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Araştırma Makalesi/*Research Article (Original Paper)*

Comparison of Artificial Neural Network and Multiple Linear Regression for Prediction of Live Weight in Hair Goats

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Abstract: Artificial neural networks are artificial intelligence based methods which learns like humans, as humans did from instances. In recent years, artificial neural networks are often preferred in prediction studies of farm animals as like in many different fields as an alternative to regression analyses. In this study, based on measurements of morphologic traits of 475 Hair goats, the impact of different morphological measures on live weight has been modelled by artificial neural networks and multiple linear regression analyses. Comparison of these two models has been done. In the analyses done with the artificial neural networks method three different back propagation algorithms, such as Levenberg-Marquart, Bayesian regularization and Scaled conjugate, have been used. Methods performances have been determined with different criteria as coefficient of determination, mean absolute deviation, root mean square error and mean absolute percentage error. According to the analyses results, it's noted that artificial neural networks method is more successful than multiple linear regression in prediction of body weight in hair goats.

Keywords: Artificial neural network, Hair goats, Multiple linear regression, Live weight, Prediction

Kıl Keçilerinin Canlı Ağırlık Tahmininde Yapay Sinir Ağları ve Çoklu Doğrusal Regresyon Yöntemlerinin Karşılaştırılması

Özet: Yapay sinir ağları, insanlara benzer şekilde, örnekler üzerinden öğrenen yapay zeka temelli bir yöntemdir. Yapay sinir ağları yöntemi birçok farklı alanda olduğu gibi son yıllarda hayvancılık alanında da özellikle tahmin çalışmalarında regresyon analizine alternatif olarak sıklıkla kullanılmaktadır. Bu çalışmada 475 baş Kıl keçisine ilişkin morfolojik özellik ölçümlerinin canlı ağırlık üzerine etkileri yapay sinir ağları ve çoklu doğrusal regresyon analizi ile modellenmiş ve yöntemler bir karşılaştırmaya tabi tutulmuştur. Çalışmada yapay sinir ağları ile gerçekleştirilen analizlerde Levenberg-Marquart, Bayesian regularization and Scaled conjugate olmak üzere üç farklı geri yayılım algoritması kullanılmıştır. Yöntemlerin performansları düzeltilmiş belirleme katsayısı, hata kareler ortalamasının karekökü, ortalama mutlak sapma ve ortalama mutlak yüzde hata istatistikleri ile değerlendirilmiştir. Analiz sonucunda, Kıl keçilerinde canlı ağırlık tahmini bakımından yapay sinir ağlarının çoklu doğrusal regresyon analizine göre daha başarılı olduğu belirlenmiştir.

Anahtar kelimeler:, Yapay sinir ağları, Kıl keçisi, Çoklu doğrusal regresyon analizi, Canlı ağırlık,Tahmin

Introduction

Associated with technological developments, computer systems have made considerable contributions to the development and applicability of artificial intelligence-based methods. In addition to the classical methods, the researcher is also helping to gain different perspectives and making predictions that are more meaningful. In progress of time, the emergence of alternative methods provides indirect benefits in terms of economy and time.

Artificial intelligence methods have been increasingly used in the study of agricultural sciences. Especially methods, such as prediction, classification, optimization, and decision support system, provide great benefits to the researchers of animal breeding and the breeders. Artificial neural networks, as one of the artificial intelligence-based methods, have the ability to learn from experiences, similar to human beings. In the mathematical modelling of the relationship between the variables of input and outputs of linear and non-linear systems, artificial neural networks are in several instances a considerably successful method compared to classical statistical methods which have a low error ratio in analysis.

Artificial neural networks have been successfully studied in animal science, such as diagnosis of mastitis and lameness (Yang et al. 1999; Cavero et al. 2008; Sun 2008; Hassan et al. 2009; Roush et al. 2001); the prediction of animal product (Grzesiak et al. 2003; Salehi et al. 1998; Sanzogni and Kerr 2001; Kominakis et al. 2002; Hosseinia et al. 2007; Görgülü 2012); animal breeding (Shahinfar et al. 2012; Salehi et al. 1997; Grzesiak et al. 2010); the prediction of the nutrient content in manure (Chen et al. 2008, 2009); and oestrus detection (Krieter et al. 2006). Artificial Neural Networks method is used in animal field as like in many different fields and for prediction studies as an alternative to regression analyses.

