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Predicting body weight in Ross 308 broiler chickens using a data mining algorithm approach

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Abstract

Ross 308 broiler chickens are raised specifically for meat production, as they are fast growing and can be slaughtered at six weeks of age. This study aimed to use multivariate adaptive regression splines (MARS) and classification and regression tree (CART) data mining algorithms to predict the live body weights of Ross 308 male and female chickens from their morphological traits, and to compare the predictive performances of these two approaches. One hundred and twenty birds (60 males and 60 females) were used. The flock was reared under intensive conditions, and the entire flock was kept in the same house. Body weight and morphological traits such as wing length, beak length, shank length, body girth, body length, and shank circumference were measured for every Ross 308 chicken. Two data mining algorithms, MARS and CART, were used for body weight prediction, and goodness-of-fit criteria were used to select the best model. The CART data mining algorithm was found to be the best model, as it had greater predictive accuracy, and higher Pearson's correlation coefficient, coefficient of determination, and adjusted coefficient of determination test results, when predicting body weight in both male and female Ross 308 chickens. These results suggest that the CART data mining algorithm could be used to help farmers recognise the morphological traits that are most influential in determining body weight.

Keywords: beak length, body girth, correlation, heat map, morphological traits

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Introduction

The world population is predicted to rise to 9.5 billion in 2050 (Soltanali *et al*., 2016). As a result of this increase, in addition to an increasing demand for food, the exploitation of energy resources is growing (Soltanali *et al*., 2016). The livestock industry is one of the most important sources of protein and food for this growing population (Soltanali *et al*., 2016). In South Africa and globally, the poultry industry makes a considerable contribution to the food security status of consumers (Manyelo *et al*., 2022). Ross 308 broiler chickens are raised specifically for meat production, and are known for their fast growth and their potential to be sold or slaughtered by six weeks of age (Amao, 2022). This makes broiler chicken farming more profitable than other livestock businesses.

Morphological traits are good indicators of the growth potential and market value of broiler chickens (Isaac & Adeolu, 2023). Moreover, these traits can serve as a basis for the characterisation,

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grouping, selection, and improvement of poultry breeds (Isaac & Adeolu, 2023). Bila & Tyasi (2022) suggested that the morphological characterisation of animal breeds is an important stage in animal development programmes, as it allows animal keepers to identify and select exceptional lines for development. Furthermore, Yakubu (2011) reported that morphological variations within a breed are of immense biological interest, both as descriptive and analytical tools.

Body weight is one of the primary traits of economic importance in animal production (Yakubu & Ari, 2017), as weight directly translates into income, especially in markets where chicken prices are based on weight. Body weight records are also used when making breeding decisions, and are required for the calculation of medication dosages (Bila *et al*., 2023). Growth rate is consequently an important trait in animal production, based on economic factors, as it impacts the adaptability and economic suitability of livestock production (Önder *et al*., 2025; Ağyar *et al*., 2022). Characteristics that define the growth course of the individual, and the rate at which that individual reaches puberty, are thus key for determining the economic efficiency of livestock production (Wojnarowska *et al*., 2022).

Tırınk (2022) reported that the accurate determination of body weight offers a basis for animal science studies such as animal health management and herd management. However, determining body weight, especially without affecting animal welfare, poses a complex challenge. More research on predicting body weight accurately and reliably is thus needed. Prediction models in which morphological traits are used to predict body weight have recently been established (Isaac & Adeolu, 2023). Two data mining algorithms in particular have been used extensively in the animal sciences. These are multivariate adaptive regression splines (MARS) and classification and regression trees (CART). Tırınk *et al*. (2023) reported that MARS is a non-parametric regression method that employs smoothing splines methodology, and Faraz *et al*. (2023) noted that it provides both innovation and substantial ease in interpreting variables and their interactions. The MARS approach has previously been used in livestock sciences to predict the body weight of Kajli sheep (Faraz *et al*., 2023). Tırınk *et al*. (2023) reported that the CART algorithm analyses data for modelling and division purposes. A decision tree is developed using instructions that group data into unique categories. Classification and regression tree analysis has also been employed in animal sciences, to predict the weight of goats (Mathapo *et al*., 2022) and the egg weights of indigenous chickens (Liswaniso *et al*., 2021). However, to the author's knowledge, there is scanty information on the use of data mining algorithms for the prediction of the body weight of Ross 308 chickens.

Hence, the objective of this study was to use MARS and CART data mining algorithms to predict the live body weight of male and female Ross 308 chickens from morphological traits, and to compare the predictive performances of the two approaches.

Materials and methods

Study area

All procedures were performed following the standards and protocols set by the Potchefstroom College of Agriculture's Animal Research Ethics Committee, under project number AREC/02/2021. This study was conducted at the Broiler Production Division of the Animal Production Department of the Potchefstroom College of Agriculture, in the North West Province. The Potchefstroom College of Agriculture is located on the site of the Agricultural Centre of the North West Department of Agriculture and Rural Development, at 26° 42' 53" S, 27° 05' 49" E (Bila & Tyasi, 2022).

Experimental animals and management

Ross 308 broiler chickens were used for this study. The broiler house contained approximately 1000 chickens; 120 of these birds (60 males and 60 females) were selected for analysis. The flock was reared in an intensive system and the entire flock was kept in the same house. The chickens were subjected to phase-feeding practices, with feed being provided *ad libitum*. Broiler starter feed was fed from day 1 to day 21, broiler grower feed was fed from day 21 to day 28, and broiler finisher feed was fed from day 28 until slaughter. The chickens had *ad libitum* access to clean water. The temperature was recorded daily and regulated by controlling the ventilation of the house. From arrival until day 3, the chicks were given a stress-pack via their drinking water to enable them to acclimatise to the new environment and to combat stress. The chickens were inoculated against Newcastle and Gumboro diseases, with both vaccines being administered through their drinking water. The chickens were weighed weekly using a sensitive scale, and their weight gains were recorded.

