Biotechnology in Animal Husbandry 39 (1), 33-49, 2023
Publisher: Institute for Animal Husbandry, Belgrade-Zemun
ISSN 1450-9156
UDC 636.39
https://doi.org/10.2298/BAH2301033O

PREDICTING THE BODY WEIGHT OF INDIGENOUS GOAT BREEDS FROM MORPHOLOGICAL MEASUREMENTS USING THE CLASSIFICATION AND REGRESSION TREE (CART) DATA MINING ALGORITHM

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Original scientific paper

Abstract: Classification and regression tree (CART) is a tree-based data mining algorithm that develops a model to predict an outcome. This study purposed to create a model to predict the body weight (BWT) of Red Sokoto (RS), Sahel (SH), and West African Dwarf (WAD) goats using morphological measurements (such as body length, BL; head girth, HG; head width, HDW; face length, FAL; height at wither, HTW; rump length, RL; shoulder width, SW; rump width, RW; and rump height, RH). In total, 600 goats were used for this study (200 each of RS, SH, and WAD goats). Pearson's Moment Correlation was used to evaluate the degree of association between BWT and each morphological measurement. Concomitantly, CART analysis was performed to estimate which independent variable (morphological measurements) played a considerable role in the BWT (dependent variable) prediction. In RS and WAD goats, a positive and statistically significant ($p < 0.0001$) correlation was observed between BWT and each morphological measurement. However, in SH goats, both positive and negative statistically significant correlations were observed between BWT and morphological measurements. The CART analysis indicated that in RS and WAD goats, HG played a considerable role in BWT prediction, while, in SH goats, BL was considered the most critical independent variable in BWT prediction. Therefore, this study suggests that HG can be used as a prognostic index for BWT estimation in Red Sokoto and West African Dwarf, while BL can be used for Sahel goats. The SAS codes used are available via a GitHub repository (https://github.com/Soullevram/CART).

Key words: algorithm, body weight, data mining, goats

Introduction

Goat rearing dates back several years. Goats were among the first sets of animals to be domesticated (*Amills et al., 2017*) and were primarily meant to serve as a source of meat and milk. By-products from goats, such as skin and hair fibre, are processed to manufacture belts. In Nigeria and other parts of Africa, subsistent goat farming is the source of livelihood and food security for many households (*Meissner et al., 2013*). There are three common breeds of goats found in Nigeria: The West African Dwarf goat which is predominantly found in the southwestern part of the country, Sokoto Red, and the Borno Sahel both of which are predominantly northern breeds of goats. However, research institutions and farmers have started to import exotic and foreign breeds because of their perceived better performance. One of the most important traits in livestock production is body weight; this is because of the market value attached to it. The body weight of a goat is emblematic of its health and weaning period *(Yakubu and Mohammed, 2012)*. *Norris et al. (2015)* classified body weight and body conformation as the two most important traits determining whether a goat farm is making profits.

Morphological measurements, such as body weight (BWT), rump height (RH), and body length (BL), are very important in selection and breeding programs *(Sam et al., 2016)*. Most commercial livestock enterprises utilize weighing scales to estimate the body weights of animals. However, rural or subsistent goat farmers usually cannot afford a weighing scale. Consequently, in undeveloped or less developed farming communities, animal body weight is determined using a highly subjective approach, visual judgment *(Chinchilla-Vargas et al., 2018)*. Morphological measurements have been used to get accurate estimates and predictions of animal body weight in livestock *(Younas et al., 2013; Eyduran et al., 2017; Sandeep et al., 2017)*.

A litany of statistical methods such as regression models, principal component analysis, factor score analysis, and canonical correlation *(Cankaya and Kayaalp, 2007; Yakubu et al., 2009; Yakubu and Musa-Azara, 2013; Oguntunji and Ayorinde, 2014)* has been used to predict body weight from morphological body measurements. Although a wide array of prediction models has been employed in predicting the body weight of animals from body measurements, their viable interpretations do not necessarily mean that they are applicable. An actionable solution to the limitations of previous prediction models is the data mining algorithm known as the Classification and Regression Tree (CART) introduced by *Breiman et al. (1984)*. CART can be used to develop an easy-to-use-and -understand statistical model to make predictions using a nominal or an ordinal scale *(Olfaz et al., 2019)*. CART analysis helps to determine which morphological measurements play a considerable role in predicting the dependent variable, body weight *(Mathapo and Tyasi, 2021)*. CART can be used even when the data is unbalanced, intricated, and missing values *(Speybroeck, 2012)*. When CART statistical technique is used to analyse categorical or continuous data, a classification or regression tree is produced. CART analysis can be applied to a wide range of data types, such as categorical, numerical, surviving, and ratings data *(De'ath and Fabricus, 2000)*. Since CART is a non-parametric statistical technique, the validity of its results is not dependent on the fulfilment of statistical assumptions about the distribution of independent variables *(Zaborski et al., 2019)*. The output of this tree-based statistical algorithm is pictorial.

