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ESTIMATION OF BODY WEIGHT FROM MORPHOLOGICAL MEASUREMENTS IN BOER GOATS WITH THE APPLICATION OF ARTIFICIAL NEURAL NETWORKS AND SOME REGRESSION MODELS

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Tyasi T.L. and Ş. Çelik (2023). *Estimation of body weight from morphological measurements in Boer goats with the application of artificial neural networks and some regression models*. - Genetika, Vol 55, No.3, 929-950.
In this study, examination of the characteristics of body measurements affecting the body weight of Boer goats and the estimation of the body weight were investigated. To examine their body morphological features, 400 live animals were taken into consideration. The morphological measurements taken from the goats in the study were body weight (BW), body length (BL), heart girth (HG), withers height (WH), rump height (RH), rump length (RL), ear length (EL) and head with (HW) respectively. These animals were between 1-6 years old; 112 of them were male and 288 of them were female. Multiple regression, ridge regression and artificial neural networks (ANN) methods were applied to estimate the body weight. In the prediction of body weight as a dependent variable, the ANNs predictive model produced high predictive performance. Mean square error (MSE), mean absolute error (MAD) and mean absolute percent error (MAPE) statistics were used to determine model performance. Using the Multi-Layer Perceptron (MLP) Artificial Neural Network (ANN) learning algorithm, the body features that had the greatest impact on body weight were determined. Comparison of the predictive performance of the put forward model against both multiple regression and state of the ridge regression methods showed that the artificial neural networks outperformed both competing models by achieving the least values for MAD, MSE and MAPE in both training and testing data sets. The results of artificial neural networks were promising and accurate in the prediction of the body weight of goats.
Key words: Artificial neural networks, body measurement, goat, ridge regression

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INTRODUCTION

The Boer goat is an improved indigenous breed, which consists of a mixture of blood from various goats, principally those from Eastern countries and India (ERASMUS, 2000). The occurrence of polledness indicates some possible influences of the European, Dutch dairy goat (STEEL, 1996). Boer goat is a breed that was developed in South Africa in the early 1900s and is reared especially for meat production (NUGROHO *et al*., 2018; MATHAPO and TYASI, 2021). The breed is known for its faster growth rate, good adaptability, good carcass quality and heavy body weight (NUGROHO *et al*., 2018). The improved Boer goat is a notable smallstock ruminant that possess distinctive qualities enabling it to excel as an efficient red meat producer (ERASMUS, 2000).

Knowing the body weight of animals is important for farmers for the purpose of marketing their animals, selection of breeding animals, feeding management and the administration of correct dosages of medication (NORRIS *et al*., 2015). Some farmers in communal areas are experiencing a challenge of determining the body weight of animals due to a lack of resources such as weighing scales. Therefore, the prediction of body weight from body measurements is the easiest, practical and cheapest procedure for determining the body weight of an animal (NSOSO *et al*., 2003). According to KHORSHIDI-JALALI *et al*. (2019), artificial neural networks (ANN) are the learning algorithms and mathematical models, which imitate the information processing ability of the human brain and can be used to non-linear and complex data. Other studies previously used ANN for the prediction of body weight from body measurements in Madras Red sheep (BALASUBRAMANYAM *et al*., 2013), hair goats (AKKOL *et al.*, 2017) and Raini Cashmere goat (KHORSHIDI-JALALI *et al*., 2019). The technique was also used for the prediction of goat milk in Turkey (KAYGISIZ and SEZGIN, 2017).

Other techniques such as classification and regression tree have been employed for the prediction of body weight from morphological traits in Balochi sheep (HUMA and IQBAL, 2019) and Beetal goats of Pakistan (EYDURAN *et al*., 2017). Most machine learning algorithms like ANN involve several hyper-parameters, such as the number of hidden layers and neurons, the activation function of each layer, and the learning rate in an artificial neural network. Moreover; the values of these hyper-parameters will affect the accuracy of body weight prediction in this study.However, the ability of ANN as the prediction model to estimate body weight using body measurement traits in the Boer goat breed is not yet known. Hence, the objectives of the study were to 1) examine the characteristics of body measurements affecting the body weight of Boer goats and to 2) estimate body weight from body measurements using ANN. The farmers will get assistance from the current study to select the best body measurement traits to be involved in the selection criteria for enhancement of body weight during Boer goats breeding. Accurate estimation of body weight is important in terms of determining the economic gain of a living thing and ensuring productivity.

MATERIALS AND METHODS

Materials

The study was conducted at Tivolie farm (Pieter Smith stud breeder) in Allays small town, Blouberg local municipality of Limpopo Province, South Africa. A total of 400 Boer goats aged between one and six years old were used. Of 400 Boer goats, 112 were males and 288 were females. Morphological measurements were measured as shown in Figure 1 following a describtion by LUKUYU *et al.* (2016). Briefly, tailor measuring tape and a wood ruler calibrated in centimeters (cm) were used to measuring the morphological traits while body weight (BW) was measured using a weighing scale calibrated in kilogrammes (kg) that weighs up to 300kg with an accuracy of 100gm. Body length (BL) was measured as a distance from the occipital protuberance to the base of the tail. Heart girth (HG) was measured as the circumference of the chest. Withers height (WH) was measured as a distance from the highest point on the shoulder to the ground surface in relation to the level of the forelegs. Rump height (RH) was measured as a distance from the ground to the rump. Rump length (RL) was measured as a distance from the hip to the pin. Ear Length (EL) was measured as a space from the position of attachment to the tip of the ear and Head width (HW) was measured as the space between the edges of the head. To avoid personal errors, only one person was taking the measurements.

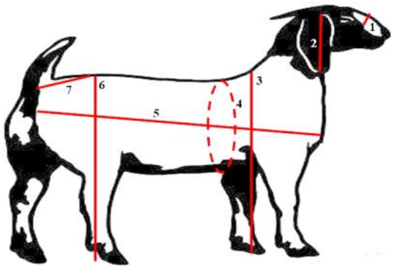

Figure 1. Morphological traits. (1) Head width (HW), (2) Ear length (EL), (3) Withers height (WH), (4) Heart girth (HG), (5) Body length (BL), (6) Rump height (RH), (7) Rump legnth (RL).

