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Comparison of Artificial Neural Network and Regression Models for Prediction of Body Weight in Raini Cashmere Goat

Research Article

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ABSTRACT

The artificial neural networks (ANN) are the learning algorithms and mathematical models, which mimic the information processing ability of human brain and can be used to non linear and complex data. The aim of this study was to compare artificial neural network and regression models for prediction of body weight in Raini Cashmere goat. The data of 1389 goats for body weight, height at withers (HAW), body length (BL) and chest girth (CG) were used. Different regression models with all fixed factors were calculated for the most possible states and with different degrees and two artificial neural networks with different hidden layers, learning functions and transform functions were used. Finally, Multilayer perceptron model with one hidden layer along with neurons was selected and used. Correlation between body weight and its measurements showed that it is possible to use body measurements for prediction of body weight though prediction of body weight can be improved when more measurements are used. Based on R^2 and mean square error (MSE) parameters, the best fitted regression equation for prediction of body weight using body measurements was selected. While all three measurements had a significant effect in the model ($P<0.0001$), height at wither had the highest correlation coefficient (0.65), hence may have the greatest effect on prediction. Comparing two models indicated that both models can predict body weight well and near to actual body weight, but the capability of artificial neural network model is higher (R2=0.86 for ANN and 0.76 for multiple regression analysis (MRA)) and closer to actual body weight. However, if more related measurements are recorded, ANN can give the desirable results. Therefore, it is possible to apply artificial neural networks, instead of customary procedures for prediction of actual body weight using body measurements.

KEY WORDS artificial neural networks, body measurements, linear models, Raini goat.

INTRODUCTION

Goat farming is practiced worldwide, with goat products having a favorable image. The number of goats has increased globally, even in countries with high and intermediate incomes, despite major changes in agriculture due to industrial mergers, globalization, and technological advances in developed countries (Shamsalddini *et al.* 2016).

There are 30 million heads of cashmere goats around the world and 4.5-5 million heads of them are in Iran that is 20% of all in the world (Baghizadeh *et al.* 2009). Goat production is one of the key elements contributing to the economy of farmers living in the arid and semi-arid regions including most areas of Iran. Raini goat is one of the most important Iranian native goats that spread in the southeast of Iran where these animals are kept for both meat and cashmere production (Barazandeh *et al.* 2012; Moghadaszadeh *et al.* 2015). Thus, traits affecting economic viability include those associated with growth and cashmere. One of the most important purposes of the genetic improvement of this breed is enhancing the meat production via programmed and accurate selection. Hence, having exact information about body weight is the first necessity for estimation of the production potential of this breed. Measuring the exact live body weight on the farm is much difficult, because in villages and mountains where these animals are reared there is not transportable weighing balance and skilled technicians. These conditions are real for nomads of Kerman province who keep this breed. Hence, in these situations, the weight of the animals is predicted via regressing body weight on different body measurements as chest girth (CG), body length (BL), height at withers (HAW) and so on. These can be measured without hesitation. To predict body weight from linear body measurements the regression analysis can commonly be applied (Thiruvenkadan, 2005; Alade *et al.* 2008). Investigations have shown that these usual regression procedures can not evaluate the multicollinearity between independent factors; hence it can lead to biased outcomes (Raja *et al.* 2012; Ruhil *et al.* 2013). In the conditions that correlation between variables is very high multicollinearity takes place, hence it is difficult to come up with reliable estimates of their individual regression coefficients. In this situation, some variables are basically measuring the same phenomenon and they give similar information, hence these variables can oppositely affect the outcomes of regression. Difficulties caused from multicollinearity in regression analysis have stated by different researchers (Eyduran *et al.* 2010; Ghazanfari *et al.* 2011). In comparison with regression approaches, there are some different methods entitled the neuro-fuzzy systems and artificial neural networks for solving the problems caused by traditional regression methods. Machine learning techniques, such as decision trees and artificial neural networks are also used increasingly in agriculture, because they are quick, powerful, and flexible tools for classification and prediction applications, particularly those involving nonlinear systems (Shahinfar *et al.* 2012). Fuzzy logic, which involves classification of variables into fuzzy sets with degrees of membership between 0 and 1, has recently found its way into agricultural research. Applications have included development of decision support systems for analyzing test-day milk yield data from dairy herd Improvement (DHI) programs, detection of mastitis and estrus from automated milking systems, and definition of contemporary groups for the purpose of genetic evaluation. A key challenge in the use of fuzzy sets is the development of appropriate membership functions (MF) (Shahinfar *et al.* 2012). The artificial neural networks are the learning algorithms and mathematical models, which are mimicking the information processing ability of the human brain and can be used to non-linear and complex data, even if the data are imprecise and noisy (Gandhi *et al.* 2009; Raja *et al.* 2012). These networks contain a set of processing components, also known as neurons or nodes whose functionality is loosely based on biological neurons. These units are formed in layers that process the input information and pass it to the following layer. The capability of the network in processing is cumulated in the inter unit connection strengths (or weights) that are acquired via a process of conformity to a collection of training pattern (Haykin, 2001; Grzesiak *et al.* 2003; Raja *et al.* 2012).

