Estimation and Classification of Physical Parameters Pumpkins (Cucurbita pepo L.) Crop S by Soft Computing Tecniques

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Abstract. Determining the seed type is very important for the correct indentification of genetic material. Some plant seeds can not be classified based on their visual diversity or small size by experts. Therefore, in this study was to develop a simple, accurate and rapid using different soft computing tecniques that estimates physical parameters for pumpkin seeds. The current investigation was devoted to determining some properties, such as physical dimensions, surface area, sphericity, density, rupture energy of pumpkin seeds. The methods using in this study are; (1) Multilayer perceptron (MLP); (2) Adaptive Neuro-Fuzzy Inference Systems (ANFIS). Different statistic parameters such as coffecient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE) are used to evaluate performance of the methods. These selected the best models predicted for plant seeds which can be used in the soft computing tecniques determined alternative approach to estimating the physical properties of estimation and clasification pumpkin seeds.

1 Introduction

In recent years, Pumpkin (*Cucurbita pepo* L.) is one of the most important rich food resources that has increased greatly due to its profitability in Turkiye [1]. Pumpkin seed is one of the important livelihood ways of semiarid Middle Anatolian Regions of Turkiye which is one of the main cucurbit-growing areas of Black Sea region in Samsun [2]. According to, the latest recent official statistics show that Turkiye is squash, and gourds of 771651 tonnes in 2021 and producer with 100,853 ha of harvested area in the World's sixth pumpkins [3]. Turkish farmers have grown pumpkin landraces to adapt to local environmental conditions that has suitability to the preference of local consumers in different regions of Turkiye[3].

The failure process of a material when subjected to loading is always linked to the consumption of energy. The energy spent by the rupture mechanism represents a parameter that determines the strength and deformability characteristics of a material [4]. The physical and mechanical properties of seeds are determination such as transportation, storage, harvesting and post-harvest processing etc. that is important in performing operations. Mathematical modeling studies are carried out for different physical and chemical species for plant, fruit and seeds and varieties in the world. For this, various modeling studies are carried that especially soft computing techniques have been widely used to evaluated speed and accuracy [5]. Among these techniques, artificial neural network (ANN) same as multilayer perceptron (MLP) and adaptive neuro fuzzy inference system (ANFIS) are widely used [6, 7]. Many studies place an increasing emphasis on 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]. The ANFIS has the ability to create a mapping network of inputs–outputs based on human knowledge in the form of the fuzzy rules of if-then, and the input, output dataset for training the neural network [9]. The artificial neural network method is used in the classification, separation, estimation, and quality evaluation of food production that reported [10].

Recently, some scientists have attempted to provide various models for the prediction of the physical and chemical parameters of the plant, for instance researchers compared ANFIS and ANN tools that used different input combination and network structure in prediction [11-17]. There are different studies conducted on these that reported by [18] in the quality of tomato through postharvest based on their physicochemical characteristics including color, size, shape, and hardness, and offered an appropriate model to predict the effects of different harvest times on the physico-chemical properties of tomato.

The present work is aimed to determine the effectiveness of artificial intelligent models in predicting the rupture energy in pumpkin seeds. And for this study focused on the possibility of predicting the rupture force

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of pumpkin seeds using MLP and ANFIS was used as a comparative model. By using the researcher's MLP and ANFIS model, it is aimed to reveal the most accurate model with various performance criteria among different inputs and different network structures. The results obtained can be considered a useful tool when the transportation and processing of that is improved and optimized. According to The MLP and ANFIS were obtained different model which, were compaired different neural network structure for MLP model and different membership founction and rules for ANFIS that were evaluated to find the best model. Due to the high sensitivity and power of this smart model, we tried to reach the best model.

2 Material and method

The present research of pumpkin seeds were obtained from manufacturer in Samsun then the seeds were selected for broken and rotten seeds. And five different pumpkin seeds variety were used that named kestane, arıcan 97, sakız, esta 818 and pan F1 in this study. Physical and mechanical properties of intact seeds were evaluated, that were measured width (W), length (L), thickness (T), sphericity (S), thousand grain weight (TGW) by digital calipers were made in pumpkins seeds. And the moisture content value for pumpkin seeds were obtained using the gravimetric method that specified with the method by [19].

In addition, geometric mean diameter (GMD), aritmetic mean (A), volume (V), surface area (SA), Sphericity (S), true density and bulk density calculations were obtained that used in the model. Dimension measurements of pumpkin seeds were made with a digital caliper with a precision of 0.01 mm (Mitutoya brand, Absolute Digimatic model, Japan) [20, 21]. The bulk density value (kg m^{-3}) was determined by measuring the weight of the material filled to a height of 150 mm and a 50 ml cylindrical container. True density (kg m^{-3}) was measured using the displacement method [20]. With the calculation of the area under the curve, rupture energy values were obtained [22].

