APPLICATION OF DATA MINING ALGORITHMS FOR ESTIMATING LIVE BODY WEIGHT FROM LINEAR BODY MEASUREMENTS OF UKRAINIAN BEEF CATTLE BREED

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Abstract. The study was conducted to estimate live body weight of Ukrainian Beef Cattle (UBC) breed using Multivariate adaptive regression splines (MARS), and Classification and regression tree (CART) data mining algorithms. A total of 50 heifers at 12 months of age were used to collect live body weight (BW), Withers height (WH), rump height (RH), elbow join height (EJH), heart girth (HG), chest width (CW), width at the hip joints (WHJ) and width at the knee cups (WKC). The correlation results indicated that BW showed a highly positive correlation ($P < 0.01$) with CW, EJH, and RH. MARS model showed that HG and CW were the most important traits for estimation of body weight of 12 months old UBC breed while CART model indicated WH, CW and RH were the most important traits. MARS and CART models were compared using Pearsons' correlation coefficient (r), coefficient of determination (R^2), adjusted R^2 (Adj.R^2), root-mean-square error (RMSE), Akaike information criteria (AIC), and coefficient of variance (CV). The results showed that CART was the best model with the highest R^2 (0.72), Adj.R^2 (0.72), and r (0.84) with the lowest RMSE (20.74), AIC (254.69), and CV (6.15). This study suggests that CART data mining algorithm might be used to determine breed standards of Ukrainian beef cattle breed for breeding program.
Keywords: *multivariate adaptive regression splines, classification and regression tree, heifers, breeding, live weight, machine learning*

Introduction

The beef cattle production is an essential part of ensuring food security in many parts of the world. The FAO shows that beef cattle production is estimated to grow by 9.27% to reach 78 million tonnes in carcass weight equivalent by 2032 (OECD/FAO, 2023). It should be noted that in the period from 2018 to 2021, there was a decrease in the production of beef and veal meat in Ukraine. Thus, in 2021, 310.5 thousand tonnes were produced, which is 13.48% less than in 2018 (Nechyporenko et al., 2024). Moreover, in 2022, Ukraine produced 268.4 thousand tonnes of beef and veal meat, which is 12.16% of the Ukrainian meat balance (Statistical yearbook "Agriculture of Ukraine" for 2022, 2023). This amount does not meet the needs of the Ukrainian population, and therefore there is a great need for increasing beef cattle production, which is limited by several reasons. Meat from specialised meat cattle breeds is considered particularly valuable (Ugnivenko et al., 2022). According to the state register, at the beginning of 2023 there were 36.7 thousand head of cattle on Ukrainian breeding farms thereby only 6.5% were specialised meat cattle breeds (Pryjma, 2023). There are 11 registered meat cattle breeds in Ukraine, of which 4 are indigenous breeds. The most common cattle breed now in Ukraine is the Aberdeen Angus (42%) cattle. The total number of beef cows in Ukraine as of 01.01.2022 was 20 thousand head (SSSU, 2024), which are mainly kept in the north of the country (Suprun et al., 2016). It is well known that high results in cattle breeding can only be achieved if animals are properly evaluated and their productivity is recorded. In beef cattle breeding, the most important economic traits are weight gain at different stages of life, calf survival rate and cow productive lifetime (Krupová et al., 2020). However, linear body measurements play an important role in the evaluation of animal growth (Hozáková et al., 2020). Weighing and measuring animals are usually carried out at regular intervals, which can be stressful for the animals. Ukraine is in the process of adapting its legislation to EU requirements, including animal welfare standards. Therefore, companies are interested in reducing the number of weighing and measurements and are ready to use AI to predict live weight. Technologies for the application of video monitoring with appropriate data interpretation are already being actively researched (Hansen et al., 2018; Dohmen et al., 2021; Liu et al., 2023; Giagnoni et al., 2024). Over time, significant amounts of data about animals accumulate on farms and their processing requires the use of specialised mathematical tools, including data mining and machine learning methods that enable genomic prediction, phenotype fraud detection, genotype imputation, mastitis detection, image analysis and microbiome analysis (Morota et al., 2018). Productivity forecasts can be made in a variety of ways. However, the use of common statistical tools (Ozkaya and Bozkurt, 2009; Merlo-Maydana et al., 2024) requires a clear understanding that the available data meet the criteria of normal distribution (Yavuz and Şahin, 2022). The use of machine learning algorithms does not require such compliance (Tyasi et al., 2020), and thus these methods have been widely used to analyse the performance of different animal species (Aksoy et al., 2018; Çanga, 2021; Portocarrero Banda et al., 2023). In the world practice, various data mining algorithms are used to predict live body weight, including multivariate adaptive regression splines (MARS), chi-squared automatic interaction detector (CHAID), exhaustive CHAID and classification and regression trees (CART) (Celik, 2019), as well as support vector machine regression (SVR) algorithms (Tırınk, 2022) and Multilayer Perceptron (MLP) algorithm (Karadas and Birinci, 2019). MARS is a non-parametric regression technique that does not involve some supposition around the dispersal of the variables and correlation between the variables entered the estimative model to be built into statistical evaluation (Fatih et al., 2021). Overall, the CART analysis is a great geometric approach that assesses the most imperative parameters in a specific data set and aids in designing a specific model (Fatih et al., 2021). Moreover, CART is known as algebraic technique which is suitable for varies forms of data such as ordinal, nominal and continuous variables (Tyasi et al.,