Moreover, artificial neural network method entirely varies from traditional statistical approaches, which need a specified algorithm to be transformed by a computer program (Grzesiak *et al.* 2003; Roush *et al.* 2006; Takma *et al.* 2012). The artificial neural networks use in different scientific fields, for example, finance, medicine, geology, engineering, physics, and biology, but unfortunately in animal sciences and particularly in animal breeding rarely have been applied (Grzesiak *et al.* 2003; Fernández *et al.* 2006; Sharma *et al.* 2006; Gandhi *et al.* 2009; Bahreini Behzadi and Aslaminejad, 2010; Raja *et al.* 2012; Ruhil *et al.* 2013).

On the other hand, although many studies have been performed on different traits of Raini Cashmere goat (Askari *et al.* 2008; Askari *et al.* 2009; Askari *et al.* 2010; Hassani *et al.* 2010; Askari *et al.* 2011; Barazandeh *et al.* 2011; Mohammadabadi *et al.* 2012; Molaei Moghbeli *et al.* 2013; Tohidi Nezhad *et al.* 2015), comparison of the artificial neural networks and regression models have not been studies yet, hence the aim of this study was to compare artificial neural network and regression models for prediction of body weight in Raini Cashmere goat for the first time.

MATERIALS AND METHODS

Measuring live body weight exactly in village situations is so hard, because in villages and mountains where these animals are kept there is no transferable weighing balance and skilled technicians. These conditions are real for nomads of Kerman province who keep the Raini Cashmere goat breed. Hence, in these situations, the weight of the animals is predicted via regressing body weight on different body measurements as CG, BL, HAW and so on. These can be measured without hesitation. Therefore, in this study, the data of 1389 Raini Cashmere goat which were recorded during 2010-2011 were obtained from the Breeding Station of Raini goat in Baft city (middle of Kerman Province, Iran) (n=701), from rural flocks in Kerman province (n=619) and from Livestock research center of Shahid Bahonar University of Kerman, Iran (n=69) (Table 1).

Table 1 Description of data structure

Trait	Body weight (kg)	Height at withers (cm)	Body length (cm)	Chest girth (cm)
Minimum	5.70	35.00	31.00	51.00
Mean	32.18	63.66	54.46	81.97
Maximum	54.30	84.00	86.00	120.00
Standard deviation	9.37	9.02	9.39	15.38
CV (%)	29.37	14.17	17.24	18.76

CV: coefficient of variation.

The obtained data were edited firstly and the outliers and the illogical data were removed from the dataset. The microsoft excel and neuro solution (http://www.neurosolutions.com) software were used to normalize standardize the data. In order to achieve the best model of body weight prediction using mentioned phenotypic traits the multiple linear regression models were applied and comparison of R^2 and MSE was conducted in R environment (https://cran.r-project.org). In this study, different regression models with all fixed factors were calculated for the most possible states and with different degrees.

Then, the data that were analyzed and investigated in the previous steps using regression models were transferred to neuro solution software and then the neural network was designed. In the present study, two artificial neural networks; multilayer perceptron and generalized feed forward with different hidden layers, learning functions, and transform functions were used. And then, the best network was selected. Finally, multilayer perceptron model with one hidden layer along with neurons was selected and used.