2.1 Dataset pre-prosiding

In this study, we used a training-testing- validation analysis strategy, which produces unbiased estimates. We have been all data 250 data.

The k-fold cross-validation technique was used a model that choose from 60% (n=150) training dataset, from 20% (n=50 and 50) testing dataset and validation dataset, respectively. The original dataset is separated randomly into *k* equal-sized subsets (k-folds) that was applied to reduce the bias related to the dataset sample randomly. A single subset of the is selected as the *k* partitions are designated as testing dataset to evaluate the model's performance, and the remaining subsets are used as training data. This procedure is repeated k times, and the k fold results are averaged cross-validation error to produce that is employed as a performance indicator.

In this research, *k* was taken as 10. Detailed the specific information about this procedure can be accessible by [23].

2.2 Use of data driven techniques

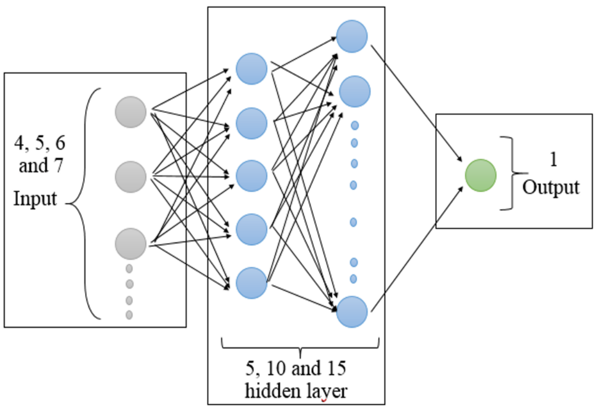
2.2.1 Multilayer perceptron (MLP)

The MLP is a widely used type of neural network for classification purposes [24]. The structure of a simple MLP is shown in Fig 1a. MLP models are composed of interconnected processing elements similar to biological neurons and weighted connections similar to brain snaps [25, 26].

This study, a double-hidden-layer MLP was considered, and tangent sigmoid (tansig) and linear (purelin) transfer functions were used in hidden and output layers, respectively. The number of hidden layer nodes altered from 5 to 15 to attain the optimal training network. The information moves from neurons in the input layer, through double-hidden-layers neurons, and to neurons in the output layer [27]. In this research, scaled conjugate grdient (SCG) training algorithm [28, 29] was employed to minimize the objective function (*Fobj*), which was the mean square error (MSE). The stop criteria were determined as *Fobj* = 1.10^{-6} and 500 epochs. The optimal result was selected based on the minimum *Fobj* values of testing dataset.

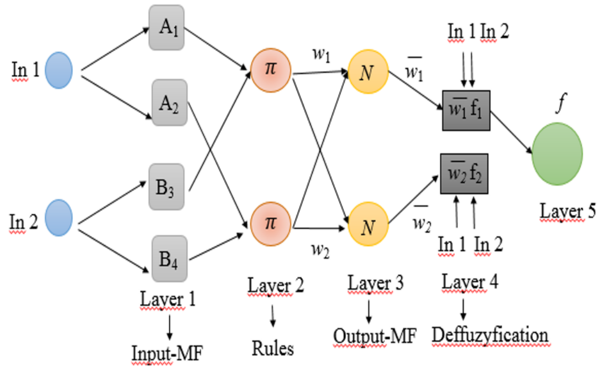
2.2.2 Adaptive neuro-fuzzy inference systems (ANFIS)

Adaptive neuro-fuzzy inference system (ANFIS) is a hybrid method that uses combin fuzzy reasoning and the learning the artificial neural network (ANN) between the input and output space [30, 31] that developed by [32]. So, the system integrates the learning capability and relational structure of the ANN with the decision making process (FIS) of the fuzzy inference system. The architecture of the ANFIS is shown in Fig. 1b. The basis of the ANFIS method is the Takagi-Sugeno - Kang fuzzy inference procedure plays an integral role in establishing If-then rules, that is the range from input to output [33]. Detailed information about ANFIS can be obtained from related reference [34].



(a)

 https://doi.org/10.1051/bioconf/20248501044



(b)

Fig. 1. Schematic diagram (a) MLP model structure ve (b) ANFIS model structure.