The visual appraisal method of body weight assessment used by rural farmers is inaccurate, and subjective and could lead to the undervaluation of an animal's market value. Consequently, an objective and simple delineation method, such as CART, is needed to assist goat farmers in the appraisal of their livestock. CART has been used to predict the body weight of Ouda sheep *(Yakubu, 2012)* and locally adapted Muscovy ducks *(Oguntunji, 2017)* in Nigeria. However, to the best of the authors' knowledge, scientific literature on the use of CART to forecast the body weight of indigenous goat breeds in Nigeria is scanty. The study, therefore, aimed to predict the body weight of three goat breeds indigenous to Nigeria from their morphological measurements using the CART data mining algorithm. The resulting regression tree will enable farmers, especially rural farmers, to make informed decisions regarding the market value of their livestock, breeding, and selection.

Materials and Methods

Study area and period

The data for this study was obtained at goat markets within Ibadan situated at 7.3775° N, 3.9470° E, in Nigeria. Data was collected from Akinyele, Oranyan, and Bodija goat markets in Ibadan, Oyo State, Nigeria. All data were collected between March and September 2021.

Experimental animals

Three goat breeds, namely Red Sokoto (RS), Sahel (SH), and West African Dwarf (WAD), were randomly selected for this study. A total of 600 goats consisting of 200 RS, 200 SH, and 200 WAD were assessed for their morphological measurements. Reported morphological features by *Adu and Ngere (1979)* were used as the baseline for assigning sampled individual animals to a breed. Animals that did not conform to strict breed descriptions and or were visibly pregnant were excluded from this study. Animals were aged between 1-3 years. The goats examined were owned by small-scale farmers who practiced an extensive management system.

Data collection

The body weight (BWT) and morphological measurements of 600 RS, SH, and WAD goats were examined. The morphological body measurements estimated were: body length (BL), head girth (HG), head width (HDW), face length (FAL), height at wither (HTW), rump length (RL), shoulder width (SW), rump width (RW), and rump height (RH). The morphological measurements were conducted according to the specifications of *Yakubu et al. (2010)* and *Okpeku et al. (2011)*. Morphological body measurements were documented in centimeters (cm) using a measuring tape, while the BWT measurements were recorded in kilograms using a 50kg spring balance.

Statistical analysis

All statistical analyses were performed using SAS 9.4 *(SAS Institute Inc., 2016)*. The PROC MEANS procedure of SAS was used to obtain the descriptive statistics for the body weight and morphological body measurements. PROC CORR was used to compute the Pearson Moment Correlation coefficients, to determine the association between the dependent variable and independent variable(s).

The regression tree (RT) was constructed using the HPSPLIT procedure in SAS. The HPSPLIT procedure produced a decision tree, which models a continuous or categorical response, presented as if-then statements. For this study, the predictor variable(s) were continuous. Testing or training data with known response values were used in building a tree model for this study. The splitting criteria used in this study were based on impurity. The residual sum of squares (RSS) splitting criterion was chosen. The cost-complexity (CC) pruning option *(Breiman et al., 1984; Quinlan, 1987; Zhang and Singer, 2010)* was used. 10-fold cross-validation (CV) was done to both the CC pruning option and model. The CV option of PROC HPSPLIT in SAS produces tables and plots that estimate the error metric of the parameters and the future prediction accuracy for each subtree *(Camdeviren et al., 2005)*. The error metric for RT is average square error (ASE). RSS and ASE were used to assess the model fit for the regression tree. Ultimately, the subtree with the minimal RSS and ASE values is selected as the final tree.

The training data contains lots of predictors, with some being more important than others. The most important predictors are identified based on their variable importance. The position of a variable, especially its closeness to the top of the tree, is not associated with the importance of that variable. Rather variable importance is estimated using the following: surrogate count, count, relative importance, and RSS. The final RT produced using the HPSPLIT procedure in SAS is labeled using base 62; that is, the encoding used are 0-9, A-Z, and a-z.

Results

Descriptive statistics for morphological body measurements

The descriptive statistics for the morphological body measurements obtained from the three goat breeds are presented in Table 1. The highest BWT mean value was observed in the Sahel (SH) breed, while the lowest mean BWT value was observed in the West African Dwarf (WAD) goat. The highest mean values for all morphological variables were observed in SH except for HTW. WAD had the lowest mean values for all morphological variables. Across all three breeds, the highest mean value for a morphological variable was recorded in HG, followed by RH in the Red Sokoto (RS) breed and BL in the West African Dwarf breed. The coefficient of variation for the RS breed ranged between 11.72% - 33.94%, 6.63% - 23.29% for the SH breed, and 12.47% - 50.54% for the WAD.

