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FINAL FATTENING LIVE WEIGHT PREDICTION IN ANATOLIAN MERINOS LAMBS FROM SOME BODY CHARACTERISTICS AT THE INITIAL OF FATTENING BY USING SOME DATA MINING ALGORITHMS

Gizem COŞKUN[1]*, Özcan ŞAHİN[1], Yasin ALTAY[2], İbrahim AYTEKİN[1]

[1]University of Selcuk, Faculty of Agriculture, Department of Animal Science, 42130, Konya, Türkiye
[2]Eskisehir Osmangazi University, Faculty of Agriculture, Department of Animal Science, 26030, Eskişehir, Türkiye

Abstract: This study's objective was to compare the performances of Random Forest (RF), eXtreme Gradient Boosting (XGBoost), and Bayesian Regularization Neural Network (BRNN) algorithms, which are some data mining algorithms used in final fattening live weight prediction. As the independent variable in the design of the algorithms, some body characteristics taken before fattening of 54 heads of Anatolian Merino lambs, with single birth and male, were withers height (WH), rump height (RH), body length (BL), chest girth (CG), leg girth (LG), and chest depth (CD) was used. The mean±standart errors for the body characteristics of Anatolian Merino lambs were determined to be 63.481±0.538, 63.315±0.501, 78.930±1.140, 60.037±0.549, 47.704±0.543, and 29.926±0.377, respectively. The mean initial live weight (ILW) and the mean final live weight (FLW) were found as 35.89±0.84 and 49.49±0.88 kg, respectively. There was difference of 13.60 kg between ILW and FLW means. The ILW and FLW were shown to positively correlate with body characteristics, and this correlation was statistically significant ($P<0.01$). While the highest Pearson's correlation ($r=0.95$) of FLW was between WH and RH, the lowest Pearson's correlation ($r=0.51$) was found between LG and CD. While the largest share of body characteristics in the total variance in the FLW estimation was BL (42.969%) in the XGBoost algorithm, the lowest share was found to be CD (0.00) in the XGBoost algorithm and LG (0.00) in the BRNN algorithm. The model evaluation criterias which were Root mean square error (RMSE), Standard deviation ratio (SDR), Mean absolute percentage error (MAPE), and Adjusted coefficient of determination (R^2_{Adj}) performed as 1.492, 0.233, 2.241 and 0.944, in the XGBoost algorithm, as 2.220, 0.347, 3.139 and 0.880 in the BRNN algorithm, as 2.859, 0.446, 4.340 and 0.792 in the RF model, respectively. As a result, it can be said that the data mining algorithms used in prediction FLW taking advantage of body measurements of Anatolian Merino lambs at the beginning of fattening will benefit from their use in fattening due to their high prediction performance.

Keywords: Anatolian Merino, Body characteristics, Data mining algorithms, Fattening, Prediction

***Corresponding author:** University of Selcuk, Faculty of Agriculture, Department of Animal Science, 42130, Konya, Türkiye
E mail: coskun.gizem96@gmail.com (G. COŞKUN)
Gizem COŞKUN https://orcid.org/0000-0003-2519-7885
Özcan ŞAHİN https://orcid.org/0000-0003-2170-2055
Yasin ALTAY https://orcid.org/0000-0003-4049-8301
İbrahim AYTEKİN https://orcid.org/0000-0001-7769-0685