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2020). CART estimations can be used by animal keepers in decision-making processes regarding herd management. Faraz et al. (2021) indicated that CART and MARS algorithms have a strong potential to overcome the multi-collinearity problems in estimating body weight. The MARS and CART algorithms have proven to be one of the most widely used in livestock production, as they have been applied to a wide range of tasks, such as determining the pregnancy status of cows (Çanga and Boğa, 2022), detecting insemination problems (Grzesiak et al., 2010), diagnosing mastitis in cows (Altay et al., 2022), estimating carcass weight of cattle (Çanga, 2022), predicting body weight based on body measurements in sheep (Faraz et al., 2021) and buffalo (Ağyar et al., 2022), modelling lactation curves (Orhan et al., 2018), predicting honey production (Karadas and Kadırhanogullari, 2017), and determining the effect of different factors on live weight at the end of fattening sheep (Şengül et al., 2022). In Ukraine, the use of artificial intelligent in livestock production for productivity prediction is not yet widespread, but such studies are underway, and the results are encouraging (Matvieiev et al., 2023). The aim of this study was to evaluate the two most common data mining algorithms (MARS and CART) for estimating live body weight from linear body measurement traits of Ukrainian beef cattle.

Materials and methods

Ethical clearance for this research was granted by the Animal Care and Use Committee of the faculty of animal husbandry and food Technologies, Poltava State Agrarian University, Ukraine (Ethical clearance number: protocol number 1 from 01.07.2024).

The study was conducted at Volia breeding farm, Zolotonosha district, Cherkasy region of Ukraine. Heifers were kept traditionally for beef cattle. From birth to 8 months of age, heifers were kept together with their mothers and received additionally roughage and crushed grain. Heifers were weaned at 8 months and kept untethered in groups of up to 50 on deep, permanent bedding. The heifers were grazed from May to September. From October to April, they were kept indoors with free access to the walking grounds. The area of the premises was at least 3 m^2 per heifer. The area of the ground-based exercise areas was more than 15 m^2 per head. Feeding during the autumn and winter included silage, hay, straw and crushed cereals (wheat, maize, peas, barley), balanced according to age and body weight. Access to water and minerals was free on the farm and three times a day during the grazing period.