Morphological traits measured

Morphological traits were measured on week five, at which time the 120 trial chickens were randomly sampled from the flock. The traits were measured in centimetres using a measuring tape, following the normal morphometric trait procedures reported by Bila & Tyasi (2022). The morphological traits measured are described in Table 1. All the morphological traits were measured by the same individual to avoid individual variations in measurements.

Table 1 Morphological traits measured for five-week-old Ross 308 broiler chickens

Traits	Description
Body weight	Measured to three decimal places using a scale.
Wing length	Measured as the distance from the humorous-coracoid junction to the distal tip of the phalange digits, using a measuring tape.
Beak length	Measured as the distance from the tip of the beak to the point of insertion of the beak into the skull.
Shank length	Measured as the length of the tars-metatarsus from the hock joint to the metatarsal pad.
Body girth	Measured as the circumference of the breast under the wing, using a measuring tape.
Body length	Measured as the distance from the bird's nasal opening to the tip of its pygostyle, by stretching a measuring tape along the bird's neck and back.
Shank circumference	Measured as the circumference of the middle of the shank, using a measuring tape.

Statistical analysis

The Statistical Package for Social Sciences (2019), version 26.0, was used to analyse the data and provide the descriptive statistics for the body weight and morphological traits of the Ross 308 chickens. Decision tree algorithms were used to design the models to predict the body weight from the morphological traits of the chickens, as described by Eyduran *et al*. (2019). Goodness-of-fit criteria were used to assess the predictive performances of the CART and MARS models, as performed by Faraz *et al*. (2021). Correlation matrix heat maps were used to determine the correlations between the body weight and the morphological traits.

MARS algorithm

The MARS algorithm is a non-parametric machine learning method that is used for managing and recognising pattern problems in regression and classification, as well as handling non-linear data (Tırınk *et al*., 2023). Iqbal *et al*. (2023) suggested that the MARS model fits a series of linear regression functions to predict values of a continuous dependent variable. The MARS algorithm was used as described by Bila *et al*. (2023) and Rashijane *et al.* (2023), and was defined as:

$$f(x) = \beta_0 + \sum_{M=1}^{M} \beta_m \prod_{k=1}^{k_m} h_m(X_{v(k,m)})$$

Where:

f(x) is the estimated value of the dependent variable;

β_0, and β_m are the intercepts; and

$h_m(X_{v(k,m)})$ is the basis function, where $v(k, m)$ is an index of the predictor for the m_{th} component of the k_{th} product, and K is the parameter regulating the order of interaction.

After building the most suitable MARS model, the basic functions that did not substantially contribute to the model's predictive performance were eliminated via a pruning process, which was based on the following generalised cross-validation error (GCV) calculation (Eyduran *et al*., 2019):

$$GCV(\lambda) = \frac{\sum_{i=1}^{n}(y_i - y_{ip})^2}{\left(1 - \frac{M(\lambda)}{n}\right)^2}$$

Where:
n is the number of training cases;
y_i is the observed value of a response variable;
y_{ip} is the estimated value of a response variable; and
$M(\lambda)$ is a penalty function for the complexity of the model, with λ terms.

CART algorithm

As a recursive data mining algorithm, CART was created by repeatedly splitting nodes into pairs of child nodes, starting from the root node containing the entire learning sample, as described by Breiman *et al.* (1984) and Kuhn & Johnson (2013).

Predictive performance of CART and MARS models

The predictive performances of the MARS and CART models were compared using goodness-of-fit test criteria (Bila *et al*., 2023). The following goodness-of-fit criteria were calculated:

Pearson's correlation coefficient (r):

$$r = \frac{cov(y_i, y_{ip})}{S_{yi}\, S_{Yip}}$$

Relative root mean square error (RRMSE):

$$RRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y) \times 2}}{\bar{y}}$$

Mean error (ME):

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

Performance index (PI):

$$PI = \frac{rRMSE}{1 + r}$$

Coefficient of determination (Rsq):

$$Rsq = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

Adjusted coefficient of determination (ARsq):

$$ARsq = 1 - \frac{\frac{1}{n-k-1}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\frac{1}{n-1}\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

Root mean square error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Standard deviation ratio (SDR):

$$SDR = \sqrt{\frac{\frac{1}{n-1}\sum_{i=1}^{n}(\varepsilon_i - \bar{\varepsilon})^2}{\frac{1}{n-1}\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

Akaike information criterion (AIC):

$$AIC = N\ Ln\left(\frac{SSE}{N}\right) + 2p$$

Mean absolute percentage error (MAPE):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Yi - \hat{Y}i}{Yi}\right| \times 100$$

Mean absolute deviation (MAD):

$$MAD = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Yi - \hat{Y}i}{Yi}\right|$$

Global relative approximation error (RAE):

$$RAE = \sqrt{\frac{\sum_{i=1}^{n}(Yi - \hat{Y}i)2}{\sum_{i=1}^{n} Y\frac{2}{i}}}$$

Coefficient of variance (CV):

$$CV = \sqrt{\frac{1}{n-1}\frac{\sum_{i=1}^{n}(\varepsilon_i - \bar{\varepsilon})^2}{\bar{Y}}} \times 100$$

Results

Descriptive statistics

Descriptive statistics for all variables by sex (male and female) are expressed as the mean ± standard error and are reported in Table 2. The results showed that the average live weight of the Ross 308 chickens was 1.84 kg for females and 1.93 kg for males. The CV for the various traits ranged between 0.10% and 92.08% in females and between 0.03% and 5.07% in males, while the standard deviation ranged between 0.31 cm and 9.60 cm in females and between 0.10 cm and 2.25 cm in males.