Table 1. Descriptive statistics for morphological measurements and body weight of Red Sokoto, Sahel, and West African Dwarf goats

	Red Sokoto Goat			**Sahel Goat**			**West African Dwarf Goat**		
Measurements	Mean	SD	CV (%)	Mean	SD	CV (%)	Mean	SD	CV (%)
BL (cm)	44.51	5.49	12.34	50.55	6.90	13.64	42.11	8.93	21.22
HG (cm)	63.06	7.39	11.72	68.39	4.53	6.63	54.65	12.52	22.91
HDW (cm)	11.74	1.96	16.70	12.89	1.57	12.19	11.69	1.87	16.04
FAL (cm)	15.40	2.03	13.20	17.00	1.58	9.30	14.05	2.50	17.81
HTW (cm)	12.53	2.23	17.77	11.96	2.79	23.29	12.47	3.06	24.54
RL (cm)	16.89	2.73	16.20	17.64	3.07	17.43	15.17	1.89	12.47
SW (cm)	31.65	4.73	14.95	37.12	4.30	11.60	27.01	5.48	20.29
RW (cm)	13.48	2.93	21.75	14.33	3.08	21.50	12.99	1.82	13.99
RH (cm)	58.44	7.89	13.50	64.67	4.77	7.38	40.95	5.64	13.77
BWT (kg)	20.43	6.93	33.94	22.79	4.56	19.99	12.41	6.27	50.54

BL: body length; HG: head girth; HDW: head width; FAL: face length; HTW: height at wither; RL: rump length; SW: shoulder width; RW: rump width; RH: rump height; BWT: body weight; SD: Standard deviation; CV: Coefficient variation.

Variable importance

The importance of each independent value in predicting the BWT of RS, SH, and WAD breeds is presented in descending order in Table 2. The highest relative importance was observed in HG for both RS and WAD breeds, while for the SH breed, the highest relatively important variable was BL. However, for the SH breed, no importance was attributed to the variables HDW and SW.

Correlation between BW and morphological measurements

Pearson moment correlation statistical test was used to assess the association between BWT and morphological measurements in the three breeds. In the Red Sokoto and West African Dwarf breeds, BWT was positively correlated, with a statistical significance at $p < 0.001$, with all the morphological measurements. In the Sahel breed, however, BWT was positively correlated with most of the morphological measurements, except HTW and RL, at different levels of significance (Tables 3-5).

Table 2. Variable importance in predicting the body weight of Red Sokoto goats, Sahel goats and West African Dwarf goats

Red Sokoto goats			Sahel goats			West African Dwarf goats		
Variable	Relative	Importance	Variable	Relative	Importance	Variable	Relative	Importance
HG	100%	69.32	BL	100%	41.11	HG	100%	76.10
RL	57%	39.43	HG	75%	30.70	RH	36%	27.04
RH	34%	23.38	RL	36%	14.73	BL	27%	20.44
RW	33%	22.65	RH	33%	13.51	FAL	24%	18.38
SW	32%	21.92	RW	26%	10.76	RL	14%	10.77
BL	31%	21.55	FAL	25%	10.31	HDW	13%	9.66
FAL	25%	17.24	HTW	15%	6.32	SW	12%	9.16
HTW	22%	15.45				HTW	10%	7.94
HDW	21%	14.48				RW	7%	5.11

BL: body length; HG: head girth; HDW: head width; FAL: face length; HTW: height at wither; RL: rump length; SW: shoulder width; RW: rump width; RH: rump height.

Table 3. Correlation coefficients between body weight and morphological measurements in Red Sokoto Goat

Measurements	BL	HG	HDW	FAL	HTW	RL	SW	RW	RH	BWT
BL		0.56***	0.29***	0.43***	0.39***	0.39***	0.52***	0.51***	0.67***	0.45***
HG			0.36***	0.57***	0.55***	0.60***	0.50***	0.49***	0.75***	0.78***
HDW				0.35***	0.03	0.50***	0.29***	0.02	0.34***	0.42***
FAL					0.29***	0.56***	0.45***	0.34***	0.58***	0.53***
HTW						0.51***	0.34***	0.33***	0.61***	0.48***
RL							0.48***	0.21*	0.69***	0.69***
SW								0.41***	0.59***	0.49***
RW									0.42***	0.38***
RH										0.67***
BWT										

BL: body length; HG: head girth; HDW: head width; FAL: face length; HTW: height at wither; RL: rump length; SW: shoulder width; RW: rump width; RH: rump height. *** p < 0.0001, ** p <0.001, * p < 0.01.