Figure 1 shows input layers, neurons, and output layer included the variables for producing the network response. MSE and R^2 were used to compare different regression models and also performance of regression models with the artificial neural network models Theoretically, if a model could explain 100% of the variance, the fitted values would always equal the observed values and, therefore, all the data points would fall on the fitted regression line. Key limitations of R^2 are: 1) R^2 cannot determine whether the coefficient estimates and predictions are biased, which is why the residual plots must be assessed. 2) R^2 does not indicate whether a regression model is adequate. One can have a low R^2 value for a good model, or a high R^2 value for a model that does not fit the data. In some fields, it is entirely expected that R^2 values will be low.

RESULTS AND DISCUSSION

Correlation between body weight and its measurements

Correlation between body weight and its measurements showed that it is possible to use body measurements for prediction of body weight (Table 2). The highest and the lowest correlations were between body weight and HAW (0.75) and body length (0.45), respectively.

Among the body measurements, the highest and the lowest correlations were obtained between HAW and chest girth (0.60) and between body length and HAW (0.35), respectively. In the other investigations, the same results have been reported by other researchers (Afolayan *et al.* 2006; Musa *et al.* 2012; Raja *et al.* 2012). To investigate the extent of multicollinearity in the variables, we calculated the variance inflation factor (Table 3).

Regression models results

Comparison of models using R^2 and MSE parameters showed that the best fitted regression equation for prediction of body weight using body measurements is as:

$$BW= -40.74 + 0.23\ BL + 0.75\ HAW + 0.41\ CG$$

The MSE and R^2 for this equation were 47.20 and 0.67, respectively. These observations indicate that body weight of Raini Cashmere goat can be predicted with relatively high accuracy HAW, BL and CG. All three measurements had a significant effect in the model ($P<0.0001$). The HAW had the most coefficient (0.65 and 0.75, unstandardized and standardized coefficients respectively), hence may have the greatest effect on prediction. Figure 2 shows correlation between actual and predicted weight using the best multiple regression model. As can be seen, this relationship is along a line representing the ability of this model for prediction of body weight.

Figures 3 and 4 suggest that changes of variables HAW, BL and CG are very similar to variations related to actual measured body weight and indicate the accuracy and precision of prediction by multiple linear regression models and also the necessity of these three variables in the model. In the other investigations, the same results have been reported by other researchers (Rani *et al.* 2010; Birteeb *et al.* 2012; Mohammad *et al.* 2012; Iqbal *et al.* 2013). Studies have shown that three factors; HAW, BL and CG in prediction of body weight have a crucial role that confirm the results of this study.

Artificial neural network results

To prevent over-fitting of the artificial neural network, 70% of the data were used as training set, 15% as testing set and 15% as the validating set.

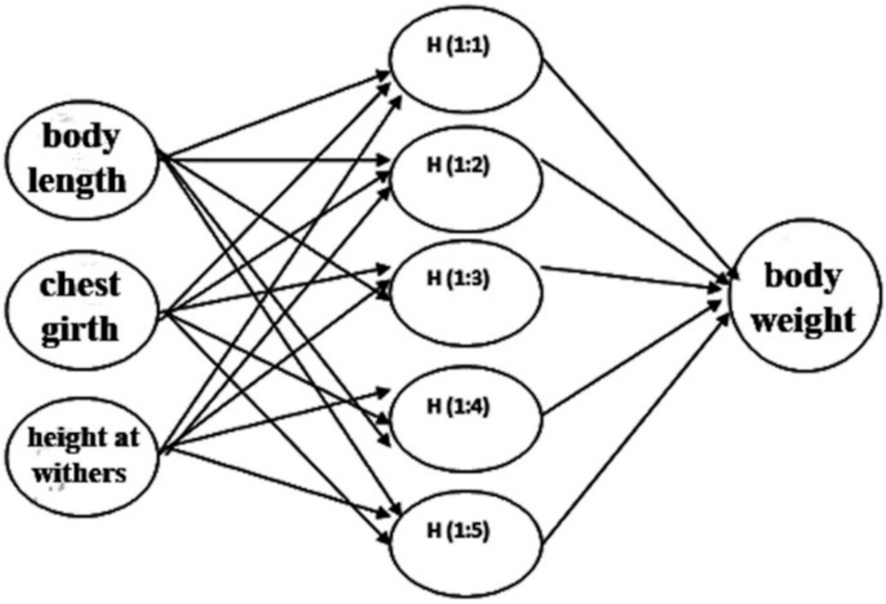

Figure 1 Variables and layers used in the experiment data sets for artificial neural networks in Raini Cashmere goat