Table 2 Descriptive statistics (mean ± standard error) for the body weights and morphological traits of male and female Ross 308 broiler chickens at five weeks of age

Traits	Males (n = 60)			Females (n = 60)		
	Mean ± SE	SD	CV (%)	Mean ± SE	SD	CV (%)
Body weight (kg)	1.93 ± 0.02	0.18	0.03	1.84 ± 0.05	0.38	0.14
Wing length (cm)	8.62 ± 0.05	0.35	0.12	9.42 ± 1.24	9.60	92.08
Beak length (cm)	1.74 ± 0.01	0.10	0.01	1.93 ± 0.04	0.31	0.10
Shank length (cm)	8.51 ± 0.04	0.34	0.11	7.72 ± 0.13	0.99	0.99
Body girth (cm)	40.49 ± 0.30	2.25	5.07	38.23 ± 0.42	3.29	10.79
Body length (cm)	28.26 ± 0.24	1.87	3.50	25.20 ± 0.24	1.82	3.32
Shank circumference (cm)	4.84 ± 0.04	0.28	0.08	4.38 ± 0.07	0.52	0.27

SE: standard error, SD: standard deviation, CV: coefficient of variance

Correlation matrix

Figure 1 shows the correlations between the body weight and the morphological traits of male Ross 308 chickens. The body weight of male Ross 308 chickens was moderately positively correlated (P <0.05) with the body length (0.55), shank length (0.40), wing length (0.36), and body girth (0.30). In contrast, body length was negatively correlated (P <0.05) with beak length (-0.09).

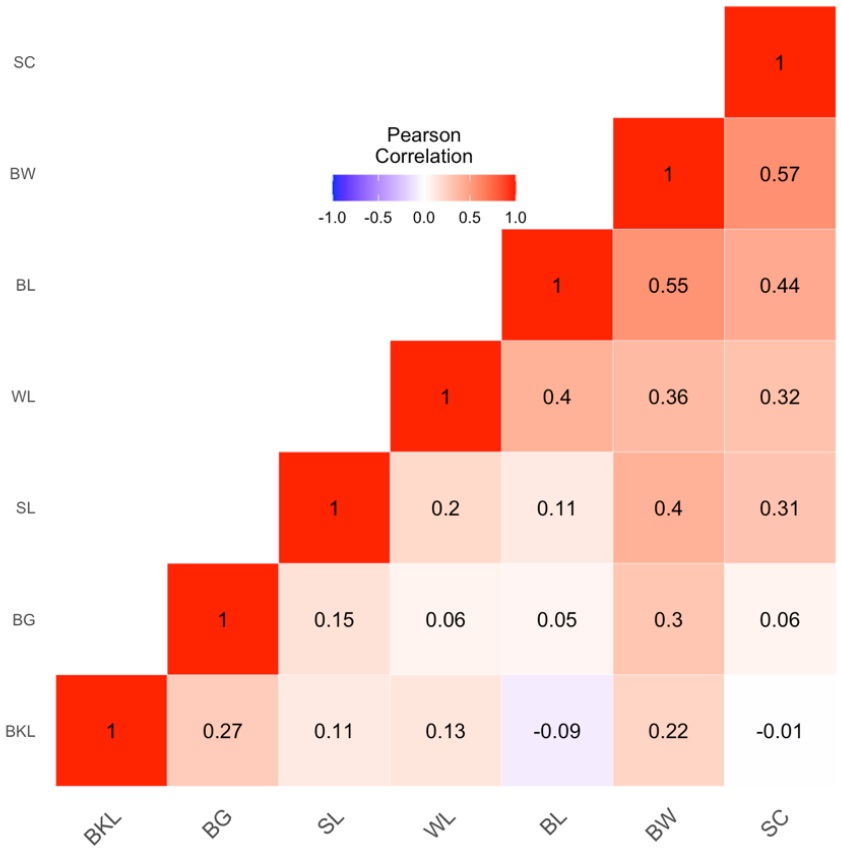

Figure 1 Heat map of the correlations between the body weight and the morphological traits of male Ross 308 chickens. High positive correlations are indicated in red, low correlations are indicated in white, and high negative correlations are indicated in blue. BW: body weight, WL: wing length, BKL: beak length, SL: shank length, BG: body girth, BL: body length, SC: shank circumference.

Figure 2 shows the correlations between the body weight and the morphological traits of female Ross 308 chickens. The body weight of female Ross 308 chickens was moderately positively correlated (P <0.05) with the shank circumference (0.33) and body girth (0.33). In contrast, body weight was negatively correlated (P <0.05) with beak length (-0.10). Moreover, beak length was highly positively correlated (P <0.01) with shank length (0.76).