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1. Introduction

The revenue from slaughter lambs is a significant portion of the income from sheep breeding. Butchery lambs are generally supplied from extensive sheep breeding in Türkiye. Lambs grazed on pastures, which are the cheapest source of roughage, with their dams in spring and summer, are evaluated as butchery lambs when they reach 25-30 kg live weight. The lambs are fattened with concentrate and roughage sources after being weaned, and when they weigh 35 to 40 kg live weight, they are sent to slaughter. However, some breeders may have to resort to early lamb slaughter due to socio-economic reasons (Boztepe et al., 1997). The goal of lamb meat production is to get the best yield and quality for the least amount of cost in the shortest fattening time (Aytekin et al., 2015). The success of an intensive fattening performance is demonstrated by selling the product at the highest price by the best satisfying consumer demand (Şahin and Akmaz, 2002). In order to avoid financial losses, it is crucial to follow growth and development during the fattening phase. Body measurements taken to monitor growth and development are also required to select the best animals based on the direction of the yield, identify issues with maintenance and feeding in the business, and estimate the number of tools and equipment, such as feeders, grazers, and drinkers (Ertuğrul, 1996).

The ideal lamb fattening program is started immediately after the lambs are weaned, by applying an adaptation period in herd management. However, in some breeding seasons, feed and meat price instability and poor enterprise management hinder both the beginning and end of fattening periods. However, some conventional sheep producers may delay the start of lamb fattening in order to complete other agricultural activities such as sowing and planting, and so on. In such cases, the breeders are working on production systems with the least cost, and the proper provision of it makes for more profitable and satisfactory sheep husbandry for breeders. For such reasons, sometimes a slightly later start of fattening may be preferred.

It is possible to compare animals by measuring their bodies at regular intervals in order to track their growth and development, express their body structures, and get an idea of how to set up care and food plans for herd management (Zülkadir et al., 2008). Body measurements vary depending on significant traits such as breed, age, sex, and type of yield during growth and development periods (Pesmen and Yardimci, 2008). There have been many studies of literature in which the relationships between body weight and body measurements are defined and the body weight estimation is made with some data mining algorithms by using body measurements (Yakubu, 2012; Ali et al., 2015; Eyduran et al., 2017; Aytekin et al., 2018; Çelik and Yılmaz, 2018; Huma ve Iqbal, 2019; Abbas et al., 2021; Louis-Tyasi et al., 2021; Mathapo and Tyasi, 2021; Altay, 2022; Coşkun et al., 2022; Mathapo et al., 2022). However, the fact that there is no study that predicts final live weight (FLW) by using both Anatolian Merino breed and initial fattening body characteristics distinguishes this study from others.

In this study, eXtreme Gradient Boosting (XGBoost), Random Forest (RF), and Bayesian Regularization Neural Network (BRNN) data mining algorithms were used to predict the live weight at the end of fattening by using some body characteristics at the initial of fattening in Anatolian Merino lambs, and they was aimed to compare the prediction evaluation performances.

2. Materials and Methods

2.1. Animal Material

This study's animal material included 54 head lambs with single birth type and male Anatolian Merino, which were fattened on a private farm in the district of Kadınhanı in Konya. Lambs were fed intensively for 45 days between October and November 2021. Lambs were fed concentrated feed *ad libitum* along with 180 g of dried alfalfa per day for 8 weeks beginning after a 14-day acclimation period. The mixed feed used during fattening is presented in Table 1.

2.2. Measurement of Body Characteristics and Live Weight of Anatolian Merino Lambs

Lambs were measured individually for live weight, withers height (WH), body length (BL), rump height (RH), chest girth (CG), leg girth (LG), and chest depth (CD) at the beginning of fattening in the morning on an empty stomach. The determination of live weights was made with a 100 g precision scale. Body measurements were determined with a measuring stick (WH, RH, BL, and CD) and measuring tape (CG and LG) as reported by Ertuğrul (1996). The fattening lasted for 45 days, and at the end of the fattening, the live weights of the animals were determined and the study was terminated. This study did not require ethical approval because different body measurements were taken from lambs in accordance with their operational procedures for each measurement.

