant, and Vitamin C contents by two dynamics of loading force and storage time. In the study, the highest R^2 value for dynamic loading in a network with five neurons in the hidden layer was determined for total phenol content (R^2 = 0.980), antioxidant (R^2 = 0.983), and Vitamin C (R^2 = 0.930). Vasighi-Shojae et al. [29] stated that using 7 inputs and 11 neurons in the Golden Delicious apple for firmness estimation, a 7-11-1 network structure is the best estimation, and a 7-17-1 network structure for elastic modulus estimation is made.

Gorzelany et al. [32] were reported to predict mechanical properties of fresh and stored fruit of large cranberry by a used artificial neural network. The best model for NNEc was determined to have a high R-value of 0.89 for the training data set and 0.88 for the validation data set with 47 neurons in the hidden layer. Mohammed et al. [33] estimated the fruit quality attributes of the pH, total soluble solids (TSS), water activity (aw), and moisture content (MC) parameters with the ANN model using 14 different inputs under storage conditions. PH, TSS, aw, and MC were determined as high determination of coefficient R^2 value as 0.938, 0.954, 0.876, 0.855, RMSE 0.121, 2.946, 0.020, and 0.803, respectively.

A multi-layer perceptron (MLP) artificial neural network evaluated the quantities of pear fruit mechanical properties after different storage times. This study is thought to be the first study to determine the mechanical properties of pear with ANN. Table 5 shows the comparison of ANN and studies for different features. Determining the rupture energy value, which is one of the mechanical properties of pear varieties, with ANN will provide practicality in the adjustment, design, and development of equipment and systems used during and after harvest, as well as time and economic benefits.

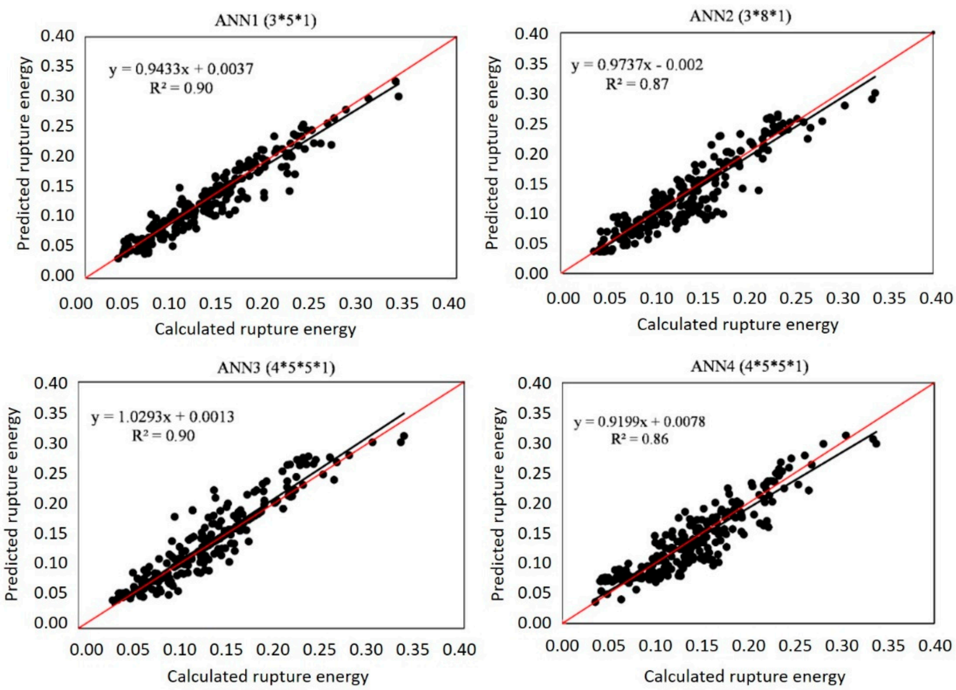
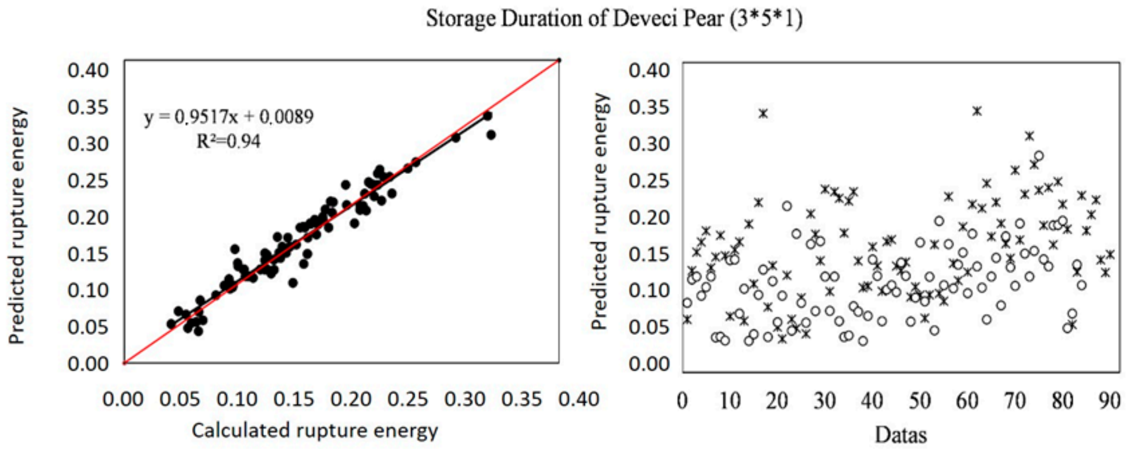
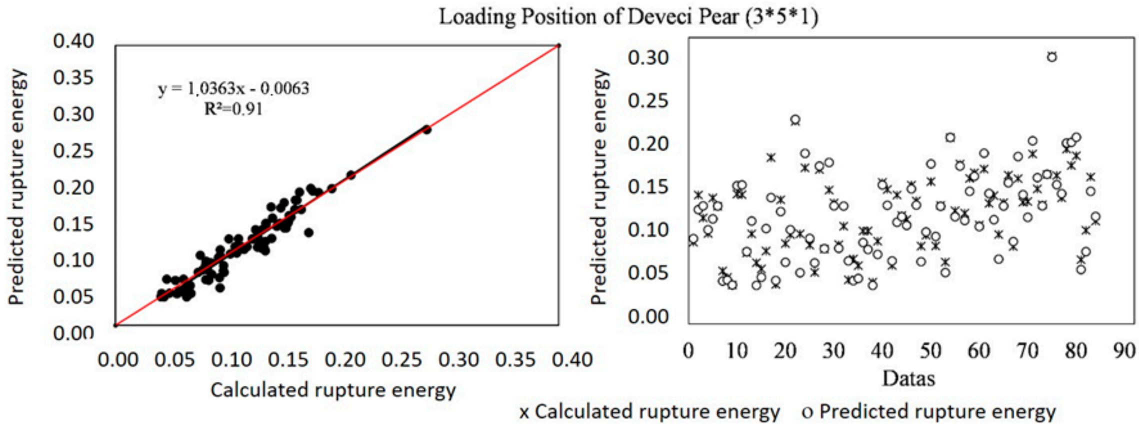