Methods

The data was analysed using Software Pacharge for Social Sciences (IBM SPSS, 2019) version 26.0. The evaluation of morphological traits on body weight in Boer goats were formed by multiple linear regression analysis and artificial networks methods and both models were compared in the study. First method employed in this study was regression analysis by studying body weight of Boer goats as multiple linear regression analysis method. It is a statistical method used to form association between dependent and independent variables with cause and effect of association. This is a model used in the analysis of more than one variables. The objective was to find the model that best describe the association between independent and dependent variables using this regression analysis (YILMAZ *et al*., 2013). The multiple linear regression model is given below: where Y is dependent variable and K is the number of independent variables.
$y = \beta 0 + X1\beta 1 + X1\beta 1 + Xk\beta k + \varepsilon$ in equation 1 the variables $\beta 0 + X1\beta 1 + X1\beta 1 + Xk\beta k$ are shown as regression coefficients.

The standard model for multiple linear regression was as follow (DRAPER and SMITH 1998):

$$y = X\beta + \varepsilon$$

where y is an $nx1$ column vector of observations on the dependent variable, X is an nxp fixed matrix of observations on the independent variables and is of full rank $p(p \leq n), \beta$ is a $px1$ unknown column vector of regression coefficients. ε is an $nx1$ vector of random errors. $E(\varepsilon) = 0, E(\varepsilon\varepsilon') = \sigma^2 I_n$, where I_n denotes the nxn identity matrix and prime indicates the transpose of a matrix. The ordinary least squares (OLS) estimator, $\hat{\beta}$ of the parameters is given by (DRAPER and SMITH, 1998).

$$\hat{\beta} = (X'X)^{-1}X'y$$

Ridge regression estimators were recommended by HOERL and KENNARD (1970) and they struggle with the problem of multicollinearity for the estimation of regression parameters. For ridge regression, generally one does not penalize the intercept term and standardize the predictors for the penalty to be meaningful (HASTIE *et al*., 2009).

The Ridge estimate of an unknown vector B for standardized observations {W, V} is given by:

$$\hat{\beta}_A = (W'W + \lambda I)^{-1}W'V$$

Where I is the identity matrix. λ>0 is called the regularization parameter. Therefore, the Ridge estimate can be viewed as an OLS estimate with an additional penalty imposed on the coefficient vector (MELKUMOVA and SHATSKIKH, 2017).

Artificial neural networks are a type of machine learning inspired by the advanced functionality of human brains where hundreds of billions of interconnected neurons process information in parallel (WANG, 2003). Artificial neural networks are constructed of three primary layers. These layers input information, output information and hidden layer. The hidden neurons lie in the form of layers between the input and output neurons (KUMAR, 2004). The hidden layer represents mathematical transformations that define the relationship between input information and output information (KRENKER *et al*., 2011).

The input neurons accept real world data. The input variables data are gathered by each neuron from the main layer and are presented based on an input vector (GOUDARZI *et al*., 2021).

$$X^p = \left(X_1^p, X_2^p, \ldots, X_N^p\right)^T$$

This input vector is elongated to the interlocutory layer in terms of the sprawl rule as follows:

$$S_i^p = \sum_{j=1}^{N} w_{ji} X_j^p + b_i$$

Here, N represents the number of the network input neurons; $\boldsymbol{w_{ji}}$ indicates the weight value of the connection between the neuron i from the interlocutory layer and the neuron j from the input layer and bi represents the bias value related to the neuron i.

The network output is as follows:

$$y_i^p = F(S_i^p)$$

The output neurons eventually compose the network output responses based on the data processed by the hidden neurons (KUMAR, 2004).

These network structures differ from one to another in the topology of the interconnection structure they are used for (KUMAR, 2004).

The equations to calculate the activation situation of any neuron k from the output layer according to GOUDARZİ *et al*. (2021) as follows:

$$S_k^p = \sum_{j=1}^{L} w_{jk} y_j^p + b_k$$

where L represents the neuron number of the intermediate layer, w_{jk} indicates the weight value of the connection between the neuron i from the intermediate layer and the neuron k from the output layer and b_k represents the bias value concerned with the neuron k. y_j^p is the network output.

Multilayer perceptron (MLP) was used mathematically to carry out a stochastic estimation of multivariate functions (PUC, 2012). The most commonly used multilayer perceptron architecture (HAYKIN, 1999) comprises three layers of nodes, namely, input, hidden and output layers. For the connection of the hidden layer, the hyperbolic tangent function was used as reported in the following. Besides, for the output layer connection, the pure linear function was exploited (FORESEE and HAGAN, 1997) as follows:

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

Here e is the Euler constant (e = 2.71828).

The back-propagation algorithm is used for optimizing the linkage weights in this study, while the Levenberg-Marquardt (LM) algorithm was used as a learning rule. It is one of the most appropriate higher-order adaptive algorithms known for minimizing the error of a neural network (PRINCIPE *et al*., 1999). While backpropagation is a steepest descent algorithm, the Marquardt-Levenberg algorithm (MARQUARDT, 1963) is an approximation to Newton's method (HAGAN and MENHAJ, 1994). Assume that a function V(x) which to minimize which it wants to minimize with respect to the parameter vector x, then Newton's method would be

$$\Delta x = -[\nabla^2 V(x)]^{-1} \nabla V(x)$$

where $\nabla^2 V(x)$ is the Hessian matrix and $\nabla V(x)$ is the gradient. If it was assumed that V(x) is a sum of squares function.

$$V(x) = \sum_{i=1}^{N} \varepsilon_i^2(x)$$

then it can be displayed that

$$V(x) = J^t(x)\varepsilon(x)$$
$$\nabla^2 V(x) = J^t(x)J(x) + S(x)$$

Where $J(x)$ is the Jacobian matrix

$$J(x) = \begin{bmatrix} \frac{\partial \varepsilon_1(x)}{\partial x_1} & \frac{\partial \varepsilon_1(x)}{\partial x_2} & \cdots & \frac{\partial \varepsilon_1(x)}{\partial x_n} \\ \frac{\partial \varepsilon_2(x)}{\partial x_1} & \frac{\partial \varepsilon_2(x)}{\partial x_2} & \cdots & \frac{\partial \varepsilon_2(x)}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial \varepsilon_N(x)}{\partial x_n} & \frac{\partial \varepsilon_N(x)}{\partial x_n} & \cdots & \frac{\partial \varepsilon_N(x)}{\partial x_n} \end{bmatrix}$$

and

$$S(x) = \sum_{i=1}^{N} \varepsilon_i(x)\, \nabla^2 \varepsilon_i(x)$$

is in the form (HAGAN and MENHAJ, 1994).