Table 1. Ingredient composition and nutritional composition of the feed used in the study

Ingredients	(%)
Barley	60.00
Corn	22.76
Sunflower seed meal	15.35
Limestone	1.39
Salt	0.25
Vitamin- mineral premix	0.25
Total	100
Calculated nutrient composition	
Crude protein, %	15.64
Metabolic energy, kcal/kg ME	2720
Ca, %	0.62
P, %	0.46

2.3. Statistical Analysis

2.3.1. Bayesian regularized neural network algorithm (BRNN)

One of the most popular artificial intelligence algorithms, Artificial Neural Networks (ANNs), is architecturally similar to the human brain and may be used for sequential, nominal, and scale-dependent variables (Ali et al., 2015). Three layers make up an ANNs: the input layer, the hidden layer, and the output layer, respectively. The hidden layer depends on the input layer, which is the first layer, which is made up of independent variables, to begin the process. The activation functions and weights of the independent variables are handled by the hidden layer, which is used to examine how independent variables affect the dependent variable (Kayri, 2016). In comparison to linear models, two types of ANN algorithms, such as radial basis functions neural networks (RBFNN) and BRNN, allow analysts to build better predictive models (Pérez-Rodríguez et al., 2013).

2.3.2. Random forest (RF)

Breiman, (2001) proposed the RF algorithm, which increases the bagging algorithm and adds a layer of arbitrariness. The RF algorithm combines sets of regression trees to create a learning algorithm. A regression tree is characterized as a collection of restrictions that are utilized hierarchically to the tree's leaves from the root (Rodriguez-Galiano et al., 2014; Wang et al., 2016). The best feature of this algorithm is how easily it can be applied to non-linear situations.

The RF algorithm requires a three-stage procedure (Liaw and Wiener, 2002). A number of the trees (n_{tree}) bootstrap samples from the initial data constitute the first step. The creation of an un-pruned classification or regression tree for each sample is the second step. Predicting the most recent data from the tree is the final step. Model parameters like n_{tree} and the number of variables tried at each split (m_{try}) are selected to be 100 and 3, respectively, for this data set.

2.3.3. eXtreme gradient boosting algorithm (XGBoost)

Chen and Guestrin (2016) proposed the XGBoost algorithm as a more efficient machine learning algorithm constructed by gradient boosting (Ma et al., 2018; Carmona et al., 2019). Additionally, the XGBoost algorithm is based on the gradient tree boosting method and the regression tree algorithm, both of which use parallel decision laws as the decision tree (Hastie et al., 2009; Zhong et al., 2018). The independent variables that can increase the effectiveness of the model created for the decision tree identifying the groups are used by XGBoost during the training process. Also, unnecessary variables are frequently created at the cost of computation time (Gertz et al., 2020). The primary goal of this process is to create decision trees with high-variance and low bias (Chen and Guestrin, 2016).

2.3.4. Performance evaluation criteria of data mining algorithms

In the study, the prediction performances of data mining algorithms were evaluated with the help of criteria commonly used in the literature, and it was given in the equations between 1 and 9 below (Zhang and Goh, 2016; Zaborski et al., 2019). In the comparison phase of algorithms, root-mean-square error (RMSE), relative root mean square error (RRMSE), coefficient of variation (CV), performance index (PI), mean error (ME), relative approximation error (RAE), mean relative approximation error (MRAE), mean absolute percentage error (MAPE), and mean absolute deviation (MAD), Akaike's information criterion (AIC), and adjusted Akaike's information criterion (AIC Adj) prediction evaluation criteria should be close to 0, while Pearson's correlation coefficients (PC), coefficient of determination (R^2), and adjusted coefficient of determination (R^2_{Adj}) criteria should be close to 1 in order to be good estimators. Also, the standard deviation ratio (SD_{ratio}) criterion must take values less than 0.10 (Eyduran et al., 2019). Equations 1 to 9 below were mathematical formulas for presenting some critical prediction performances criteria.