The study was conducted on 50 heifers of the Ukrainian Beef Cattle (UBC) breed at 12 months of age. The breed was created at the end of the 20^{th} century by reproductive crossbreeding of Charolais (C), Kian (K), Simmental (S) and Ukrainian Grey (UG). Modern animals have a genotype of 3/8 K, 3/8 Sh, 1/8 C and 1/8 UG (Ugnivenko and Nosevych, 2019). The live weight of the heifers was determined by weighing them on the first day after birth and once a month during the growing period. Withers height (WH), rump height (RH), elbow join height (EJH), heart girth (HG), chest width (CW), width at the hip joints (WHJ) and width at the knee cups (WKC) were collected at 12 months of age (*Figure 1*). All measurements were made following the guideline defined by Bochkov (2014).

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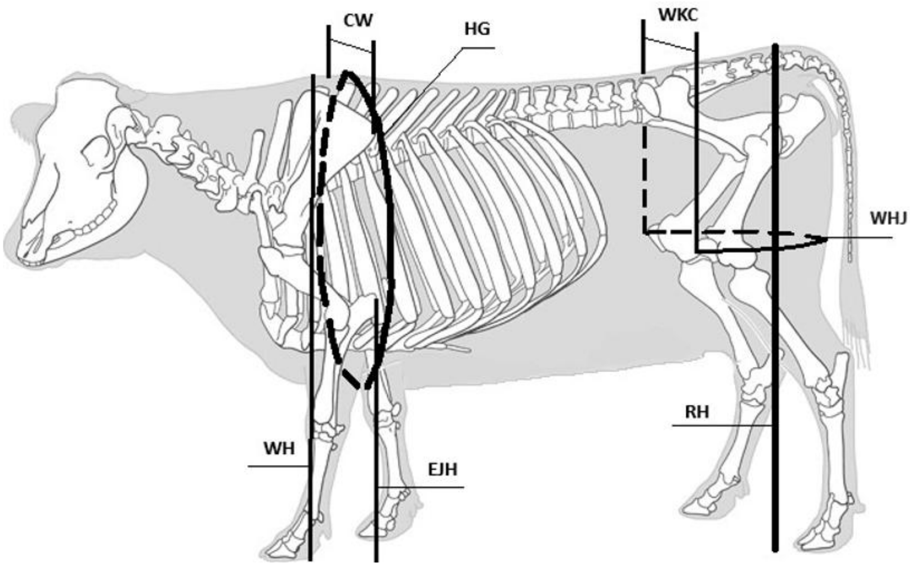

Figure 1. *The diagram illustrates the linear body measurement traits*

The statistical Package for Social Sciences (IBM SPSS. 2019) version 26.0 with a probability of 5 % for significance was used to analyse the data for analysis of descriptive statistics of body weight and linear body measurement traits. The MARS and CART were performed using EhoGof package (version 0.1.1, Igdir, Turkiye) following the procedure explained by Eyduran et al. (2019).

MARS algorithm fits a series of linear regression functions for predicting the values of the continuous dependent variable (Friedman, 1991; Iqbal et al., 2023). The MARS was carried out as defined by Bila et al. (2023) and Rashijane et al. (2023). MARS data mining algorithm can be defined as:

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

where:
f(x) is the estimated value of the dependent variable, β_0 and β_m are intercept, $h_m(X_{v(k,m)})$ is the basis function, where $v(k, m)$ is an index of the predictor for the m_{th} component of the k_{th} product, K is the parameter regulating the order of interaction. The cross-validation error (GCV) was used to prune after MARS was developed following the procedure explained by Eyduran et al. (2019).

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

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 replicating data mining algorithm tree was created by splitting a node into pairs of child nodes as explained by Breiman et al. (1984) and Kuhn and Johnson (2020).

