How to cite: Altıkat, S. 2020. The modelling of rupture force of white kidney beans (*Phaseolus vulgaris* L.) using the multiple linear regression (MLP) and artificial neural networks (ANN), Ege Üniv. Ziraat Fak. Derg., 57 (1):129-136, DOI: 10.20289/zfdergi.554929

Araştırma Makalesi
(Research Article)

Ege Üniv. Ziraat Fak. Derg.,2020, 57 (1):129-136
DOI: 10.20289/zfdergi.554929

The modelling of rupture force of white kidney beans (*Phaseolus vulgaris* L.) using the multiple linear regression (MLP) and artificial neural networks (ANN)

Fasulyede (*Phaseolus vulgaris* L.) Kırılma Direnci Değerlerinin Çoklu Lineer Regresyon ve Yapay Sinir Ağları ile Modellenmesi

Sefa ALTIKAT[1*]

[1]Iğdır University Agriculture Faculty Department of the Biosystems Engineering / Iğdır

[1]**Orcid No:** 0000-0002-3472-4424

***sorumlu yazar:** sefa.altikat@igdir.edu.tr

Alınış (Received): 17.04.2019 **Kabul Tarihi** (Accepted): 15.10.2019

Keywords:

Physical property, mechanical property, simulink, moisture, variety

ABSTRACT

Objective: The objective of this study modelling the rupture force of white kidney beans with the multiple linear regression (MLR) and artificial neural networks (ANN).

Material and Methods: It was used four different white kidney bean varieties (Akman, Topçu, Göynük and Karacaşehir) at the five different moisture contents (14.28%, 24.32%, 33.45%, 42.54% and 53.48%). In the MLR and ANN models the moisture contents, length, width, thickness, arithmetic mean diameters, geometric mean diameters, surface area and sphericity of the beans were used as input parameters while the rupture force as output parameter. In addition, 24 different ANN architectures were used in the ANN.

Results: The highest R^2 values for the Akman (0.979) and Karacaşehir (0.986) varieties were obtained in the ANN11 architecture used by the Levenberg-Marquard learning function and the logarithmic sigmoid - linear transfer function pairs with 12 neurons. However, the best prediction values for Topçu (0.963) and Göynük (0.944) were obtained in ANN 7 and ANN 2 architectures, respectively. In addition, the best pair of learning functions for Topçu and Göynük were observed in Logarithmic sigmoid - Symmetric sigmoid and Logarithmic sigmoid- linear transfer functions, respectively.

Conclusion: The results of the study clearly showed that the ANN successfully modeled rupture force in all the white kidney bean varieties.

Anahtar Sözcükler:

Fiziksel özellik, mekanik özellik, simülasyon, nem, çeşit

ÖZ

Amaç: Bu çalışma fasulyenin kırılma direnci değerlerini çoklu liner regresyon (MLR) ve yapay sinir ağlarıyla (ANN) modellemek amacıyla yapılmıştır.

Materyal ve Metot: Araştırmada dört farklı fasulye çeşidi (Akman, Topçu, Göynük ve Karacaşehir) beş farklı tohum nem içeriğinde (%14.28, %24.32, %33.45, %42.54 ve %53.48) kullanılmıştır. Çoklu liner regresyon ve yapay sinir ağı modellerinde tohumların; uzunluk, genişlik, kalınlık, aritmetik ortalama çap, geometrik ortalama çap, yüzey alanı ve küresellik değerleri giriş parametresi, kırılma direnci değerleri ise çıkış parametresi olarak dikkate alınmıştır. Ayrıca, yapay sinir ağı modellinde 24 farklı ağ yapısı dikkate alınmıştır.

Bulgular: Araştırmada Akman (0.979) ve Karacaşehir (0.986) için en yüksek R^2 değerleri Levenberg-Marquard öğrenme fonksiyonu ve logarithmic sigmoid – liner transfer fonksiyonlarının 12 nöron ile kullanıldığı ANN 11 ağında elde edilmiştir. Bununla beraber Topçu (0.963) ve Göynük (0.944) için en iyi tahmin değerleri sırasıyla ANN 7 ve ANN 2 ağlarında belirlenmiştir. Ayrıca Topçu ve Göynük için en iyi öğrenme fonksiyon çifti sırasıyla logarithmic sigmoid - symmetric sigmoid ve logarithmic sigmoid- lineer fonksiyon çiftlerinde belirlenmiştir

Sonuç: Çalışma sonuçları açıklıkla göstermiştir ki tüm fasulye çeşitlerindeki kırılma dirençleri ANN ile başarılı bir şekilde modellenmiştir.