Table 4. Correlation coefficients between body weight and morphological measurements in Sahel Goat

Measurements	BL	HG	HDW	FAL	HTW	RL	SW	RW	RH	BWT
BL		0.32***	0.23**	-0.16	-0.71***	-0.58***	0.09	0.80***	-0.14	0.61***
HG			0.22*	0.38***	0.04	0.11	0.19*	0.18*	0.35***	0.56***
HDW				0.31***	0.06	0.13	-0.05	0.06	0.30***	0.19*
FAL					0.35***	0.45***	-0.04	-0.22**	0.50***	0.17*
HTW						0.76***	0.14	-0.79	0.38***	-0.35***
RL							0	-0.57***	0.40***	-0.27***
SW								0.1	-0.02	0.18*
RW									-0.32***	0.51***
RH										0.18*
BWT										

BL: body length; HG: head girth; HDW: head width; FAL: face length; HTW: height at wither; RL: rump length; SW: shoulder width; RW: rump width; RH: rump height. *** p < 0.0001, ** p <0.001, * p < 0.01.

Table 5. Correlation coefficients between body weight and morphological measurements in West African Dwarf Goat

Measurements	BL	HG	HDW	FAL	HTW	RL	SW	RW	RH	BWT
BL		0.78***	0.43***	0.79***	0.75***	0.48***	0.66***	0.64***	0.65***	0.82***
HG			0.27***	0.70***	0.66***	0.49***	0.61***	0.61***	0.63***	0.84***
HDW				0.33***	0.30***	0.19**	0.32***	0.35***	0.37***	0.33***
FAL					0.66***	0.43***	0.59***	0.59***	0.57***	0.76***
HTW						0.34***	0.52***	0.47***	0.46***	0.63***
RL							0.39***	0.51***	0.58***	0.50***
SW								0.64***	0.71***	0.73***
RW									0.70***	0.66***
RH										0.73***
BWT										

BL: body length; HG: head girth; HDW: head width; FAL: face length; HTW: height at wither; RL: rump length; SW: shoulder width; RW: rump width; RH: rump height. *** p < 0.0001, ** p <0.001,* p < 0.01.

CART models for the Red Sokoto, Sahel, and West African Dwarf goats

The optimal regression trees (RT) for all three breeds are presented in Figures 1-3. The CART model used for constructing the regression tree for all three breeds had BWT as the dependent, explained or predicted variable and morphological measurements as the independent, explanatory or predictor variable.

The optimum RT for Red Sokoto (RS) breed consists of 15 nodes; RT for Sahel (SH) breed has 13 nodes; and the RT for West African Dwarf (WAD) breed has 15 nodes.

For the RS breed, the root node (labelled node 0) has 200 number of observations (n) and an average (or mean) of 20 kg – which corresponds to the mean of BWT to the nearest whole number. Animals in node 0 were divided into two different nodes on the basis of HG, namely node 1 (< 59.18 cm) and node 2 (≥ 59.18 cm). The predicted average (13 kg) for node 1 was lower than that of node 2 (23 kg). Node 1 was further split into node 3 (< 10.08 cm) and node 4 ((≥ 10.08 cm) based on RW. Node 3 was subdivided into node 7 (< 10.06 cm) and node 8 ((≥ 10.06 cm) based on HDW. Both node 7 and 8 were terminal nodes, however, their predicted means were low. Node 4 was split on the basis of BL into node 9 (< 41.02 cm) and node A (≥ 41.02 cm). Node 2, on the other hand, had a number of observations and was split based on RL into node 5 (< 19.05 cm) and node 6 (≥ 19.05 cm). The relative importance of HG resurfaced in the splitting of node 5 into node B (< 68.17 cm) and node C (≥ 68.17 cm), as well as in the subdivision of node 6 into node D (< 69.04 cm) and node E (≥ 69.04 cm). Out of all the terminal nodes, node 10 – a child node of node k, whose splitting decision was based on HG ≥ 71.07cm – had the highest mean prediction (34.22 kg). Further demonstrating the relative importance of HG in BWT prediction of RS goats.

The RT for the SH breed has 200 n and an average of 22.79 kg at its root node, corresponding to the BWT mean of the breed. The root node was divided based on BL into node 1 (< 48.05 cm) and node 2 (≥ 48.05 cm). Node 1 was subdivided on the basis of HG into node 3 (< 67.23 cm) and node 4 (≥ 67.23 cm). Node 3 was further divided based on FAL into node 7 (< 17.08 cm) and node 8 (≥ 17.08 cm). Node 4, on the basis of RW, was subdivided into node 9 (< 13.15 cm) and node A (≥ 13.15 cm). On the other hand, node 2, based on HG, was subdivided into node 5 (< 75.06 cm) and node 6 (≥ 75.06 cm). Out of the two child nodes of node 2, only node 5 was subdivided into node B (< 20.16 cm) and node C (≥ 20.16 cm) based on RL. Among all the terminal nodes, node 6 was observed to be the best node because its mean prediction (32 kg) was the highest.