Some of the studies comparing neural networks and linear regression analysis in the field of animal husbandry have been given. Studies for determining milk yield are as follows: Grzesiak et al. (2003) compared multiple regression and artificial neural network methods for 305-day lactation yield estimation using partial lactation records. At the end of the study it was stated that artificial neural networks could be an alternative method to regression analysis. Sharma et al. (2007) used artificial neural networks with multiple linear regression models for prediction 305-day milk yield of the first lactation of hybrid dairy cattle. In the study, it was reported that the artificial neural network model gives 92% better results in estimation of milk yield than the multiple linear regression model. In the study of Takma et al. (2012), the effects of lactation time, calving age and service period on lactation milk yield of Holstein cows were modeled by multiple regression and artificial neural networks and compared in terms of the goodness of fit of these models. They stated that artificial neural networks could be an alternative method to regression analysis. Results show that the determination coefficient is calculated as 85%.

Studies on different topics besides milk yield are included in the literature: Craninx et al. (2008) used artificial neural networks and multiple linear regression analysis to predict the volatile fatty acids produced by the rumen microorganisms on their way out of the milk fatty acid profile. Chen et al. (2008) investigated the utility of multiple linear regression, polynomial regression and artificial neural networks in predicting nutrient content in manure. The authors indicated that artificial neural networks could be used successfully in predicting the nutrient content of fertilizers. Dong and Zhao (2014) comparatively examined multiple linear regression analysis and artificial neural network methods to model the production of methane gas in the rumen in mixed feed cattle. As a result of the analysis, it was stated that the artificial neural network provided better results.

In this study, the influence of morphological features on live weights in Hair goats was modeled comparatively via the artificial neural networks and multiple linear regression analysis methods.

Materials and Methods

Materials

Study materials consists of measured morphological characteristics, age, gender and live weight (LW) of 475 Hair goats, grown in 2013 and 2014, from private farms in Denizli province of Turkey. The morphological characteristics of the data set are chest width (CW), rump height (RH), withers height (WH), back height (BH), chest depth (CD), chest girth (CG) and body length (BL). Considering the present study, the independent variables of the model are CW, RH, WH, BH, CD, CG, BL, age and gender. The LW is included into the model as the dependent variable. The study analyses were performed with SPSS 22 statistical package program and Matlab (Roush et al. 2011).

Methods

The effects of morphological characteristics on body weight in Hair goats modelled by artificial neural networks and multiple linear regression analysis methods and both model were compared in this study. The first method used in this study was regression analysis by studying the live weight of the Hair goats as the multiple linear regression analysis method. Regression analysis is one of the statistical methods used in mathematically to model the relationship between the dependent and independent variable/s with a cause-and-effect form of relationship. The regression model that consists of one independent and one dependent variable and has a linear relationship between each other are called simple linear regression; while the model deployed in the analysis of multiple variables are called multiple linear regression analysis (MLR). The objective is to find the equation that best describes the relationship between dependent and independent variables in regression analysis (Yilmaz et al. 2013). The independent variable and the dependent variable are represented by "X" and "Y", respectively. In Equation 1, the multiple linear regression model is given. Here, Y is the dependent variable and k is the number of independent variables.

$$Y = \beta_0 + \beta_1 X_1 + \beta_1 X_1 + ... + \beta_k X_k + e \qquad [1]$$

In the equation [1] the parameters, $\beta_0, \beta_1, ..., \beta_k$ are expressed as regression coefficients. Prediction of model parameters in multiple linear regression can be performed with least squares and maximum likelihood estimation methods. The least squares technique was used in this study. Hypothesis tests are used to investigate the general adequacy of the model and the importance of independent variables included in the model.