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Predictive performance of the models was performed to determine the best fit model using goodness of fit criteria. The following goodness of fit criteria were used as explained by Bila et al. (2023):

Pearson's correlation coefficient (r):

$$r = \frac{\mathrm{cov}(y_i, y_{ip})}{S_{yi}\, S_{Yip}} \quad \text{(Eq.3)}$$

Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad \text{(Eq.4)}$$

Adjusted Coefficient of Determination (Adj.R^2):

$$\mathrm{Adj.}R^2 = 1 - \frac{\frac{1}{n-k-1}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\frac{1}{n-1}\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad \text{(Eq.5)}$$

Root-mean-square error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad \text{(Eq.6)}$$

Akaike Information Criteria (AIC):

$$\mathrm{AIC} = \mathrm{N\ Ln}\left(\frac{\mathrm{SSE}}{N}\right) + 2p \quad \text{(Eq.7)}$$

Coefficient of variance (CV):

$$\mathrm{CV} = \sqrt{\frac{\frac{1}{n-1}\sum_{i=1}^{n}(\varepsilon_i - \bar{\varepsilon})^2}{\bar{Y}}} \times 100 \quad \text{(Eq.8)}$$

Results

Descriptive statistics

Descriptive statistics of body weight age and linear body measurement traits at 12 months of UBC breed are presented in *Table 1*. The results showed that the yearly body weight of UBC breed ranged from 279 kg to 425 kg.

Correlation matrix

Figure 2 denotes Pearson's correlation coefficients for estimating the correlation between body weight and linear body measurements of UBC breed at 12 months of age. The results showed that BW was positive moderately correlated ($P < 0.01$) with CW (0.55), EJH (0.49), and RH while positively low correlated ($P < 0.05$) with WHJ (0.22).

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Table 1. *Descriptive statistics of body weight and linear body measurements of UBC*

TRAITS	MEAN ± SD	Minimum	Maximum
BW (kg)	342.02 ± 39.73	279.00	425.00
WH (cm)	115.38 ± 6.95	100.00	127.00
EJH (cm)	71.70 ± 4.32	63.00	81.00
RH (cm)	122.56 ± 7.58	106.00	136.00
HG (cm)	148.24 ± 12.37	123.00	172.00
CW (cm)	39.94 ± 2.79	36.00	49.00
WHJ (cm)	38.98 ± 2.19	34.00	45.00
WKC (cm)	40.84 ± 2.19	36.00	46.00

BW: body weight, WH: wither height, EJH: elbow joint height, RH: rump height, CW: chest width, WHJ: width at the hip joint, LW:, and WKC: width at the knee cup

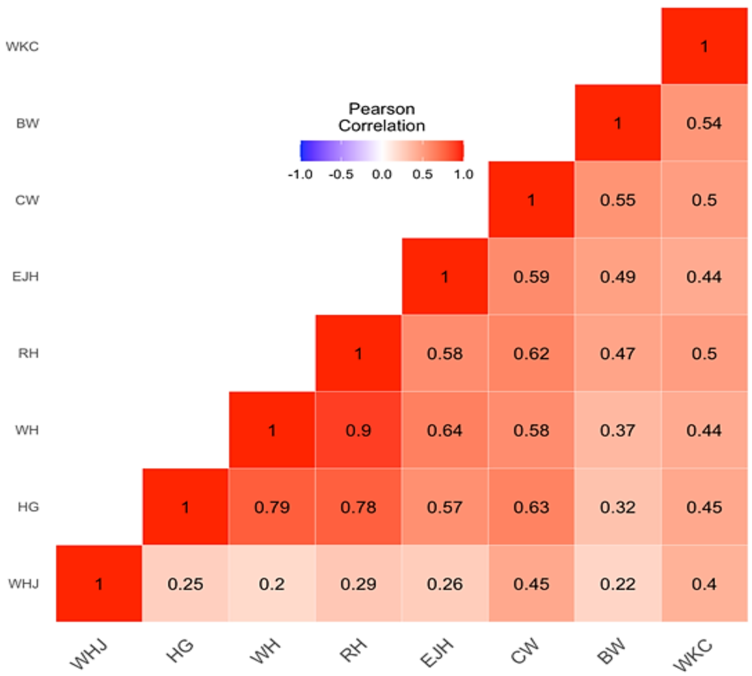

Figure 2. *Heat map of body weight correlation of measured traits in UBC breed. Correlation colour demonstration is as follows: high correlation is red, mid correlation is white and low correlation is blue BW: body weight, WH: wither height, EJH: elbow joint height, RH: rump height, CW: chest width, WHJ: width at the hip joint, LW:, and WKC: width at the knee cup*