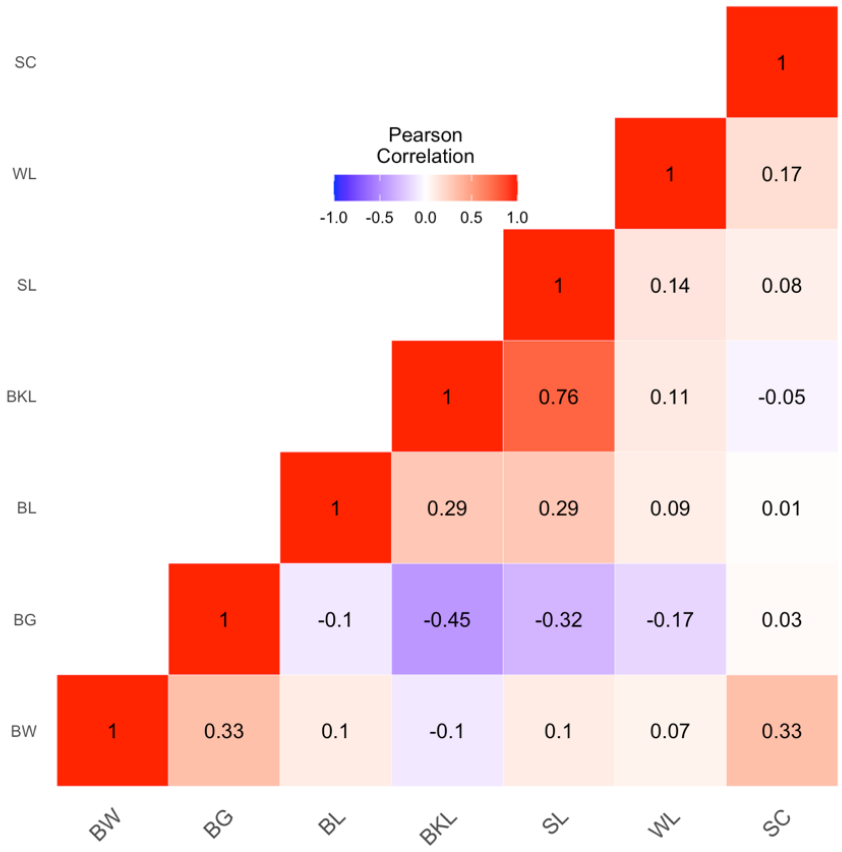

Figure 2 Heat map of the correlations between the body weight and the morphological traits of female Ross 308 chickens. High positive correlations are indicated in red, low correlations are indicated in white, and high negative correlations are indicated in blue. BW: body weight, WL: wing length, BKL: beak length, SL: shank length, BG: body girth, BL: body length, SC: shank circumference.

The CART model

At the top of the regression tree diagram in Figure 3, the root node showed that the overall body weight of male Ross 308 chickens was 1.9 kg. The node was split into one group based on body length, with a cut-off point of 30 cm. This body length node was then split into two sub-groups based on the body girth, with a cut-off point of 42 cm. For the first sub-group, where the body girth was less than 42 cm, the average body weight was 1.8 kg, representing 55% of the flock. When the body girth was greater than 42 cm, the obtained body weight was 2 kg, representing 27% of the flock.

At the top of the regression tree diagram in Figure 4, the root node showed that the overall body weight of female Ross 308 chickens was 1.8 kg. The node was split into two sub-groups based on body girth, with a cut-off point of 35 cm. For the first sub-group, where the body girth was less than 42 cm, the average body weight was 1.4 kg, representing 17% of the flock. When the body girth was greater than 35 cm, the obtained body weight was 1.9 kg, representing 83% of the flock. This part of the tree was further split into two sub-groups based on shank length, with a cut-off point of 8 cm. When the shank length was less than 8 cm, the mean body weight was 1.6 kg, representing 17% of the flock. When the shank length was greater than 8 cm, the mean body weight was 1.9 kg, representing 67% of the flock.

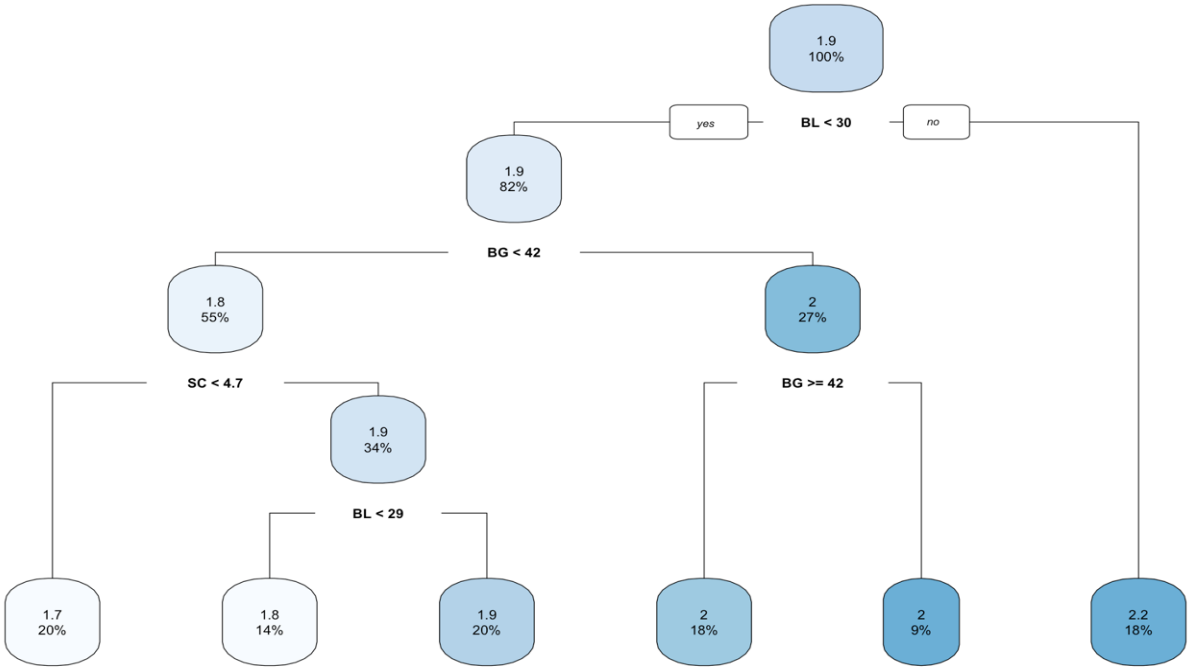

Figure 3 Classification and regression tree model for the prediction of body weight in male Ross 308 broiler chickens.