2.2 Performance criteria of models in evaluation

Model performance was assessed through statistical indicators including coffecient of determination (R^2), root mean square error (RMSE), mean square error (MSE), mean absolute error (MAE) and mean relative percentage absolute error (MRPE) that was used Eqs.1, 2, 3, 4 and 5 respectively [35]. The best model was determined according to the highest R^2 [36, 37] value and lowest RMSE [38] and MAE [36] values that is using the equations given below. The higher the R^2 value (with 1 being the maximum value), the better is the performance for the models [39].
Equations:

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

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m}(yi-Oi)^2}{n}} \tag{2}$$

$$MSE = \frac{\sum_{i=1}^{n}\left(y_i-O_i\right)^2}{n} \tag{3}$$

$$MAE = \frac{\sum_{i=1}^{n}\left|\left(y_i-O_i\right)\right|^2}{n} \tag{4}$$

$$MRPE = \frac{\sum_{i=1}^{n}\left(\frac{x_{mea,i}-x_{est,i}}{x_{mea,i}}\right)}{n} x100 \tag{5}$$

Where n is number of data instances, y_i is measured repture energy, y is predicted repture energy, O_i *is* calculated repture energy values from the model for R^2, RMSE, MSE, MAE and MRPE parameters.

3 Results and discussion

Descriptive statistics for pumpkin seeds selected of measure data in properties that including minimum (Min.), maximum (Max.), mean, standard deviation (SD), skewness (Sk), kurtosis (Kr), and coefficient of variation (CV) are summarized in Table 1 for training, testing and validation dataset that using input and output data.

Table 1. Descriptive statistics for measure data in pumpkin seed.

Training dataset							
Data	Max.	Min.	Avg.	SD	Skevnes	Kurtosis	CV
Width	15.76	7.33	11.62	2.07	-0.51	-0.52	17.82
Lenght	25.53	12.96	18.68	3.05	-0.23	-0.72	16.36
Thicknes	5.92	1.78	4.05	0.98	-0.62	-0.63	24.13
Thousand grain weight	439.00	52.00	354.96	124.14	-1.51	0.32	34.97
Moisture	77.23	50.03	57.67	6.03	1.54	1.59	10.45
Geo. Mean diameter	12.04	5.91	9.55	1.68	-1.00	-0.36	17.59
Aritmetic mean	14.74	7.53	11.45	1.89	-0.72	-0.55	16.48
Volume	913.88	107.98	494.66	207.32	-0.60	-0.77	41.91
Surface area	455.34	109.64	294.88	92.17	-0.81	-0.59	31.26
Sphericity	64.64	43.05	51.08	4.23	0.43	0.06	8.28
Bulk density	413.60	181.57	338.75	75.89	-1.21	-0.11	22.40
True density	757.60	327.02	605.30	136.92	-1.40	0.15	22.62
Repture energy	0.90	0.02	0.23	0.14	1.44	5.63	60.87
Testing dataset							
Width	15.24	7.31	11.92	2.36	-0.70	-0.68	19.82
Lenght	24.55	13.39	19.00	3.10	-0.54	-0.66	16.30
Thicknes	5.64	2.16	4.17	1.03	-0.72	-0.80	24.76
Thousand grain weight	446.00	98.00	350.30	122.77	-1.53	0.40	35.05
Moisture	71.17	52.37	58.22	6.14	1.20	-0.11	10.55
Geo. Mean diameter	11.69	6.15	9.77	1.79	-1.19	-0.11	18.29
Aritmetic mean	14.37	7.74	11.70	1.99	-1.03	-0.25	17.05
Volume	835.08	121.57	532.26	222.10	-0.86	-0.53	41.73

Surface area	428.78	118.65	309.37	98.38	-1.03	-0.32	31.80
Sphericity	61.12	44.36	51.31	4.50	0.27	-0.74	8.78
Bulk density	401.44	184.68	329.71	73.89	-1.26	-0.01	22.41
True density	708.38	333.83	603.22	134.88	-1.50	0.34	22.36
Repture energy	0.33	0.03	0.21	0.09	-0.99	-0.46	44.08
Validation dataset							
Width	15.64	7.51	11.78	2.31	-0.42	-0.70	19.60
Lenght	25.22	13.03	18.77	3.23	-0.34	-0.68	17.21
Thicknes	5.32	2.33	4.10	0.93	-0.71	-0.74	22.69
Thousand grain weight	425.00	76.00	341.66	122.41	-1.48	0.31	35.83
Moisture	71.10	52.74	58.25	6.18	1.21	-0.12	10.61
Geo. Mean diameter	11.58	6.17	9.64	1.71	-1.05	-0.26	17.73
Aritmetic mean	14.44	7.70	11.55	1.96	-0.90	-0.46	16.97
Volume	811.89	123.19	509.46	213.89	-0.65	-0.69	41.98
Surface area	420.80	119.71	300.75	94.45	-0.86	-0.48	31.40
Sphericity	61.39	42.87	51.40	4.22	0.31	-0.10	8.21
Bulk density	386.38	187.60	329.66	71.90	-1.42	0.23	21.81
True density	711.45	331.63	603.27	133.38	-1.50	0.34	22.11
Repture energy	0.30	0.04	0.20	0.09	-0.91	-0.60	43.92