INTRODUCTION

White kidney bean (WKB) has important nutritional qualities; high in protein and low in fat content. The product has also contains some key nutrients, vitamins, fiber, zinc, and copper. WKB has been produced in Turkey for more than two hundred years (Sehirali, 1988). Currently, Turkey has a 4938 ha cultivation land of bean with an annual production of 630347 tons of WKB.

During the cultivation process from sowing to transportation the size, shape and mechanical behaviours of bean seeds or grains are necessary to know when choosing appropriate types of machinery for separating, harvesting, sizing and grinding. Further, these properties are used to develop and design new machineries.

Artificial neural network (ANN) has been successfully utilized for modelling many of complex systems (Droulia et al. 2009). This is an efficient method for modelling the nonlinear systems. This method uses input and output parameters for prediction with different transfer-learning function combinations and neuron numbers (Franch and Panigrahi, 1997; Gevrekçi et al. 2011). In addition, it has been used different neural network types such as Back-propagation neural network (BPN) and radius basic function neural network (Van et al. 2002).

Recently, computer-aided modeling techniques have been employed in many different study areas. By using these modeling techniques, various simulations can be made for nonlinear relations. Latrille et al. (1993), used the ANN method successfully in the simulation of fermentation properties. In addition, the drying behavior of different food and agricultural materials such as carrot (Erenturk and Erenturk, 2007; Kerdpiboon et al. 2006), tomato (Movagharnejad and Nikzad, 2007), ginseng (Martynenko and Yang, 2006), cassava and mango (Hernandez-Perez et al., 2004) and osmotic dehydration (Trelea et al. 1997), were successfully modeled by ANN method.

One of the mechanical quality criteria of agricultural products after harvest is the resistance against the rupture. The rupture force can be affected by many factors such as variety, moisture content and dimensional properties. In addition there is a little information about application of artificial neural networks in rupture force of white kidney bean.

The aim of this study was simulate of rupture force for white kidney bean varieties at the different seed moisture content by using artificial neural network and multiple linear regression model.

MATERIALS and METHODS

In the study, WKB varieties of Akman, Topcu, Karacaşehir and Göynük, each with five seed moisture contents (14.28%, 24.32%, 33.45%, 42.54% and 53.48%) were used as the study materials. All the WBK varieties were produced in Turkey. The initial moisture content of the seeds was determined by the ASAE method (ASAE, 1999). Approximately 10 g of the bean was dried in an oven (a for 20 h at the 130 °C) to reach a constant the sample weight. The initial seed moisture content was calculated as 14.28% for all of the varieties. Then the equation 1 was used to obtain a 24.00, 34.00, 44.00 and 54.00% water contents.

$$Q = \frac{Bi(Mf - Mi)}{Mi + 100} \quad \text{.........……….. (1)}$$

In this equation; Q: the mass of water to suffix (kg), Bi: The initial samples mass (kg); Mi: the initial moisture content (% db) and Mf: the final content of the samples (% db).

Moistening was performed by preserving the sample primed with the essential amount of water in each status in a hermetic container turning around periodically over a period of 48 h. These samples were laid in plastic cases in a freezer at 4 °C for a week to permit uniform moisture content within the seeds (Sun and Woods, 1994). Eventually, the final moisture levels of the samples were determined to be 24.32%, 33.45%, 43.54% and 53.48%. All the physical and engineering specifications of the samples were determinate for each of five moisture levels in the range of 14.28% to 53.48%.

In order to define the physical specification of the seeds, three sub-samples of 0.5 kg each were arbitrary separated from the entire samples. Two hundred seeds were collected from each of three sub-samples and thus 600 seeds were acquired and combined. The end of this process 50 seeds was arbitrarily selected (Sologubik et al. 2013). A digital micrometer was used to detect the size of the seeds. The arithmetic (Da) and geometric (Dg) mean of seed diameters were calculated by the equations 2 and 3, respectively ((Jain and Ball, 1997). In these equations L, W, and T are length, width and thickness, respectively.

$$Da = \frac{L + W + T}{3} \quad \text{........... (2)}$$

$$Dg = \sqrt[3]{L * W * T} \quad \text{......... (3)}$$

The sphericity (Φ) was calculated as equation 4 (Jain and Ball, 1997)

$$\theta = \left(\frac{\sqrt[3]{L * W * T}}{L}\right) * 100 \quad \text{.....................} (4)$$

The surface area of the samples (S) was determined by the equation 5 (Sologubik et al. 2013; Nimkar et al. 2005).

$$S = \pi * Dg^2 \quad \text{............................} (5)$$

Data set of the rupture force for modelling

In this research, 4000 data (10 parameters x 400 measurments) were used for rupture force prediction model.