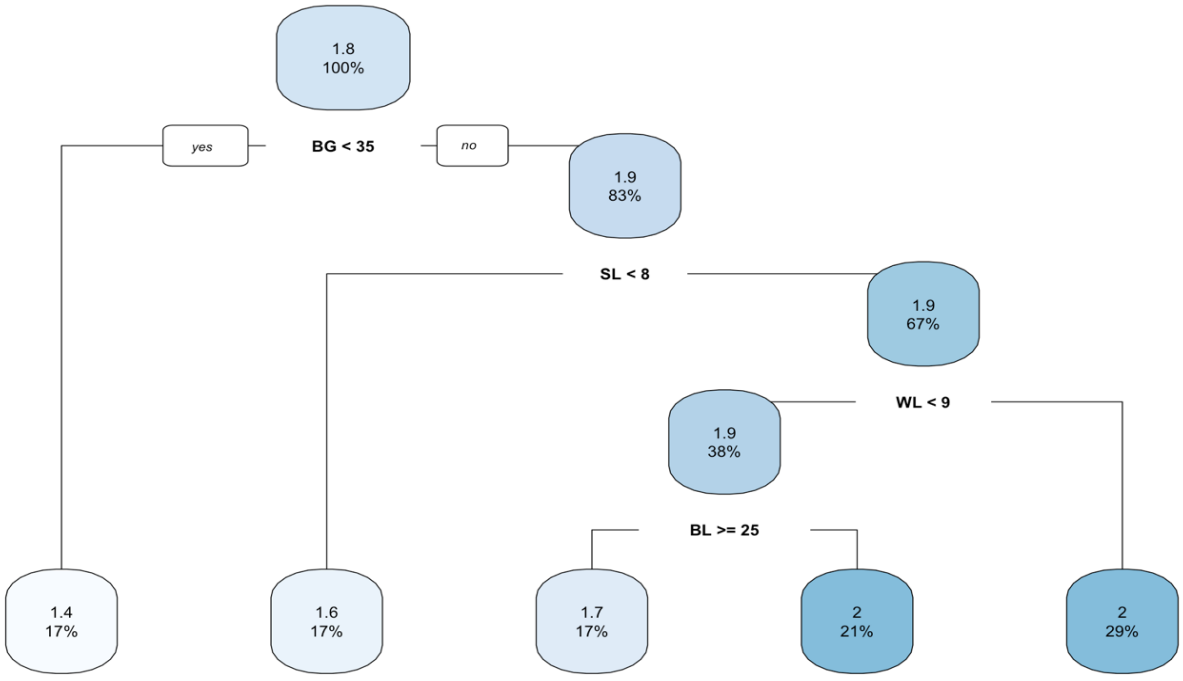

Figure 4 Classification and regression tree model for the prediction of body weight in female Ross 308 broiler chickens.

The MARS model

Table 3 shows the results of the MARS data mining algorithm for the prediction of body weight in male and female Ross 308 broiler chickens. The MARS model showed that body length was included in the developed model for male Ross 308 chickens, while shank length was included in the developed model for female Ross 308 chickens. In male Ross 308 chickens, the model's first term had an intercept with a coefficient of 1.86, while in the second term, body length had a cut-off point of 28.8 cm for a positive coefficient of 0.13. In female Ross 308 chickens, the model's first term had an intercept with a

coefficient of 1.53, while in the second term, shank length had a cut-off point of 7 cm for a positive coefficient of 0.31.

Table 3 Multivariate adaptive regression splines models for the prediction of body weight in male and female Ross 308 chickens

Variables	Coefficients
Males	
Intercept	1.86
h(body length−28.8)	0.13
Females	
Intercept	1.53
h(shank length−7)	0.31

Comparison of the MARS and CART data mining algorithms for male Ross 308 chickens

Goodness-of-fit criteria were used to assess the predictive performances of the two algorithms, and the test data set was used to confirm the comparison between the MARS and CART data mining algorithms. The goodness-of-fit criteria (Table 4) showed that the CART algorithm had better predictive performance than the MARS algorithm. The CART algorithm had higher r, Rsq, and ARsq values, and lower RMSE, SDR, CV, PI, RRMSE, MAPE, AIC, and corrected AIC values than the MARS algorithm.

Table 4 Goodness-of-fit criteria for multivariate adaptive regression splines (MARS) and classification and regression tree (CART) algorithms for the prediction of body weight in male Ross 308 chickens

Criteria	MARS		CART		Decision
	Training	Test	Training	Test	
r	0.70	0.25	0.84	0.46	Greater is better
RMSE	0.13	0.17	0.10	0.16	Smaller is better
SDR	0.72	0.98	0.55	0.92	Smaller is better
CV	6.53	9.02	5.02	8.44	Smaller is better
PI	3.81	7.06	2.70	5.67	Smaller is better
ME	0.00	0.02	0.00	0.03	Smaller is better
RRMSE	6.46	8.79	4.96	8.30	Smaller is better
RAE	0.00	0.01	0.00	0.01	The expected value is zero
MRAE	0.01	0.02	0.01	0.02	The expected equal value is one
MAPE	5.38	7.60	3.84	6.59	Smaller is better
MAD	0.10	0.14	0.08	0.13	The expected equal value is one
Rsq	0.45	0.02	0.70	0.13	Greater is better
ARsq	0.46	−0.13	0.70	0.13	Greater is better
AIC	−178.67	−53..03	−205.91	−58.90	Smaller is better
CAIC	−178.38	−52.10	−205.91	−58.90	Smaller is better

r: Pearson's correlation coefficient, RMSE: root mean square error, SDR: standard deviation ratio, CV: coefficient of variation, PI: performance index, ME: mean error, RRMSE: relative root mean square error, RAE: relative approximation error, MRAE: mean relative approximation error, MAPE: mean absolute percentage error, MAD: mean absolute deviation, Rsq: coefficient of determination, ARsq: adjusted coefficient of determination, AIC: Akaike's information criterion, CAIC: corrected Akaike's information criterion.

