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ESTIMATION OF FRICTION COEFFICIENTS OF SOYBEAN SEEDS WITH SOFT COMPUTING APPROACH

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Abstract: Determination of physical and mechanical properties of agricultural products plays an important role in the usage areas of the products and industrial applications. Correct determination and evaluation of physical and mechanical properties of agricultural products is of critical importance in determining the quality, durability and usage potential of the product. In this study, the relationship between moisture content and friction coefficients of Samsoy variety soybean seed, which is a trial material, was determined in order to contribute to making correct decisions in industrial design and material selection. The central aim of this research is to expose with different moisture contents and friction surfaces well-accepted data-driven models to predict friction coefficients for soybean seed using different soft computing techniques. Determination of friction coefficient of agricultural products is important in terms of design and functionality of equipment used in post-harvest technologies and agricultural applications. In the study, 3 different moisture contents and five different friction surfaces (steel, stainless steel, galvanized sheet, PVC, court fabric) were used. Artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), group method of data handling (GMDH) are used to predict of friction coefficients. The best accuracy values were recorded as GMDH 7-7-1 for seven input and 7-15-1 model for five input structures for kinetic and static friction that were calculated performance criteria R^2 = 0.99-0.98, RMSE =0.00004-0.00006 , MSE = 0.00009 -0.00011, respectively. These selected the best models predicted which can be used in the soft computing techniques determined different conditions to estimating the friction coefficient for soybean seeds.

Keywords: Soft computing, Friction coefficients, Soybean seeds, Predict friction

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1. Introduction

Soybeans have a very high nutritional value are among the legumes used in animal nutrition. Soybean seeds contain high amounts of protein, the amino acid composition is not close to that of animal proteins, but it is quite good (Altuntaş et al., 2021). It is also the main source of valuable vegetable protein and the second source of oil, and global demand for soybeans is constantly increasing (Niedbała et al., 2022). Postharvest biotechnical properties of soybean play an important role in the engineering design of equipment and machinery for grading, sorting, transportation, processing and storage. In addition, some of the main post-harvest biotechnical properties of soybean as an agricultural material are shape, size, mass, 1000-grain weight, volume weight, porosity and coefficient of kinetic and static friction on different surfaces as well as mechanical properties of soybean seeds against force (Mohsenin, 1980). It is also important to know the physical properties of soybean seeds, especially in the design of precision planting machines. In addition, it is important to know the mechanical properties of soybean, post-harvest processing and processing into flour, power breaking force, deformation, energy and power values (Altuntaş et al., 2021). For example; (Tavakoli et al., 2009) investigated the physical and mechanical properties of Williams soybean variety seeds; (Shirkole et al., 2011) investigated the physical and mechanical properties of TAMS-38 soybean variety seeds; (Alibaş and Köksal, 2015) investigated the physical and mechanical properties of ATAEM-II soybean variety at different moisture contents; (Altuntaş et al., 2021) investigated the biotechnical properties of Türksoy, Adasoy and Yeşilsoy soybean varieties.

Around the world and in our country, various methods are used to estimate the physical and chemical properties of different plants under various environmental conditions, as well as to predict yield and parameters that are difficult to measure or calculate. Determination of static and dynamic friction coefficients of grain and other agricultural products on surfaces made of different materials is needed for correct design of warehouse, silo structures and transport equipment. The friction coefficient, which is one of the important physical and mechanical properties of grain and other agricultural products, affects the time of unloading of grain products from the warehouse (Gupta and Das,1988: Savenkov et al., 2019). Especially in recent years, estimation with artificial intelligence models is current. The reason for the great interest in neural networks is that they are called “universal function estimators” and can solve linear and nonlinear problems (Niedbała et al., 2022). Unfortunately, linear methods are characterized by much lower analysis results than artificial neural network (ANN) (Majkovič et al., 2016; Gorzelany et al., 2022; Sabzi-Nojadeh et al., 2021). In the literature, one can often come across the simultaneous use of multiple linear regression and artificial neural networks. So alternatively, soft computing methods (Shibata et al., 1996), which deal with computation in uncertain environments, have grown in importance. The main components of soft computing have shown great ability in solving complex nonlinear system identification and control problems, such as fuzzy logic, neural network, group method of data handling, least-square support vector machine, multivariate adaptive regression splines and genetic algorithm (Ghazi et al., 2021; Mozaffari et al., 2022; Poursaeid et al., 2022).

Artificial neural networks operate on a “black box” principle; that is, they may not provide complete information about the method of obtaining certain responses or detailed relationships between input and output variables (Lu et al., 2001). For this, new models can be developed using different techniques such as adaptive neuro-fuzzy inference systems (ANFIS), group method of data handling (GMDH). Studies have increasingly emphasized the accuracy of modeling and prediction of artificial intelligent models by exploiting input and output data relationships without making any prior assumptions about physical data (Wu et al., 2017). ANN is a type of neural network that is widely used for classification purposes. The application of artificial neural networks (ANNs) has attracted significant attention in agricultural and environmental sciences in recent years. ANNs consist of interconnected processors known as neurons that Inspired by the information processing capabilities of the human brain (Mohammadi et al., 2019). These neurons interact cooperatively and adapt through a learning process to perform tasks that are evaluatedsuch as pattern recognition, information classification, prediction, and modeling (Taki et al., 2016).

ANFIS has the ability to create an input-output matching network based on human knowledge in the form of if-then fuzzy rules and input-output dataset to train the neural network (Farzaneh et al., 2017). In one study, basic parameters for flaxseed were investigated, including emergence day, flowering day, plant height, branch number, number of capsules per plant, number of seeds per capsule, 1000 seed weight and seed yield per plant. Machine learning techniques, especially multilayer perceptron (MLP) and multiple linear regression (MLR), were used for seed yield. The results showed that MLP had better predictions than MLR according to RMSE and MAPE performance criteria. In addition, R^2 values were calculated above 0.97 for training, validation and testing stages. As a result, MLP served as a value function in genetic algorithm (GA) aiming to determine optimum trait levels to maximize flaxseed yield (Mohammadi Mirik et al., 2023). ANNs have been much preferred in agriculture in recent years due to their fault tolerance and capacity to extrapolate directly from data, thus eliminating the need for statistical forecasts (Saeidirad and Zarifneshat, 2013; Taheri-Rad et al., 2017; Mohammadi Mirik et al., 2023). It has various applications in agriculture using artificial intelligent techniques and has been studied in areas such as image processing of different products (Jayas et al., 2000), distinguishing vegetation and weeds in remote sensing (Karimi et al., 2005), solar radiation prediction (Elizondo et al., 1994), evapotranspiration prediction (Yıldırım et al., 2023) food production prediction (Mukerji et al., 2009), biomass prediction (Jin and Liu, 1997) and soil erosion prediction (Kim and Gilley, 2008; Mohammadi Mirik et al., 2023). The effectiveness of ANN models in predicting corn and soybean yields under Maryland's climatic conditions was investigated. In the study, it was compared with multiple linear regression models including various development parameters at different scales. ANN models outperformed regression models and predicted crop yields more accurately (Kaul et al., 2005).

A composite edible film was developed by combining soybean aqueous extract with different materials and response surface methodology (RSM) using artificial neural network (ANN) models of physico-mechanical properties and barrier properties was used to predict the effect of independent variables on responses such as tensile strength, elongation at break, water vapor permeability, moisture content, water solubility and optical parameters. The best results were obtained in ANN model predictions (Kumar et al., 2022). Some research has been conducted to predict with a combination of ANN, ANFIS, GMDH methods using mechanical and physical properties in different plant seeds and there is no study in the literature comparing all these methods for the data sets used in the study for soybean seed.

The aims of this study, the kinetic and static friction of soybean seeds are predicted that are compared different artificial intelligence techniques (ANN, ANFIS and GMDH) to evaluated the performances of these methods. Different models were created in ANN, ANFIS and GMDH techniques with different input combinations and the best model was selected according to different statistical parameters including coefficient of determination (R^2), root mean square error (RMSE), and mean square error (MSE).