Table 2 Phenotypic correlation coefficients between body linear measurements

Trait	Body weight (kg)	Height at withers (cm)	Body length (cm)	Chest girth (cm)
Body weight (kg)	1	0.75	0.45	0.68
Height at withers (cm)	0.75	1	0.34	0.60
Body length (cm)	0.45	0.34	1	0.35
Chest girth (cm)	0.68	0.60	0.35	1

Table 3 The variance inflation factor (VIF) values calculated based on the three variables

Trait	Body length	Height at withers	Chest girth
Body length	-	1.57	1.57
Height at withers (cm)	1.14	-	1.14
Chest girth	1.13	1.13	-

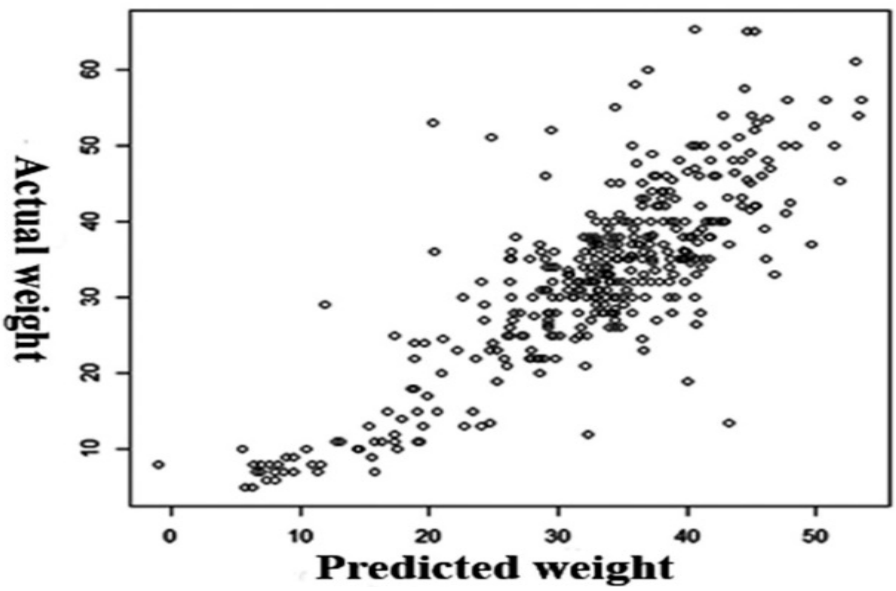

Figure 2 Correlation between actual weight and predicted weight in multiple linear regression model for Raini Cashmere goat

The neural network models were trained using the training data sets to predict the body weight and a maximum goal of 99% accuracy was set to be achieved in 2000 epochs (cycles).

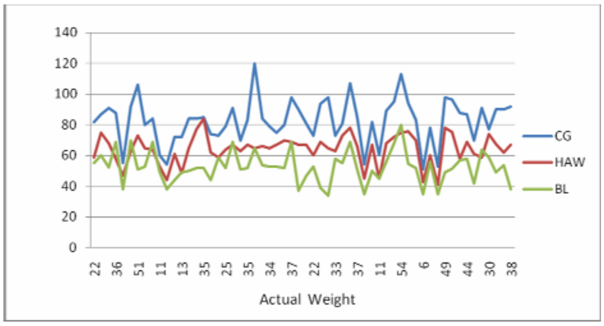

Figure 3 Variation of height at withers (HAW), body length (BL) and chest girth (CG) in comparison to actual weights for Raini Cashmere goat

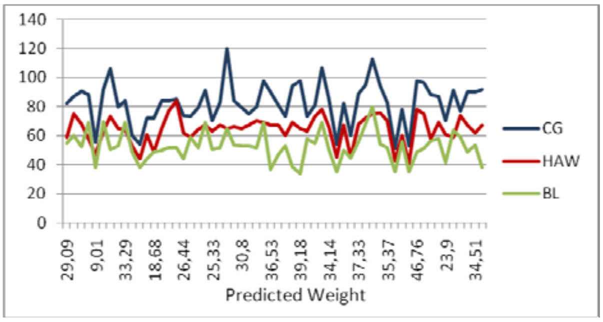

Figure 4 Variation of height at withers (HAW), body length (BL) and chest girth (CG) in comparison to predicted weights by multiple linear regression model for Raini Cashmere goat

Then, prediction of body weight using different training functions was performed. Correlation coefficient (R^2) and root mean square error (RMSE) for the training and testing data sets were estimated (Table 4). Results showed that trainlm function (Table 4) has the least RMSE and it was better than other functions for prediction of body weight in Raini Cashmere goat.