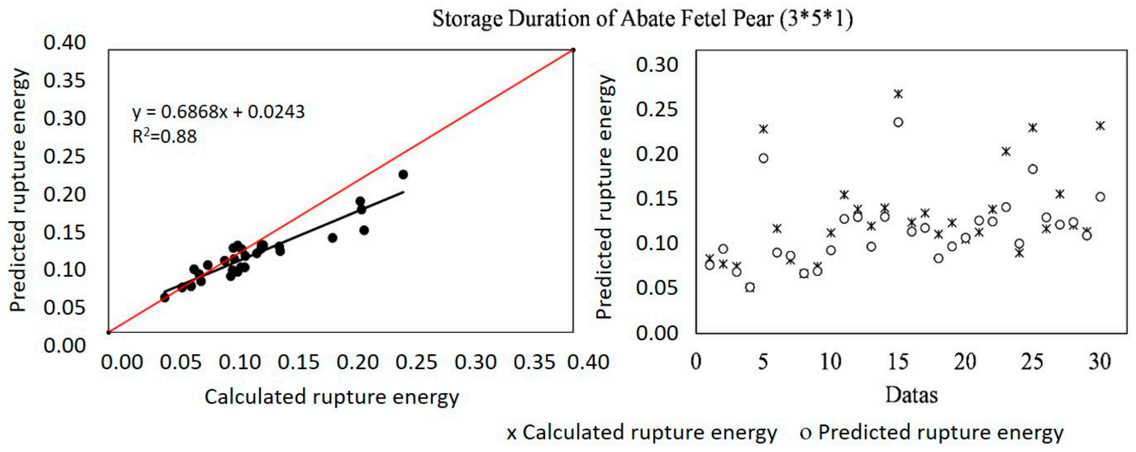
Figure 2. Rupture energy results for all data by the best ANN models.



(**a**)