Artificial neural networks method is the second method used in this study. A large number of artificial neuron exists in the structure of artificial neural networks and it is structured similarly to biological neurons. The basic components of an artificial neuron are inputs, weights, transfer function, activation function, and output. Artificial neural networks are composed of artificial neurons that come together systematically in the each of input layer, hidden layer and the output layers (Küçükönder et al. 2016). The data received from the outside in the input layer is transferred to the hidden layer for processing. Depending on the nature of the problem being solved, the number of hidden layers may vary or may be more than one. The processed data in the hidden layer is transmitted to the output layer and the output value corresponding to the inputs is generated. The values of the links connecting artificial neural networks are called weight values and the process of determining the weight values is called network training (Negnevitsky 2005; Haykin 2008).

Different artificial neural network models for different problem structures have been developed. The most used networks in literature are known as single and multilayer perceptron, vector quantization models (LVQ), self-organizing model (SOM), adaptive resonance theory models (ART), Hopfield networks, Elman network and radial based networks (Öztemel 2006). The Multilayer perceptron model was used in this study, as shown in Figure 1.

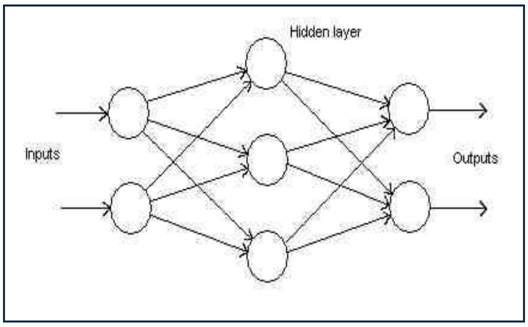

Figure 1. Multilayer Perceptron ANN.

Multilayer perceptron model has feed forward topology and works with back propagation algorithm. Operation of back propagation algorithm occurs in two stages: forward and backward calculation steps. In the first stage, a training set of input patterns is presented to the neural network. The neural network spreads the input pattern from layer to layer. The activation phase is the second stage. Here, the weight sums of the neurons in the hidden layer are computed through the activation function and transmitted to the output layer. The same process is performed for neurons in the output layer. It usually uses the sigmoid activation function. In the next step, a difference between the desired output and the actual output is calculated. The back propagation of the error occurs from the output layer to the input layer. The steepest descent method is used in the error minimization process.

In the analyses conducted via artificial neural networks, we have utilized three back propagation algorithms; namely Levenberg-Marquart, Bayesian regularization and Scaled conjugated. Additionally, sigmoid activation function is used. The mathematical representation of sigmoid activation function is in Equation 2. In Equation 2, x represents inputs and w represents weights $(i = 1,2,3..., n)$

$$Y^{sigmoid} = \frac{1}{1+e^{-X}} \quad [2]$$

$$X = \sum_{i=1}^{n} w_i x_i$$

Normalization process is carried out in order to reduce the difficulties during the training of the network, run faster in the training process of the network and provide balance in the importance of the parameters of the study. Normalization technique in the study is defined as Min-Max method shown as Equation 3 (Zhang and You 2015).

$$x' = \frac{(x_i - x_{\min})}{(x_{\max} - x_{\min})} \quad [3]$$

In Equation 1, x' represents normalized value of x_i $(i = 1,2,3..., n)$. $x_{\min}$ and $x_{\max}$ indicated the minimum and maximum value of related variable, respectively. Training of neural network is performed through normalized data. After obtaining the predicted values, the normalized data is converted back into the former in calculation of error criteria stage.

The performance criteria used to compare the neural networks and regression analysis results for goodness of fit are as follows: Coefficient of determination (R^2), the root mean square error (RMSE), mean absolute deviation (MAD) and mean absolute percentage error (MAPE). Best fit of model depends on these criteria: high value R^2 and error variance expressing the low value of RMSE, MAD and MAPE statistics (Atıl and Akıllı 2016). Calculation formulas of R^2, RMSE, MAD and MAPE criteria are located respectively in Equation 4-7. In equations n: number of observations, Y_i: observed value, $\hat{Y}_i$: predicted value $(i = 1,2,3..., n)$.