Multiple Linear Regression

One of the methods used in the research is multiple linear regression (MLR). This method used to model the linear relationship between dependent and independent variables. The MLR model used in the study is given in equation 6.

$$Y=a_0+a_1 x_1+ a_2 x_2+\cdots+ a_k x_k \quad \text{...........}(6)$$

In this equation; Y is the rupture force prediction; x_1, x_2, …x_k input parameters and ak is the regression coefficients. The MATLAB software was used for MLR model. The input and output parameters for this model was given in table 1.

Artificial Neural Network (ANN)

Another model used in research is artificial neural network (ANN). The ANN made up of a number of simple and highly interconnected processing components, which process information by its dynamic state response to external inputs. The ANN can be single or multi-layer. Depending on the structural features of the problem, the neurons can be connected to the network in different ways (Gardner and Dorling, 1998). In this research, two learning functions, three different transfer function combinations and four different numbers of neurons were used as ANN architectures (ANNs). The architecture of an ANN model was given table2.

Table 1. The input and output parameters in the MLR
Çizelge 1. *MLR yöntemindeki giriş ve çıkış parametreleri*

Input parameters	Abbreviation	Output parameter	Abbreviation
Moisture content (%)	mc		
Length (mm)	l		
Width (mm)	w		
Thickness (mm)	t	Rupture force (N)	rf
The arithmetic mean diameters (mm)	amd		
The geometric mean diameters (mm)	gmd		
Surface area (mm^2)	sa		
The sphericity (%)	sp		

Table 2. Functions and neurons numbers used in the ANNs
Çizelge 2. ANN yapılarında kullanılan fonksiyon ve nöronlar

Input parameters	ANN Structures			Output parameter
	Learning functions	Transfer functions	Neurons	
Moisture content (mc)			3	
Length (l)				
Width (w)	LM	Ls-ts	6	
Thickness (t)		Ls-pr		Rupture force
The arithmetic mean diameters (mm)(am)		Ts-pl	9	(rf)
The geometric mean diameters (mm) (gm)	GD			
Surface area (mm^2) (sa)			12	
The sphericity (%) (sp)				

LM: Levenberg-Marquardt; GD: Gradient Descent; ls: Logarithmic sigmoid; ts: Symmetric sigmoid; pr: Linear transfer; Pl: Positive linear

Performance evaluation of the models

The performance of constructed ANN architectures were statistically measured, in terms of the mean square error (RMSE) (eq.7), mean absolute error (MAE) (eq.8) and coefficient of determination (R^2) (eq:9). The coefficient of determination (R^2) is a number that indicates how well data fit into a statistical model such as a regression line or curve. The RMSE is used to measure the error rate of a regression model and it represents the standard deviation of the model prediction error. The model is considered accurate when R^2 is close to 1.0, while *RMSE* must be as small as possible. MAE is a measure used to evaluate how close the estimates are to the measured results. The acceptable values of RMSE, MAE and R^2 mean that the model is able to describe the actual behavior of system. In the MLR, the R^2 values were taken into account as performance evaluation.

$$RMSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_{pi} - Y_{di}\right)^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_{pi} - Y_{di}\right| \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}\left(Y_{pi} - Y_{di}\right)^2}{\sum_{i=1}^{n}\left(Y_{pi} - \bar{Y}\right)^2}\right) \ldots\ldots (9)$$

In these equations; where, *n* is the number of data, Y_{pi} is the predicted value from observation *i*, Y_{di} is the real value from observation *i*, and $\bar{Y}$ is the average of the real value.

RESULTS and DISCUSSION

In the research firstly, the multiple linear regression model was used in order to estimate the rupture force. For this purpose; the moisture contents (mc), length (l) ,width (w), thickness (t), arithmetic mean diameters (amd), geometric mean diameters (gmd), surface area (sa) and sphericity of the bean (sp) were used as input parameters while the rupture force as output parameter. The table 3 illustrates the statistical results of the MLR. When examined the table 3 it can be seen that R^2 values were 0.812, 0.911, 0.850 and 0.815 for Akman, Topçu, Karacaşehir and Göynük, respectively. In addition, the equations of the MLR model and predicted –measured values were given in equation 10-13 and figure 1, respectively.