The Levenberg-Marquardt algorithm is based on the calculation of the second derivative of the cost function and the network parameters are modified according to the following equation (NIU *et al.*, 2020).

$$w(i) = w(i-1) - \left[\nabla^2 V(x)\big(w(i-1)\big) + \lambda_i I\right]^{-1} \nabla J(w(i-1))$$

Here λ_i is a constant parameter strictly greater than zero, $\nabla^2 V(x)$ is the Hessian or second derivative with respect to the parameters.

After achieving a trained model, its performance must be validated using data sets that have not been used during the learning process, this data set is called testing set. The purpose of the model validation stage is to make sure that the model has the ability to generalize the input-output relations that are contained in the training data (SHAHIN *et al*., 2002).

The training was performed by exploiting several ANNs structured to achieve the best performance. The ANNs performance was evaluated using the mean absolute percentage error (MAPE), mean absolute deviation (MAD) and the Means Square Error (MSE) values as follows (FORESEE and HAGAN, 1997; HAYKIN, 1999; PUC, 2012):

$$MSE = \frac{\sum_{i=1}^{n}(y_i - y_{ip})^2}{n}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - y_{ip}}{y_i}\right| * 100$$

$$MAD = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_{ip}\right|$$

where ‘‘n’’ represents the sample number, y_i is the actual value, y_{ip} is the forecast value. The ANNs reported in this research were implemented in the MATLAB programme.

According to these measurements, WITT and WITT (2000) classified the prediction models as "high accuracy" if the MAPE values were below 10% and the models with 10% to 20% were classified as "correct predictions" (WITT and WITT, 2000). LEWIS (1982) models with MAPE values below 10% are “very good”, models between 10% and 20% are “good”, models between 20% and 50% are “acceptable” and models with MAPE values above 50% are “very good” and classified the models as “wrong and faulty”.

The shift in weights,

$$\Delta w_{ij}^{n} = -\eta \frac{\partial MSE}{\partial w_{ij}^{n}}$$

with can be minimized. Here η was the learning rate. The optimum number of the ANN structure (numbers of neurons and hidden layers, activation function) was achieved by the hyperparameter tuning method. While developing model, the ANN architectures such as number of hidden layers and number of neurons in each layer were kept identical to extract some added benefits later.

Besides, numerous additional parameters have been modified to direct the learning phase, known as the hyper-parameter. These are type of activation function and number of k-fold cross-validation. These hyper-parameters can be adjusted to make possible the model to resolve the specified master learning problem better.

The learning rule provides a mechanism for training a neural network with a training set of input-output pairs of data relationships (KUMAR, 2004). The target of the algorithm is to compensate the network system error by modifying the interconnection weights and to make possible the network to arrive at the desired end result (BHATTACHARYYA, 2012).

The purpose of learning is to adjust the connection parameters of the neurons until the encored behavior (ZABORSKI *et al*., 2019). In order to determine the best value of the parameter vector w, it must be minimized the cost function which is a measure of the differences between the measure $\{y_p^k\}$ and $\{y^k(W)\}$ provided by the model. For this aim, a quadratic cost function J (w) is used and it is written following.

$$J(w) = \sum_{k=1}^{N} \frac{1}{2}\left(y_p^k - y^k(W)\right)^2$$

A MATLAB programme was used to apply artificial neural networks to the data.

RESULTS

Descriptive statistics

The summary of body weight and morphological traits for both sexes (Table 1) showed that the coefficient of variance ranges from 8.64 to 24.10 and 9.86 to 24.71 percents for 112 males and 288 females respectively. The results showed that HG was the morphological trait with the highest mean values of 73.02 in males and 73.85 in females followed by the BL with mean values of 68.84 in males and 68.37 in females.

Table 1. Descriptive statistics of measured traits

	Male (n = 112)		Female (n = 288)	
TRAITS	MEAN ± SE	CV (%)	MEAN ± SE	CV (%)
BW (kg)	37.30 ± 0.85	24.10	36.82 ± 0.54	24.71
BL (cm)	68.84 ± 0.64	9.91	68.37 ± 0.42	10.41
HG (cm)	73.02 ± 0.60	8.64	73.85 ± 0.43	9.86
WH (cm)	63.98 ± 0.61	10.12	63.22 ± 0.39	10.50
RH (cm)	65.01 ± 0.54	8.80	63.05 ± 0.39	10.36
RL (cm)	16.80 ± 0.19	11.92	17.02 ± 0.15	14.87
EL (cm)	21.46 ± 0.22	10.98	21.24 ± 0.15	11.79
HW (cm)	15.64 ± 0.15	10.09	15.45 ± 0.09	10.17

SE: standard error, CV: Coeffient of variation, BW: Body weight, BL: Body length, HG: Heart girth, WH: Withers height, RH: Rump height, RL: Rump length, EL: Ear length, HW: Head width.

Correlation matrix

Pearson correlation was employed to determine the relationship between body weight and body measurements (BL, HG, WH, RH, RL, EL) are presented in Table 2. In males, the results showed that BW had a non-significant correlation (P>0.05) with all the measured traits except BL. In females, the findings indicated that BW had highly significant correlation (P<0.01) with BL, HG, WH, RH and RL not not significantly correlated (P>0.05) with EL and HW.

