Prediction of Birth Weight from Body Measurements with the CART Algorithm in Morkaraman Lambs

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SUMMARY

Morkaraman sheep breed is a major breed reared in Eastern Anatolia of Turkey. This study was organized to predict birth weight from biometrical measurements such as withers height (WH), rump height (RH), chest circumference (CC) and body length (BL) taken from 44 Morkaraman lambs. For birth weight prediction, the CART data mining algorithm was performed for ten cross-validation procedures. Also, the optimum CART tree was achieved with 4 terminal nodes for the lowest RMSE value. The Pearson's correlation coefficient between the real and predicted birth weight value was determined as 0.935. As a result of the CART algorithm we used, which showed that Morkaraman lambs with CC > 41 cm, male and RH > 41 cm had the heaviest birth weight, with an average of 5.4 kg. To evaluate the performances of the CART model, the goodness of fit criteria such as RMSE, rRMSE, SD_{ratio}, AIC, MAD, RAE, MAPE, R^2 and R^2_{adj} were used. As a result, the model obtained by CART data mining algorithms can be recommended for the estimation of birth weight in lambs, since the determination coefficient is high. In this way, the characterization of the breed will be facilitated, and an important step can be taken for herd management. In conclusion, it will be easier to select a population consisting of traits superior to some biometrical measurements with the CART model.

Key words

CART, Morkaraman, Lamb, Birth Weight, Data Mining.

INTRODUCTION

Archaeological and genetic studies show that sheep were among the first domesticated animals in the world[1]. In this context, sheep breeding, one of the production branches in animal science, is a multipurpose small ruminant animal that is very valuable not only in raising healthy civilizations but also in the development of rural economies, in order to obtain animal products such as milk, meat, and fleece[2]. According to the Food and Agriculture Organization (FAO), 35 million head of sheep are adapted to several regions in Turkey[3]. Although domestic sheep breeds raised in Turkey have low meat and milk yields, they are quite resistant to changes in temperature and diseases[4]. Many sheep breeds have adapted to the conditions of the region. Herd management is of great importance in small ruminant[5]. In this context, the most common breed in the Eastern Anatolia Region, where the study was conducted, is the Morkaraman sheep breed. Morkaraman sheep are fat-tailed, and the form of the tail resembles that of Akkaraman (S-shape), but its size is bigger[6]. Morkaraman sheep breed is resistant to low temperatures and due to its fat tail structure, tail fat is used as an energy source during periods of malnutrition in long winter conditions. In terms of live weight, it is approximately 74.75 kg/head in males; reported as 53.90 kg/head in females[6]. In sheep breeding, the live weight information of the flock has a very important place in terms of both determining the breeding strategy and herd management. In this context, knowing the live weight is an important task to calculate the optimum feed amount per sheep, determine the drug doses, determine the market price more reliably and determine the optimum slaughter time of the animals[7]. Due to the difficulties of finding a weighing instrument in rural conditions, it is a very common method to estimate body weight by examining the structure of the animal. In this context, body measurements have a positive effect on live weight and provide information about the structure of the animal[2]. Multivariate statistics are used to transform the obtained body measurements into information.

In the literature, there are many studies in which body measurements are used together with statistical methods, such as multivariate statistical methods, to compose the breed characterization[8,9,10]. Numerous authors have estimated body weight from biometrical measurements using several breeds of sheep within the scope of many multivariate statistical procedures[7,8,10]. In multivariate statistical methods within the scope of regression assumption, Within the scope of the regression assumption, conditions such as linearity, constant variance, normality and multicollinearity conditions should be required in multivariate statistical methods[11]. In addition, data mining algorithms such as Classification and Regression Tree (CART) and Chi-square Automatic Interaction Detector (CHAID) do not need such assumptions[12]. In this context, many studies have been conducted on different breeds and species, such as sheep, cattle, dogs and goats[13,14,15,16]. The research was aimed to estimate weaning weight in the Karayaka sheep breed using CART and CHAID algorithms, different farm conditions, birth type, birth weight, sex, and weighting period[17]. The second research was compared the estimation performances of data mining and artificial neural network (ANN) algorithms to estimate body weight in the Mengali sheep breed from body measure-

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ments[2]. Although there are studies in which adult live weight is estimated in sheep, there are deficiencies in the study in which birth weight is estimated. The knowledge to be gained about birth weight has a critical role in determining herd management practices such as ease of lambing, survivability of lamb and next generation growth characteristics that will be facilitated[18,19,20,21,22,23,24].