$$R^2 = \frac{\sum_{i=1}^{n} (\hat{Y}_i - \bar{Y})^2}{\sum_{i=1}^{n} (Y_i - \bar{Y})^2} \quad [4]$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (\hat{Y}_i - \bar{Y})^2}{n}} \quad [5]$$

$$MAD = \frac{\sum_{i=1}^{n} \left| \mathrm{Y_i} - \hat{Y}_i \right|}{n} \quad [6]$$

$$MAPE = \frac{\sum_{i=1}^{n} \left| \frac{\mathrm{Y_i} - \hat{Y}_i}{\mathrm{Y_i}} \right|}{n} \times 100 \quad [7]$$

Results and Discussion

In this research, the aim was to predict live weight of Hair goats using multilayer feed forward back propagation artificial neural network. In addition, it's aim was to predict Hair goats' live weight using the multi-layered feedback artificial neural network. Based on this aim, data set was randomly divided into two groups by 80% traning and 20% test data sets. Training data set sums up 380 and test data set sums up 95 Hair goats' morphological measurements. The layer and processor elements were identified via a detailed literature review and by trial and error method. The layer and processor elements were found to be of optimum number that fulfils the process of prediction with the least error. The hidden layer number in the designed artificial neural network is found to be "1" and the neuron number in this layer is found as '5'. The criterion of convergence is taken as 10^{-6}, and the maximum iteration number as 1000.

Table 1 reveals the results of analysis performed with artificial neural networks. Three different back-propagation algorithms were used in the analysis. Each algorithm used was analyzed separately for numbers varying between 3 and 10 neurons. Thus, the optimal number of neurons for the data set used was determined. The results of the analysis show that the algorithm with the highest determination coefficient and the lowest error statistics is Bayesian regularization. The most successful analysis in the Bayesian regularization algorithm is the analysis of the number of neurons 3. Most successful neuron numbers are five and ten in Levenberg-Marquart algorithm and scaled conjugate algorithms, respectively.

Table 1. The results with different number of neurons

Back-propagation Algorithms	Number of Neuron	Performance Criteria			
		R^2	RMSE	MAD	MAPE
Levenberg-Marquart (LM_Ann)	3	80.4%	5.6460	3.5480	5.4841
	4	88.9%	4.2782	3.2310	5.3481
	5	90.1%	4.0342	3.0522	4.8975
	6	88.4%	4.2798	3.1644	5.1004
	7	88.6%	4.4481	3.2275	5.1670
	8	89.2%	4.9479	3.9585	6.9284
	9	86.2%	4.6688	3.4185	5.4686
	10	87.7%	4.5409	3.2895	5.2191
Bayesian Regularization (BR_Ann)	**3**	91.0%	3.8380	2.9446	4.7957
	4	89.4%	4.1270	2.9648	4.7540
	5	89.2%	4.1590	3.1192	5.0581
	6	89.7%	4.0657	3.0524	4.9131
	7	89.1%	4.2272	3.1408	5.0699
	8	89.9%	4.0694	3.0280	4.8609
	9	89.2%	4.1975	3.1112	5.0065
	10	88.1%	4.3985	3.1152	4.9916
Scaled Conjugate (SCG_Ann)	3	82.4%	5.3108	3.7557	6.0350
	4	86.7%	4.6111	3.4950	5.6035
	5	87.1%	4.5684	3.3534	5.3776
	6	88.2%	4.4191	3.3370	5.3736
	7	89.6%	4.1552	3.0042	4.8679
	8	88.5%	4.2768	3.1909	5.2543
	9	79.2%	5.7687	4.0884	6.4878
	10	89.8%	4.0970	3.0101	4.8248

Table 2 illustrates the results of artificial neural networks and multiple linear regression analysis. In this table, the results of the best neuron numbers of algorithms used in artificial neural network analysis and the best regression model results obtained by the stepwise technique in multiple linear regression analysis are presented. The best goodness of fit value belongs to Bayesian regularization algorithm.