2. Materials and Methods

In this study, five different friction surface features (steel, galvanized sheet, rubber, sheet and PVC) and three different moisture contents were measured and calculated for soybean seed varieties. Physical and mechanical properties such as width (W), length (L), sphericity (S), surface properties (SF), moisture (M), geometric mean diameter (GMD), arithmetic mean (MA) of intact seeds were evaluated. And the moisture content value for pumpkin seeds were obtained using the gravimetric method that specified with the method by (Wang et al., 2023). Dimension measurements of soybean seeds were measured with a digital caliper with a precision of 0.01 mm (Mitutoya brand, Absolute Digimatic model, Japan) (Mohsenin, 1970; Cevher et al., 2016).

The Lloyd Biologicals Test device was used to determine the friction coefficients of soybean seeds (Figure 1a). Data obtained from the compression test experiments were processed using the NEXYGEN Plus software (Figure 1b). A wooden box with dimensions of 60x120x100 mm was connected to the load cell on the test device with a connection element. An opening was left between the box and the surface, ensuring that only the soybean seeds came into contact with the friction surfaces during the measurements (Figure1c). The experiments were carried out on stainless steel, galvanized sheet, PVC, rubber and sheet surfaces at a speed of 100 mm/min and with 10 repetitions.

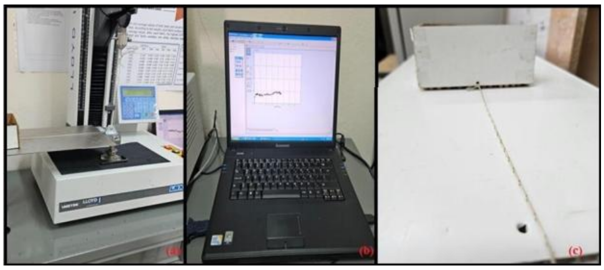

Figure 1. Biologicals Test device (a), computer and data collection (b) contact of soybean seed with friction surface (c).

Must list the authority that provided approval and the corresponding ethical approval code. The initial moisture content of seed was determined by using the standard hot air oven method at 105±1 1C for 24 h. In the study, water was added in the amount calculated according to the following equation 1 to achieve different moisture levels of soybean seeds (Cevher, 2022):

$$Q = \frac{W_i\left(M_f - M_i\right)}{100 - M_f} \tag{1}$$

Q : Mass of water to be added (kg),
Wi : Initial mass (kg),
Mi : Initial moisture content of the sample in % d.b percent and
Mf : Final moisture content of the sample in % d.b

In order for the soybean seeds to reach a homogeneous moisture distribution, the samples were placed in polyethylene bags (Figure 2) and kept in a refrigerator at 5°C for 1 week. Humidity control was performed before starting the experiments. The experiments were carried out with soybean seeds with 4.22%, 6.27% and 8.31% d.b moisture content.

Figure 2. Samples in polyethylene bags.

2.1. Dataset pre-proceeding

In this study, different artificial intelligence methods are applied to estimation of kinetic and static friction parameters under different friction features and moisture content, namely artificial neural networks (ANN) and adaptive neuro fuzzy inference system (ANFIS) and group data of handling (GMDH). The optimal structure of the models was determined using a trial-and-error procedure. As a study strategy, a training-test analysis dataset that produces unbiased predictions was created. A model with 70% (n=105) from the training dataset, 30% (n=45) from the test dataset and all datasets having 150 data was used, respectively.

The success of using models is directly related to factors variables such as input combination, model structure, basic parameters, and performance criteria. The first step in developing a prediction model is to identify the input variables. The first step in developing a prediction model is to determine the input variables, for which different input combinations are created to predict kinetic and static friction to achieve the best prediction. Many factors affect kinetic and static friction, including friction surface features, mechanical and physical parameters for different seeds features. In this study, all these features were used to create a simple and applicable approach. Different input combinations were evaluated to assess the degree of influence of each variable on the friction concentration values. Table 1 shows the different combinations (3 input in Model 1, 5 input in Model 2, 6 input in Model 3 and 7 input in Model 4) used in the training, testing phases. Figure 3 shows the flow chart of the artificial intelligence models used to selected the best model that estimated for kinetic friction and static friction of soybean seeds. The methods used in the study are briefly described in the following sections.

Table 1. The conbination of input for models.

Input name	Input conbination					
Model 1	Moisture (M)	Width (W)	Length (L)			
Model 2	Surface feature(SF)	Moisture (M)	Width (W)	Length (L)	Surface area (SA)	
Model 3	Moisture (M)	Width (W)	Geo. Mean diameter (GMD)	Sphericity (S)	Aritmetic mean (MA)	Surface area (SA)
Model 4	Surface feature(SF)	Moisture (M)	Length (L)	Geo. Mean diameter (GMD)	Sphericity (S)	Aritmetic mean (MA)	Surface area (SA)

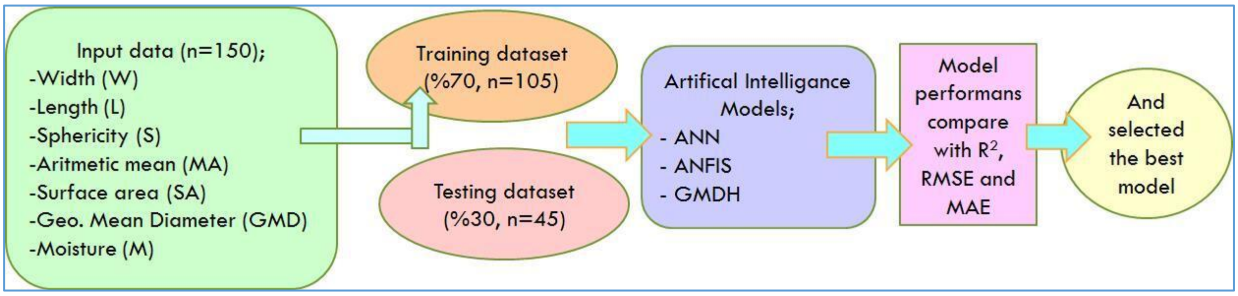

Figure 3. The flow chart of artificial intelligant model to selected best model.

2.1.1. Artificial neural network (ANN)

An ANN is a computational method that mimics the functional behavior of a biological nerve cell in terms of information processing by linking inputs and outputs in an organized way (Hamad et al., 2020). The ANN approach is biologically inspired by the human brain (Patel et al., 2022). This the model approaches the brain in two stages: (a) information is acquired by the network from its environment as a result of a learning procedure and (b) interneuron connectivity strengths are used to collect the resulting knowledge (Haykin, 1994). The structure of a typical ANN consists of neurons (processing units), connection weights, biases and multiple layers. Traditional ANNs contain one or more hidden layers, where neurons in each layer are fully connected to every neuron in the next layer.

An ANN procedure consists of five stages: selecting the inputs, choosing an appropriate architecture, the neural network construction, training and testing procedure and finally evaluation of the developed system model (Sahoo and Jha, 2013; Samani et al., 2022). Input data is fed into the input layer and travels through the network to all connected neurons in subsequent layers (Samani et al., 2022). The ANN can have more than one hidden layer (Küçüktopcu and Cemek, 2021). ANNs offer several advantages over other models due to their robustness in interpreting complex structures, nonlinear data with high degrees of volatility.

In this study, single layer and multilayer ANN networks were applied as modeling techniques. Matlab software was used to process model predictions and performance. Tansig and purelin as transfer functions were used in the input layer and the output layer, respectively. The estimation of friction coefficients for layer network structures using different input combinations with SCG training algorithm to train ANN was used. Separation of data into training and test datasets model
can have significant effects on the results. Therefore, the measured dataset was divided into two subgroups: 70% of the data was used for training and 30% of the data was used for testing. The training and test data were randomly split. The MLP architecture created within the scope of this study is presented in Figure 4a. Four different models were created with the inputs (moisture, length, width, surface feature, geometric mean diameter, sphericity, arithmetic mean) used in the study. The inputs used for the models are given in Table 2. Estimations were made for 3, 5, 6 and 7 input on double-layer networks as 7-7-1, 7-10-1, 7-15-1 model structure.

Table 2. The combination of input number and model structure for ANN and GMDH.