Therefore, the main idea of this study is to predict the birth weight of Morkaraman lambs from some biometrical measurements such as withers height, chest circumference, rump height, body length via the CART data mining algorithm. In this way, breed characterization will be facilitated, and an important step can be taken for herd management.

MATERIALS AND METHODS

Animals

In the study, Morkaraman sheep breeds were used as a material. The Morkaraman sheep are widely bred in the Eastern Anatolia Region, which is the coldest region of Turkey, with its fat tail structure as well as a genetic structure that is highly adaptable to the region. According to the literature, the live weight of Morkaraman sheep is approximately 74.75 kg/head in males and reported as 53.90 kg/head in females[6]. In addition, Morkaraman sheep have a nearly 145-day lactation period and a total milk yield of 65-80 kg[25].

The data were obtained from the Research Center of Animal Science of I dır University. In the study, in which various measurements taken from 44 lambs (24 female, 20 male) were used, the lambs were fed by sucking from the sheep. Body measurements taken in the Morkaraman lambs data set were withers height (WH), chest circumference (CC), rump height (RH), body length (BL) and birth weight (BW), respectively. A tape measure was used to determine body measurements. In addition, scales were used to determine the birth weight of the lambs.

Statistical analysis

Descriptive statistics such as mean, standard error, minimum, maximum and coefficient of variation (CV) were applied to explanatory and response variables, i.e., BW, WH, RH, BL, and CC. The Kolmogorov-Smirnov test was used to determine normality, and test results showed a normal distribution for all characteristics (p>0.05). In addition, Levene's test was used to determine homogeneity, and the test results showed that the data was homogeneously distributed for all features (p>0.05). To compare the sexes for explanatory and response variables, independent two sample t test was utilized.

Data mining algorithms are among the multivariate statistical methods commonly used in the framework of estimating a quantitative feature[9,12,13,16,26,27,28,29,30]. In the present study, the CART (Classification and Regression Tree) algorithm, which is one of the tree-based algorithms used to estimate lamb birth weight, was first proposed by Breiman et al. (1984)[31]. One of the tree-based algorithms is the CART algorithm, which is a binary decision tree structure created by dividing a feature homogeneously into two sub-nodes. According to the cross-validation resampling method, the process starts with the root node containing the entire data set and continues until a large number of homogeneous nodes are obtained that will provide minimum error variance.

The following goodness-of-fit criteria were used to evaluate the performance of the optimal CART algorithm[13,32,33]:

1. Root-mean-square error (*RMSE*):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_{ip}\right)^2} \tag{1}$$

2. Relative Root Mean Square Error (rRMSE)

$$rRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_{ip}\right)^2}}{\bar{y}} * 100 \tag{2}$$

3. Standard deviation ratio (SD_{ratio}):

$$SD_{ratio} = \frac{s_m}{s_d} \tag{3}$$

4. Akaike information criterion (*AIC*):

$$\begin{cases} AIC = n.\ln\left[\frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_{ip}\right)^2\right] + 2k, & \text{if } n/k > 40 \\ AIC_c = AIC + \frac{2k(k+1)}{n-k-1} & otherwise \end{cases} \tag{5}$$

5. Mean absolute deviation (*MAD*):

$$MAD = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_{ip}\right| \tag{6}$$

6. Global relative approximation error (*RAE*):

$$RAE = \sqrt{\frac{\sum_{i=1}^{n}\left(y_i - y_{ip}\right)^2}{\sum_{i=1}^{n} y_i^2}} \tag{7}$$

7. Mean absolute percentage error (*MAPE*):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - y_{ip}}{y_i}\right| * 100 \tag{9}$$

8. Coefficients of determination (R^2)

$$R^2 = \left[1 - \frac{\sum_{i=1}^{n}\left(y_i - y_{ip}\right)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}\right] \tag{10}$$