Table 2. Artificial neural networks and multiple linear regression results

Statistics	LM_Ann	BR_Ann	SCG_Ann	MLR
R^2	90.10%	91.00%	89.80%	88.40%
RMSE	4.0342	3.838	4.097	3.7929
MAD	3.0522	2.9446	3.0101	3.0374
MAPE	4.8975	4.7957	4.8248	4.8706

Figure 2 presents visual presentations of actual and predicted live weight values of the Hair goats. In the graphs, Levenberg-Marquartd, Bayesian regularization, scaled conjugate and multiple linear regression analysis results were found to be very close to each other. Performance criteria were evaluated over the whole data set for multiple linear regression analysis and over the test data for the artificial neural network.

The graphical representations of the values for the error statistics are given in Figure 3. Figure 3(a) shows that the Bayesian regularization algorithm has the highest coefficient of determination (R^2). The lowest MAD, MAPE values are shown in Figures 3(c) and Figure 3(d), respectively. It can be seen in Figure 3 (b) that the Bayesian regularization algorithm with multiple linear regression analysis is very similar to the RMSE value. The summary of the research results is as follows: Artificial neural network explains a higher value of coefficient of determination for predicting hair goats. The best back propagation algorithm of artificial neural network achieves 91% of the prediction accuracy for optimum model, whereas the multiple linear regression explained 88.4%.

In a similar vein to the present study, there are some studies on neural networks and comparisons with regression analysis in the literature. Salawu et al. (2014) used artificial neural networks to predict live weight in rabbits of eight weeks of age. Variables related to body measurements were used in the analyses. As a result of the comparison with the regression analysis, the determination coefficient was calculated as 67.9% (10000 iteration), 71% (1000000 iterations) for artificial neural network and 65.9% for regression analysis. Our results are presented with different number of neuron for different algorithms. In addition, different error statistics are given for each method. The success rate is much higher in the present study using similar theoretical structures. Our work is consistent with the results of the work carried out by Salawu et al. (2014). Szyndler-Nedza et al. (2015) used artificial neural networks and regression analysis to predict carcass meat percentage in young pigs. In their study, which is similar to our study, from the point of theory, artificial neural networks were found to be more successful than regression analysis. Unlike the present study, the researchers who made use of the variables involved in body measurements worked on six different pig breeds.