The repture energy value (RE) was estimated of that used different input combinations of width (W), length (L), thickness (T), sphericity (S), moisture (M), thousand grain weight (TGW), bulk density (BD), true density (TD), geometric mean diameter (GMD), aritmetic mean (A), volume (V) and surface aarea (SA) values that used that presented in Table 2 as weel for MLP and ANFIS models. The different 4, 5, 6 and 7 combinations of input data used to estimate of repture energy values for MLP 1 and ANFIS 1, MLP 2 and ANFIS 2, MLP 3 and ANFIS 3 and MLP 4 and ANFIS 4, respectively. Different input combinations for MLP and ANFIS models were evaluated to asses the degree of each variable's effect on the rupture energy values that shows the various model structure and membership founchion type, respectively.

Table 2. The model input variables.

Model	Input						
MLP 1 ANFIS 1	W	T	M	BD			
MLP 2 ANFIS 2	L	T	TGW	M	BD		
MLP 3 ANFIS 3	T	M	GMD	V	S	TD	
MLP 4 ANFIS 4	W	L	T	TGW	S	BD	TD

In this study, the estimation of rupture energy was obtained for double-layer network structures that used different input combinations with SCG training algorithm to train MLP. In MLP models, different numbers of hidden layer were examined and the most appropriate number was created and the optimal number of the hidden layer neurons (5-5, 10-10 and 15-15) also provided in the thirt column of the Table 3 that was selected the lowest RMSE value in the testing phase.

Table 3. The conbination of input and model structure for MLP.

Model	Model Number	Input	Model structure
MLP-1	1	4	5-5-1
	2	4	10-10-1
	3	4	15-15-1
MLP-2	4	5	5-5-1
	5	5	10-10-1
	6	5	15-15-1
MLP-3	7	6	5-5-1
	8	6	10-10-1
	9	6	15-15-1
MLP-4	10	7	5-5-1
	11	7	10-10-1
	12	7	15-15-1

In the ANFIS technique, the most appropriate outputs were tested for gaussmf, trapmf with varying numbers of membership founction (MFs) and different rural number that show in Table 4

Table 4. The conbination of input and membership founction for ANFIS.

Model	Model Number	Membership founction type	Rural
ANFIS_1	1	gaussmf	3*3*3*3
	2	trapmf	
	3	gaussmf	4*4*4*4
	4	trapmf	
ANFIS_2	5	gaussmf	3*3*3*3
	6	trapmf	
	7	gaussmf	4*4*4*4
	8	trapmf	
ANFIS_3	9	gaussmf	3*3*3*3
	10	trapmf	
	11	gaussmf	4*4*4*4
	12	trapmf	
ANFIS_4	13	gaussmf	3*3*3*3
	14	trapmf	
	15	gaussmf	4*4*4*4
	16	trapmf	

The training, testing and validation results of the MLP and ANFIS models in the estimation repture energy in pumpkin seeds are showen in Table 5 and Table 6, respectively.

Table 5. R^2, RMSE and MSE values of the data-driven techniques in training, testing and validation to estimating rupture energy in MLP models.

Training algorithm			SCG								
			Training			Testing			Validation		
	No	Model structure	R^2	RMSE	MSE	R^2	RMSE	MSE	R^2	RMSE	MSE
MLP 1	1	4-5-5-1	0.739	0.0734	0.0054	0.831	0.03863	0.00149	0.867	0.03543	0.00126
	2	**4-10-10-1**	**0.767**	**0.0703**	**0.0049**	**0.880**	**0.03315**	**0.00110**	**0.903**	**0.03133**	**0.00098**
	3	4-15-15-1	0.713	0.0775	0.0060	0.855	0.03645	0.00133	0.838	0.03988	0.00159
MLP 2	4	5-5-5-1	**0.783**	**0.0695**	**0.0048**	**0.850**	**0.04174**	**0.00174**	**0.8211**	**0.03648**	**0.00133**
	5	5-10-10-1	0.745	0.0707	0.0050	0.818	0.04242	0.00180	0.8163	0.03697	0.00137
	6	5-15-15-1	0.717	0.0758	0.0057	0.739	0.04854	0.00236	0.7999	0.04487	0.00201
MLP 3	**7**	**6-5-5-1**	**0.810**	**0.0636**	**0.0040**	**0.903**	**0.03710**	**0.00138**	**0.909**	**0.04227**	**0.00179**
	8	6-10-10-1	0.766	0.0704	0.0050	0.880	0.03714	0.00138	0.888	0.04264	0.00182
	9	6-15-15-1	0.726	0.0734	0.0054	0.846	0.04289	0.00184	0.858	0.04286	0.00184
MLP 4	10	7-5-5-1	0.746	0.0709	0.0050	0.868	0.03680	0.00135	0.848	0.03591	0.00129
	11	**7-10-10-1**	**0.775**	**0.0668**	**0.0045**	**0.910**	**0.03519**	**0.00124**	**0.893**	**0.04311**	**0.00186**
	12	7-15-15-1	0.725	0.0732	0.0054	0.827	0.04044	0.00164	0.839	0.04440	0.00197