ANN model	GMDH model	Input	Model Structure
ANN 1	GMDH 1	3	7--7--1
ANN 2	GMDH 2	3	7--10--1
ANN 3	GMDH 3	3	7--15--1
ANN 4	GMDH 4	5	7--7--1
ANN 5	GMDH 5	5	7--10--1
ANN 6	GMDH 6	5	7--15--1
ANN 7	GMDH 7	6	7--7--1
ANN 8	GMDH 8	6	7--10--1
ANN 9	GMDH 9	6	7--15--1
ANN 10	GMDH 10	7	7--7--1
ANN 11	GMDH 11	7	7--10--1
ANN 12	GMDH 12	7	7--15--1

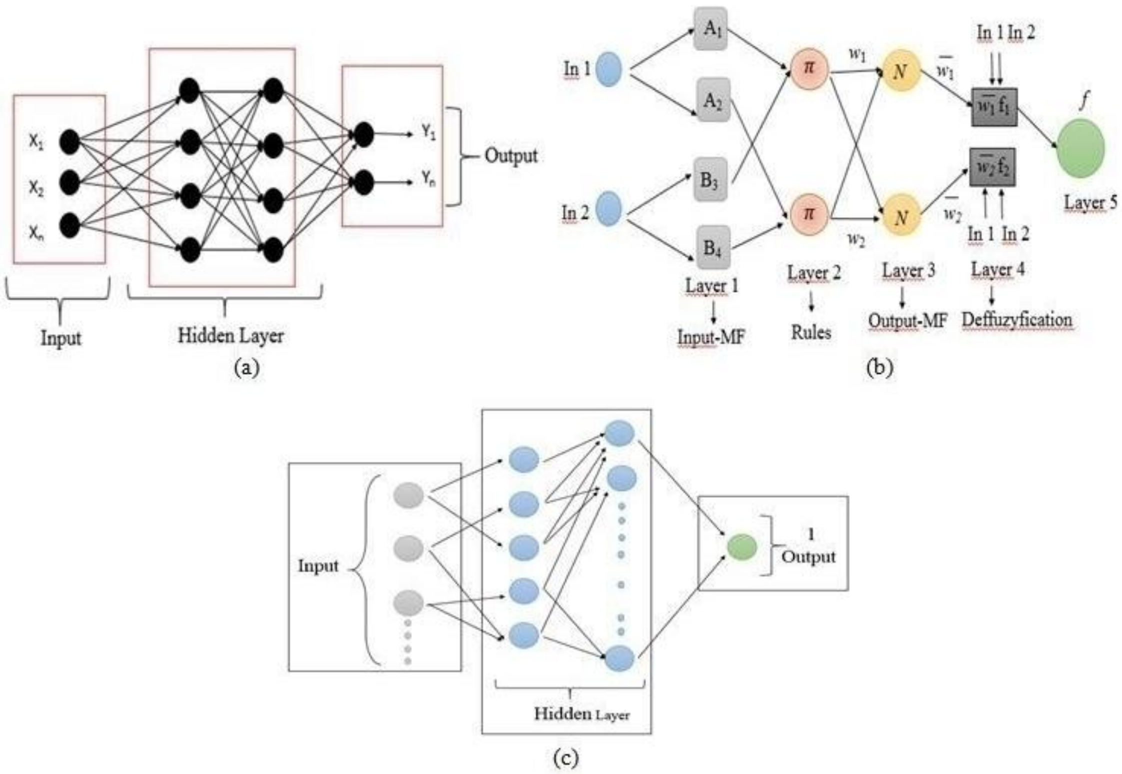

Figure 4. Double hidden layer ANN architecture (a), Anfis structure (b) and GMDH structure.

2.1.2. Adaptive neuro-fuzzy inference systems (ANFIS)

Adaptive neuro-fuzzy inference system (ANFIS), introduced for the first time by Jang, (1993). And ANFIS is an artificial intelligence method that uses the parallel computation and learning ability of artificial neural networks and the inference feature of fuzzy logic. The ANFIS model uses the Sugeno type fuzzy inference system and the Hybrid learning algorithm. Adaptive networks consist of directly connected nodes and these nodes represent a processing unit (Jang, 1993). ANFIS uses a given input-output dataset and uses either a backpropagation algorithm alone or a combination of backpropagation algorithm and least squares method, where the membership functions are regularized to form an FIS (Abdulshahed et al., 2015). The ANFIS model has the advantage of having both numerical and linguistic knowledge. The Sugeno fuzzy structure of the ANFIS model consists of five layers and an ANFIS structure is given in Figure 4b. In the present study, different variables were used as input variables to estimate firictin coefficient parameters. The inputs used for four models are given in Table 3. Different data set were obtained for soybean and we used a training and testing analysis strategy. The chose our model with a training dataset that constituted 70% of the data (n =105) and a testing dataset of the remaining 30% (n = 45). 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 3.

Table 3. The conbination of input and membership founction for ANFIS.

Model	Input	Membership founction type	Rural
ANFIS 1	3	gaussmf	3*3*3*3
ANFIS 2	3	trapmf	
ANFIS 3	3	gaussmf	4*4*4*4
ANFIS 4	3	trapmf	
ANFIS 5	5	gaussmf	3*3*3*3
ANFIS 6	5	trapmf	
ANFIS 7	5	gaussmf	4*4*4*4
ANFIS 8	5	trapmf	
ANFIS 9	6	gaussmf	3*3*3*3
ANFIS 10	6	trapmf	
ANFIS 11	6	gaussmf	4*4*4*4
ANFIS 12	6	trapmf	
ANFIS 13	7	gaussmf	3*3*3*3
ANFIS 14	7	trapmf	
ANFIS 15	7	gaussmf	4*4*4*4
ANFIS 16	7	trapmf	

2.1.3. Group method of data handling (GMDH)

GMDH is similar to ANN as a polynomial neural network used to solve complex and nonlinear problems. It is considered that GMDH systems can be called “perceptron-type systems” since the differences between perception and GMDH are not fundamental (Ivakhnenko, 1970).

GMDH is considered a regression-based technique that combines the best of both neural networks and statistical analysis, with the additional feature of basic induction (Lemke, 1997). GMDH can overcome the shortcomings of

ANNs and statistical neural networks.

Self-organizing classification generates models to solve prediction and other system questions. The number of neurons, hidden layers, influential input variables and network framework are necessarily defined in the model. All model structures for example number of neurons and layers are determined by default. In a classic GMDH algorithm, different pairs of neurons in each layer are connected via a quadratic polynomial and represented as a set of neurons with new neurons in the next layer. This type of representation can be used in modeling to map inputs to outputs (Nariman-Zadeh, 2002) and a simple GMDH model structure is given in Figure 4c. The inputs and model structures are given in Table 2 for GMDH model.

2.2. Performance criteria of models to evaluation

Tree different statistical parameters were used to assess the performance of ANN, ANFIS and GMDH models. These statistical parameters coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE) and then using to determined by Eq, 2, 3 and 4, respectively by Waller (2023). The best compliance between the estimated and calculated values is achieved at R^2 = 1, RMSE = 0, MAE = 0. For this reason, using the equations given below, the best model was determined according to the highest R^2 value and lowest RMSE, MSE values for testing data values (equations 2-4).

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

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m}(yi-Oi)^2}{n}} \quad (3)$$

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

Where;

yi is the observed value, Oi is the estimated value, $\overline{y}$ is the mean of observed value, $\overline{O}$ is the mean of estimated value, n is the number of observations used in those models. The best compliance between the estimated and observed values is achieved at R^2 = 1, RMSE = 0, MSE = 0 (Taşan, 2023).

3. Results

The best model were evaluated ANN, ANFIS, GMDH models that were estimated in kinetic friction and static friction for soybean seeds using different combinations of data in average width (W), length (L), sphericity (S), surface features (SF), moisture (M), geometric mean diameter (GMD), arithmetic mean (MA).

Summary statistical parameters of the data used in the study, such as the test and training data; the maximum, minimum, mean value, skewness and standard deviation values are given in Table 4. Mean values of randomly selected training and testing data were close to each other. As seen from the Table 4, surface feature (SF) values were ranged from 0.1 to 1.1 with an average value of 0.5 for the training and testing dataset. The moisture of soybean seeds samples are varied between 4.8 and 6.5. Average values of L, W, GMD, S, MA and SA values are 7.9, 6.8, 6.7, 84.8, 6.7 and 140.5 for trining data and 7.8, 6.8, 6.6, 84.6 6.7 and 137.6 for testing dataset, respectively.