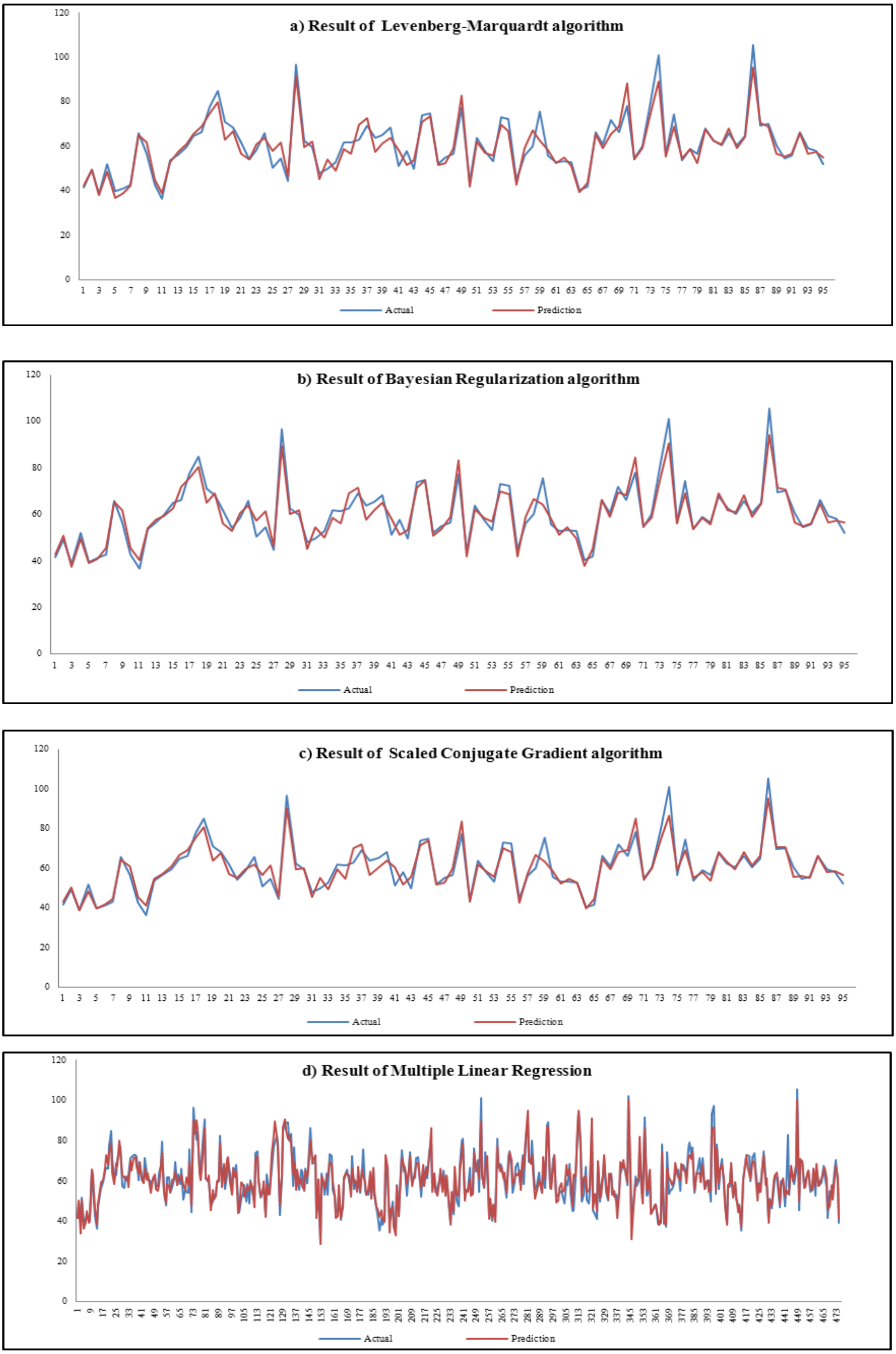

Figure 2. Prediction and observed values of body weight with Levenberg-Marquardt (a), Bayesian regularization (b), scaled conjugate gradient (c) and multiple linear regression (d).