$$Yrf(akman) = -1315.5 + 22.1X_1 + 353 * 10^7(X_2 + X_3 + X_4) - 11 * 10^9X_5 + 473X_6 - 7.7X_7 + 0.12X_8 \quad \ldots\ldots (10)$$

$$Yrf(topçu) = -1315.5 + 22.1X_1 + 353 * 10^7(X_2 + X_3 + X_4) - 11 * 10^9X_5 + 473X_6 - 7.7X_7 + 0.12X_8. \quad \ldots (11)$$

$$Yrf(karacaşehir) = -811.5 + 13.8X_1 - 170 * 10^6(X_2 - X_3 - X_4) + 511 * 10^6X_5 - 77X_6 + 1.01X_7 - 7.4X_8 \quad \ldots\ldots\ldots\ldots (12)$$

$$Yrf(göynük) = -192.9 + 22.7X_1 + 132 * 10^7(X_2 + X_3 + X_4) - 396 * 10^7X_5 + 115X_6 - 1.4X_7 + 1.7X_8 \quad \ldots\ldots\ldots (13)$$

In these equation; X_1: mc; X_2: l; X_3: w; X_4: t; X_5: amd; X_6: gmd, X_7: sa and X_8:sp

Table 3. The statistical results for MLR
Çizelge 3. *MLR yöntemine ait istatistiksel sonuçlar*

	R^2	F	P	Estimated error variance
Akman	0.812	49.22	0.000	33.60
Topçu	0.911	123.8	0.000	71.60
Karacaşehir	0.850	64.30	0.000	86.30
Göynük	0.815	50.27	0.000	304.89

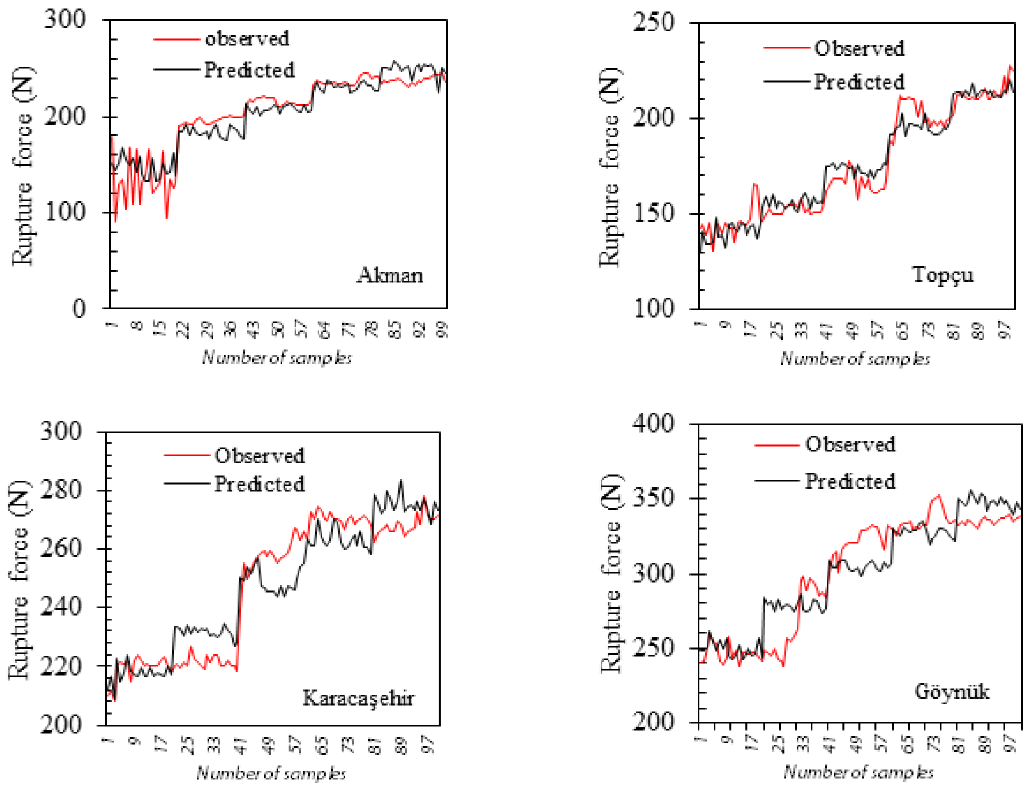


Figure 1. The measured and predicted values of rupture force for MLR
Şekil 1. *MLR yönteminde kırılma direncinin ölçülen ve tahmin edilen değerleri*

The results of the artificial neural network (ANN)

The statistical results of ANN architecture (ANNs) for modeling rupture force were given in Table 4. When Table 4 was examined, it was understood that ANN architecture which gives the best results for Akman and Karacaşehir was ANN 11 architecture. In this 12 neurons ANN 11 model, it was used Levenberg - Marquardt as learning functions, and Logarithmic sigmoid - Linear function pairs as transfer functions. The R^2 values in ANN 11 architecture were determined as 0.979 and 0.986 for Akman and Karacaşehir, respectively (Figure 2).