Table 4. Descriptive statistics of parameters

	Parameters	Max.	Min.	Mean	S. Deviation	Kutosis	Skewnes	CV
Training	SF	1.1	0.1	0.5	0.34	-1.04	0.48	63.3
	L	9.1	6.2	7.9	0.65	0.46	-0.31	8.3
	W	7.6	5.5	6.8	0.46	1.54	-1.09	6.8
	GMD	7.3	5.4	6.7	0.45	2.07	-1.45	6.8
	S	90.5	79.7	84.8	2.94	-0.82	-0.05	3.5
	MA	7.4	5.4	6.7	0.46	1.85	-1.31	6.9
	SA	165.7	90.0	140.5	18.05	1.53	-1.25	12.9
Testing	SF	1.1	0.1	0.5	0.34	-1.03	0.49	63.7
	L	8.9	7.3	7.8	0.52	-0.06	0.82	6.7
	W	7.7	6.4	6.8	0.39	1.36	1.34	5.8
	GMD	7.3	6.2	6.6	0.36	-0.66	0.58	5.5
	S	90.5	78.2	84.6	3.29	0.09	-0.21	3.9
	MA	7.5	6.3	6.7	0.37	-0.26	0.78	5.5
	SA	168.4	121.2	137.6	15.23	-0.50	0.66	11.1

4. Discussion

Authors should discuss the results and how they can be interpreted from the perspective of previous studies and the working hypotheses. The findings and their implications should be discussed in the broadest context possible. Future research directions may also be highlighted.

4.1. Results of ANN models

In ANFIS, 3, 5, 6 and 7 inputs were used and kinetic and static friction in soybean seeds, which were estimated with different membership functions such as trapmf, gausmf to determine the optimum result as in ANN. In total, 16 models were established for prediction with ANFIS and the best model was determined by comparing model performance according to R^2, RMSE and MSE values.

The model performance results obtained for kinetic friction and static friction with different input combinations that are given in Table 5 for test and training dataset. In columns 2 and 4 are given of Table 5, model numbers and two different rule structures (3*3*3*3 and 4*4*4*4) used in the study. The best results were obtained in ANFIS models. It is clear taht from these figures, the ANFIS in 7. and 11. model result values measured more closely than do the other models for kinetic and static friction, respectively. Considering the test step, the model using the five combinations (SF, M, W, L, SA) as input and kinetic energy estimation as output presented the best results compared to the other combinations. For ANFIS-7 model results, R^2 was 0.97, RMSE was 0.00013 and MSE was 0.00027 that using of membership function of gaussmf and 4*4*4*4 rural. The scatterplots of the measured and estimated kinetic friction for soybean seed by using the optimal ANFIS model that are given Figure 7. and figure 5 are shown distribution of all data that calculated 0.94, 0.0214 and 0.00046 for R^2, RMSE and MSE, respectively.

Table 5. R^2, RMSE, and MSE values of the ANFIS for kinetic and static friction estimates

Kinetic friction									
				Testing			Training		
Input	Model	Membership founction type	Rural	R^2	RMSE	MSE	R^2	RMSE	MSE
M, W, L	1	gaussmf	3*3*3*3	0.899	0.00043	0.00086	0.88728	0.00040	0.00080
	2	trapmf		0.909	0.00039	0.00078	0.87808	0.00044	0.00087
	3	gaussmf	4*4*4*4	0.904	0.00036	0.00071	0.90589	0.00034	0.00067
	4	trapmf		0.858	0.00056	0.00113	0.87241	0.00046	0.00091
SF, M, W, L, SA	5	gaussmf	3*3*3*3	0.926	0.00017	0.00034	0.92547	0.00032	0.00064
	6	trapmf		0.932	0.00034	0.00069	0.90709	0.00044	0.00088
	7	gaussmf	4*4*4*4	0.966	0.00013	0.00027	0.93057	0.00027	0.00054
	8	trapmf		0.952	0.00017	0.00034	0.91407	0.00033	0.00066
M, W, GMD, S, MA, SA	9	gaussmf	3*3*3*3	0.930	0.00026	0.00052	0.94702	0.00019	0.00039
	10	trapmf	4*4*4*4	0.922	0.00029	0.00058	0.93529	0.00024	0.00047
	11	gaussmf		0.936	0.00023	0.00047	0.95940	0.00015	0.00030
	12	trapmf		0.920	0.00030	0.00059	0.92805	0.00027	0.00053
SF, M, L, GMD, S, MA, SA	13	gaussmf	3*3*3*3	0.921	0.00030	0.00060	0.93620	0.00024	0.00048
	14	trapmf		0.910	0.00035	0.00070	0.93325	0.00025	0.00050
	15	gaussmf	4*4*4*4	0.960	0.00016	0.00031	0.97514	0.00010	0.00019
	16	trapmf		0.928	0.00031	0.00061	0.93135	0.00026	0.00051
Static friction									
M, W, L	1	gaussmf	3*3*3*3	0.894	0.00041	0.00082	0.898	0.00040	0.00080
	2	trapmf		0.888	0.00044	0.00088	0.880	0.00047	0.00094
	3	gaussmf	4*4*4*4	0.915	0.00037	0.00074	0.896	0.00040	0.00081
	4	trapmf		0.900	0.00041	0.00083	0.897	0.00040	0.00081
SF, M, W, L, SA	5	gaussmf	3*3*3*3	0.922	0.0004	0.00084	0.930	0.0004	0.00074
	6	trapmf		0.901	0.0010	0.00203	0.928	0.0004	0.00081
	7	gaussmf	4*4*4*4	0.937	0.00028	0.00056	0.94	0.00039	0.00043
	8	trapmf		0.922	0.00046	0.00092	0.92	0.00078	0.00086
M, W, GMD, S, MA, SA	9	gaussmf	3*3*3*3	0.941	0.00026	0.00052	0.943	0.00021	0.00042
	10	trapmf	4*4*4*4	0.924	0.00029	0.00058	0.912	0.00033	0.00065
	11	gaussmf		0.976	0.00009	0.00019	0.935	0.00024	0.00047
	12	trapmf		0.907	0.00038	0.00075	0.928	0.00027	0.00053
SF, M, L, GMD, S, MA, SA	13	gaussmf	3*3*3*3	0.941	0.0002	0.00043	0.930	0.0004	0.00074
	14	trapmf		0.922	0.0003	0.00060	0.928	0.0004	0.00081
	15	gaussmf	4*4*4*4	0.972	0.00017	0.00033	0.939	0.00039	0.00078
	16	trapmf		0.964	0.00023	0.00046	0.918	0.00043	0.00086

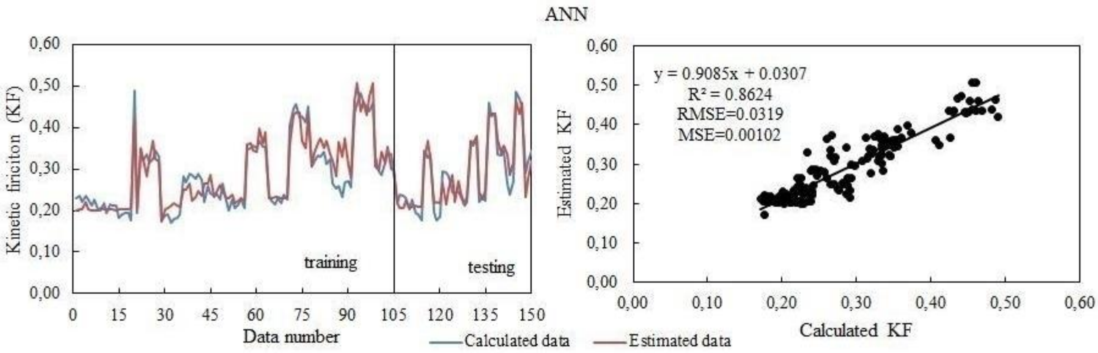

Figure 5. The best model results to estimate kinetic friction.