Comparison of the MARS and CART data mining algorithms for female Ross 308 chickens

Goodness-of-fit criteria were used to assess the predictive performances of the two algorithms, and the test data set was used to confirm the comparison between the MARS and CART data mining algorithms. The goodness-of-fit criteria (Table 5) showed that the CART algorithm had better predictive performance than the MARS algorithm. The CART algorithm had higher r, Rsq, and ARsq test results and lower RMSE, SDR, CV, PI, RRMSE, MAPE, AIC, and CAIC values than the MARS algorithm.

Table 5 Goodness-of-fit criteria for multivariate adaptive regression splines (MARS) and classification and regression tree (CART) algorithms for the prediction of body weight in female Ross 308 chickens

Criteria	MARS		CART		Decision
	Training	Test	Training	Test	
r	0.38	-0.11	0.56	0.07	Greater is better
RMSE	0.38	0.31	0.34	0.34	Smaller is better
SDR	0.92	1.17	0.83	1.29	Smaller is better
CV	21.50	14.19	19.27	15.65	Smaller is better
PI	15.37	17.76	12.21	16.56	Smaller is better
ME	0.00	0.15	0.00	0.18	Smaller is better
RRMSE	21.24	15.84	19.04	17.66	Smaller is better
RAE	0.04	0.03	0.03	0.03	The expected value is zero
MRAE	0.03	0.04	0.03	0.04	The expected equal value is one
MAPE	22.33	14.61	17.35	14.68	Smaller is better
MAD	0.30	0.25	0.23	0.25	The expected equal value is one
Rsq	0.15	−0.81	0.31	−1.25	Greater is better
ARsq	0.10	−1.05	0.31	−1.25	Greater is better
AIC	−77.44	−38.40	−90.60	−38.48	Smaller is better
CAIC	−77.14	−37.60	−90.60	−38.48	Smaller is better

r: Pearson's correlation coefficient, RMSE: root mean square error, SDR: standard deviation ratio, CV: coefficient of variation, PI: performance index, ME: mean error, RRMSE: relative root mean square error, RAE: relative approximation error, MRAE: mean relative approximation error, MAPE: mean absolute percentage error, MAD: mean absolute deviation, Rsq: coefficient of determination, ARsq: adjusted coefficient of determination, AIC: Akaike's information criterion, CAIC: corrected Akaike's information criterion.

Discussion

Morphological traits often influence animals' live body weights and are used as indirect selection criteria in breeding strategies (Celik & Yilmaz, 2018). These traits have also been employed in numerous studies to predict animal body weight (Faraz *et al*., 2021; Amao, 2022; Bila & Tyasi, 2022). This study examined the associations between the morphological traits and live body weights of male and female Ross 308 chickens. The correlations found showed that in male Ross 308 chickens, body weight was moderately correlated with body length, shank length, wing length, and body girth, while body length was negatively correlated with beak length. This suggests that there is a positive and directly proportional relationship between body weight and body length, indicating that as body length increases, body weight also increases. These findings are in line with the results of Isaac *et al*. (2024), who also studied broiler chickens. This correlation may be because the two traits are controlled by a single common gene (Hedayat-Evrigh *et al*., 2023), or because of a gene interaction that exists within the specific species and breed. Hedayat-Evrigh *et al*. (2023) reported that gene functioning and expression differed between different animals and breeds.

In female Ross 308 chickens, body weight was positively correlated with shank circumference and body girth, while beak length was highly positively correlated with shank length. These results concur with those of Amao (2018), who studied Nigerian indigenous chickens reared intensively in the Southern Guinea savanna. Moreover, these results also concur with the results of Amao (2022), who found that there was a highly significant positive correlation between the body weight and the body

length, wing length, and shank length in Ross 308 broiler chickens. In contrast, Isaac *et al*. (2024) reported that other morphological traits, such as thigh circumference, wing span, and shank length, were highly correlated with body weight, and that these traits could be used in a selection index for the improvement of body weight in broiler chickens. Habashy *et al*. (2021) published similar findings to those found in this study, with body weight being highly correlated with body length and moderately correlated with shank length at twelve weeks of age. Differences between the results of this study and those of previous studies may be due to differences in production environments, feed consumption, and feeding programmes. Moreover, Bila *et al*. (2023) noted that while morphological correlations help to specify the degree of association between traits, they do not identify the causes of associations between traits.

Faraz *et al*. (2021) argued that data mining algorithms have the potential to overcome multicollinearity problems in predicting animal body weight. Therefore, in this study, the data mining algorithm approach was used to predict the live body weights of male and female Ross 308 broiler chickens based on their morphological traits. Multivariate adaptive regression splines and CART data mining algorithms were compared in terms of their ability to predict the live body weights of male and female Ross 308 chickens. The study's findings showed that body length was the best determinant factor for males, while shank length was the key determinant in the model for female Ross 308 chickens. These findings contradict those of Tyasi *et al*. (2020), who found that wing length was the best determinant factor of body weight in Hy-line Silver Brown chickens. This might be because of differences in the breeds studied, as well as differences in nutritional and environmental factors.