9. Adjusted Coefficients of determination (R^2_{adj})

$$R^2_{adj} = \left[1 - \frac{\frac{1}{n-k-1}\sum_{i=1}^{n}\left(y_i - y_{ip}\right)^2}{\frac{1}{n-k}\sum_{i=1}^{n}(y_i - \bar{y})^2}\right] \tag{11}$$

where, n is the sample size of the data set, k is the number of model parameters, y_i is the actual value of the response variable (BW), y_{ip} is the predicted value of the response variable (BW), s_m is the standard deviation of the model errors, s_d is the standard deviation of the response variable (BW).

Every part of the statistical evaluation was performed by using the R program[34]. Descriptive statistics for all traits were estimated by using the "psych" package in the R package[35]. For performing statistical analysis of the CART algorithm, "rpart" and "rpart.plot" packages in the R environment were used with the scope of predicting BW[36,37]. The "ehaGoF" package (version 0.1.1) developed by Eyduran (2020) was used to determine the prediction performance of the constructed CART tree[38].

RESULTS

The results for the study aimed at estimating birth weight from various body measurements are presented below. Descriptive statistics obtained without considering sex are given in Table 1.

Table 2 showed the Pearson's correlation coefficients for determining the relationship between explanatory and response variables. The greatest correlation coefficient was between WH and RH, with a value of 0.877. And also, the relationship between BW and RH was the lowest coefficient between them. All the correlation coefficients were statistically significant ($p<0.01$).
A regression tree diagram obtained using the CART algorithm was given in Figure 1. According to Figure 1, the child node of the tree was recorded as 4.5 kg. At the first depth of tree, the mean 3.9 kg BW of Morkaraman lambs with CC<41 cm was lighter by 1.1 kg than the mean 5 kg BW of Morkaraman lambs for CC≥41 cm. At the second depth of the tree, BW mean of 3.1 kg for WH<35. In addition, the second depth of tree, 4.2 kg BW for WH≥35. When WH<35 for depth, it branched in terms of sex. For these branches, they were divided into two subgroups: females with a mean of 2.9 kg, and males with a mean of 3.5 kg. For WH≥35 cm, the tree was divided into two

Table 1 - Descriptive statistics for response and explanatory variables in Morkaraman lambs.

Variables	Sex	Mean	Standard error	Minimum	Maximum	Coefficient of variation	p-value
BW	Female	4.27[b]	0.18	2.6	5.6	21.31	0.03
	Male	4.80[a]	0.16	3.2	5.8	14.58	
WH	Female	38.69[b]	0.57	34.0	44.0	7.26	0.03
	Male	40.55[a]	0.61	33.5	44.5	6.71	
RH	Female	39.27	0.48	34.4	43.0	5.96	0.07
	Male	40.58	0.53	34.0	44.0	5.79	
BL	Female	35.23	0.55	30.4	40.0	7.72	0.12
	Male	36.43	0.52	32.5	39.5	6.31	
CC	Female	40.53	0.57	35.0	45.0	6.86	0.16
	Male	41.77	0.66	36.3	46.5	7.06	

Table 2 - Correlation coefficients of all traits.