Table 6. Compares the calculated and predicted results of kinetic and static friction

Kinetic friction													
Input		Testing						Training					
		7-1	10-1	15-1	7-7-1	7-10-1	7-15-1	7-1	10-1	15-1	7-7-1	7-10-1	7-15-1
M, W, L	R^2	0.922	0.913	0.904	0.921	0.932	0.938	0.906	0.889	0.909	0.934	0.917	0.946
	RMSE	0.00028	0.00034	0.00035	0.00030	0.00025	0.00023	0.00035	0.00040	0.00036	0.00027	0.00031	0.00020
	MSE	0.00057	0.00068	0.00070	0.00060	0.00051	0.00045	0.00070	0.00080	0.00073	0.00055	0.00061	0.00041
SF, M, W, L, SA	R^2	0.953	0.940	0.941	0.977	0.960	0.935	0.903	0.890	0.921	0.955	0.952	0.958
	RMSE	0.00017	0.00022	0.00022	0.00009	0.00015	0.00024	0.00038	0.00045	0.00028	0.00016	0.00017	0.00015
	MSE	0.00034	0.00045	0.00043	0.00018	0.00030	0.00047	0.00076	0.00090	0.00056	0.00032	0.00035	0.00030
M, W, GMD, S, MA, SA	R^2	0.910	0.924	0.923	0.966	0.932	0.927	0.904	0.865	0.901	0.932	0.928	0.924
	RMSE	0.00035	0.00031	0.00028	0.00013	0.00027	0.00027	0.00036	0.00053	0.00035	0.00024	0.00026	0.00027
	MSE	0.00069	0.00062	0.00056	0.00026	0.00055	0.00054	0.00073	0.00106	0.00070	0.00048	0.00052	0.00055
SF, M, L, GMD, S, MA, SA	R^2	0.939	0.946	0.953	0.988	0.964	0.952	0.927	0.900	0.933	0.938	0.925	0.925
	RMSE	0.00023	0.00020	0.00017	0.00004	0.00013	0.00018	0.00027	0.00038	0.00024	0.00024	0.00028	0.00028
	MSE	0.00045	0.00040	0.00035	0.00009	0.00027	0.00035	0.00054	0.00077	0.00048	0.00048	0.00055	0.00055
Static friction													
M, W, L	R^2	0.881	0.929	0.903	0.924	0.923	0.932	0.907	0.897	0.919	0.922	0.934	0.932
	RMSE	0.00047	0.00035	0.00046	0.00036	0.00034	0.00032	0.00038	0.00042	0.00035	0.00031	0.00028	0.00029
	MSE	0.00093	0.00069	0.00093	0.00073	0.00069	0.00063	0.00076	0.00084	0.00070	0.00062	0.00056	0.00057
SF, M, W, L, SA	R^2	0.952	0.947	0.953	0.962	0.954	0.985	0.839	0.925	0.931	0.949	0.951	0.977
	RMSE	0.00021	0.00026	0.00025	0.00018	0.00020	0.00006	0.00064	0.00027	0.00025	0.00019	0.00018	0.00008
	MSE	0.00042	0.00052	0.00049	0.00036	0.00040	0.00011	0.00129	0.00054	0.00050	0.00037	0.00036	0.00017
M, W, GMD, S, MA, SA	R^2	0.9142	0.8611	0.9303	0.9678	0.9521	0.9346	0.894	0.915	0.956	0.961	0.965	0.971
	RMSE	0.00034	0.00055	0.00031	0.00016	0.00021	0.00027	0.00039	0.00032	0.00020	0.00017	0.00016	0.00013
	MSE	0.00069	0.00109	0.00062	0.00032	0.00041	0.00053	0.00078	0.00063	0.00039	0.00034	0.00031	0.00026
SF, M, L, GMD, S, MA, SA	R^2	0.921	0.932	0.933	0.943	0.941	0.959	0.893	0.917	0.928	0.928	0.924	0.931
	RMSE	0.00031	0.00026	0.00024	0.00021	0.00022	0.00015	0.00039	0.00030	0.00026	0.00026	0.00028	0.00026
	MSE	0.00063	0.00052	0.00048	0.00042	0.00043	0.00029	0.00078	0.00060	0.00053	0.00052	0.00056	0.00051

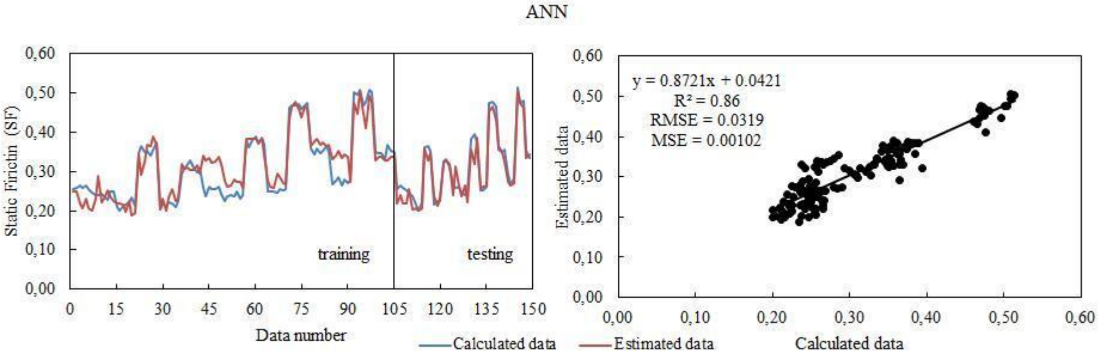

Figure 6. The best model results to estimate kinetic friction friction.

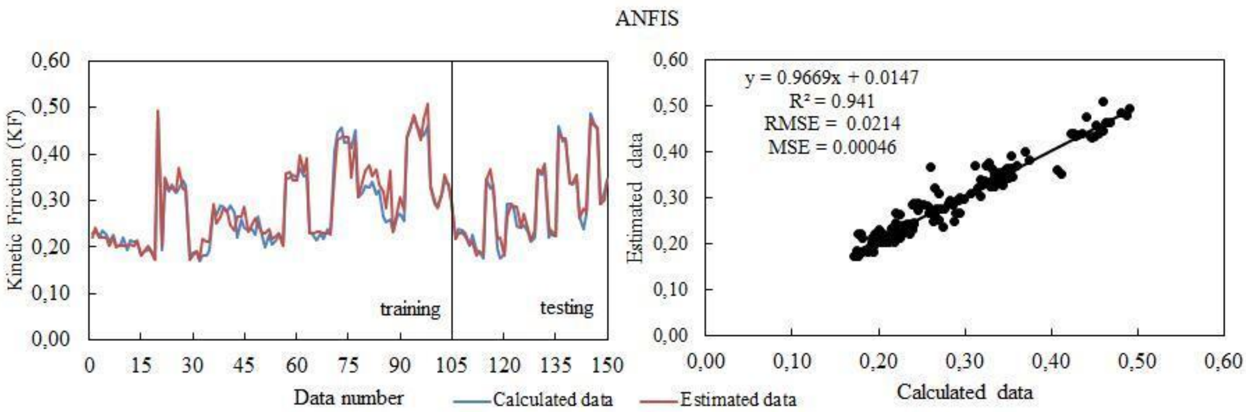

Figure 7. Performance chart of model with gausmf membership function estimated by ANFİS 7 model.

The best models for different combinations of inputs in the test dataset were calculated for the static friction prediction with R^2 of 0.98, RMSE of 0.00009 and MSE of 0.00019. The graphical comparison of the obtained optimum model (ANFIS 11) is shown in Figure 8 that are estimated static friction. In the ANFIS 11 model, M, W, GMD, S, MA and SA of 6 input data were used and gaussmf and 4*4*4*4 rule were obtained as the membership function and rule respectively. For the model used in the estimation of static friction in the all data, R^2, RMSE and MSE values were calculated as 0.95, 0.0230 and 0.00053, respectively.