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

$$SD_{ratio} = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y_i})^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{ip} - \overline{y_{ip}})^2}} \quad (2)$$

$$RAE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - y_{ip})^2}{\sum_{i=1}^{n} y_i^2}} \quad (3)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - y_{ip}}{y_i}\right| x100 \quad (4)$$

$$MAD = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_{ip}\right| \quad (5)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - y_{ip})^2}{\sum_{i=1}^{n}(y_{ip} - \overline{y_{ip}})^2} \quad (6)$$

$$R^2\text{Adj} = 1 - \frac{\sum_{i=1}^{n}(y_i - y_{ip})^2/(n-1)}{\sum_{i=1}^{n}(y_{ip} - \overline{y_{ip}})^2/(n-p-1)} \quad (7)$$

$$AIC = n.In\left[\frac{1}{n}\sum_{i=1}^{n}(y_i - y_{ip})^2\right] + 2k \quad (8)$$

$$\text{if } n/k>40\text{, or } AIC_{Adj} = AIC + \frac{2k(k+1)}{n-k-1} \quad (9)$$

where: n is the number of lambs, k is the number of model parameters, p is the number of body characteristics, y_i is the actual value of live weight of Anatolian Merino lambs at ending fattening, and y_{ip} is the predicted FLW.

R software was used for all analyses, taking cross-validation as 5 (R Core Team, 2020). Results were obtained by using RF algorithm "randomForest", XGBoost and BRNN algorithms "e1071" packages. Data mining algorithms' model evaluation performance criteria were evaluated using the "ehaGoF" package (Eyduran, 2020). Using the R software "corrplot" package, Pearson correlation coefficients between FLW and body characteristics were calculated. Also, the multicollinearity problem between the independent variables was examined at the outset of the analysis, and it was discovered that there was none.

3. Results and Discussion

Table 2 showed that some descriptive statistics on the live weight at the beginning of fattening, the live weight at the end of fattening, and some body characteristics of Anatolian Merino male lambs. While the average live weight of lambs at the beginning of the fattening was 35.891 kg, the average live weight at the end of the fattening was 49.487 kg. The average daily live weight gain of the lambs during the 45-day fattening period was calculated to be 0.302 g. The variation coefficient of the live weight at the beginning of fattening, and the variation coefficient of the live weight at the conclusion of fattening were 17.20 % and 13.05 %, respectively, this situation indicates that there were more homogeneous lambs at the end of fattening (Table 2).

The Pearson correlation coefficients of the live weights of the lambs at the beginning and end of fattening and some body characteristics of the lambs at the beginning fattening were shown in Figure 1 (P<0.01). The characteristics of WH and RH had the highest correlation coefficient (r=0.95), while LG and CD had the lowest (r=0.51). Sensitivity analysis was performed for each data mining algorithm to predict the variable importance values of the independent variables on live weight at the fattening (Table 3).

Table 2. Some descriptive statistics on body characteristics and live weights at the initial and final of fattening

Variable	N	$\bar{X} \pm S_{\bar{x}}$	CV
ILW	54	35.891±0.840	17.20
WH	54	63.481±0.538	6.22
RH	54	63.315±0.501	5.82
CG	54	78.930±1.140	10.57
BL	54	60.037±0.549	6.72
LG	54	47.704±0.543	8.36
CD	54	29.926±0.377	9.27
FLW	54	49.487±0.879	13.05

Table 3. Variable importance of data mining algorithms

Variable importance	XGBoost	BRNN	RF
WH	7.779	26.656	22.472
RH	6.951	25.700	13.157
CD	0.000	19.203	14.437
BL	42.969	18.123	15.408
CG	23.571	10.317	17.792
LG	18.729	0.000	16.733

While the body characteristic with the highest relative importance value in the XGBoost (42.969) algorithm was BL, it was determined that it was the WH characteristic in the BRNN (26.656) and RF (22.472) algorithms. Also, the CD characteristic in the XGBoost algorithm and the LG characteristic in the BRNN algorithm did not contribute to estimating the live weight at the end of fattening.