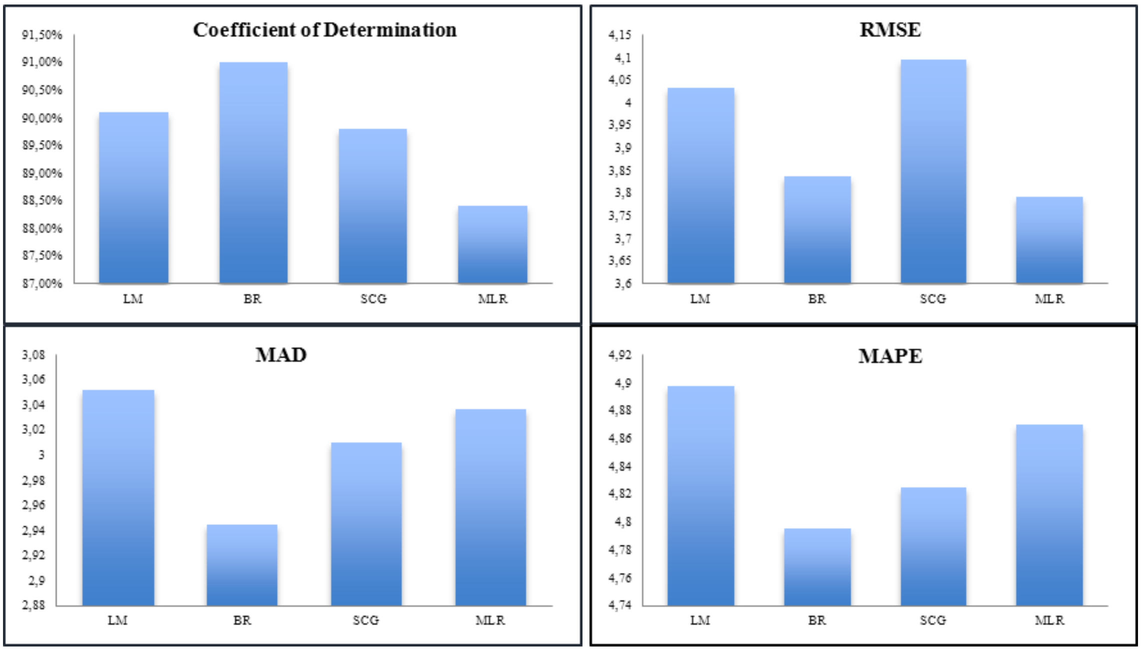

Figure 3. Error criteria results with coefficient of determination (a), RMSE (b), MAD (c) and MAPE (d).

Conclusion

In this study, it was aimed to predict the livestock weight of Hair goats through multiple linear regression analysis and artificial neural network method. In the data analyses through artificial neural networks, it was noted that "Bayesian Regularization" algorithm has the best prediction value among three different back propagation algorithms. Nonetheless, it was seen that artificial neural network method is more suitable than multiple linear regression analyses. The results of the study show that artificial neural network method can be used as an alternative to multiple linear regression analyses in the animal field. The most important advantage of neural networks is that there is no need to satisfy assumptions, which is a necessity in regression analysis. At this point the neural networks have a more flexible structure. Studies on productivity predictions of livestocks provide great convenience to decision-makers and researchers in animal breeding and herd management. Predisposition of high-yielding animals may have an effect on accelerating breeding studies. Neural networks, which have a very strong structure in the modelling of linear and linear relations, are rapidly developing in the field of animal husbandry. The aim is to design systems that can work integrated with different artificial intelligence based methods in the following studies.

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References

Alpar R (2011). Uygulamalı Çok Değişkenli İstatistiksel Yöntemler. Detay Yayıncılık, Ankara, 853p.

Atıl A, Akıllı A (2016). Comparison of artificial neural network and K-means for clustering dairy cattle. Int. J. Sustainable Agricultural Management and Informatics. 2(1): 40-52.

Cavero D, Tölle KT, Buxade C, Krieter J (2006). Mastitis detection in dairy cows by application of fuzzy logic. Livest. Prod. Sci. 105(1-3): 207-213.

Chen LJ, Cui LY, Xing L, Han LJ (2008). Prediction of the nutrient content in dairy manure using artificial neural network modeling. J. Dairy. Sci. 91: 4822-4829.

Craninx M, Fievez V, Vlaeminck B, De Baets B (2008). Artificial neural network models of the rumen fermentation pattern in dairy cattle. Comput. Electron. Agric. 60: 226-238.

Dong R, Zhao G (2014). The use of artificial neural in vitro rumen methane production using the CNCPS carbohydrate fractions as dietary variables. Livest. Prod. Sci. 162: 159-167.

Görgülü O (2012). Prediction of 305-day milk yield in Brown Swiss cattle using artificial neural networks. South African Journal of Animal Science, Vol. 42, No. 3: 280-287.

Grzesiak W, Zaborski D, Sablik P, Zukiewicz A, Dybus A, Szatkowska I (2010). Detection of cows with insemination problems using selected classification models. Computers and Electronics in Agriculture, Vol. 74, No. 2: 265-273.

Grzesiak W, Lacroix R, Wójcik J, Blaszczyk P (2003). A comparison of neural network and multiple regression predictions for 305-day lactation yield using partial lactation records. Can. J. Anim. Sci. 83: 307-310.

Hassan KJ, Samarasinghe S, Lopez- Benavidest MG (2009). Use of neural networks to detect minor and major pathogens that cause bovine mastitis. J. Dairy. Sci. 92: 1493-1499.

Haykin S (2008). Neural Networks and Learning Machines. Pearson Prentice Hall, New Jersey, 906p.

Hosseinia P, Edrisi M, Edriss MA, Nilforooshan MA (2007). Prediction of second parity milk yield and fat percentage of dairy cows based on first parity information using neural networks system. J. Appl. Sci. 7: 3274-3279.