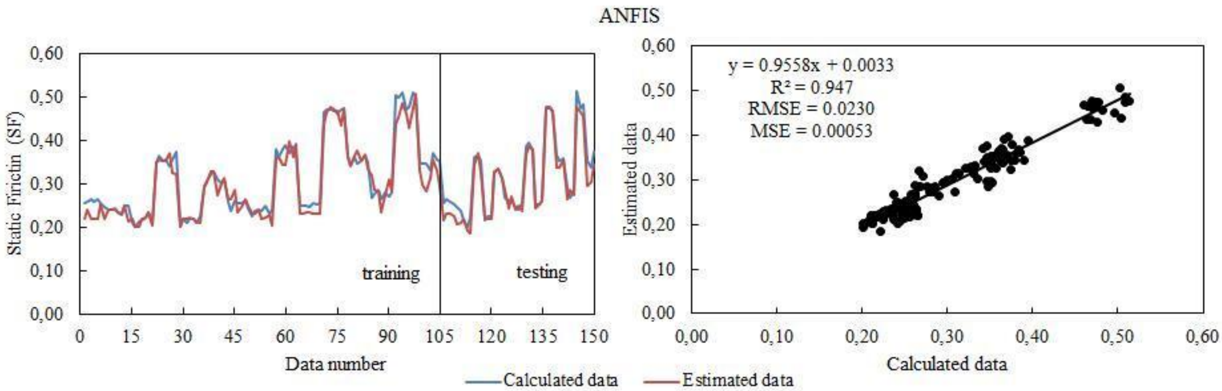

Figure 8. Performance chart of model with gausmf membership function estimated by ANFİS 11 model.

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 (Saiedirad and Mirsalehi, 2010). The temperature and moisture content of the output seeds of the cooking pot were considered as inputs (independent variables) and the insoluble fine partial content of the extracted oil, moisture content of the extracted oil and obtained meals, as well as the oil content of the achieved meals and acidity value of the extracted oil were considered as output that were applied three different membership functions, including Gaussian and triangular and trapezoidal for ANFIS model (Farzaneh et al., 2017).

4.2. Results of ANFIS models

In ANFIS, 3, 5, 6 and 7 inputs were used and kinetic and static friction in soybean seeds, which were estimated with different membership functions such as trapmf, gausmf to determine the optimum result as in ANN. In total, 16 models were established for prediction with ANFIS and the best model was determined by comparing model performance according to R^2, RMSE and MSE values.

The model performance results obtained for kinetic friction and static friction with different input combinations that are given in Table 5 for test and training dataset. In columns 2 and 4 are given of Table 5, model numbers and two different rule structures (3*3*3*3 and 4*4*4*4) used in the study. The best results were obtained in ANFIS models. It is clear taht from these figures, the ANFIS in 7. and 11. model result values measured more closely than do the other models for kinetic and static friction, respectively. Considering the test step, the model using the five combinations (SF, M, W, L, SA) as input and kinetic energy estimation as output presented the best results compared to the other combinations. For ANFIS-7 model results, R^2 was 0.97, RMSE was 0.00013 and MSE was 0.00027 that using of membership function of gaussmf and 4*4*4*4 rural. The scatterplots of the measured and estimated kinetic friction for soybean seed by using the optimal ANFIS model that are given Figure 7. and figure 5 are shown distribution of all data that calculated 0.94, 0.0214 and 0.00046 for R^2, RMSE and MSE, respectively.

The best models for different combinations of inputs in the test dataset were calculated for the static friction prediction with R^2 of 0.98, RMSE of 0.00009 and MSE of 0.00019. The graphical comparison of the obtained optimum model (ANFIS 11) is shown in Figure 8 that are estimated static friction. In the ANFIS 11 model, M, W, GMD, S, MA and SA of 6 input data were used and gaussmf and 4*4*4*4 rule were obtained as the membership function and rule respectively. For the model used in the estimation of static friction in the all data, R^2, RMSE and MSE values were calculated as 0.95, 0.0230 and 0.00053, respectively.

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4.3. Results of GMDH models

As an intelligent tool, the GMDH model showed promising results for predicting kinetic and satatic friction. A GMDH model structure including three and four layers as well as 7, 10, 15 different numbers of neurons was studied that are predicted kinetic and static friction in soybean seeds. Table 6 compares the calculated and predicted results of kinetic and static friction that are evaluated the performance criteria of the GMDH models built using different inputs. According to the GMDH model results, 7 inputs are shown as a suitable input dataset for the predicted kinetic friction. From Table 6, it is clear that the GMDH (7-7-1) model that includes the SF, M, L, GMD, S, MA, SA inputs and the other models during the testing period according to the criteria: R^2 = 0.99, RMSE =0.00004 , MSE = 0.00009.

The static friction values of GMDH best model were calculated as 0.98 for R^2, 0.00006 for RMSE and 0.00011 for MSE in the testing stage (Table 6). It is clear from the table that the GMDH (7-15-1) model with five input parameters as SF, M, W, L, SA provided the best accuracy according to the highest R^2 and the lowest RMSE and MSE criteria in the testing period. Figure 10 displays calculated and estimated static friction results produced by the best GMDH model.

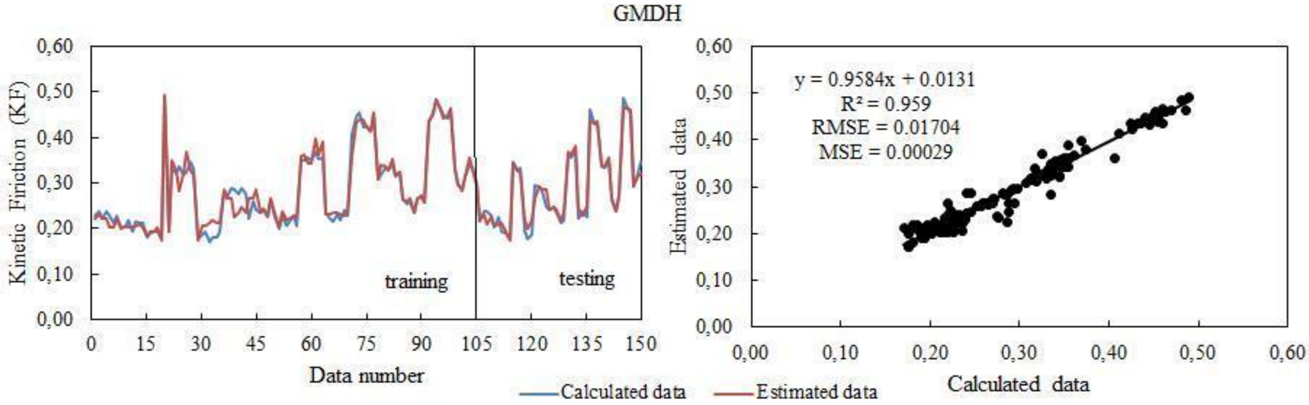

Figure 9. The scatterplots of calculated and estimated kinetic friction by GMDH 7-7-1.

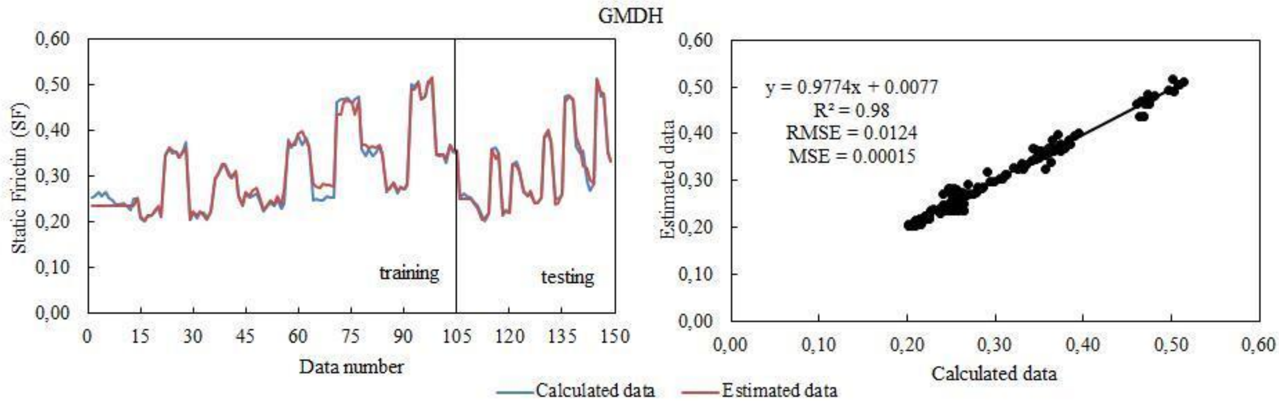

Figure 10. The scatterplots of calculated and estimated kinetic friction by GMDH 7-15-1 model.