Furthermore, the results of this study showed that the CART algorithm had a higher predictive performance than the MARS algorithm for both sexes of Ross 308 chickens. These results concur with those of Tyasi *et al*. (2021), who found that the CART data mining algorithm exhibited much higher predictive accuracy than the chi-square automatic interaction detector (CHAID) and exhaustive CHAID algorithms, when the algorithms were used to predict live body weight in Hy-line Silver Brown commercial layer hens and indigenous Potchefstroom Koekoek chickens. However, the results of the current study contradict those of Hlokoe *et al*. (2022), who suggested that the MARS data mining algorithm performed better than the CART algorithm, when working with Nguni cows. In contrast, Karadas & Birinci (2019) used CART, CHAID, exhaustive CHAID, MARS, and multilayer perceptron algorithms to determine the factors affecting dairy cattle performance, and found that MARS outperformed the other algorithms tested. Despite the limited previous literature reporting on the use of MARS for predicting body weight from morphological traits in chickens, MARS has been successfully used to predict body weight from linear body measurements in other species. For instance, Faraz *et al*. (2023) reported on models that could predict the body weight of Kajli sheep. Interestingly, Oyebanjo *et al*. (2023) reported that the CART model revealed that heart girth was the best predictor of body weight in indigenous goat breeds.

Conclusion

This study found positive correlations between body weight and specific morphological traits in male and female Ross 308 chickens. Furthermore, the CART data mining algorithm demonstrated that body length in males and shank length in females significantly influenced the live body weight of Ross 308 chickens. It is essential that further research on the utilisation of data mining techniques for the prediction of body weight in the Ross 308 chicken breed is conducted using larger sample sizes, to enhance our understanding of this technology.

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Conflict of interest

The author has no conflicts of interest to declare.

References

Ağyar, O., Tırınk, C., Önder, H., Şen, H., Piwczyński, D., & Yavuz, E., 2022. Use of multivariate adaptive regression splines algorithm to predict body weight from body measurements of Anatolian buffaloes in Türkiye. *Animals*, 12(21):2923. DOI: 10.3390/ani12212923

Amao, S.R., 2022. Sexual dimorphism on body weight and some conformation traits of Ross 308 broiler chickens using Principal Component Analysis. *ADAN Journal of Agriculture*, 3:49–58. DOI: 10.36108/adanja/2202.30.0160

Amao, S.R., 2018. Application of principal component analysis on the body morphometric of Nigerian indigenous chickens reared intensively under southern guinea savanna condition of Nigeria. *Journal of Environmental Issues and Agriculture in Developing Countries*, 10(1):1–12.

Bila, L. & Tyasi, T.L., 2022. Multivariate principal component analysis of morphological traits in Ross 308 broiler chicken breed. *Asian Journal of Agriculture and Biology*, 2022(3):202103132. DOI: 10.35495/ajab.2021.03.132

Bila, L., Malatji, P.D., & Tyasi, T., 2023. Predicting body weight of South African Sussex cattle at weaning using multivariate adaptive regression splines and classification and regression tree data mining algorithms. *Journal of Applied Animal Research*, 51:608–615. DOI: 10.1080/09712119.2023.2258976

Çelik, Ş. & Yilmaz, O., 2018. Prediction of body weight of Turkish tazi dogs using data mining techniques: Classification and regression tree (CART) and multivariate adaptive regression splines (MARS). *Pakistan Journal of Zoology*, 50(2):575–583. DOI: 10.17582/journal.pjz/2018.50.2.575.583

Eyduran, E., Akin, M., & Eyduran, S., 2019. Application of multivariate adaptive regression splines in agricultural sciences through r software. Nobel Academic Publishing, Ankara, Türkiye.

Faraz, A., Tırınk, C., Önder, H., Şen, U., Shaq, H.M., Tauqir, N.A., Waheed, A., & Nabeel, M.S., 2023. Usage of the XGBoost and MARS algorithms for predicting body weight in Kajli sheep breed. *Tropical Animal Health and Production*, 55:276. DOI: 10.1007/s11250-023-03700-6

Faraz, A., Tirink, C., Eyduran, E., Waheed, A., Tauqir, N.A., Nabeel, M.S., & Tariq, M.M., 2021. Prediction of live body weight based on body measurements in Thalli sheep under tropical conditions of Pakistan using CART and MARS. *Tropical Animal Health and Production*, 53(2):301. DOI: 10.1007/s11250-021-02748-6

Habashy, W., Enab, A., & El-Tahawy, W., 2021. Prediction of body weight and other linear body weight measurements of leghorn versus two Egyptian strains of chicken. *Journal of Animal and Poultry Production*, 12(8):287–291. DOI: 10.21608/jappmu.2021.88242.1017

Hedayat-Evrigh, N., Khalkhali-Evrigh, R., Ramezani, Y., Seyed Sharifi, R., & Shakouri, M., 2023. Integrating analysis of publicly available microarray data to study the immune response of cattle to infection with *Mycobacterium bovis*. *Iranian Journal of Applied Animal Science*, 13(1):11–19.

Hlokoe, V., Mokoena, K., & Tyasi, T.L., 2022. Using multivariate adaptive regression splines and classification and regression tree data mining algorithms to predict body weight of Nguni cows. *Journal of Applied Animal Research*, 50:534–539. DOI: 10.1080/09712119.2022.2110498

Statistical Package for Social Sciences (SPSS), 2019. Statistical Packages for Social Sciences for Windows: Base System User's Guide, release 26.0 SPSS Inc., Chicago, USA.