Table 4 showed that the prediction performance results for the XGBoost, BRNN, and RF algorithms. When all prediction performance criteria were considered, it became clear that the XGBoost algorithm outperforms the BRNN and RF algorithms in terms of estimating the live weight at the end of fattening.

Table 4. Predictive performance of data mining algorithms in a 5-fold cross-validation

Good of Fit Model Criteria	XGBoost	BRNN	RF
RMSE	1.492	2.220	2.859
RRMSE	3.014	4.486	5.777
SDR	0.233	0.347	0.446
CV	3.040	4.530	5.820
PC	0.973	0.938	0.895
PI	1.528	2.315	3.049
ME	0.039	0.000	0.168
RAE	0.001	0.002	0.003
MRAE	0.004	0.006	0.008
MAPE	2.241	3.139	4.340
MAD	1.068	1.488	2.058
R^2	0.946	0.880	0.800
R^2_{Adj}	0.944	0.880	0.792
AIC	47.190	86.121	117.441
AIC_{Adj}	47.426	86.121	117.676

Distribution of the actual final live weight values at the end of the fattening and the values predicted by the data mining algorithm is given in Figure 2.

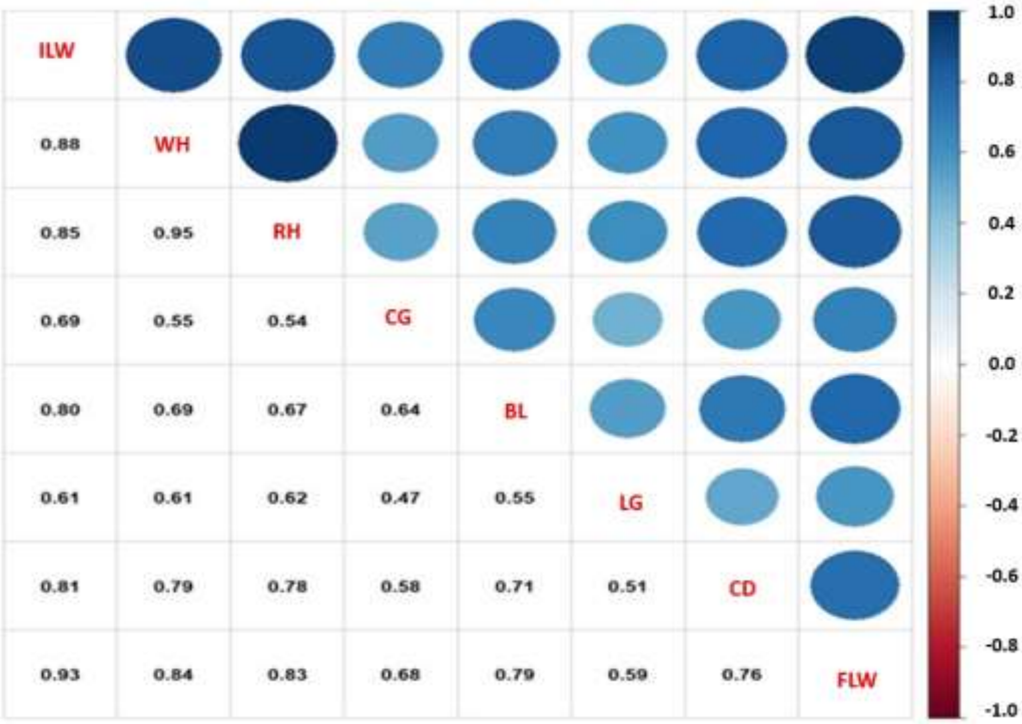

Figure 1. Pearson correlation coefficients between the ILW with some body characteristics and the FLW at the fattening.