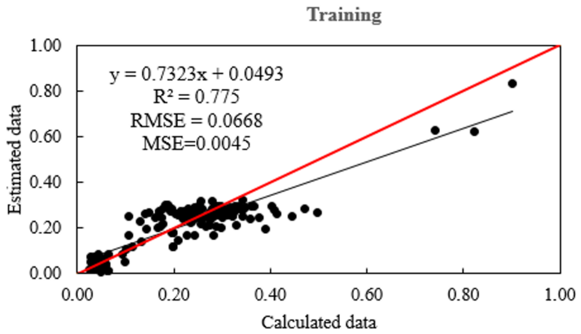
Table 6. R^2, RMSE and MSE values of the data-driven techniques in training, testing and validation to estimating rupture energy in ANFIS models.

				Training			Testing			Validation		
Model		Membership founction type	rural	R^2	RMSE	MSE	R^2	RMSE	MSE	R^2	RMSE	MSE
ANFIS_1	1	gaussmf	3*3*3*3	0.831	0.0569	0.00324	0.905	0.0288	0.00083	0.888	0.0316	0.00100
	2	trapmf		0.809	0.0621	0.00386	0.904	0.0297	0.00088	0.921	0.0274	0.00075
	3	gaussmf	4*4*4*4	**0.841**	**0.0556**	**0.00309**	**0.933**	0.0263	**0.00069**	**0.936**	**0.0232**	**0.00054**
	4	trapmf		0.815	0.0616	0.00379	0.869	0.0346	0.00120	0.885	0.0324	0.00105
ANFIS_2	5	gaussmf	3*3*3*3	0.866	0.0520	0.00271	0.877	0.0381	0.00145	0.928	0.0241	0.00058
	6	trapmf		**0.857**	**0.0523**	**0.00274**	**0.915**	**0.0284**	**0.00081**	**0.946**	**0.0234**	**0.00055**
	7	gaussmf	4*4*4*4	0.827	0.0582	0.00339	0.888	0.0316	0.00100	0.914	0.0268	0.00072
	8	trapmf		0.880	0.0479	0.00230	0.911	0.0282	0.00080	0.959	0.0184	0.00034
ANFIS_3	9	gaussmf	3*3*3*3	0.924	0.0382	0.00146	0.937	0.0472	0.00086	0.935	0.0277	0.00077
	10	trapmf		0.909	0.0417	0.00174	0.941	0.0441	0.00065	0.929	0.0283	0.00080
	11	gaussmf	4*4*4*4	**0.868**	**0.0505**	**0.00255**	**0.966**	**0.0399**	**0.00032**	**0.944**	**0.0244**	**0.00059**
	12	trapmf		0.929	0.0368	0.00136	0.942	0.0420	0.00050	0.963	0.0175	0.00031
ANFIS_4	13	gaussmf	3*3*3*3	0.974	0.0226	0.00051	0.927	0.0260	0.00067	0.937	0.0225	0.00051
	14	trapmf		0.969	0.0247	0.00061	0.942	0.0269	0.00072	0.941	0.0274	0.00075
	15	gaussmf	4*4*4*4	0.962	0.0271	0.00074	0.928	0.0259	0.00067	0.926	0.0245	0.00060
	16	trapmf		**0.966**	**0.0258**	**0.00067**	**0.969**	**0.0167**	**0.00028**	**0.969**	**0.0157**	**0.00025**

According to training stage, the RMSE values were changed between 0.0636-0.0775, 0.0226-0.621 for MLP and ANFIS models, respectively. The lowest RMSE value (0.0636) was calculated for MLP 3 (6-5-5-1) in 7th model number which the inputs were used T, M, GMD, V, S and TD. The lowest value MAE were between 0.0045 for MLP 4 (7-10-10-1) in 11th model. The R^2 values were obtained between 0.71 and 0.81 for MLP model and between 0.81 and 0.97 for ANFIS models between measured and estimated repture energy.

Similarly, in the testing stage, the RMSE and MSE values were ranged between 0.03315-0.0485, 0.0263-0.0472 and 0.0259-0.0472, 0.00028-0.00145 for MLP and ANFIS models, respectively. The R^2 values for MLP models were obtained 0.91 and the lowest RMSE and MSE values were 0.0352 and 0.00124 that were calculated 11th models in MLP 4 of 7-10-10-1 model structure. The input were used W, L, T, TGW, S, BD and TD. And for the ANFIS, the R^2, RMSE and MSE values were 0.97, 0.0167 and 0.00028, respectively which the input W, L, T, TGW, S, BD and TD for membership function of trap and 4x4x4x4 rural.