Table 2. Pearson correlation coefficients between body weight and body measurements male above diagonal and female below diagonal

Traits	BW	BL	HG	WH	RH	RL	EL	HW
BW (kg)		0.64**	0.02^{ns}	0.08^{ns}	0.14^{ns}	0.03^{ns}	-0.05^{ns}	0.07^{ns}
BL (cm)	0.58**		-0.02^{ns}	0.25**	0.09^{ns}	0.13^{ns}	-0.16^{ns}	0.04^{ns}
HG (cm)	0.27**	0.13*		0.18^{ns}	0.08^{ns}	-0.09^{ns}	0.08^{ns}	0.07^{ns}
WH (cm)	0.33**	0.31**	0.11^{ns}		0.12^{ns}	0.22*	0.01^{ns}	-0.01^{ns}
RH (cm)	0.33**	0.07^{ns}	0.08^{ns}	0.33**		-0.01^{ns}	0.29**	-0.05^{ns}
RL (cm)	0.24**	0.05^{ns}	0.15**	0.03^{ns}	0.13*		-0.17^{ns}	-0.06^{ns}
EL (cm)	0.03^{ns}	-0.05^{ns}	-0.03^{ns}	0.11^{ns}	0.24**	-0.11^{ns}		0.26**
HW (cm)	-0.03^{ns}	0.05^{ns}	0.10^{ns}	0.09^{ns}	-0.01^{ns}	0.12*	0.16**	

BW: Body weight, BL: Body length, HG: Heart girth, WH: Withers height, RH: Rump Height, RL: Rump length, EL: Ear length, HW: Head width, ** : Significant at p<0.01, * : Significant at p<0.05, ns : non-significant.

Regression analysis

Multiple and regression model parameter coefficient shown in Table 3. The estimation coefficients of the sex, WH, EL and HW variables were found to be statistically insignificant. Model's R^2=0.4804 and Adjusted R^2=0.4684 are calculated as low values. The MSE value was found to be 42.551. Since Variance Inflation Factors (VIF)<10, there is no multicollinearity problem. However, the R^2 value is low. For some explanatory variables (sex, WH, EL, and HW) significance values for the t value were found to be insignificant. Therefore, alternative models should be tried.

Table 3. Multiple regression model parameter coefficients

Coefficients	Estimates	Std. Error	t value	Pr(>t)	VIF	Tolerance (T)
(Intercept)	-37.86	7.15	-5.30	1.98e-07 ***		
AGE	1.86	0.38	4.90	1.44e-06 ***	1.51	0.90
SEX	-0.06	0.75	-0.09	0.93	1.03	0.88
BL	0.61	0.06	10.98	< 2e-16 ***	1.38	0.91
HG	0.15	0.05	3.17	0.00 **	1.05	0.76
WH	0.03	0.05	0.46	0.65	1.20	0.98
RH	0.22	0.06	3.65	0.00 ***	1.29	0.72
RL	0.43	0.14	3.03	0.00 **	1.06	0.83
EL	-0.13	0.15	-0.83	0.41	1.28	0.94
HW	-0.22	0.22	-1.01	0.31	1.08	0.67

Residual standard error: 6.606 on 390 degrees of freedom, Multiple R-squared: 0.4804, Adjusted R-squared: 0.4684, F-statistic: 40.06 on 9 and 390 DF, p-value: < 2.2e-16.

Table 4. showing the ridge regression model parameter estimation. Results indicated age (1.86), BL (0.56), and RL (0.41), were factors that has the most positive effect on live weight in goats, respectively. The MSE value was found to be 42.64 and is not smaller than the MSE obtained in the multiple regression model.

Table 4. Ridge regression model parameter estimation

Factors	Coefficients	Std. Error	t value	Pr(>t)
(Intercept)	-34.11	5.98	-5.70	1.99e-07 ***
AGE	1.86	0.38	4.85	1.27e-06 ***
SEX	-0.04	0.02	-1.99	0.0462 *
BL	0.56	0.05	11.09	< 2e-16 ***
HG	0.14	0.04	3.38	0.00 **
WH	0.04	0.02	2.09	0.0427 *
RH	0.20	0.06	3.19	0.00 ***
RL	0.41	0.11	3.68	0.00 **
EL	-0.13	0.05	-2.41	0.0387 *
HW	-0.19	0.06	-2.94	0.0219 *

MSE=42.64, Multiple R-squared: 0.5562, Adjusted R-squared: 0.5396

Artificial neural networks

Therefore, it is useful to try artificial neural networks, which is one of the alternative statistical methods instead of the ridge regression model. To predict body weight (BW) in goats with artificial neural networks, body length (BL), heart girth (HG), withers height (WH), rump height (RH), rump length (RL), ear length (EL), Head width (HW), age and sex (male and female) information were used. The data was normalized. Of the data used, 70% is split for training, 20% for validity and 10% for testing. The researcher determined the number of hidden layers in the initial model. In case of bad performance of the neural network model and inappropriate results because of the analysis, the researchers re-analyzed by changing the number of hidden layers relatively. In this study, 10 hidden layers were used. Artificial neural network models can make predictions for classification and future periods if there are various data groups available. Levenberg-Marquardt Back Propagation algorithm was used to train the artificial neural network. After the network was trained, the error difference between the real situation and the results produced by the network was examined. In multi-layer neural networks, the transfer function between the input, hidden and output layers makes a difference. Hyperbolic tangent function (TANSIG) was used as an activation function in the study. To train the existing data, networks with 10 neurons hidden layer were run in large numbers according to TANSIG. The performance data obtained as a result of each run were recorded and the averages of performance of the networks, training, validity and test stages were determined. The 10-neuron hidden layer network has achieved a good performance value when using the TANSIG function. There is 1 neuron (dependent variable) in the output layer. While evaluating the networks created the network with small predictive performance measurements was preferred. Thus, with the help of the best performing network, the estimation values of the dependent variable were obtained according to various values of the independent variables. The MSE gives the mean of the squares of the difference between the observed value and the values predicted by the network. R, which takes values in the range of [-1, 1], expresses the correlation between the observed and predicted values. R value