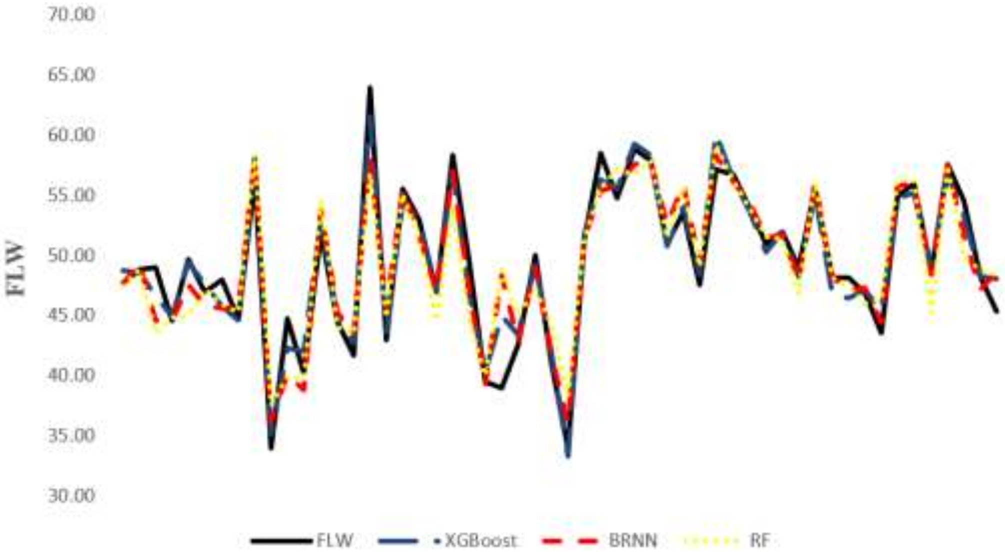

Figure 2. Actual final live weight values at the end of fattening and predicted values with data mining algorithms.

In herd management, many approaches based on body measurements are commonly used to monitor or evaluate the growth and development of animals. The reliability of the statistical methods used in estimating the live weight of animals is also of great importance. It was also stated that model comparison criteria should be used in the selection of the best model in multivariate statistics in literature (Salawu et al., 2014; Tırınk, 2022). The lowest RMSE, rRMSE, PI, SDR, MAPE, RAE and the highest r, R^2 and R^2_{Adj} values in the choice between the models in the study are taken into account. Despite the fact that there are many algorithms in the literature, some of them have still not received enough interest from researchers.

It is critical for herd management to contribute to selection by determining the algorithm or algorithms that best predict growth and development Since algorithms such as Multivariate Adaptive Regression Splines (MARS), Classification and Regression Tree (CART), Chi-Square Automatic Interaction Detection (CHAID), Random Forest (RF) and Artificial Neural Network (ANN) are widely used in the literature, some findings in this study have been partially compared with these algorithms.

To predict body weight from body measurements in Thalli sheep by using four algorithms in study made of Tırınk (2022), R^2 values of BRNN and RF algorithms were found to be 75.8% and 72.9%, respectively. As a result, the researcher stated that the MARS algorithm, which has a slightly higher R^2 (76.6%) compared to BRNN, can be used to obtain an elite Thalli sheep breed population. Akkol et al. (2017) stated that Bayesian regularization (BR) algorithm has the best prediction values (R^2: 91.00%, RMSE: 3.838, MAD: 2.9446 and MAPE: 4.7957) according to R^2, RMSE, MAD and MAPE values within BRNN, Levenberg-Marquart (LMNN) and Scaled Conjugate Gradient (SCGNN) and Multiple Linear Regression (MLR) results. As a result, they reported that this algorithm can be used as an alternative method. Akıllı and Atıl (2020) reported that the best successful performance value was obtained with Decimal Scaling normalization technique with the BR algorithm (R^2_{Adj} = 0.8181, RMSE= 0.0068, MAPE= 160.42 for test set; R^2_{Adj} =0.8141, RMSE= 0.0067, MAPE= 114.12 for validation set) for the prediction of 305-day milk yield in Holstein Friesen cows. Balta and Topal (2020) stated that Boosting, Bagging, RF and CART algorithms have obtained similar results in order to determine the best decision tree algorithm in order to determine the effects of the birth type, herd type, main age, pasture type, sex and lamb color variables in the Hemşin lambs. But, researchers stated that the Bagging algorithm with the lowest MSE (970.09), MAE (1362.65) and SMAPE (3.03) was formed. This algorithm was followed by the RF algorithm with the lowest MSE (1050.857), MAE (1404.448) and SMAPE (3.06) via best predictive performance.