Contrastingly, the root node of the RT for WAD breed had an average (12.41 kg), which was lower than the averages of RS and SH. Node 0 was divided into node 1(< 60.15cm) and node 2 (≥ 60.15 cm) based on HG. On the basis of HG again, node 1 was subdivided into node 3 (< 48.09 cm) and node 4 (≥ 48.09 cm). Based on BL node 3 was subdivided into node 7 (< 53.40 cm) and node 8 (≥ 53.40 cm). Node 4, on the basis of RH, was subdivided into node 9 (< 39.18 cm) and node A (≥ 39.18 cm). However, node 2, whose n was less than node 1, was subdivided into node 5 (< 47.01 cm) and node 6 (≥ 47.01 cm). Based on FAL, node 5 was further divided into node B (< 16.03 cm) and node C (≥ 16.03 cm). Node 6 was subdivided into node D (< 41.25 cm) and node E (≥ 41.25 cm). Node E was the best node because it had the highest mean prediction (27.5 kg) than all other terminal nodes.

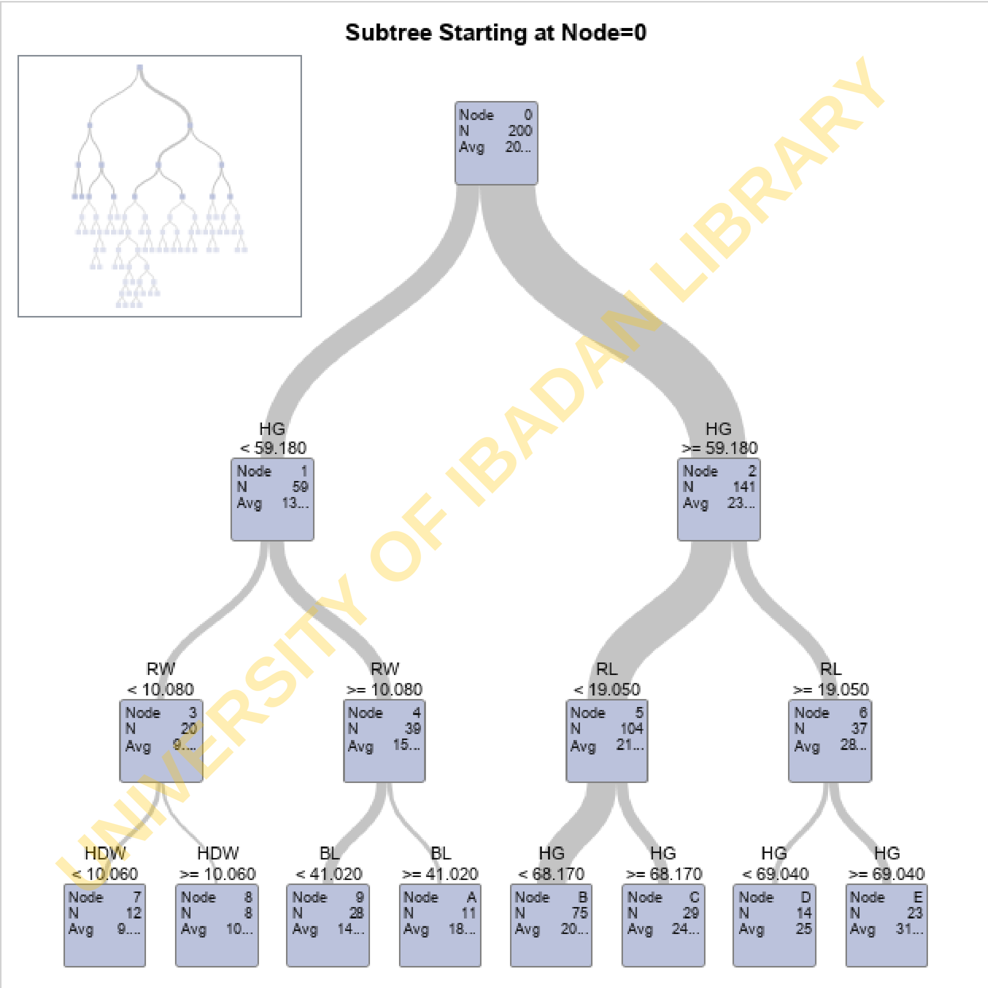

Figure 1. Classification and regression tree (CART) algorithmic model for Red Sokoto goats
HG: heart girth; RW: rump width; RL: rump length; HDW: head width; BL: body length