$$R = \frac{\sum_{i=1}^{n}(y_i y_{ip}) - (\sum_{i=1}^{n} y_i)(\sum_{i=1}^{n} y_{ip})/n}{\sqrt{(\sum_{i=1}^{n} y_i^2 - (\sum_{i=1}^{n} y_i)^2/n)(\sum_{i=1}^{n} y_{ip}^2 - (\sum_{i=1}^{n} y_{ip})^2/n)}}$$

is expressed as. The obtained values are required to be close to 1 to show the strength of the relationship. When the performance measures of the ANN method were examined, it was found that MSE=0.0142, RMSE=0.1192, MAD=0.0894 and MAPE=18.642 (%). It is seen that the MSE and RMSE values are very small. The MAPE value was 18.642% and since this value was between 10% and 20%, it was seen as a "good guess" or "correct guess". In short, as a result of the analysis, it is seen that the MSE, MAPE and R values are at the desired levels. Input and output data of 400 pieces of data were used to train the network. In this case, a structure was created from a hidden layer with 10 neurons and an output layer with 1 neuron (Figure 2).

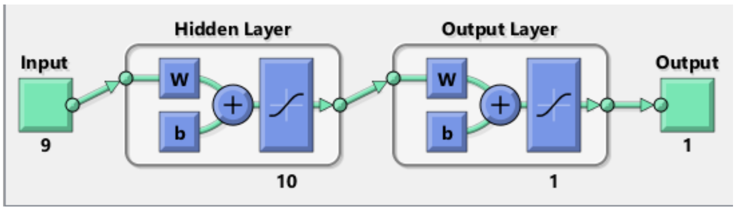

Figure 2. Artificial neural network model structure

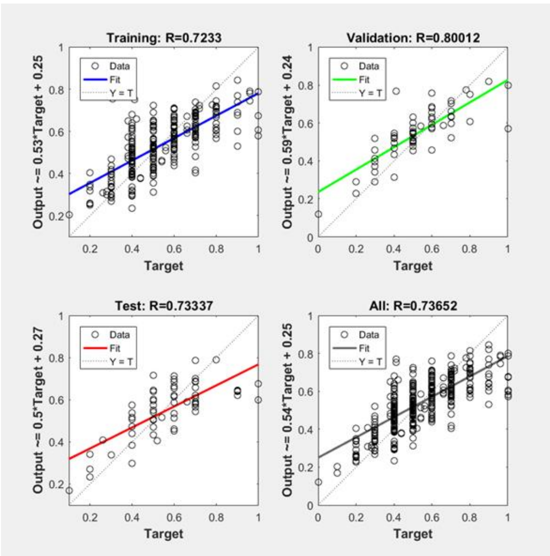

Figure 3. Training, Validity and Test Regression Graphs in ANN

Better R values were obtained after many trials for training and validation in the network. The R values for training, validity, testing and all were 0.7233, 0.80012, 0.73337 and 0.73652, respectively. The regression graphs for this network are presented in Figure 3. Figure 4 shows the performance graph of the network. As seen in Figure 4, the number of iterations was taken as 6 and the best performance was obtained at the initial iteration. The lowest error value for testing and validity was obtained in the initial iteration. Figure 5 shows the comparison of the results obtained through the model using the studied input set and the actual error values.

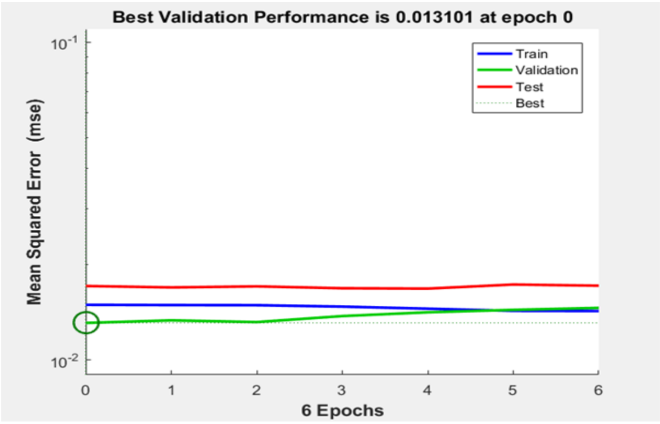

Figure 4. Performance Graph of the Network

In Figure 5, the X-axis is the sequence number of each goat examined. The Y axis is the observed and predicted live weight values of goats. With the ANN method, it is possible to estimate body weight by giving different values to body measurements.

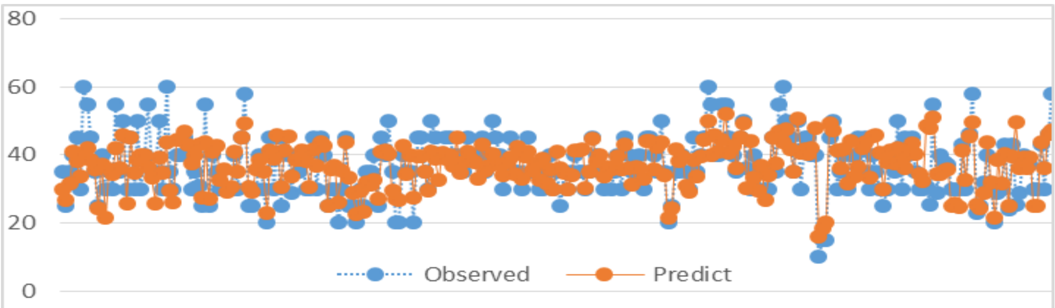

Figure 5. ANN Forecast Chart

The estimated body weight values of goats for the values given to the variables related to age, gender and body characteristics used for the independent variable are presented in Table 5.