MARS model

Table 2 below shows the MARS model results. The first term of the model had an intercept that had a coefficient of 317.71. The second term, HG, had a cut-point of 158 cm for a negative coefficient of 4.42. Meanwhile the last term, CW, had a cut-point of 38 cm with a positive coefficient of 14.20. The basic functions that decrease the performance of the model attained after the forward and backward pass phases were eliminated due to the GCV in MARS modeling.

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Table 2. *MARS model*

Variables	Coefficients
Intercept	317.71
h(HG-158)	-4.42
h(CW-38)	14.20

HG: heart girth and CW: chest width

CART model

Figure 3 depicts the regression tree diagram formed by the CART algorithm in estimating body weight of UBC breed at 12 months of age from the linear body measurements. At the topmost of the regression tree diagram, overall body weight of the UBC breed was recorded as 341 kg. At the first tree average, the body weight was 327 kg with CW < 41 cm was lighter by 14 kg. At the second depth of the tree, the average body weight was 319 kg with WH ≥ 112 cm. Furthermore, at the third depth of the tree, the average body weight was 313 kg of UBC breed at 12 months of age.

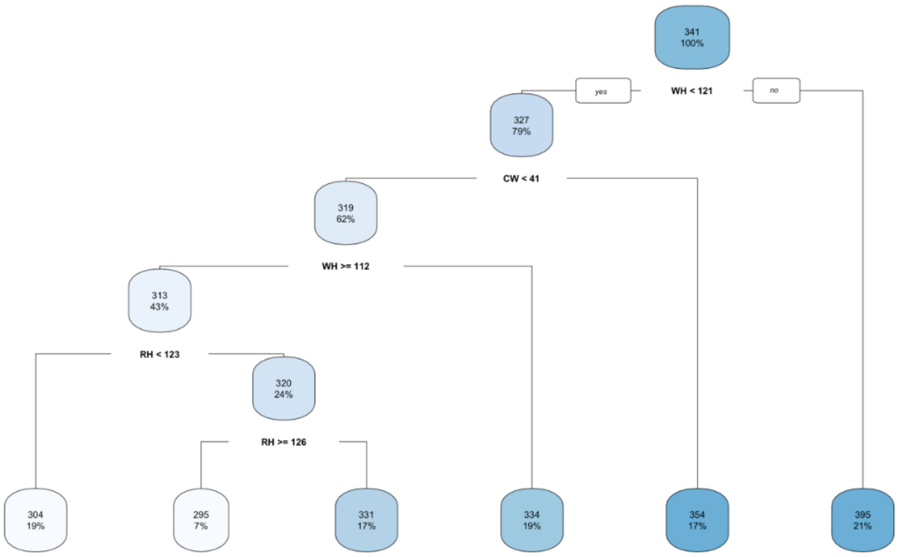

Figure 3. *CART model*

MARS and CART predictive performance

The quality of the live weight predictions obtained using the MARS and CART algorithms is shown in *Table 3*, which contains the goodness of fit criteria for both the Training and Test data sets. In general, both algorithms had better/higher goodness of fit criteria for the training set than for the test one, which is explained by the larger number of animals in the training set. Analysing the criteria for the training set, six out of six goodness of fit criteria were better for the CART algorithm. In particular, the Pearson's correlation coefficient between actual and predicted body weight for CART was 0.84, while for MARS – 0.75. For example, Akaike's information criterion for CART was 254.69, while for MARS – 279.97. Although the RMSE were better for MARS, their advantage was not significant. Thus, we can note that the CART algorithm better predicted the live weight of beef cattle in our study.