Several combinations of hidden layers (1-2 layers) with varying number of neurons (3-25 neurons), 2 models (generalized feed forward and multilayer perceptron), 2 algorithms (conjugated gradient and Levenberg Marquardt) and 2 transform functions (Tanh Axon and Sigm Axon) were experimented to train the network. Finally, from a comparison of total neuro solution analysis, multilayer perceptron (MLP) model with one hidden layer, 5 nodes in the layer, 1000 repeats, 10 runs, conjugated gradient algorithm, tanh axon function, R^2= 0.86 and the lowest root mean square error (RMSE)= 0.13 was selected as the best model.

Average mean square error along with standard deviation and 10 runs in the case of training and validation for the best model showed that after 120 epochs were not any reduction in mean square error both training and validation cases (Figure 5), hence the training must be stopped. If this process does not stop, network instead of learning will memorize data and prediction accuracy will be low. As shown in Figure 5, average mean square error for validation data in comparison with training is low, hence this network will be used for prediction of body weight in Raini Cashmere goat.

Output resulted from predicted and actual data showed that weights predicted with the network are very close to actual weights (Figure 6), so it can be concluded that this model has the high capability for accurately prediction of body weight in Raini Cashmere goat.

Variation for 3 variables; HAW, BL and CG in comparison of measured actual weight (Figure 3) and predicted body weight using artificial neural network (Figure 7) in Raini Cashmere goat demonstrated that variations of these 3 variables into predicted body weights is very similar to variations into measured actual weights, thus it can be concluded that artificial neural network has the high capability for accurate prediction of body weight in Raini Cashmere goat and also indicates the necessity of these three variables in the model.

Table 4 Evaluation of multilayer perceptron network in terms of the training function type for predicting the body weight in Raini Cashmere goat

Training function of network[1]	Train set	Test set	RMSE[2]
Trainlm	0.84	0.84	0.06
Traincgp	0.81	0.80	0.07
Traincgb	0.80	0.80	0.07
Traincgf	0.80	0.79	0.07
Trainoss	0.80	0.80	0.07
Trainscg	0.80	0.79	0.07
Trainrp	0.80	0.80	0.07
Traingda	0.50	0.51	0.11
Traingdx	0.73	0.74	0.08
Traingd	0.38	0.39	0.15
Traingdm	0.57	0.58	0.13

[1] Trainlm: Levenberg-Marquardt back propagation; Traincgp: conjugate gradient with Polak-Ribiere updates; Traincgb: conjugate gradient with Powell-Beale restarts; Traincgf: conjugate gradient with Fletcher-Reeves updates; Trainoss: one step secant; Trainscg: scaled conjugate gradient, Trainrp: resilient back propagation; Traingda: gradient descent with adaptive (variable) learning rate; Traingdx: gradient descent with momentum and adaptive learning rate; Traingd: gradient descent and Traingdm: gradient descent with momentum.
RMSE: root mean square error.

Raja *et al*. (2012) used the artificial neural network and multiple regression to predict body weight from body measurements in Attappady Black goats. They reported that in the case of artificial neural network the value of root mean square error is low and the value of R^2 is high, in comparison of multiple regression models. They concluded that artificial neural network model is a better tool to predict body weight in goats than multiple regression models that confirmed our results in Raini Cashmere goat.

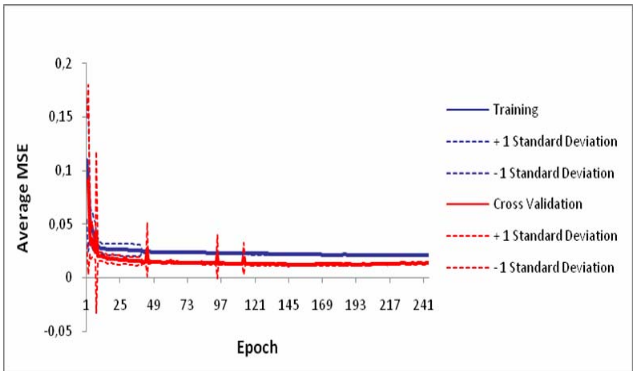

Figure 5 Diagram of mean square error with standard deviation for 10 runs in Raini Cashmere goat