The body weight of goats is estimated when various values are given to body measurements. For example, when age=3, sex="female", BL=72, HG=74, WH=65, RH=56, RL=25, EL=23 and HW=17, it is estimated that BW=46,654kg. The properties of variables affecting body weight in goats were also investigated with the application of Multilayer Perceptron

Table 5. Estimated body weight realised by ANN based on body morphological characteristics

Age	Sex	BL	HG	WH	RH	RL	EL	HW	BW (predict)
1	Female	55	70	53	55	18	20	16	16.48
1	Male	59	71	56	57	20	22	16	13.72
3	Female	61	73	60	60	22	24	17	22.88
4	Male	65	75	62	64	24	26	15	39.19
3	Female	62	80	60	59	26	22	16	41.46
5	Male	64	85	55	60	20	20	17	49.22
3	Female	70	80	50	61	25	25	15	40.15
3	Male	65	82	55	62	25	25	16	35.87
3	Female	72	74	65	56	25	23	17	46.45
6	Male	75	86	67	60	24	27	18	48.51

In Figure 6, the elliptical nodes are hidden layers. These hidden layers are H(1:1), H(1:2), H(1:3), H(1:4), H(1:5), H(1:6) and H(1:7). There are 7 hidden layer units. Thickness and darker lines between units and variables give information about the level of relationship between them. The thicker and darker the lines, the higher the relationship. The relationship between the bias unit and the variables is expected to be weak. The figure shows that there is a strong relationship between H(1:2) and the dependent variable (BW).

Table 6. Model Summary

Training	Sum of Squares Error	62.04
	Relative Error	0.46
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.02
Testing	Sum of Squares Error	27.15
	Relative Error	0.50

Dependent Variable: BW, a. Error computations are based on the testing sample

The model summary is given in Table 6. The results of the training of the artificial neural network are given. The model summary contains information about the application of the artificial neural network to the "hold out" data. It contains information about the strength of the model related to artificial neural networks. In the table above, the sum of squares error (SSE) was calculated as 62,044. In the analysis of artificial neural networks, the error values of the training and test phases are calculated separately. The partial error value was 0.46 during the training phase. The partial error value in the testing phase is 0.5. In addition, the error sum of squares value was found to be 27.146 for the test phase. Below the model summary table, there is information about the dependent variable, and on which sample the error calculations were performed. Perhaps the error values are not very high in the example application of artificial neural networks and in this case, the model established for artificial neural networks has a strong structure.

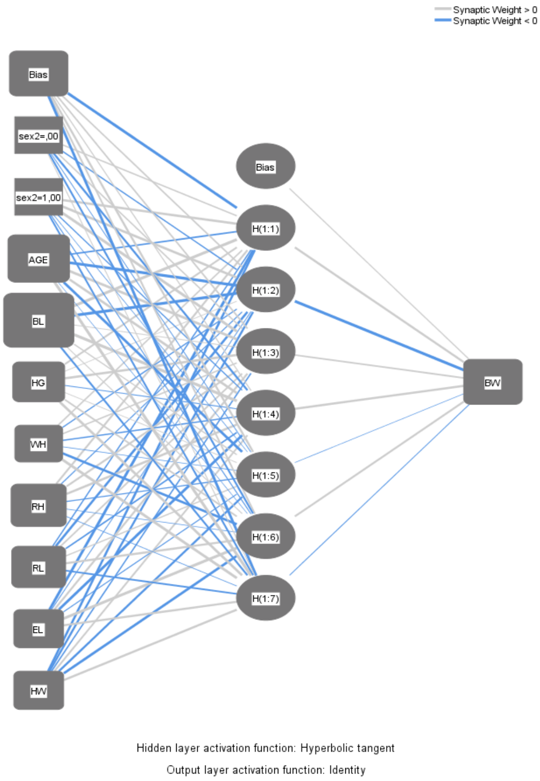

Figure 6. Artificial Neural Networks application model architecture

Parameter estimates for this analysis are shown in Table 7a and Table 7b below. The parameter estimates table is a numerical representation of the relationships that are presented as a drawing of the model architecture. When the thickness and darkness of the lines for the relationships in the Artificial Neural Networks application model architecture in Figure 6 are examined, it is seen that they are compatible with the values in the parameter estimates table. For example, in the relationship of Age and BL variables with the H(1:2) unit in the hidden layer, the relationship levels of the Age variable were found to be between -0.959-0.328 and the correlation levels of the BL variable were between -0.7-0.978.

For example, the connection weight value between the Age neuron in the input layer and the 1st neuron (H(1;1)) of the hidden layer is 0.122. The connection weight value between the BL neuron in the input layer and the 5th neuron of the hidden layer (H(1;5)) is 0.978. It is seen that the connection weight value between the HG neuron in the 4th layer and the 4th neuron of the hidden layer (H(1;4)) is 0.341 and the connection weight value between the WH neuron in the input layer and the 4th neuron of the hidden layer (H(1;5)) is -1.291. In addition, the connection weight value between the 1st neuron of the hidden layer (H(1;1)) and the output layer is 0.574. Similarly, the 2nd, 3rd, 4th, 5th, 6th and 7th neurons of the hidden layer namely H(1:2), H(1:3), H(1:4), H(1:5). The link weight values between H(1:6) and H(1:7) and the output layer were obtained as 0.282, -0.795, 0.876, 0.669, 0.220 and -0.379, respectively. In short, the values found in the output layer are -0.302, 0.574, 0.282, -0.795, 0.876, 0.669, 0.220 and -0.379 values transferred from the hidden layer to the output layer.