In addition, the mean square error (RMSE) and mean absolute error (MAE) values were lower in the ANN 11 for Akman and Karacaşehir compared to other ANN architectures. The best results for Topçu were obtained from ANN 7 architecture. In the ANN 7 architecture the highest R^2 (0.963) and lowest RMSE (0.109) and MAE (0.074) values were obtained (Table 4). The observed and predicted rupture force values for Topçu in the ANN 7 architecture was illustrated in the Figure 3.

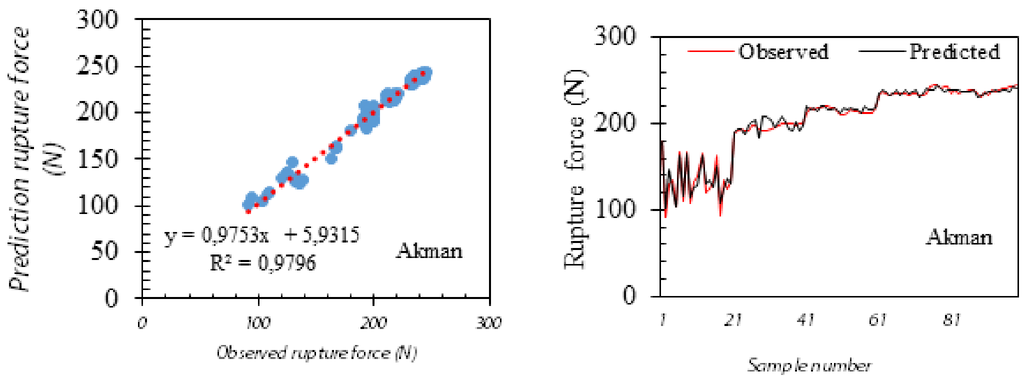
The best results in Göynük variety were obtained in ANN 2 architecture (table 4). In this ANN architecture the rupture force of Göynük was modeled with 0.944 R^2 value (figure 4).

Empirical methods such as MLR used in modeling studies are used to solve non-linear problems (Gardner and Dorling, 1998). But these models such as MLR does not explain complex relationship between the inputs and outputs parameters of the problems. (Emamgholizadeh et al. 2015). To solve such problems the artificial neural networks have been used for modelling studies. In the modelling studies, it has been compared to the MLR and ANN methods. For example, in a research for shear strength modeling the MLR and ANN methods were used According to the results, ANN method successfully modeled the shear strength value (Sivrikaya, 2009). In another study the seed yield were modelled with the MLR and ANN methods. According to obtained results the best modelling was obtained from the ANN methods (Niazian et al. 2018). In another study to model deformation of wheat seeds among the mathematical models, the best results were obtained in the ANN method (Khazaei et al. 2008). Similar results were obtained from this study. In this study, the ANN method modeled the rupture force in the best way.

Table 4. Statistical results ANNs architecture
Çizelge 4. *ANN yapılarına ait istatistiksel sonuçlar*