	BW	WH	RH	BL	CC
BW	1				
WH	0.627	1			
RH	0.539	0.877	1		
BL	0.413	0.590	0.663	1	
CC	0.597	0.775	0.700	0.496	1

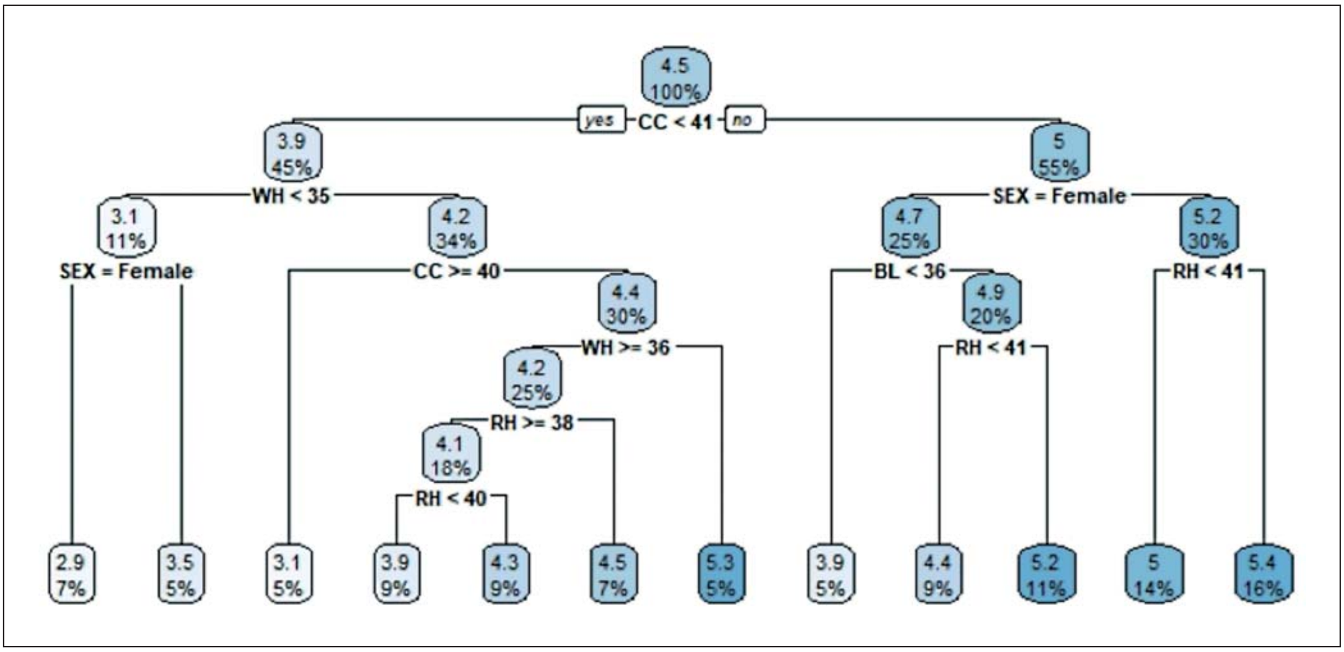

Figure 1 - Tree diagram predicton birth weight using CART algorithm.

Table 3 - Goodness-of-fit criteria for constructed CART algorithm.

Criterion	CART model
Root mean square error (RMSE)	0.299
Relative root mean square error (RRMSE)	6.641
Standard deviation ratio (SDR)	0.355
Coefficient of variation (CV)	6.72
Pearson's correlation coefficients (PC)	0.935
Performance index (PI)	3.432
Mean error (ME)	0
Relative approximation error (RAE)	0.004
Mean relative approximation error (MRAE)	0.01
Mean absolute percentage error (MAPE)	5.421
Mean absolute deviation (MAD)	0.232
Coefficient of determination (R^2)	0.874
Adjusted coefficient of determination (R^2_{adj})	0.861
Akaike's information cCriterion (AIC)	-98.113
Corrected Akaike's information criterion (cAIC)	-97.087

sub-groups. The first sub-group is for CC<40 with a mean of 3.1 kg. In addition, CC≥40 was divided into two groups as WH<36 and WH≥36. For WH<36 cm, tree was divided into two sub-groups for RH<38 and RH≥38 with the mean of 3.9 and 4.5, respectively.

For WH≥36, BW mean of 5.3 kg. For CC≥41 cm, there were two divisions by sex. Of these divisions, in the group for females, divisions occurred for RH<41 within the scope of BL≥36. When the means in this division were analyzed as BL<36, RH<41 and RH≥41, they are 3.9, 4.4, and 5.2, respectively. For CC≥41 and male Morkaraman lambs were divided into two groups for RH<41 and RH≥41. For this division, Morkaraman lambs showed a mean BW of 5 kg and 5.4 kg.