Table 7a: Model parameter estimate (input layer)

Predictor		Predicted							
		Hidden Layer 1							Output Layer
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	H(1:7)	BW
Input Layer	(Bias)	0.13	-0.29	-0.41	0.40	0.79	-0.3	0.26	
	[sex2=0.00]	-0.22	-0.36	0.29	-0.29	1.11	0.13	0.60	
	[sex2=1.00]	0.52	-0.35	-1.02	-0.47	-0.68	0.28	0.69	
	Age	0.12	-0.54	-0.96	-0.31	-0.03	0.33	-0.35	
	BL	0.32	0.42	-0.7	0.02	0.98	-0.25	0.20	
	HG	0.01	-0.12	0.49	0.34	0.27	0.33	-0.08	
	WH	1.09	0.73	-0.16	-1.29	-0.17	0.42	-0.78	
	RH	-0.23	-0.08	-0.05	0.36	-0.11	0.25	-0.15	
	RL	0.62	0.86	-0.13	-0.08	-0.31	0.18	0.32	
	EL	-0.65	0.11	0.64	0.62	0.34	0.37	0.08	
	HW	-0.7	-0.29	-0.56	-0.25	0.47	0.31	0.03	

Table 7b. Model parameter estimates (Hidden Layer)

Predictor		Predicted							
		Hidden Layer 1							Output Layer
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	H(1:7)	BW
Hidden Layer 1	(Bias)								-0.30
	H(1:1)								0.57
	H(1:2)								0.28
	H(1:3)								-0.80
	H(1:4)								0.88
	H(1:5)								0.67
	H(1:6)								0.22
	H(1:7)								-0.38

The significance level of the independent variables obtained in the analysis is presented in Table 8. When Table 8 is examined, the most effective variable affecting the BW variable is the BL variable. The significance coefficient of this variable is 0.303. Then, the most important variable is Age, and its coefficient is 0.196. These variables are followed by HG (0.111) and RH (0.109), respectively. The variable with the lowest effect was determined as the sex2 variable and its value was 0.015. The values in the other column are the percentages of the importance of the variables.

The bar diagram showing the importance of artificial neural networks and independent variables is presented in Figure 7. The values of the significance level of the independent variables in Figure 7 can be compared to the Beta values in the multiple regression analysis.

Table 8. Independent Variable Importance in artificial neural network analysis

Variables	Importance	Normalised Importance
Sex2	0.01	5.1%
BL	0.30	100.0%
HG	0.11	36.7%
WH	0.04	13.6%
RH	0.11	35.9%
RL	0.10	32.5%
EL	0.09	28.4%
HW	0.04	13.3%
Age	0.20	64.7%

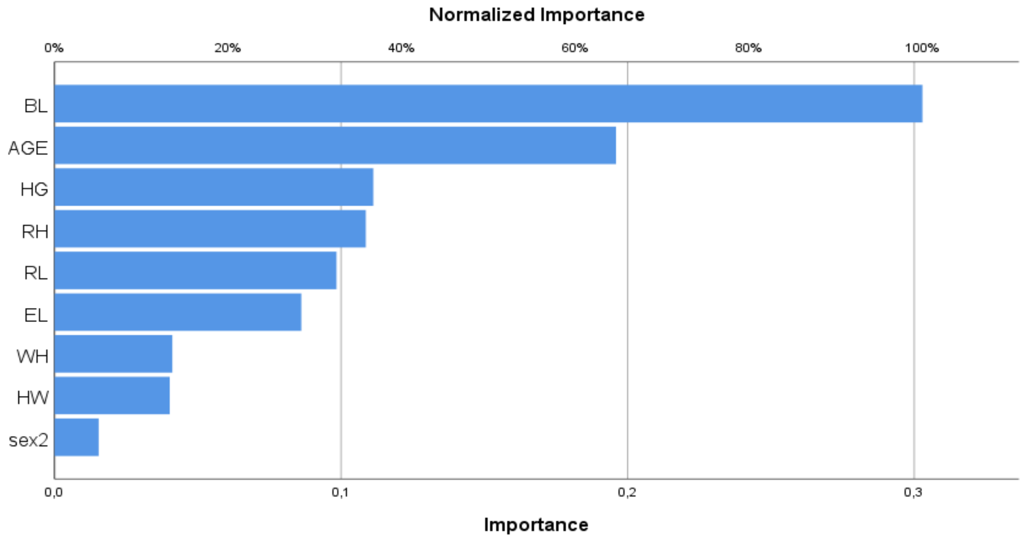

Figure 7. Bar diagram showing the importance level of independent variables with artificial neural networks.

DISCUSSION

In a study, for hair goat kids various body measurements, wither height, rump height and body length were determined 50.3, 51.0 and 50.4 cm at the 150th day, respectively (MAIER and DANDY, 1999). In this study, the measured values were higher. In HIRAKAWA *et al*. (2007) study, the average body weight, withers height, rump length and body length in females and males Boer goats for over one year old were 44.7, 67.7 kg; 66.6, 76.3 cm; 21.7, 24.4 cm, 67.7, 79.4 cm respectively. The obtained values are higher than the results obtained in this study. In another study, the average body length, withers height and heart girth were detected 55,615, 53,538 and 75,435 cm of Boer goats bred in the Philippines, respectively (WITT and WITT, 2000). Differences in study results may be caused by factors such as the region grown, environmental conditions and different genotypes. RAJA *et al.* (2012) study, for the prediction of the body weight of goats, three different morphometric measurements such as chest girth, body length and height at withers were used as input variables. Artificial neural network (ANN) and multiple regression analysis were applied. The prediction efficiency of both models was compared using the R2 value and root mean square error (RMSE). The correlation coefficients between the actual and predicted body weights in the case of ANN were positive and highly significant and ranged from 90.27 to 93.69%. There was a low value of RMSE and high value of R2 in the case of connectionist network (RMSE: male 1.9005, female 1.8434; R2: male 87.34%, female 85.70%) in comparison with multiple regression analysis. Model (RMSE: male 2.0798, female 2.0836; R2: male 84.84%, female 81.74%) displays that the ANN model is a better tool to predict body weight in goats than multiple regression analysis.