In the validation, the RMSE values for MLP and ANFIS were between 0.3133-0.04487, 0.0157-0.0324 and the MSE values were 0.00098-0.00201 and 0.00025-0.00105, respectively. The highest R^2 (0.90) was attained for the MLP 1 (4-10-10-1) model, whereas the highest value (0.97) obtained for ANFIS 4 in 16th model which were MFs of trap for 4x4x4x4 rural. It is clear from the table that the ANFIS 4 (trapmf) model with According to the best the MLP and ANFIS model results in the measured and estimated rupture force values for pumpkin seeds were shown in Fig. 2 and Fig. 3, respectively that were training, testing and validation data. The ANFIS 4 in 16th model (trapmf) seem to have better results than the other MLP and other ANFIS models that tested for rupture energy estimation. The scatter plots of the ANFIS 4 in 16th model (trapmf) for the measured and estimated rupture energy values in the all datasets (training, testing and validation) are shown in Fig 4. According to, the applied all dataset model results, the R^2 value is obtained the highed 0.97 that revealed performance accuracy of ANFIS model.



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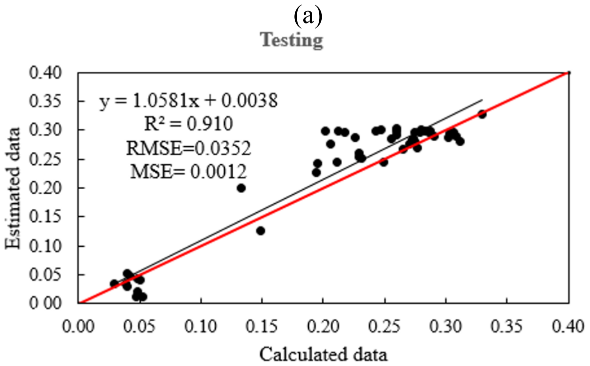

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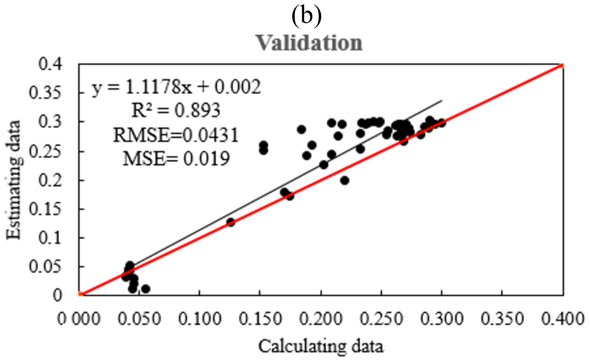
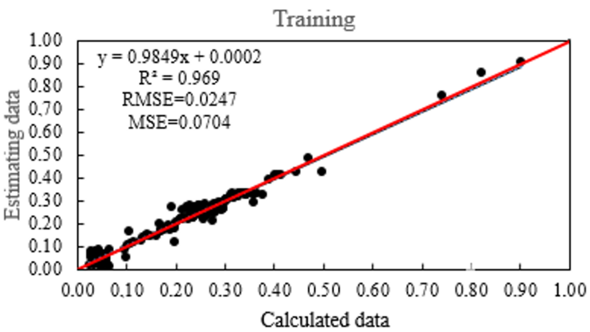
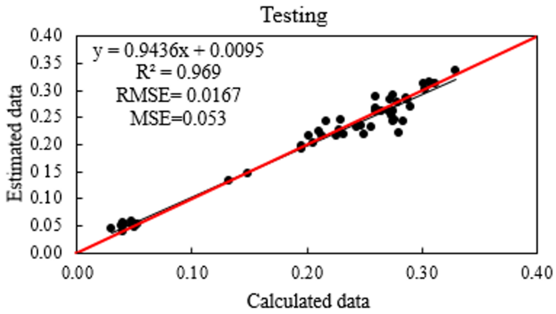


(c)

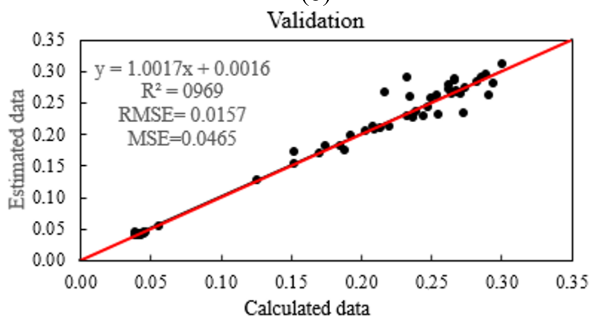
Fig. 2. The best model results a) training b) testing c) validation for MLP 4 (7-10-10-1) model.