Usman et al. (2020) stated that the highest coefficient of determination observed for Bayesian Regularization (BR), Levenberg Marquardt (LM) and Scaled Conjugate Gradient (SCG) respective algorithms were 82.67, 74.22 and 76.69 % respectively, in the comparative study of artificial neural network algorithms performance for prediction of first lactation 305-day milk yield in crossbred cattle. In a study made of Abbas et al. (2021), R^2 values of ANN algorithms were found to be 61.45 % to predict body weight from body measurements by using four algorithms in 152 head Thalli sheep. Although the researchers stated that all algorithms could be used in prediction, they stated that CHAID was the best prediction algorithm. When the current study and the R^2 values of both studies are compared, it is thought that the reason for the difference is due to breed and independent variables in the models. On the contrary to Akkol et al. (2017) study, Coşkun et al. (2022) stated that the MLR algorithm can be used safely for prediction by using data

mining algorithms (MLR, RF, Decision Tree (DT) and K-Nearest Neighbours (kNN) used in predictive of live weight from body measurements in Holstein cattle at different growth and development periods. In addition, researchers also stated that the RF algorithm (R^2: 91.2%, MSE: 404.08, RMSE: 20.102 and MAE: 14.718 values) has the best predictive performance after MLR algorithm (R^2: 93.9%, MSE: 277.544, RMSE: 16.66 and MAE: 13.197 values).
When the current study's results are compared to those of previous studies, the choice of algorithms with the best predictive performance in the literature may be altered due to characteristics such as the differences of species, breeds, animal numbers, animal age, and herd management method.

4. Conclusion

The results obtained from the current study show that there was a significant relationship between live weight and some body measurements. Since the predictive performance of the XGBoost model is as high as 94.6% among the data mining algorithms used in the estimation of the live weight at the end of fattening, it can be used safely in the estimation of the live weight. In addition, in the 63-day fattening period of Anatolian Merino Male lambs made by Şahin and Boztepe, (2010) study, in the group with a live weight of 35 kg at the beginnig of fattening, the total average live weight gain and daily live weight gain from fattening performans values were found to be 20.43 kg and 0.324 g, respectively. In this values in the current study, it was determined as 13.59 kg and 0.302 g, respectively. As a result, it can be said that male Anatolian merino lambs can be fattened in intensive conditions with an average initial live weight of 35 kg at fattening, and it is a good slaughter lambs material since the end of fattening can be achieved at 50 kg. In addition, the use some body measurements and algorithms used in estimating live weight at the end of fattening will be useful in other scientific studies with practical, reliable and accurate results, and their use in fattening studies will benefit breeders in selection and marketing strategy.

Author Contributions

The percentage of the author(s) contributions is present below. All authors reviewed and approved final version of the manuscript.

	G.C.	Ö.Ş	Y.A.	i.A.
C	25	25	25	25
D	25	25	25	25
S	25	25	25	25
DCP	25	25	25	25
DAI	25	25	25	25
L	25	25	25	25
W	25	25	25	25
CR	25	25	25	25
SR	25	25	25	25
PM	25	25	25	25
FA	25	25	25	25

C=Concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management, FA= funding acquisition.

Conflict of Interest

The authors declared that there is no conflict of interest.

Ethical Consideration

Data collection and animal husbandry procedures were carried out in compliance with Law No. 5996's Article 9's rules for animal welfare. There is no violation of animal rights within the scope of this study.

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