Iqbal, F., Raziq, A., Zil-E-Huma., Tirink, C., Fatih, A., & Yaqoob, M., 2023. Using the artificial bee colony technique to optimize machine learning algorithms in estimating the mature weight of camels. *Tropical Animal Health and Production*, 55:86. DOI: 10.1007/s11250-023-03501-x

Isaac, U. & Adeolu, A., 2023. Linear models for predicting body weight of crossbred chickens. *International Journal of Research and Innovation in Applied Science*, VIII(IV):62–70. DOI: 10.51584/IJRIAS.2023.8407

Isaac, U.S., Okafor, N.J., Nwachukwu, B.C., Albert, J.C., Aniemena, C.F., & Igbokwe, C.A., 2024. Stepwise canonical discriminant analysis for morphometric characterization of three strains of broiler chicken. *Genetik*a, 56(1):43–54. DOI: 10.2298/GENSR2401043I

Karadas, K. & Birinci, A., 2019. Determination of factors affecting dairy cattle: a case study of Ardahan province using data mining algorithms. *Revista Brasileira de Zootecnia*, 48:e20170263. DOI: 10.1590/rbz4820170263

Kuhn, M. & Johnson, K., 2013. Applied Predictive Modeling, Volume 26. Springer, New York, USA.

Liswaniso S., Qin, N., Tyasi, T.L., & Chimbaka, I.M., 2021. Use of data mining algorithms CHAID and CART in predicting egg weight from egg quality traits of indigenous free-range chickens in Zambia. *Advances in Animal and Veterinary Sciences*, 9(2):215–220. DOI: 10.17582/journal.aavs/2021/9.2.215.220

Manyelo, T.G., Sebola, N.A., Ng'ambi, J.W., Weeks, W., & Mabelebele, M., 2022. The influence of different amaranth leaf meal inclusion levels on performance, blood profiles, and gut organ characteristics of Ross 308 broiler chickens. *Frontiers in Veterinary Science*, 9:869149. DOI: 10.3389/fvets.2022.869149

Mathapo, M., Mugwabana, T., & Tyasi, T.L., 2022. Prediction of body weight from morphological traits of South African non-descript indigenous goats of lepelle-nkumbi local municipality using different data mining algorithm. *Tropical Animal Health and Production*, 54:1–9. DOI: 10.1007/s11250-022-03096-9

Önder, H., Tirink, C., Yakubets, T., Getya, A., Matvieiev, M., Kononenko, R., Şen, U., Özkan, Ç.Ö., Tolun, T., & Kaya, F., 2025. Predicting live weight for female rabbits of meat crosses from body measurements using LightGBM, XGBoost and support vector machine algorithms. *Veterinary Medicine and Science*, 11(1):e70149. DOI: 10.1002/vms3.70149

Oyebanjo, M., Coker, O., & Osaiyuwu, O., 2023. Predicting the body weight of indigenous goat breeds from morphological measurements using the classification and regression tree (CART) data mining algorithm. *Biotechnology in Animal Husbandry*, 39:33–49. DOI: 10.2298/BAH2301033O

Rashijane, L., Mokoena, K., & Tyasi, T.L., 2023. Using multivariate adaptive regression splines to estimate the body weight of Savanna goats. *Animals*, 13:1–11.

Soltanali H., Emadi B., Rohani A., Khojastehpour M., & Nikkhah A., 2016. Optimization of energy consumption in milk production units through integration of data envelopment analysis approach and sensitivity analysis. *Iranian Journal of Applied Animal Science*, 6(1):15–29.

Tirink, C., 2022. Comparison of Bayesian regularized neural network, random forest regression, support vector regression and multivariate adaptive regression splines algorithms to predict body weight from biometrical measurements in Thalli Sheep. *Kafkas Üniversitesi Veteriner Fakültesi Dergisi*, 28(3):411–419. DOI: 10.9775/kvfd.2022.27164

Tırınk, C., Onder, H., Francois, D., Marcon, D., Şen, U., Shaikenova, K., Omarova, K., & Tyasi, T.L., 2023. Comparison of the data mining and machine learning algorithms for predicting the final body weight for Romane sheep breed. *PLoS One*, 18(8):e0289348. DOI: 10.1371/journal.pone.0289348

Tyasi, T.L., Eyduran, E., & Celik, S., 2021. Comparison of tree-based regression tree methods for predicting live body weight from morphological traits in Hy-line silver brown commercial layer and indigenous Potchefstroom Koekoek breeds raised in South Africa. *Tropical Animal Health and Production*, 53:7. DOI: 10.1007/s11250-020-02443-y

Tyasi, T.L., Makgowo, K.M., Mokoena, K., Rashijane, L.T., Mathapo, M.C., Danguru, L.W., Molabe, K.M., Bopape, P.M., Mathye, N.D., & Maluleke, D., 2020. Multivariate adaptive regression splines data mining algorithm for prediction of body weight of Hy-line silver brown commercial layer chicken breed. *Advances in Animal and Veterinary Sciences*, 8(8):794–799. DOI: 10.17582/journal.aavs/2020/8.8.794.799

Wojnarowska, A., Palka, S., Otwinowska-Mindur, A., & Ptak, E., 2022. Comparison of two nonlinear functions describing the growth of Popielno White and New Zealand White rabbits. *Animal Science and Genetics*, 18(4):1–13. DOI: 10.5604/01.3001.0016.1097

Yakubu, A. & Ari, M., 2017. Principal component and discriminant analyses of body weight and conformation traits of Sasso, Kuroiler and indigenous Fulani chickens in Nigeria. *Journal of Animal and Plant Sciences*, 28:46–55.

Yakubu, A., 2011. Discriminant analysis of sexual dimorphism in morphological traits of African Muscovy Ducks. *Archivos de Zootecnia*, 60(232):1115–1123.