Model	Lf	Tf	Nn	Akman			Topçu			Karacaşehir			Göynük		
				RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2
1	LM	**Ls-ts**	**3**	0.129	0.081	0.940	0.115	0.081	0.959	0.094	0.068	0.979	0.175	0.127	0.935
2	LM	**Ls-pr**	**3**	0.126	0.089	0.942	0.122	0.088	0.954	0.094	0.067	0.979	0.116	0.109	0.944
3	LM	**Ts-pl**	**3**	0.140	0.086	0.928	0.115	0.083	0.959	0.097	0.072	0.978	0.170	0.119	0.937
4	LM	**Ls-ts**	**6**	0.100	0.062	0.964	0.114	0.081	0.960	0.094	0.071	0.979	0.169	0.118	0.939
5	LM	**Ls-pr**	**6**	0.093	0.070	0.969	0.116	0.081	0.958	0.096	0.071	0.978	0.187	0.130	0.924
6	LM	**Ts-pl**	**6**	0.101	0.068	0.962	0.120	0.088	0.957	0.086	0.066	0.983	0.167	0.116	0.940
7	LM	**Ls-ts**	**9**	0.133	0.070	0.936	0.109	0.074	0.963	0.091	0.065	0.981	0.184	0.138	0.926
8	LM	**Ls-pr**	**9**	0.128	0.097	0.940	0.112	0.079	0.961	0.093	0.069	0.980	0.164	0.113	0.942
9	LM	**Ts-pl**	**9**	0.109	0.074	0.958	0.121	0.086	0.955	0.094	0.068	0.979	0.187	0.137	0.926
10	LM	**Ls-ts**	**12**	0.090	0.063	0.970	0.112	0.083	0.961	0.086	0.062	0.983	0.173	0.113	0.938
11	LM	**Ls-pr**	**12**	0.075	0.057	0.979	0.132	0.102	0.947	0.077	0.058	0.986	0.168	0.100	0.940
12	LM	**Ts-pl**	**12**	0.084	0.058	0.974	0.113	0.081	0.961	0.091	0.068	0.981	0.165	0.107	0.941
13	GD	**Ls-ts**	**3**	0.162	0.118	0.904	0.121	0.086	0.955	0.137	0.113	0.958	0.206	0.154	0.908
14	GD	**Ls-pr**	**3**	0.171	0.113	0.893	0.128	0.088	0.950	0.155	0.122	0.943	0.215	0.154	0.899
15	GD	**Ts-pl**	**3**	0.154	0.101	0.912	0.124	0.090	0.953	0.118	0.097	0.967	0.205	0.146	0.909
16	GD	**Ls-ts**	**6**	0.198	0.135	0.855	0.137	0.097	0.943	0.130	0.099	0.961	0.215	0.158	0.900
17	GD	**Ls-pr**	**6**	0.167	0.119	0.898	0.139	0.102	0.941	0.139	0.110	0.954	0.223	0.165	0.892
18	GD	**Ts-pl**	**6**	0.152	0.097	0.915	0.131	0.093	0.947	0.198	0.163	0.908	0.200	0.142	0.913
19	GD	**Ls-ts**	**9**	0.160	0.104	0.907	0.140	0.103	0.939	0.158	0.133	0.944	0.199	0.151	0.915
20	GD	**Ls-pr**	**9**	0.182	0.127	0.879	0.152	0.115	0.929	0.171	0.144	0.931	0.269	0.206	0.843
21	GD	**Ts-pl**	**9**	0.158	0.103	0.909	0.129	0.092	0.949	0.103	0.077	0.975	0.202	0.145	0.911
22	GD	**Ls-ts**	**12**	0.174	0.123	0.889	0.135	0.101	0.944	0.166	0.136	0.942	0.229	0.191	0.896
23	GD	**Ls-pr**	**12**	0.235	0.175	0.798	0.165	0.121	0.916	0.172	0.141	0.930	0.204	0.152	0.909
24	GD	**Ts-pl**	**12**	0.159	0.109	0.908	0.132	0.100	0.946	0.182	0.144	0.922	0.190	0.136	0.922

Lf: learning function; Tf: transfer function; Nn: Neuron number; LM: Levenberg-Marquardt; GD: Gradient Descent; ls: Logarithmic sigmoid; ts: Symmetric sigmoid; pr: Linear transfer; pl: Positive linear; RMSE: mean square error; MAE: mean absolute error; R2: coefficient of determination



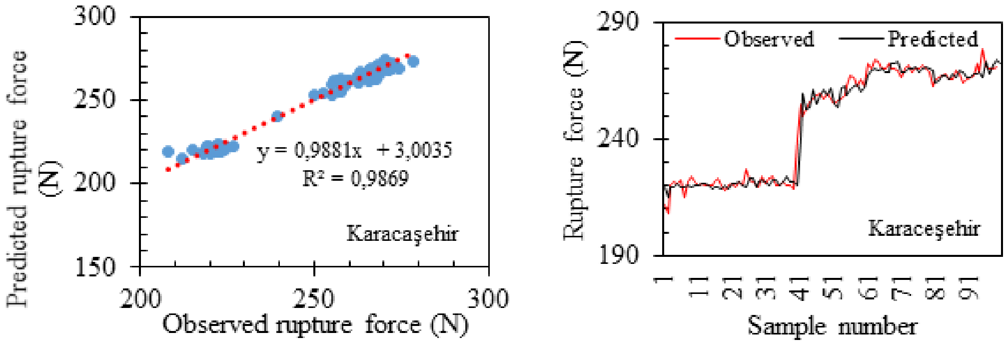


Figure 2. The measured and predicted values of rupture force for Akman and Karacaşehir for ANN
Şekil 2. *ANN yönteminde Akman ve Karacaşehir için kırılma direncinin ölçülen ve tahmin edilen değerleri*