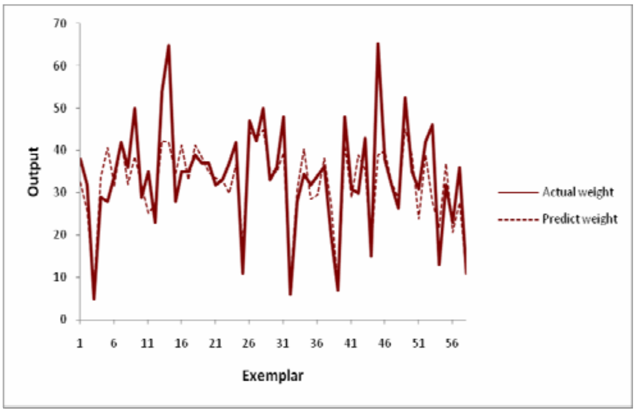

Figure 6 Diagram of actual and predicted of artificial neural network outputs in Raini Cashmere goat

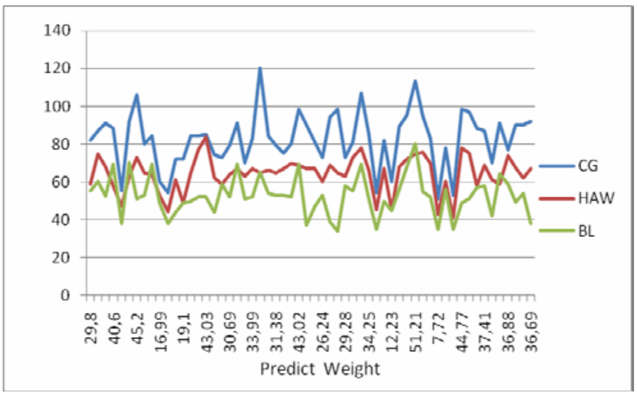

Figure 7 Variations of input variables into predicted weights by artificial neural network in Raini Cashmere goat

Comparison of artificial neural network model and multiple regression model

As has shown in Figure 8, both artificial neural network model and multiple regression model can predict body weight well and near to actual body weight, but capability of artificial neural network model in comparison of multiple regression model is higher and closer to actual body weight.

Results showed that R^2 achieved from artificial neural network is higher than from multiple regression (Figure 9) demonstrating high predictability of artificial neural network.

Table 5 shows that artificial neural network has higher R^2 and pearson correlation coefficient and lower standard deviation and mean square error in comparison with multiple regression model declaring high predictability of artificial neural network.

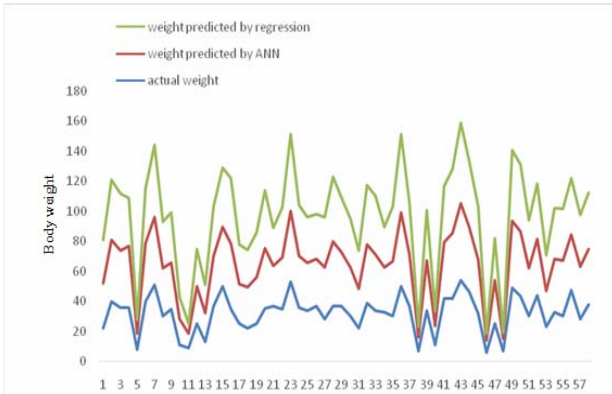

Figure 8 Comparison of actual and predicted weights using artificial neural network model and multiple regression model in Raini Cashmere goat

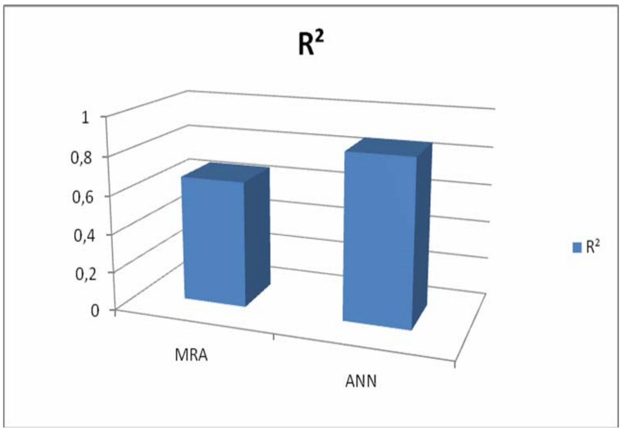

Figure 9 Comparison of R^2 achieved from artificial neural network and multiple regression model in Raini Cashmere goat

Roush *et al*. (2006) compared the Gompertz nonlinear regression model and neural network modeling for prediction of body weight in Broiler and showed that neural network modeling has the lowest bias.