Kominakis AP, Abas Z, Maltaris I, Rogdakis E (2002) A preliminary study of the application of artificial neural networks to prediction of milk yield in dairy sheep. Computers and Electronics in Agriculture, 35(1): 35-48.

Krieter J, Stamer E, Junge W (2006). Control charts and neural networks for oestrus detection in dairy cows. Lecture Notes in Informatics, Land- und Ernährungswirtschaft im Wandel-Aufgaben und Herausforderungen für die Agrar und Umweltinformatik, Referate der 26, GIL Jahrestagung, 6–8 March 2006, Potsdam, pp.133-136.

Küçükönder H, Boyacı S, Akyüz A (2016). A modeling study with an articial neural network: Developing estimation models for the tomato plant leaf area. Turkish Journal of Agri. and Forest., 40: 203-212.

Szyndler-Nędza M, Eckert R, Blicharski T, Tyra M, Prokowski A (2015). Prediction of carcass meat percentage in young pigs using linear regression models and artificial neural networks. Annals of Animal Science, DOI: 10.1515/aoas-2015-0069.

Negnevitsky M (2002). Artificial Intelligence, A Guide to Intelligent Systems. Pearson Ed., Harlow, 415 p.

Öztemel E (2006). Yapay Sinir Ağları. Papatya Yayıncılık, Istanbul.

Roush WB, Wideman Jr RF, Cahaner A, Deeb N, Cravener TL (2001). Minimal number of chicken daily growth velocities for artificial neural network detection of pulmonary hypertension syndrome PHS, Poultry Science. 80(3): 254-259.

Salawu EO, Abdulraheem M, Shoyombo A, Adepeju A, Davies S, Akinsola O, Nwagu B (2014). Using Artificial Neural Network to Predict Body Weights of Rabbits. Open J. of Animal Sci. 4, 182-186.

Salehi F, Lacroix R, Yang XZ, Wade KM (1997). Effects of data preprocessing on the performance of artificial neural networks for dairy yield prediction and cow culling classification. Transactions of the American Society of Agricultural and Biological Engineers. 40(3): 839–846.

Salehi F, Lacroix R, Wade KM (1998). Improving dairy yield predictions through combined record classifiers and specialized artificial neural networks. Comput. Electron. Agric. 20: 199-213.

Sanzogni L, Kerr D (2001). Milk production estimates using feed forward artificial neural networks. Computers and Electronics in Agriculture. 32(1): 21-30.

Shahinfar S, Mehrabani-Yeganeh, H, Lucas C, Kalhor A, Kazemian M, Weigel KA (2012). Prediction of breeding values for dairy cattle using artificial neural networks and neuro-fuzzy systems. Comput. Math. Methods Med. Article ID 127130, 9 pages.

Sharma AK, Sharma RK, Kasana HS (2007). Prediction of first lactation 305-day milk yield in Karan Fries dairy cattle using ANN modeling. Appl. Soft Comput. 7: 1112-1120.

Sun Z (2008) Application of Artificial Neural Networks in Early Detection of Mastitis from Improved Data Collected On-Line by Robotic Milking Stations, dissertation, Lincoln University, New Zealand.

Takma Ç, Atıl H, Aksakal V (2012). Çoklu doğrusal regresyon ve yapay sinir ağı modellerinin laktasyon süt verimlerine uyum yeteneklerinin karşılaştırılması. Kafkas Ü. Vet. Fak. Derg. 18(6): 941-944.

Yang XZ, Lacroix R, Wade KM (2000). Investigation into the production and conformation traits associated with clinical mastitis using artificial neural networks. Can. J. Anim. Sci. 80: 415–426.

Yilmaz O, Cemal I, Karaca O (2013). Estimation of mature live weight using some body measurements in Karya sheep. Trop Anim Health Prod 45:397-403. DOI:10.1007/s11250-012-0229-7

Zhang T, You X (2015). Improvement of the training and normalization method of artificial neural network in the prediction of indoor environment. Procedia Engineering. 121: 1245-1251.