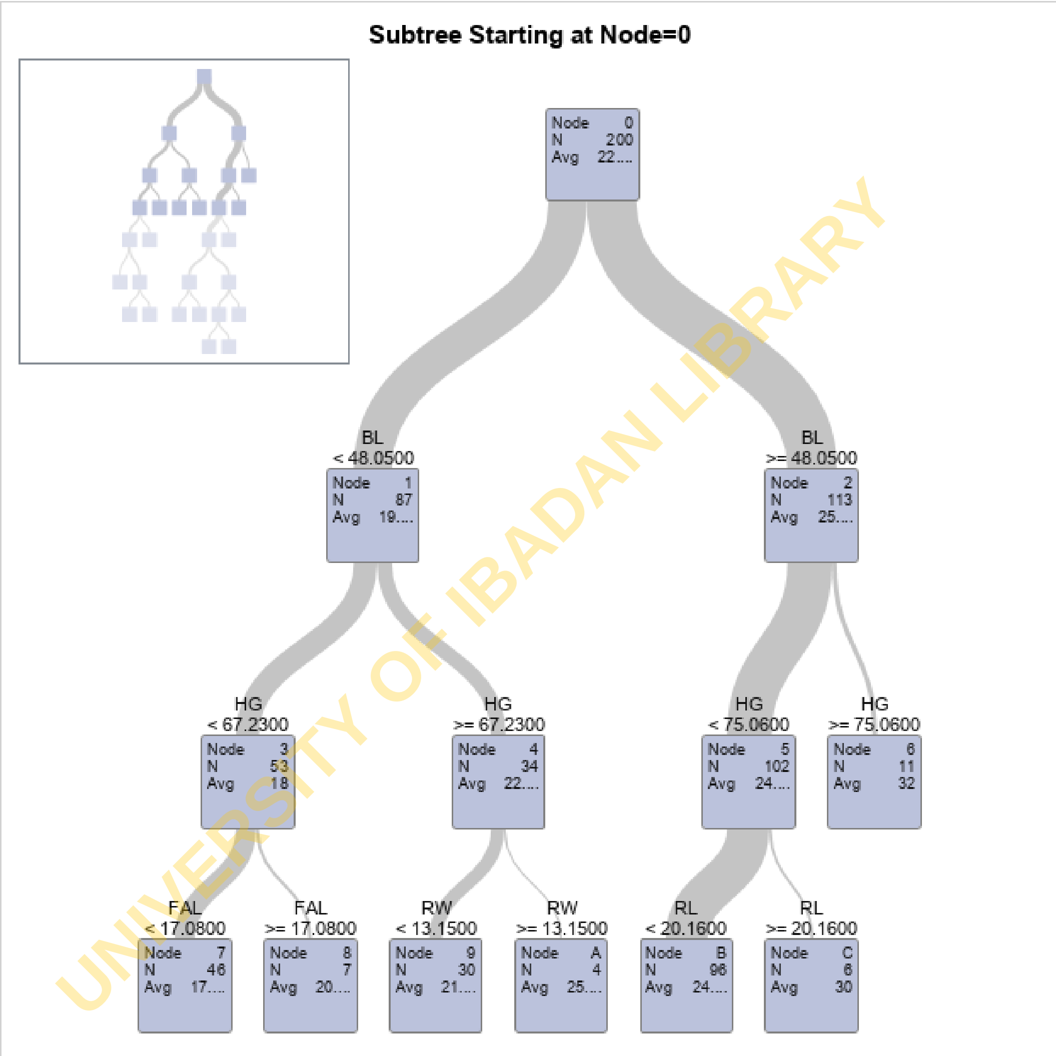

Figure 2. Classification and regression tree (CART) algorithmic model for Sahel goats
BL: body length; HG: heart girth; FAL: face length; RW: rump width; RL: rump length