Group data processing method (GMDH) type neural networks were used to model the explosive cutting process of plates with shaped loads and to show how the penetration depth changes with the change of important parameters (Nariman-Zadeh, 2002).

Recently, in different literatures studies were conducted on the variability of seed traits captured using imaging sensors for soybeans (Yuan et al., 2019; Baek et al., 2020; Yang et al., 2021; Lu et al., 2022). In a study for soybean, paraemtres such as area size (AS), perimeter length (PL), length (L), width (W), length-width ratio (LWR), intersection of length and width (IS), seed circularity (CS) and distance between IS and CG (DS) were used for digital image analysis of seed traits for estimation of hundred seed weight (HSW). Seven popular machine learning (ML) algorithms, namely Simple Linear Regression (SLR), Multiple Linear Regression (MLR), Random Forest (RF), Support Vector Regression (SVR), LASSO Regression (LR), Ridge Regression (RR) and Elastic Network Regression (EN), were used in the study, along with image-based models derived from Red-Green-Blue (RGB)/visual images. Among the models, random forest and multiple linear regression models using multiple explanatory variables related to seed size traits (AS, L, W and DS) were identified as the best models to predict seed weight with the highest prediction accuracy (R^2=0.98 and 0.94) and the lowest RMSE and MAE (Duc et al., 2023). Models such as imaging and machine learning, random forests, support vector machines and ANN are gaining popularity and importance for the prediction of genotypes relative to phenotypes, including yield, day of heading and thousand seed weight (Crossa et al., 2019; Khaki and Wang, 2019; Grinberg et al., 2020; Khaki et al., 2021). They used and compared models consisting of ANN, RF, SVM, SVM, KRR and KNN for grain size and weight prediction. They found that the normalized pixel area of the rice kernel predicted the single kernel weight with an accuracy of 0.95% (Singh et al., 2020).

In this study, the suitability of ANN, ANIF and GMDH models were evaluated to predict kinetic and static drift of soybean seed. Furthermore, these models were compared with ANN to predict kinetic and static friction parameters using some physical and chemical properties as inputs.

Three different statistical parameters (R^2, RMSE, MSE) were used to compare the performance of ANN, ANFIS and GMDH models. In the estimation of kinetic and static friction parameters for seeds, very good results were obtained in the models used when comparing between models. The GMDH models almost outperformed the ANN and ANFIS models.

Based on the R^2, RMSE and MSE performance criterion values of the GMDH 7-7-1 and 7-15-1 model structures, it is observed that the models have better prediction capability for kinetic friction and static friction parameters, respectively.

The inputs of SF, M, L, GMD, S, MA, SA and SF, M, W, L, SA were used the best models of chosen that were predicted kinetic and static friction, respectively. As a result, the predictions to be made in the soft computing methods actually used can be used as an effective tool in the current field of study.

Overall, the results of this study revealed that artificial intelligent techniques can be used effectively to determine seed quality and make accurate predictions according to different environments and friction surfaces using mechanical and physical properties and can be recommended as an alternative approach.

Author Contributions

Percentages of the authors' contributions are present below. All authors reviewed and approved final version of the manuscript.

	E.Y.C.	D.Y.	G.A.K.G.
C	60	20	20
D	60	20	20
S	60	20	20
DCP	50	25	25
DAI	50	25	25
L	50	25	25
W	40	30	30
CR	40	30	30
SR	40	30	30

C= concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision.

Conflict of Interest

The authors declared that there is no conflict of interest.

Ethical Consideration

Since no studies involving humans or animals were conducted, ethical committee approval was not required for this study.

References

Abdulshahed AM, Longstaff AP, Fletcher S. 2015. The application of ANFIS prediction models for thermal error compensation on CNC machine tools. Appl Soft Comput, 27: 158-168.

Alibaş I, Köksal N. 2015. The effect of moisture content on physical, mechanical and rheological properties of soybean (Glycine max cv. ATAEM-II) seed. Legume Res, 38(3): 324-333.

Altuntaş E, Gül EN, Olgaç M. 2021. Farklı soya çeşitlerinde hasat sonrası bazı biyoteknik özelliklerin belirlenmesi. Kahramanmaraş Sütçü İmam Üniv Tarım Doğa Derg, 24(5): 1037-1047.

Baek J, Lee E, Kim N, Kim SL, Choi I, Ji H, Chung YS, Choi MS, Moon JK, Kim KH. 2020. High Throughput Phenotyping for Various Traits on Soybean Seeds Using Image Analysis. Sensors, 20(1): 248.

Cevher Yeşiloglu E, Yıldırım D, Öztekin YB. 2016. Effect of loading position and storage duration on the mechanical properties of abate fetel pear variety. In: Proc 6th Int Conf Trends Agric Eng (TAE), Prague, Czech Republic, pp: 7-9.

Cevher Yeşiloglu E. 2022. Some technical properties of dried Terminalia chebula (kara halile) for use in harvest and post-