Table 5 Different criteria resulted from comparison of artificial neural network (ANN) and multiple regression analysis (MRA)

Statistical criteria	Test data set	
	MRA	ANN
Mean square error (MSE)	47.20	19.86
R^2	0.67	0.86
Standard deviation (SD)	11.41	10.41
Pearson correlation coefficient	0.9210	0.9237

In the other study, Bahreini Behzadi and Aslaminejad (2010) used 6 nonlinear regression forms of von Bertalanffy, Gompertz, Logistic (with 3 and 4 parameters), Brody and Richards and artificial neural network to predict Baluchi sheep growth and concluded that artificial neural network generates a slightly better descriptive sheep growth curve in comparison with nonlinear models and makes the most accurate prediction. They proposed that artificial neural network is a valuable tool for prediction of lamb body weight. Neural network models also have been used for detecting mastitis (Hassan *et al.* 2009) and estimating clinical mastitis cases with milk production traits (Yang *et al.* 2000) and have demonstrated their ability for these purposes. Grzesiak *et al.* (2003) have used multiple regression and artificial neural networks methods to estimate the 305-days milk yield. Takma *et al.* (2012) also applied multiple regression and neural network to predict milk yield of Holstein. Favaro *et al.* (2014) tested the reliability of a Multilayer perceptron feed forward artificial neural network, (ANN) to automate the process of classification of calls according to individual identity, group membership and maturation in goat. They showed successful examples of signal recognition by a MLP for individuality, group membership and maturation in domestic goat kids, suggesting that ANNs could be considered a reliable tool to study vocalizations of domestic livestock from a source-filter perspective.

They also demonstrated that ANNs have the potential to exhibit substantially greater predictive power than traditional statistical approaches and argued that these algorithms can be adopted to classify contact calls of many different species. In the other study, Kaygisiz and Sezgin (2017) predicted goat milk production in Turkey using artificial neural networks and Box-Jenkins models. Akkol *et al.* (2017) reported that the artificial neural networks method is more successful than multiple linear regression in prediction of body weight in hair goats.

Pour Hamidi *et al.* (2017) predicted breeding values for the milk production trait in Holstein cows applying artificial neural networks and showed that capability of artificial neural network model was higher and closer to the estimated breeding values. Therefore, it is possible to apply artificial neural networks, instead of commonly used procedures for predicting the breeding values for milk production.

All researchers showed that artificial neural networks can be an alternative method to regression analysis. Results of the same investigations in different farm animals have shown that artificial neural networks have better precision, accuracy and efficiency that confirm our results achieved in Raini Cashmere goat.

Results of studied on different organisms have shown that it is very difficult to predict and identify genes that contribute to body weight regulation, regardless of the tremendous progress in understanding physiological, endocrine, and metabolic changes in fat, muscle, liver, brain, and many other cells, tissues, and organs as a result of malnutrition and in response to diet, behavior, and physical activity (Brockmann *et al.* 2009). On the other hand, growth of domestic animals may be described by several non-linear models (NLM), as a function of time and a number of parameters that can have a biological interpretation. The Gompertz, von Bertalanffy, Brody, Richards, and Logistic growth models are commonly used to explain animal growth (Brockmann *et al.* 2009), hence it is impossible to demonstrate biochemical / physiological causes of our obtained results. But, since artificial neural networks take into account more factors and have higher R^2 values, they are more suitable than traditional methods in this field.

CONCLUSION

Our results demonstrated that for prediction of body weight in Raini Cashmere goat artificial neural networks are better and more accurate than multiple regression models due to the higher R^2 and pearson correlation coefficient and lower standard deviation and mean square error compared with the multiple regression models. Although both artificial neural networks and multiple regression models can remarkably predict body weights very close to the actual values, performance of artificial neural networks for prediction of body weights applying body measurements of Raini Cashmere goat was higher and more precise. Therefore, it is possible to apply artificial neural networks, instead of customary procedures for prediction of actual body weight using body measurements.

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