The goodness-of-fit criteria used to measure the performance of the model obtained from the CART algorithm are summarized in Table 3. According to the goodness of fit criteria used in this study, the model with an RMSE value close to 0, rRMSE value below 10%, SDR value below 0.40 and an R^2 value above 85% is called the model with the best fit[39,40,41]. For a model with a good fit, the SDR ratio, one of the goodness-of-fit criteria, should be less than 0.40[41,42,43,44]. For this reason, according to the goodness of fit criteria given in Table 3, it is seen that the obtained CART model has a good fit. In addition, the birth weight between real and predicted values from the CART algorithm has a very strong correlation coefficient with a value of 0.935.

DISCUSSION

In the present study, sex is an important factor in the source of the variation to estimating birth weight from body measurements in Morkaraman lambs. Although there are many studies in the literature on the factors that are important in estimating the mature live weights of sheep, studies on the estimation of birth weights that are important for breed characterization are scarce.

In the context of correlation, there are many studies between body weight and body measurements. Yakubu (2012) was performed the regression tree algorithm to predict body weight[45]. In this context, the relationship between BW and other body measurements varies between 0.43 and 0.76. When all variables are considered, it is seen that they have similar correlation coefficients with the variables we used. Faraz et al. (2021) was performed CART and MARS algorithms to predict live body weight from different body measurements for Thalli sheep[10]. According to this study, the correlation coefficient between live body weight and various body measurements varies between 0.547 and 0.850. When all variables are considered, it is seen that some correlation coefficient was different with the variables we used. These differences can be used for different sheep breed.

In addition, many researchers suggested that there should be many variables to get higher accuracy for estimating the body weight[24,46,47,48]. Sabbioni et al. (2020) have shown that the use of multiple body measurements leads to much more accurate estimates of body weights for growing and mature Cornigliese sheep[7]. Topai and Macit (2004) were performed simple and multiple linear regression to pedict body weight from various biometrical measurements for Morkaraman sheep breed[49]. According to this study, the model accuracy was lower than our results within the scope of R^2 (determination of coefficient). Topal et al. (2003) were performed simple and multiple linear regression for estimating the body weight from various body measurements and the result of this study has the similar coefficients within the scope of R^2 with our results[50]. Eyduran et al. (2017) were performed the CART, CHAID, RBF, ANNs, and multiple regression to predict body weight from several body measurements for Beetal goat[16]. The results of this study showed that these results have lower value (0.82) with our study within the scope of correlation coefficient between real and predicted body weight value. Faraz et al. (2021) were performed CART and MARS algorithms to predict body weight for Thalli sheep breed[10]. The results of this study showed the similar results with our study within the scope of R^2 value for CART algorithm.

Ali et al. (2015) used the CART algorithm for the live weight estimation of Harnai sheep and estimated the R^2 and SD_{ratio} values (0.82644 and 0.417) for the CART algorithm, respectively[9]. Malkova et al. (2021) aimed to predict birth weight for Charollais, Kent, and 13 of their crossbred lambs by using the chest circumference, head circumference, and shin circumference[24]. Among the obtained models, they determined that the most reliable models were those with chest circumference, and head circumference. Compared with our results, Ali et al. (2015) obtained results that were close to the CART algorithm used in the study. However, in Malkova et al. (2021), it was seen that different variables were used and the only common variable, CC, was not statistically significant even if the model was significant.

CONCLUSIONS

It is a significant task to get some biometrical measurements that contribute to live weight increase, which is vital for improving selection plans in order to increase the income from animal breeding, which is the purpose of animal science activities. In this context, estimations from birth will provide convenience in herd management. For this aim, many statistical methods, such as data mining and artificial neural networks, can be used to predict more reliable models, since the reliability of the obtained data will decrease in the event of a violation of the basic assumptions of classical statistical methods. As a result of the CART algorithm we used, which showed that Morkaraman lambs with CC > 41 cm, male and RH > 41 cm had the heaviest birth weight, with a mean of 5.4 kg.

In conclusion, modeling based on the CART algorithm will help breeders obtain elite sheep herds. This situation, on the other hand, will increase the income obtained from animal husbandry in rural areas and contribute to the formation of the breeding scheme. Therefore, more studies are needed to estimate the birth weight of lambs.

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Statement of conflict of interest

Authors have declared no conflict of interest.

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