(a)



(b)



(c)

Fig. 3. The best model results a) training b) testing c) validation for ANFIS 4 (16^{th}) model.

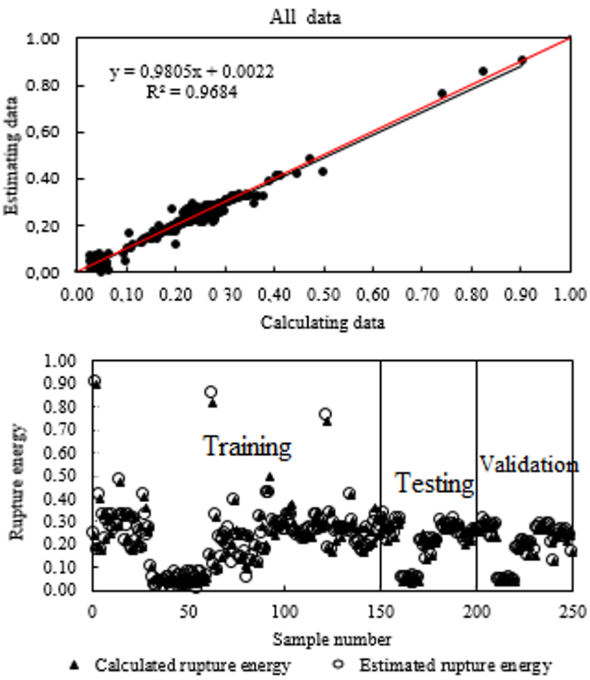
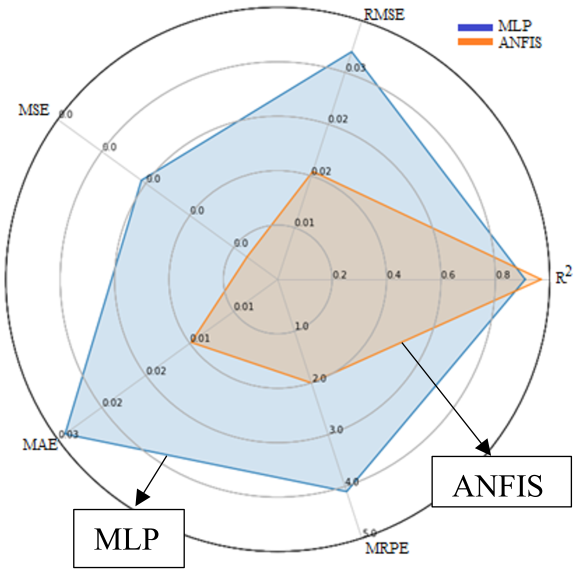


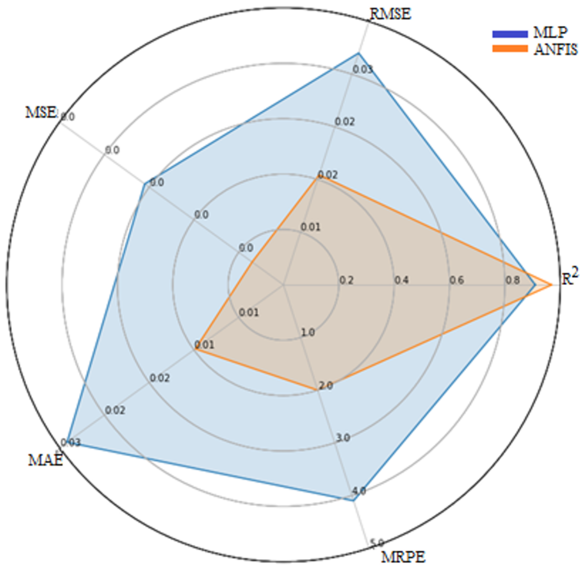
Fig. 4. The calculated and estimated rupture energy values for all data distribution graphs by ANFIS 4 (16^{th}) model (the best model).

The different researchers have made artificial intelligant for different physical properties for plant fruit, seeds etc. by [16, 40, 41]. The different MLP were using 5, 10 [12] to evaluated the physiological proerties of pear. [42] that reported between 2 and 20 neurons, LM training algorithm [9] who reported application of ANFIS to estimated rapeseeds' oil extraction. An artificial neural network was used that determine the mechanical properties of cumin seeds to estimate the rupture energy value. And It is seen that the 6-1 artifical neural network structure was chosen as the best model for the estimation of the force required to break the cumin seed [43]. The performance of pea seed yield prediction to compared by multi linear regression (MLR) and of non-linear ANN model. And as a results of the analysis (R^2 > 0.90) were determined that an artificial neural network model is a useful [17].