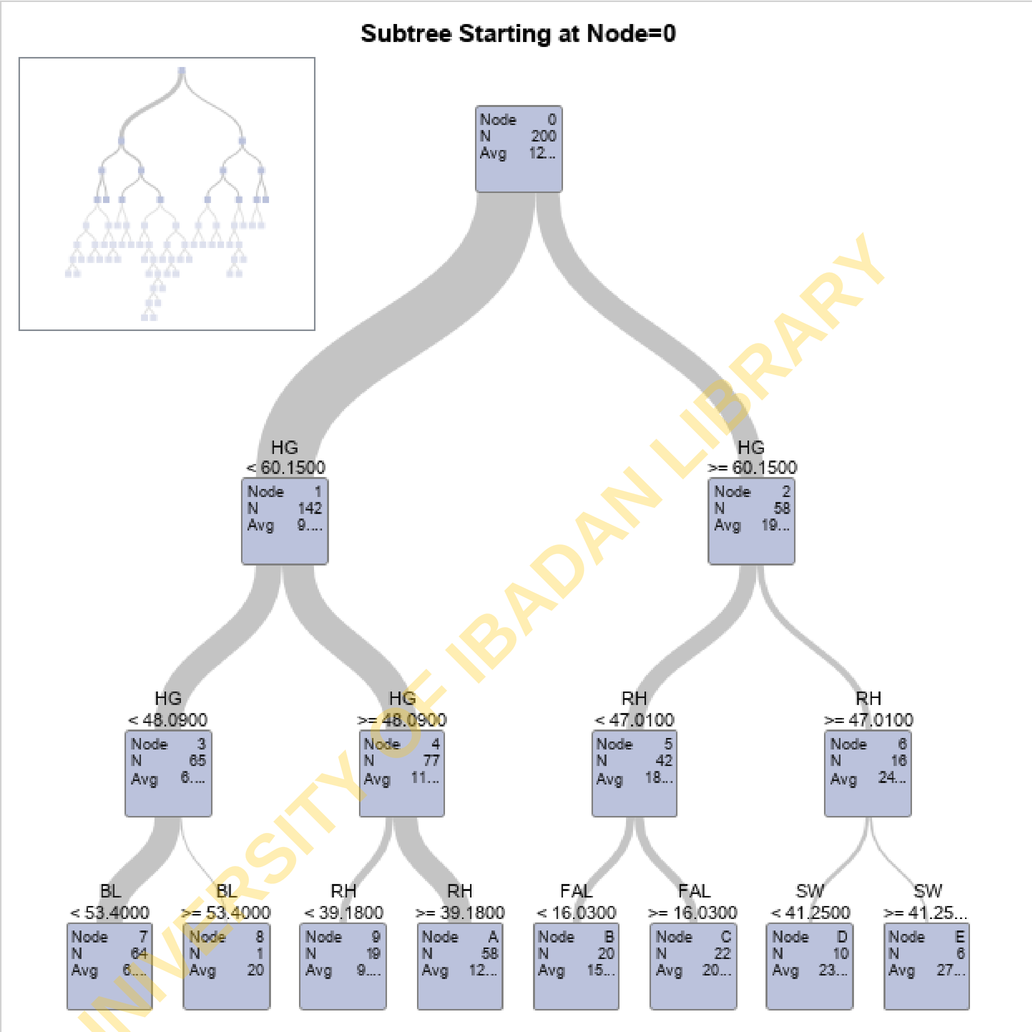

Figure 3. Classification and regression tree (CART) algorithmic model for West African Dwarf goats

HG: heart girth; RH: rump height; BL: body length; RH: rump height; FAL: face length; SW: shoulder width

Discussion

A viable alternative for the prediction of body weight (BWT) in goats among small-scale or rural farmers is morphological body measurements *(Norris et al., 2015; Eyduran et al., 2017; Tyasi et al., 2020)*. The classification and regression tree (CART) data mining algorithm is an effective tree-based statistical technique that can be used to identify morphological measurements that are important in predicting the BWT of live animals.

This study further cements the association between body weight and morphological measurements in goats, especially Red Sokoto (RS), Sahel (SH), and West African Dwarf (WAD) goats. Previous studies reported a positive and statistically significant correlation between BWT and body length (BL) in yearling Boer does *(Mathapo and Tyasi, 2021)*, Ganjam goats native to Odisha *(Karna et al., 2020)*, and Assam Hill goats *(Khargharia et al., 2015)*. Additionally, heart girth (HG) and BWT were observed to have a statistically significant correlation by *Tekin et al. (2019)*.

In Red Sokoto goats, there was a positive and statistically significant correlation between BWT and body morphological measurements. However, the degree of correlation with BWT varied among the morphological measurements. Heart girth (HG), rump length (RL), face length (FAL), and rump height (RH) were all highly correlated with BWT (that is, correlation coefficient, r, was > 0.5). The positive and significant correlation between HG and BWT by *Yakubu and Mohammed (2012)* agrees with this study. On the other hand, a low correlation coefficient (< 0.5) was observed in body length (BL), head width (HDW), height at wither (HTW), shoulder width (SW), and rump width (RW). Similarly, *Mokoena et al. (2022)* reported a low correlation coefficient between BWT and HDW in female Kalahari Red goats. In addition, *Yakubu and Mohammed (2012)* obtained a positive and statistically significant association between BWT and BL in Red Sokoto goats; *Tsegaye et al. (2013)* reported that the correlation between BWT and BL in Ethiopian Hararghe Highland goats was low.

High, positive and significant correlation coefficients was observed between BWT and morphological measurements in WAD goats. The correlation coefficients obtained for the association between BWT and morphological measurements in WAD goats was higher than the remaining two breeds, except for HDW. Likewise, *Yakubu (2009)* reported positive and statistically significant correlation between BWT and HTW, RH, BL and HG in WAD goats.