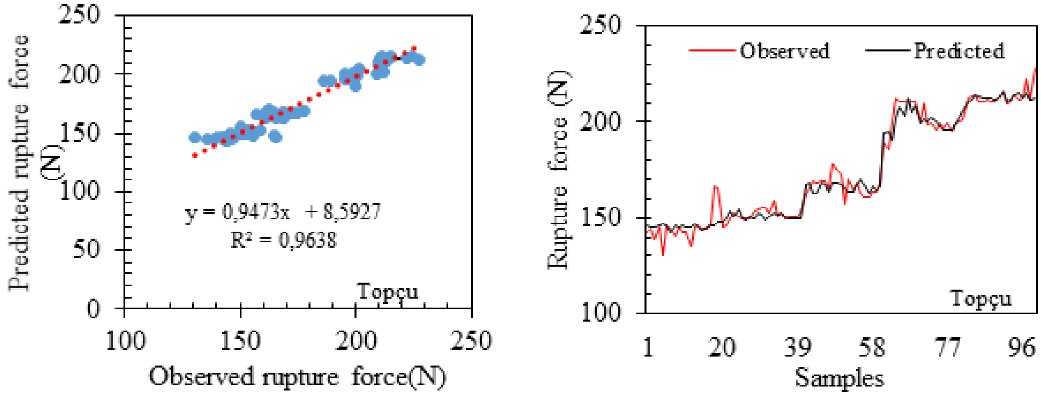


Figure 3. The measured and predicted values of rupture force for Topçu at the ANN
Şekil 3. *ANN yönteminde Topçu için kırılma direncinin ölçülen ve tahmin edilen değereleri*

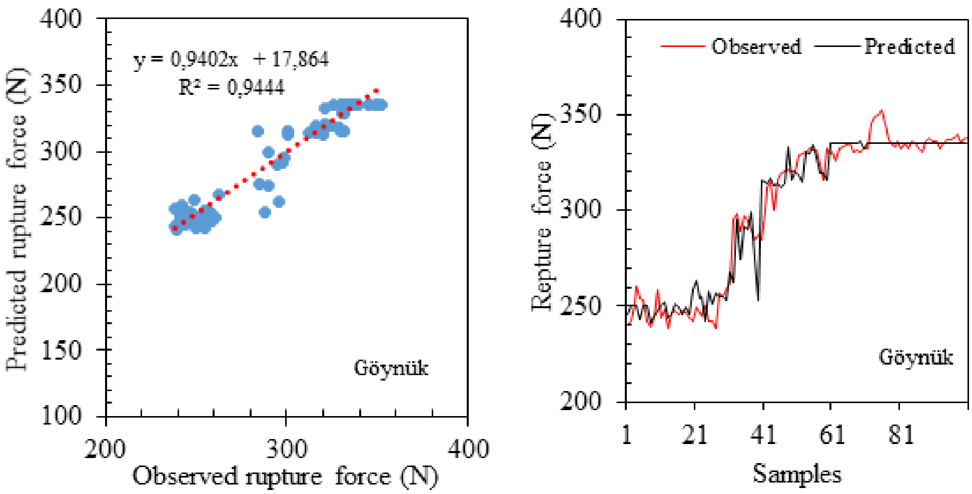


Figure 4. The measured and predicted values of rupture force for Göynük
Şekil 4. *Göynük için kırılma direncinin ölçülen ve tahmin edilen değerleri*

CONCLUSION

Among the methods conducted to model rupture force of the different varieties white kidney bean the ANN gave best results compare to MLR. In the MLR the R^2 values were determined as 0.812, 0.911, 0.850 and 0.815 for Akman, Topçu, Karacaşehir and Göynük, respectively. In the models with ANN, the R^2 values were determined as 0.979, 0.963, 0.986 and 0.944 for Akman, Topçu, Karacaşehir and Göynük, respectively. The best results for Akman and Karacaşehir were modelled in the ANNs11 architectures. In the ANNs11 architectures were used the Levenberg-Marquardt and Logarithmic sigmoid - Linear function pairs, as learning and transfer function, with 12 neurons, respectively. However, the ANNs7 and ANNs2 architectures were better simulated of rupture force for Topçu and Göynük varieties compare to the other ANN architects. In the ANN7 it was used Levenberg-Marquard and Logarithmic sigmoid - Symmetric sigmoid for learning and transfer functions, while in the ANN 2 were used Levenberg-Marquard and Logarithmic sigmoid –Linear function for learning and transfer functions, respectively. Finally, the rupture force of white kidney bean varieties were successfully modeled using artificial neural network compare to the MLR.