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Table 3. *Goodness of fit criteria for MARS and CART algorithms*

CRITERIONS	MARS		CART		DECISION
	Training	**Test**	**Training**	**Test**	
Pearson's correlation coefficient (r)	0.75	0.15	0.84	0.26	Greater is better
Root mean square error (RMSE)	26.09	42.26	20.74	43.28	Smaller is better
Coefficient of variation (CV)	7.74	13.05	6.15	12.75	Smaller is better
Akaike's information criterion (AIC)	279.97	65.90	254.69	60.28	Smaller is better
Coefficient of determination (Rsq)	0.56	-0.23	0.72	-0.29	Greater is better
Adjusted coefficient of determination (Arsq)	0.52	-1.16	0.72	-0.29	Greater is better

Discussion

The linear body measurement traits are positively influential on live body weight cattle and are used as indirect selection criteria in breeding strategies (Bila et al., 2023). This study firstly investigated the relationship between body weight and certain linear body measurements of Ukrainian beef cattle breed. The correlation results showed that the live body weight of UBC breed at 12 month of age was highly correlated with chest width, elbow joint height, and rump height. The results of the current study disagree with the reports made by Tyasi et al. (2020) who reported that male Nguni cattle, linear body measurement traits such as sternum height, heart girth, withers height and rump width had a significant positive correlation with live body weight. The variation might be due to cattle breed and sex of the used cattle. The correlation coefficient does not specify the effect of linear body measurement traits on the live body weight of animals; it only shows the degree of the relationship among the measured traits (Celik, 2019). Hence the application of data mining algorithms was used to estimate the live body weight from linear body measurement traits of UBC breed at 12 months of age. Mathapo et al. (2022) reported that the regression models cannot overcome the challenge of the multi-collinearity. Hence, data mining algorithms had been used to estimate live body weight from linear body measurements of UBC breed. In this study, MARS and CART data mining algorithms had been adopted to compare the results for the estimating live body weight of UBC breed. The results of the present study showed that CART had a higher predictive performance in the criteria as compared to MARS algorithm. The results of this study suggest that CART algorithm can be used to predict the live body weight of UBC breed at 12 months of age. These finding are not in-lined with the reports made by Bila et al. (2023) who revealed that MARS had a higher predictive performance in the criteria as compared to CART algorithm in South African Sussex cattle at weaning. MARS data mining algorithm had been recommended on estimation of live body weight in South African Nguni cows by Hlokoe et al. (2022). MARS had been also recommended based on the training and test data set by Canga (2022) on prediction of hot carcass weight of seven cattle breeds such as Aberdeen-Angus, Simmental, Limousine, Holstein–Friesian, Charolais, Zebu and Hereford using breed, age and live body weight. MARS was suggested as the best model for prediction of body weight in Anatolian buffalo in Turkey (Ağyar et al., 2022). Although Ukraine has a beef cattle evaluation manual that is valid for all breeds, this study has shown the possibility of applying of the mentioned mathematical approaches to the prediction of body weight of Ukrainian beef cattle breeds. For other beef cattle breeds available in Ukraine, additional further research is needed.

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Conclusions

It is concluded that live body weight of Ukrainian beef cattle breed at 12 months of age is highly correlated with chest width, elbow joint height and rump height. Therefore, increasing CW, EJH and RH might improve body weight of Ukrainian beef cattle breed at 12 months of age. This study showed that CART data mining algorithm is the best model to predict live body weight of Ukrainian beef cattle at 12 months of age. It might be suggested that CART data mining algorithm can help to determine breed standards of Ukrainian beef cattle breed for breeding program.

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Conflict of interests. All authors declare no conflict of interest.

Availability of data and materials. All the data used in the study is available on request from the corresponding author.

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