harvest processing. Ital J Food Sci, 34(4): 33-43.
Crossa J, Martini JW, Gianola D, Pérez-Rodríguez P, Jarquin D, Juliana P, Montesinos-López O, Cuevas J. 2019. Deep kernel and deep learning for genome-based prediction of single traits in multienvironment breeding trials. Front Genet, 10: 1-13.
Duc NT, Ramlal A, Rajendran A, Raju D, Lal SK, Kumar S, Sahoo RN, Chinnusamy V. 2023. Image-based phenotyping of seed architectural traits and prediction of seed weight using machine learning models in soybean. Front Plant Sci, 14: 1-15.
Elizondo D, Hoogenboom G, McClendon RW. 1994. Development of a neural network model to predict daily solar radiation. Agric For Meteorol, 71(1-2): 115-132.
Farzaneh V, Bakhshabadi H, Gharekhani M, Ganje M, Farzaneh F, Rashidzadeh S, Carvalho IS. 2017. Application of an adaptive neuro_fuzzy inference system (ANFIS) in the modeling of rapeseeds' oil extraction. J Food Process Eng, 40(6): 1-8.
Ghazi B, Jeihouni E, Kalantari Z. 2021. Predicting groundwater level fluctuations under climate change scenarios for Tasuj plain, Iran. Arab J Geosci, 14(2): 115.
Gorzelany J, Belcar J, Kuźniar P, Niedbała G, Pentoś K. 2022. Modelling of mechanical properties of fresh and stored fruit of large cranberry using multiple linear regression and machine learning. Agriculture, 12(2): 200.
Grinberg NF, Orhobor OI, King RD. 2020. An evaluation of machine-learning for predicting phenotype: studies in yeast, rice, and wheat. Machine Learning, 109(2): 251-277.
Gupta RK, Das SK. 1998. Friction coefficients of sunflower seed and kernel on various structural surfaces. J Agric Eng Res, 71(2): 175-180.
Hamad K, Khalil MA, Alozi AR. 2020. Predicting freeway incident duration using machine learning. Int J Intell Transp Syst Res, 18(2): 367-380.
Haykin S. 1994. Neural Networks: A Comprehensive Foundation (1st ed.). Prentice Hall PTR, USA, pp:56-69.
Ivakhnenko AG. 1970. Heuristic self-organization in problems of engineering cybernetics. Automatica, 6(2): 207-219.
Jang JS. 1993. ANFIS: adaptive-network-based fuzzy inference system. IEEE Trans Syst Man Cybern, 23(3): 665-685.
Jayas DS, Paliwa J, Visen NS. 2000. Review paper (AE—automation and emerging technologies): multi-layer neural networks for image analysis of agricultural products. J Agric Eng Res, 77(2): 119-128.
Jin YQ, Liu C. 1997. Biomass retrieval from high-dimensional active/passive remote sensing data by using artificial neural networks. Int J Remote Sens, 18(4): 971-979.
Karimi Y, Prasher SO, McNairn H, Bonnell RB, Dutilleu P, Goel PK. 2005. Classification accuracy of discriminant analysis, artificial neural networks, and decision trees for weed and nitrogen stress detection in corn. Trans ASAE, 48(3): 1261-1268.
Kaul M, Hill RL, Walthall C. 2005. Artificial neural networks for corn and soybean yield prediction. Agric Syst, 85(1): 1-18.
Khaki S, Wang L. 2019. Crop yield prediction using deep neural networks. Front Plant Sci, 10: 1-10.
Khaki S, Pham H, Han Y, Kuhl A, Kent W, Wang L. 2021. Deepcorn: A semi-supervised deep learning method for high-throughput image-based corn kernel counting and yield estimation. Knowl-Based Syst, 218: 1-12.
Kim M, Gilley JE. 2008. Artificial Neural Network estimation of soil erosion and nutrient concentrations in runoff from land application areas. Comput Electron Agric, 64(2): 268-275.
Küçüktopcu E, Cemek B. 2021. Comparison of neuro-fuzzy and neural networks techniques for estimating ammonia concentration in poultry farms. J Environ Chem Eng, 9(4): 1-8.
Kumar A, Srivastav PP, Pravitha M, Hasan M, Mangaraj S, Verma DK. 2022. Comparative study on the optimization and characterization of soybean aqueous extract based composite film using response surface methodology (RSM) and artificial neural network (ANN). Food Packag Shelf Life, 31: 1-18.
Lemke F. 1997. Knowledge extraction from data using self-organizing modeling technologies. In: Proc SEAM'97 Conf., pp:56-74.
Lu M, AbouRizk SM, Hermann UH. 2001. Sensitivity analysis of neural networks in spool fabrication productivity studies. J Comput Civ Eng, 15(4): 299-308.
Lu W, Du R, Niu P, Xing G, Luo H, Deng Y, Shu L. 2022. Soybean yield preharvest prediction based on bean pods and leaves image recognition using deep learning neural network combined with GRNN. Front Plant Sci, 12: 1-11.
Majkovič D, O'Kiely P, Kramberger B, Vračko M, Turk J, Pažek K, Rozman Č. 2016. Comparison of using regression modeling and an artificial neural network for herbage dry matter yield forecasting. J Chemom, 30(4): 203-209.
Mohammadi Torkashvand A, Ahmadi A, Gómez PA, Maghoumi M. 2019. Using artificial neural network in determining postharvest LIFE of kiwifruit. J Sci Food Agric, 99(13): 5918-5925.
Mohammadi Mirik A, Parsaeian M, Rohani A, Lawson S. 2023. Optimizing Linseed (Linum usitatissimum L.) Seed Yield through Agronomic Parameter Modeling via Artificial Neural Networks. Agriculture, 14(1): 25.
Mohsenin NN. 1970. Physical properties of plant and animal materials. Gordon and Breach Science Publishers, New York, pp: 51-83.
Mohsenin NN. 1980. Thermal properties of foods and agricultural materials. Gordon Breach Sci Publ, New York, USA, pp: 198-224.
Mozaffari S, Javadi S, Moghaddam HK, Randhir TO. 2022. Forecasting groundwater levels using a hybrid of support vector regression and particle swarm optimization. Water Resour Manag, 36(6): 1955-1972.
Mukerji A, Chatterjee C, Raghuwanshi NS. 2009. Flood forecasting using ANN, neuro-fuzzy, and neuro-GA models. J Hydrol Eng, 14(6): 647-652.
Nariman-Zadeh N, Darvizeh A, Darvizeh M, Gharababaei H. 2002. Modelling of explosive cutting process of plates using GMDH-type neural network and singular value decomposition. J Mater Process Technol, 128(1-3): 80-87.
Niedbała G, Kurasiak-Popowska D, Piekutowska M, Wojciechowski T, Kwiatek M, Nawracała J. 2022. Application of artificial neural network sensitivity analysis to identify key determinants of harvesting date and yield of soybean (Glycine max (L.) Merrill) cultivar Augusta. Agriculture, 12(6): 754.
Patel MB, Patel JN, Bhilota UM. 2022. Comprehensive modelling of ANN. In: Research anthology on artificial neural network applications. IGI Global, pp: 31-40.
Poursaeid M, Poursaeid AH, Shabanlou S. 2022. A comparative study of artificial intelligence models and a statistical method for groundwater level prediction. Water Resour Manag, 36(5): 1499-1519.
Sabzi-Nojadeh M, Niedbała G, Younessi-Hamzekhanlu M, Aharizad S, Esmaeilpour M, Abdipour M, Kujawa S, Niazian M. 2021. Modeling the Essential Oil and Trans-Anethole Yield of Fennel (Foeniculum vulgare Mill. var. vulgare) by Application Artificial Neural Network and Multiple Linear Regression

Methods. Agriculture, 11(12): 1191.
Saiedirad MH, Mirsalehi M. 2010. Prediction of mechanical properties of cumin seed using artificial neural networks. J Texture Stud, 41(1): 34-48.
Sahoo S, Jha MK. 2013. Groundwater-level prediction using multiple linear regression and artificial neural network techniques: a comparative assessment. Hydrogeol J, 21(8): 1865-1887.
Samani S, Vadiati M, Azizi F, Zamani E, Kisi O. 2022. Groundwater level simulation using soft computing methods with emphasis on major meteorological components. Water Resour Manag, 36(10): 3627-3647.
Savenkov D, Kirischiev O, Kirischieva Y, Vifliantceva T, Mikhailova P, Serduk V. 2019. Static and dynamic friction coefficients of grain crops and mineral materials. In: IOP Conf Ser Earth Environ Sci, 403(1): 012069.
Shibata T, Abe T, Tanie K, Nose M. 1996. Skill based motion planning in hierarchical intelligent control of a redundant manipulator. Robot Auton Syst, 18(1-2): 65-73.
Shirkole SS, Kengh RN, Nimkar PM. 2011. Moisture dependent physical properties of soybean. Int J Eng Sci Technol, 3(5): 3807-3815.
Singh SK, Vidyarthi SK, Tiwari R. 2020. Machine learnt image processing to predict weight and size of rice kernels. J Food Eng, 274: 1-10.
Taheri-Rad A, Khojastehpour M, Rohani A, Khoramdel S, Nikkhah A. 2017. Energy flow modeling and predicting the yield of Iranian paddy cultivars using artificial neural networks. Energy, 135: 405-412.
Taki M, Ajabshirchi Y, Ranjbar SF, Rohani A, Matloobi M. 2016. Heat transfer and MLP neural network models to predict inside environment variables and energy lost in a semi-solar greenhouse. Energy Build, 110: 314-329.
Taşan S. 2023. Estimation of groundwater quality using an integration of water quality index, artificial intelligence methods and GIS: Case study, Central Mediterranean Region of Turkey. Appl Water Sci, 13(1): 15.
Tavakoli H, Rajabipour A, Mohtasebi SS. 2009. Moisture-dependent some engineering properties of soybean grains. Agric Eng Int CIGR J, pp:45-56.
Waller DL. 2003. Operations Management: A Supply Chain Approach. Cengage Learning Business Press: Boston, MA, USA, pp:12-23.
Wang Z, Li J, Zhang C, Fan S. 2023. Development of a general prediction model of moisture content in maize seeds based on LW-NIR hyperspectral imaging. Agriculture, 13(2): 359.
Wu SW, Zhou XG, Cao GM, Liu ZY, Wang GD. 2017. The improvement on constitutive modeling of Nb-Ti micro alloyed steel by using intelligent algorithms. Mater Des, 116: 676-685.
Yang S, Zheng L, He P, Wu T, Sun S, Wang M. 2021. High-throughput soybean seeds phenotyping with convolutional neural networks and transfer learning. Plant Methods, 17(1): 50.
Yıldırım D, Küçüktopcu E, Cemek B, Şimşek H. 2023. Comparison of machine learning techniques and spatial distribution of daily reference evapotranspiration in Türkiye. Appl Water Sci, 13(4): 107.
Yuan W, Wijewardane NK, Jenkins S, Bai G, Ge Y, Graef GL. 2019. Early prediction of soybean traits through color and texture features of canopy RGB imagery. Sci Rep, 9(1): 1-17.