REFERENCES

ASAE (1999). Moisture measurement – unground grain and seeds. S352.2, DEC97.ASAE Standards, Standards Engineering Practices Data. ASAE, St. Joseph, MI.

Droulia F, Lykoudis S, Tsiros I, Alvertos N, Akylas E , Garofalakis I (2009). Ground temperature estimations using simplified analytical and semi-empirical approaches. Solar Energy 83: 211-219

Emamgholizadeh S, Parsaeian M, Baradaran M (2015). Seed yield prediction of sesame using artificial neural network. European Journal of Agronomy 68: 89-96.

Erenturk S, Erenturk K (2007). Comparison of genetic algorithm and neural network approaches for the drying process of carrot. Journal of Food Engineering 78: 905–912.

Franch LJ, Panigrahi S (1997). Artificial neural network models of wheat leaf wetness. Agricultural and Forest Meteorology 88: 57—65.

Gardner MW, Dorling SR (1998). Artificial neural networks (the multilayer perceptron) - a review of applications in the atmospheric science. Atmospheric Environment 32: 2627-2636.

Gevrekçi Y, Yeğenoğlu E, Akbaş Y, Sesli M (2011). Yapay sinir ağlarının tarımsal alanda kullanımı. Ege Üniversitesi Ziraat Fakültesi Dergisi, 48(1): 71-76.

Hernandez-Perez JA, Garcia-Alvarado MA, Trystram G, Heyd B (2004). Neural networks for heat and mass transfer prediction during drying of cassava and mango. Innovative Food Science Emergency Technology 5:57–64.

Jain RK, Bal S (1997). Physical properties of pearl millet. Journal of Agricultural Engineering Research, 56, 89-98.

Kerdpiboon S, Kerr WL, Devahastin S (2006). Neural network prediction of physical property changes of dried carrot as a function of fractal dimension and moisture content. Food Research International 39: 1110–1118.

Khazaei J, Shahbazi F, Massah J, Nikravesh M, Kianmehr M (2008). Evaluation and modeling of physical and physiological damage to wheat seeds under successive impact loadings: mathematical and neural networks modeling. Seed physiology, production & technology 48(4):1532-1544

Latrille E, Corrieu G, Thibault J (1993). pH prediction and final fermentation time determination in lactic acid batch fermentations. Escape 2. Computer Chemical Engineering 17: 423–428.

Martynenko AI, Yang SX (2006). Biologically inspired neural computation for ginseng drying rate. Biosystems Engineering 95 (3): 385–396.

Movagharnejad K, Nikzad M (2007). Modelling of tomato drying using artificial neural network. Computers and Electronics in Agriculture 59: 78–85

Nimkar PM, Mandwe DS, Dudhe RN (2005). Physical properties of moth gram. Biosystems Engineering 91 (2): 183–189.

Nizian M. Noori S, Abdipour M (2018). Modeling the seed yield of Ajowan (Trachyspermum ammiL.) using artificial neural network and multiple linear regression models. Industrial Crops & Products 117:224-234

Sehirali S (1988). Edible Pulses. Publications of Agricultural Faculty of Ankara University No: 1089. Ankara/Turkey (in Turkish).

Sivrikaya O (2009). Comparison of artificial neural networks models with correlative works on undrained shear strength. Eurasian Soil Science 42 (13): 1487–1496.

Sologubik CA, Campa˜none LA, Pagano AM, Gely MC (2013). Effect of moisture content on some physical properties of barley. Industrial Crops and Products: 43:762– 767

Sun DW, Woods JL (1994). Low temperature moisture transfer characteristics of barley: thin-layer models and equilibrium isotherms. J. Agric. Eng. Res. 59: 273–283

Trelea IC, Raoult-Wack AL, Trystram G (1997). Application of neural network modelling for the control of dewatering and impregnation soaking process (osmotic dehydration). Food Science and Technology International 3:459–465

Van Wijk M , Bouten T, Verstraten J M (2002). Comparison of different modeling strategies for simulating gas exchange of a douglas-fir forest. Ecological Modeling 158: 63—81