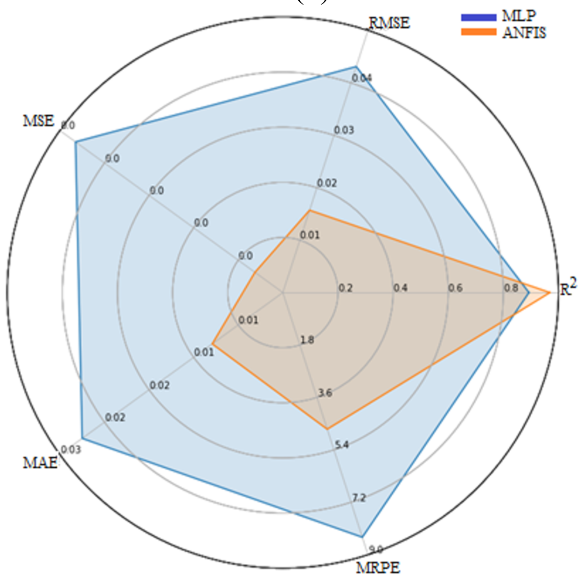
In addition to the model evaluation criteria, MAE and MRPE values were calculated for the best model results. The MAE values were calculated 0.0493, 0.029 and 0.027 for MLP 4 (11th), 0.0176, 0.0118 and 0.0095 values for ANFIS 4 (16th) model by training, testing and validation dataset. According to training, testing and validation dataset, the MRPE values 2.8 – 10.6, 4.1- 2.0, 8.4 - 4.7 for MLP and ANFIS model, respectvely. In this study, model results was evaluated of quite difficult that the similar results were obtained between MLP and ANFIS models. For this reason, many statistical and graphical methods have been used. The spider plot was utilized to determine robustness of model's forecast. Finally, the spider plots, which are used to evaluate five error criteria (R^2, RMSE, MSE, MAE and MRPE) of the best approaches, were drawn in the study that are shown in Fig. 5 by training, testing and validation results. It can be easy seen that ANFIS 4 (16th) model is less than MLP 4 (11th) model according to RMSE, MSE, MAE and MRPE statistical criteria and another R^2 criteria is highest for ANFIS model.



(a)



(b)



(c)

Fig. 5. The spider graph a) training b) testing c) validation dataset for best models.

High-accuracy predictions were made in the created these models. According to these models, determining to classify five pumpkin varieties estimations that can be made with high accuracy that presented in Table 7. Other statistical parameters (MAE and MRPE) changes are given in Table 7. In the best model selected in ANFIS 4 (16th) model that R^2 value was changed between 0.87 and 0.97 in RMSE value between 0.0069 and 0.0240 values. In the ANFIS model, the formation of membership founction was trap, designed as 7 input, 4x4x4x4 in rural and 1output. Classifications are made for different characteristics of plants and seeds as shape, color, and texture of different varieties to use artificial neural network technique. The classifying eight pepper seed varieties achieved this by using 30 neurons with an accuracy rate of 84.94% in the hidden layer of the network using the sequential feature selection to estimate the training algorithm of resilient backpropagation [44].

Table 7. Classification of pumpkin variety by the best model.

Variety	R^2	RMSE	MSE	MAE	MRPE
Kestane	0.95	0.0240	0.00058	0.0146	5.8
Sakız	0.87	0.0069	0.00005	0.0048	11.7
Arıcan 97	0.96	0.0218	0.00048	0.0138	7.5
Esta 818	0.90	0.0179	0.00032	0.0146	5.2
Pan F1	0.93	0.0231	0.00053	0.0162	6.4

4 Conclusion

Seeds are one of the most important factors in increasing productivity and obtaining quality products for plant production.

In this study, the all MLP and ANFIS model accurately estimated the rupture energy which were obtained a determination coefficient (R2 > 0.9) and the lowest RMSE and MAE values. The best model (ANFIS 4 in 16th model) determined rupture energy for pumpkin seeds that were made high accuracy prediction which comparative analysis of the results obtained by the models indicated. The ANFIS 4 in 16th model (trapmf) results were obtained the highest R2, the lowest RMSE and MAE values that were 0.97, 0.0167 and 0.00028, respectively, the inputs which are W, L, T, TGW, S, BD and TD rupture energy for the testing dataset. According to test data model results was evaluated that were determine accuracy by validation. It was classified that the ANFIS model obtained pumpkin seed varieties in a fast and reliable way. According to, the results of model are a necessary and reliable source of information in agricultural production management

The analyses conducted show that an artificial intelligence model is a useful tool in predicting rupture energy. According to this study results, further research will evaluate on comparative analysis of other machine learning techniques. Artificial intelligence techniques are a valuable source of information that is particularly relevant for agronomists and decision makers that are examined in the studies and as an alternative approach is recommended.

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