Artificial neural network and regression models for prediction of body weight in Raini Cashmere goat were compared by KHORSHIDI-JALALI *et al.* (2019). The data of 1389 goats for body weight, height at withers, body length and chest girth were used. Comparison of these models displayed that both models can predict body weight well and near to observed body weight but the capability of the artificial neural network model is higher (R2 = 0.86 for ANN and 0.76 for multiple regression analysis) and closer to observed body weight. In AKKOL *et al.* (2017) study, based on measurements of morphological 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. The artificial neural network explained a higher value of the coefficient of determination (R2) for predicting hair goats. The best back propagation algorithm of artificial neural networks method achieves 91% of the prediction accuracy for the optimum model while the multiple linear regression explained 88.4%. Because of these analyses, it is noted that the artificial neural networks method is more suitable than multiple linear regression in the prediction of body weight in hair goats. Also, in this study, the ANN method gave better results than multiple regression analysis. In another study, a stepwise multiple linear regression model was used for the estimated body weight of Beetal goat in Lahore, Pakistan. Live weight and other body characteristics recorded were body length, height at withers, chest girth, rump (RP) and forehead that were (inches) 27.16±3.94 (Kg), 27.00±1.35, 28.34±1.32, 27.00±1.41, 5.28±1.48 and 3.18±1.26, respectively. Significant and positive correlation coefficients between live weight and other body characteristics: body length, height at withers, heart girth, rump and forehead (0.805, 0.766, 0.767, 0.088 and 0.229, respectively) were obtained. The most appropriate combination of body characteristics (R2= 69.1 %) was observed between height at withers and heart girth for prediction of live body weight estimation, here as rump and forehead were the poor estimators of body weight with a coefficient of variation (R2) as 25.93% and 16.64%, respectively (BOLACALI *et al*., 2017). A study found that G2 bucks (0.69) and all goats (0.85) had the greatest and most positive correlation coefficient values between BW and HG (ADHIANTO *et al*., 2020). ADEYINKA and IBRAHIM, 2006; IBRAHIM *et al*., 2014; TEKLE, 2014;

TADESSE *et al*., 2012; TSEGAYE *et al*., 2013; FAJEMILEHIN and SALAKO, 2008; LORATO *et al*., 2015; JIMMY *et al*., 2010) reported that a number of studies found that the r values between HG and BW (>2.0 years age) in several African native bucks were high. These included the Nigerian Red Sokoto (0.73), Red Sokoto (0.89), Afar (0.51), Abergelle (0.83), Hararghe Highland (0.89), West African Dwarf (0.93), Woyto-Guji (0.85), Mubende (0.79), Teso (0.75), and 0.59 for Lugware. The difference in this study may be due to different environment, age and rearing conditions. According to S et al. (2019), head length (HEL) and BL measures had the strongest relationships (r=0.95–0.86) with female BW. However, with R^2=0.92, BL and paunch girth (PG) were highly effective in predicting the female's BW. BL and HG were found to be the primary significant contributions to the BW prediction equation of total (male and female) by stepwise regression analysis. The best-fitted regression models included body length as the first independent variable, then HG, NC, and PG. They were therefore the variables that were entered to produce the best regression models. The validity of applying these models to estimate the live weights of Shami goats is supported by the strong correlation values between the predicted and actual live body weight measurements. In another analysis, the fittest prediction of BW with model regression BW= -67.86 + 0.87*CG + 0.51*BL had the highest r (0.87), R^2 (0.76), and adjusted R^2 (0.75). The study's findings revealed that CG and BL might be utilized as predictors of body weight and as an indicator of indirect selection to increase genetic merit in EG goat body weight (DAKHLAN *et al*., 2020).

CONCLUSION

The performance of a multi-layered perceptron format of the artificial neural network with multiple and ridge regression models was compared in the present study. The obtained findings demonstrate that the highest accuracy was attained using the multilayer perceptron neural network with 9-10-1 partition, the activation function a hyperbolic tangent with 10 units in one hidden layer and the back-propagation algorithm. High regression and low MSE (Mean Error Squares) values in the training, testing and validation phases also supported this. When the normalised significance (%) of body measurements was examined from the ANN model, the most important variables were BL (100%), age (64.7%) and HG (36.7%), respectively. HG contribute 36.7% alone which shows that it is the main contributor of the live body weight in goats. In addition, it was possible to estimate the body weight of goats according to body morphological characteristics, age and sex using ANNs. In future forecasting studies, it is expected that the comparative analysis of forecasting performances by combining artificial neural networks with different alternative techniques will yield more effective results.

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PROCENA TELESNE TEŽINE IZ MORFOLOŠKIH MERENJA KOD BOER KOZA PRIMENOM VEŠTAČKIH NEURALNIH MREŽA I NEKIH REGRESIJSKIH MODELA

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Izvod

U ovoj studiji ispitivane su karakteristike telesnih merenja koje utiču na telesnu težinu burskih koza i procena telesne težine. Za ispitivanje morfoloških karakteristika uzeto je u obzir 400 živih životinja. Morfološka merenja bila su telesna težina (BV), dužina tela (BL), obim srca (HG), visina grebena (VH), visina stražnjice (RH), dužina ostatka (RL), dužina uha (EL) i glava sa (HV) respektivno. Ove životinje su bile stare između 1-6 godina. Njih 112 bili su muškog pola, a 288 ženskog. Za procenu telesne težine primenjene su metode višestruke regresije, regresije grebena i veštačkih neuronskih mreža (ANN). U predviđanju telesne težine kao zavisne varijable, prediktivni model ANN je proizveo visoke prediktivne performanse. Statistika srednje kvadratne greške (MSE), srednje apsolutne greške (MAD) i prosečne apsolutne greške procenta (MAPE) korišćena je za određivanje performansi modela. Koristeći algoritam učenja višeslojnog perceptrona (MLP) veštačke neuronske mreže (ANN), određene su karakteristike tela koje su imale najveći uticaj na telesnu težinu. Poređenje prediktivnih performansi predloženog modela u odnosu na metode višestruke regresije i stanja grebenske regresije pokazalo je da su veštačke neuronske mreže nadmašile oba konkurentska modela postižući najmanje vrednosti za MAD, MSE i MAPE u skupovima podataka za obuku i testiranje. Rezultati veštačkih neuronskih mreža bili su obećavajući i tačni u predviđanju telesne težine koza.

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