Unlike the other breeds, negative correlation was observed between BWT and HTW and RL, respectively, in SH goats. Positive and high correlation coefficients were estimated for the association between BWT and BL, HG, and RW. However, the correlation between BWT and HDW, FAL, SW, and RH, respectively, even though positive, was low. Except for HTW and RL in Sahel goats, there is a positive correlation between BW and other morphological measurements across the three breeds. This positive correlation posits that an increase in the designated morphological measurements is associated with an increase in BWT.

CART data mining algorithm was utilized to develop a prediction model for BWT in RS, SH and WAD goats using ten morphological body measurements (BL, HG, HTW, RW, RL, RH, HDW, SW, and FAL). The prediction model developed for this study indicates that, in Red Sokoto goats, HG played a critical role in predicting body weight, followed by RW, RL, HDW, and BL, respectively (Figure 1). In Sahel goats, BL was critical in predicting the body weight, then HG, FAL, RW, and RL, individually (Figure 2). In West African Dwarf goats, HG played the most important role in body weight prediction, followed by RH, BL, FAL, and SW, correspondingly (Figure 2).

The report of *Mokoena et al. (2022),* where HG and BL were found to be highly useful in predicting BWT of Kalahari Red goats, corroborates the findings of this study. In addition, *Tyasi et al. (2021)* reported that BL was the most critical parameter in body weight prediction of South African non-descript goats, followed by HG, sternum height, and RH, respectively. Similarly, *Celik (2019)* reported BL to be the most important morphological measurement in the body weight prediction of Pakistan goats. The relevance of certain morphological measurements, such as HG and BL – and the association between these morphological measurements and BWT – in the prediction of BWT is suggestive of these traits having the same monogenic effect.

Conclusion

Results from this study indicate that there is a positive and statistically significant correlation between BWT and morphological measurements in Red Sokoto and West African Dwarf goats. However, negative correlation was observed between BWT and HTW and RL in Sahel goats. This positive association observed among the breeds for most morphological measurements suggests that body measurements can be used as selection criteria in the body weight improvement of Red Sokoto, Sahel, and West African Dwarf goats. CART analyses indicated that HG plays an important role in predicting the BWT of Red Sokoto and West African Dwarf goats, while BL is crucial in the BWT prediction of Sahel goats. In other words, HG and BL are indicative of the body weight of certain goat breeds. Consequently, the results of this study will facilitate educating small-scale or rural farmers on how to predict the BWT of their livestock using simple morphological measurements, in the absence of weighing scales.

Predviđanje telesne mase autohtonih rasa koza na osnovu morfoloških merenja korišćenjem algoritma rudarenja podataka klasifikacijskog i regresionog stabla (CART)

Marvellous Olugbuyi Oyebanjo, Oluwakayode Michael Coker, Osamede Henry Osaiyuwu

Rezime

Stablo klasifikacije i regresije (CART) je algoritam za rudarenje podataka zasnovan na stablu koji razvija model za predviđanje ishoda. Cilj ovog istraživanja je bio da se stvori model za predviđanje telesne mase (BWT) koza rase crveni sokoto (RS), sahela (SH) i zapadnoafričkih patuljastih koza (WAD) koristeći morfološka merenja (kao što je dužina tela, BL; obim glave, HG ; širina glave, HDV; dužina lica, FAL; visina grebena, HTV; dužina karlice, RL; širina ramena, SV; širina karlice, RV; visina karlice, RH). Ukupno, 600 koza je korišćeno za ovo istraživanje (po 200 koza RS, SH i WAD). Pirsonova korelacija momenata je korišćena za procenu stepena povezanosti između BWT i svakog morfološkog merenja. Istovremeno, izvršena je CART analiza da bi se procenilo koja nezavisna varijabla (morfološko merenje) ima značajnu ulogu u predviđanju BWT (zavisne varijable). Kod koza RS i WAD uočena je pozitivna i statistički značajna ($p < 0,0001$) korelacija između BWT i svakog morfološkog merenja. Međutim, kod SH koza, uočene su i pozitivne i negativne statistički značajne korelacije između BWT i morfoloških merenja. CART analiza je pokazala da je kod koza RS i WAD HG igrala značajnu ulogu u predviđanju BWT, dok se kod SH koza BL smatrala najkritičnijom nezavisnom varijablom u predviđanju BWT. Stoga, ovo istraživanje sugeriše da se HG može koristiti kao prognostički indeks za procenu BWT koza rase crveni sokoto i zapadnoafričkih patuljastih koza, dok se BL može koristiti za sahelske koze. Korišćeni SAS kodovi dostupni su preko GitHub repozitorijuma (https://github.com/Soullevram/CART).

Ključne reči: algoritam, telesna masa, rudarenje podataka, koze

Competing interests
The authors declare no competing of interest.

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Received 17 December 2022; accepted for publication 21 March 2023