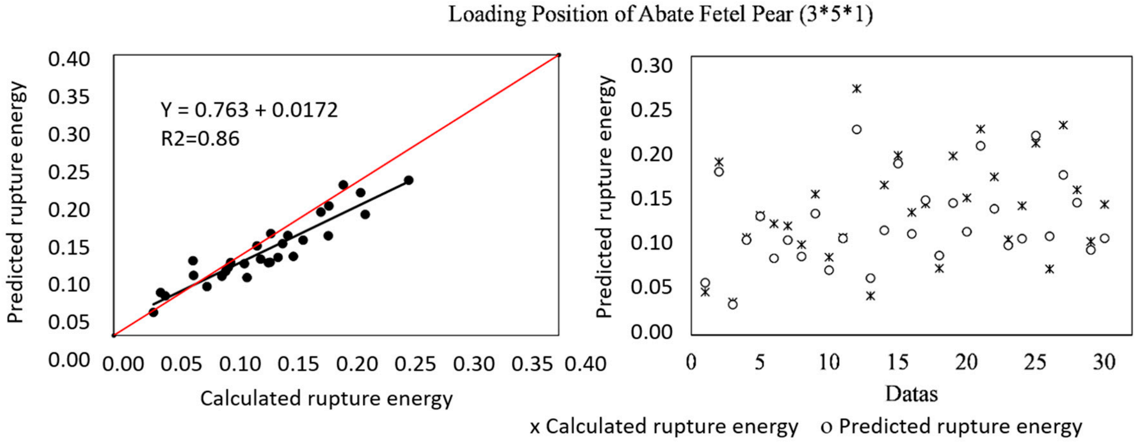


(**b**)



(**c**)

Figure 3. *Cont.*



(**d**)

Figure 3. Scatter plots between calculated and predicted rupture energy results according to ANN1 (**a**) storage duration of Deveci pear; (**b**) loading position of Deveci pear; (**c**) storage duration of Abate Fetel pear, and (**d**) loading position of Abate Fetel pear.

Table 5. Studies of ANN for different properties.

Reference	Model Structure	Material	Model Input	Model Output	The Best Model
Azadbakht et al. [11]	5 and 10 neurons in the hidden layer	Physiological characteristic changes in pears	Loading storage period	Total phenol content, Antioxidant Vitamin C	2-5-3 model total phenol content (R^2 = 0.980), antioxidant (R^2 = 0.983), Vitamin C (R^2 = 0.930)
Ziaratban et al. [12]	5, 10, 15 neurons in a hidden layer	Mathematical modeling of volume and surface area in Golden Delicious apples	Major diameter Minor diameter	The volume surface area	15 neurons, 2-15-1 (R^2, 0.999)
Vasighi-Shojae et al. [28]	11 neurons in the hidden layer	Mechanical properties of Golden Delicious apples	Attenuation on D1, ultrasound velocity, attenuation on D2, the main diameters D1, D2, vertical diameter (D3)	Firmness Elastic modulus	7-11-1 network structure, R^2 0.999, 7-17-1 network structure, R^2 0.999
Vahedi-Torshizi et al. [29]	MLP is a feed-forward network, 3, 9 neurons	Physical properties of kiwifruit during different loadings, storage	Loading force, storage period, loading direction, spherical coefficient, rounding coefficient, aspect ratio coefficient, length, width, and thickness	Weight Volume Density	6-9-3 network structure R^2, 0.995
Saiedirad et al. [30]	Single hidden layer (5, 6, 7, 8, 9 neurons), Double (4-2, 4-4,4-5, 4-6,4-7,5-5,5-6,5-7 neurons)	Mechanical properties of cumin seeds	Moisture content, seed size, loading rate, seed orientation	Rupture force energy	6-1 neural network structure for force and energy RMS values lower 4.16 and 6.85
Gorzelany et al. [32]	47 neurons in the hidden layer (MLP)	Mechanical properties of fresh and stored fruit of large cranberry	Storage temperature, duration of storage, x, y, and z dimensions of the fruits	Mechanical parameters	6-47-1 network structure R-value in 0.89
Mohammed et al. [33]	15 neurons in the hidden layer	Physicochemical properties during cold storage	Electrical properties for 14 different inputs	pH, total soluble solids, water activity, moisture content	14-15-4 network structure R^2, 0.938 (pH), 0.954 (TSSW), water activity (0.876), moisture content (0.855)

4. Conclusions

Especially in pome fruits, it is important to carry out modeling studies to determine the storage conditions and mechanical properties. In the study, the mechanical properties of rupture energy were modeled for the loading position and storage duration conditions of Deveci and Abate Fetel pear cultivars using the artificial neural network method. In the study, R^2, RMSE, MSE, and MAE parameters were used as an acceptability indicator in the estimation of the rupture energy for pear.

High-accuracy predictions were made in the created 4 ANN models. According to the input parameters, by 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 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. In the best RMSE, MSE, and MAE performance estimation for pear, 0.0184, 0.0003, and 0.0932 were obtained in the SCG training algorithm in the ANN1 model, respectively. According to the ANN 1 (3*5*1) model, the Device and Abate Fetel pear rupture energy values were estimated at 0.94, 0.91, 0.88, 0.86 (R^2) under loading position and storage duration conditions.

In conclusion, this study recommends the artificial neural network technique developed as an alternative to estimating rapture energy because it quickly yields accurate estimations. Soft computing techniques are commonly used in many applications (agricultural, mechanical, environmental, etc.) because they explain complex problems. Rupture energy data were difficult; hence, it is estimated quickly and accurately using ANN models. It is thought that the study's results will help estimate the rupture energy from the mechanical properties of the fruit using the artificial neural network method and develop stronger models. The study will also enable the development of models to determine the mechanical and physical properties of different fruits grown in different regions.

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