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Estimation of Marketing Live Weight of Lambs by Different Machine Learning Algorithms

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ABSTRACT

Background: Further research is needed to estimate the marketable live weight of lambs with high accuracy and reliability while minimizing contact and measurement. This study aimed to estimate the 120th-day marketing weight of Morkaraman lambs by different machine learning algorithms, considering the variables of dam age, sex, birth type, birth weight, as well as 30^{th} day, 60^{th} day and 90^{th} day live weights.

Methods: Artificial neural networks (ANN), classification and regression trees (CART), support vector machines with radial basis function kernel (SVMR) and Random Forest (RF) algorithms for estimation of the marketing weight were performed for training (75%) and testing (25%) datasets. Models used in this study were compared based on mean absolute error (MAE), root mean squared error (RMSE) and mean absolute per cent error (MAPE) performance metrics. The most significant predictor of the marketing live weight in all models was the 90^{th} day live weight, whereas the birth weight, birth type and dam age were the least important predictors. The correlation coefficients between live weight values estimated by the SVMR, CART, RF and ANN models and the actual marketing live weight were determined as 0.82, 0.82, 0.82 and 0.84, respectively.

Result: The best prediction for the marketing live weight of Morkaraman lambs in the 4^{th} month was obtained from the ANN model. Using artificial neural networks to determine the marketing weight of lambs can save time and labor because of the reduced number of weighings. It may improve decisions made in flock management.

Key words: Artificial neural networks, Lamb, Live weight estimation, Machine learning.

INTRODUCTION

Live weight estimation is required to decide on herd management practices, such as growth monitoring, proper drug dosage, determination of daily feed amount and marketing time (Khan *et al.*, 2014; Önk *et al.*, 2018). The live weights of farm animals are currently determined by direct weighing techniques or indirect techniques based on correlations between live weight and body measurements. Although the scales used to measure the live weight of farm animals make accurate and sensitive measurements, problems arise due to the acquisition, intended function, size, repeated calibration and maintenance expenses associated with these devices. These issues limit the affordability and sustainability of these devices, especially for small and medium-sized farms (Wang *et al.*, 2021). In addition, measurements made with these conventional weighing devices require intense labor and time, cause physical stress in animals and pose a risk of disease spread. With the spread of modern breeding, the need to replace these methods with more stress-free and contactless methods has emerged (Li *et al.*, 2022).

Numerous studies have addressed the issue of multicollinearity and complex relationships among variables when using regression analyses, such as linear, multiple and ridge regression, to estimate the live weights of sheep based on biometric and morphometric measurements obtained at various growth periods (Tarig *et al.*, 2012; Jahan *et al.*, 2013; Khan *et al.*, 2014). Since these traditional statistical methods are insufficient to explain complex relationships, various data mining algorithms have recently been used to predict animal live weight (Huma and Iqbal, 2019; Erdoğan Ataç *et al.*, 2022). Data mining algorithms that create homogeneous sub-groups as soon as possible are unaffected by multicollinearity problems caused by the strong correlations between morphological features, outliers, and missing data (Ali *et al.*, 2015).

Machine learning is a discipline of artificial intelligence and computer science that focuses on using data and algorithms to emulate the learning process of humans (Khanikar *et al.*, 2022; Priya Dutt *et al.*, 2024). Various studies conducted on sheep have revealed that live weight (Huma and Iqbal, 2019; Çakmakçı, 2022; Coşkun *et al.*, 2023; Tırınk *et al.*, 2023a; Hamadani *et al.*, 2024), fat tail weight (Norouzian and Alavijeh, 2016), metabolizable energy consumption (Suparwito *et al.*, 2021), breeding value (Ghotbaldini *et al.*, 2019), milk yield (İnce and Sofu, 2013;

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Angeles-Hernandez *et al*., 2022), carcass traits (Shahinfar *et al.*, 2019) and adult wool growth and quality traits (Shahinfar and Khan, 2018) can be predicted by machine learning techniques. In addition, machine learning techniques have been successfully applied to classify lameness (Kaler *et al.*, 2019), evaluate pain from facial expressions (McLennan and Mahmoud, 2019), identify factors affecting lamb survival (Odevci *et al.*, 2021) and monitor animal health and welfare (AlZubi and Al-Zu'bi, 2023).

More information is needed to evaluate the performance of various machine learning algorithms for estimating marketing live weight in lambs. this study aimed to estimate the 120th-day marketing weight of morkaraman lambs with different machine learning algorithms, considering dam age, sex, birth type, birth weight, and 30th day, 60th day and 90th day live weights.

MATERIALS AND METHODS

The study was carried out in the farms of the Morkaraman sheep breeding sub-project, which was implemented in Ağrı province between the years 2022-2023. The animal material for this study consisted of 5835 Morkaraman lambs born in 2022. The study area, Ağrı province, is in the east of Türkiye and between 39°43′7″N latitude and 43°3′3″E longitude. the altitude of the province is 1640 m above sea level and the annual average rainfall is 521.8 mm.

Morkaraman sheep is one of the most important fat-tailed local sheep breeds in Türkiye. this breed, resistant to adverse environmental conditions, has high adaptability and is primarily bred for meat yield (şahin and Kopuzlu, 2022). In the enterprises where the study was conducted, lambs are housed with their mothers until weaning at an average of 90 days. During the pasture period, they are suckled with their mothers in the evenings. the lambs are grazed in the pasture between May and July and no additional feeding is done during this period. In late July-September, the lambs are fed with alfalfa hay and crushed barley until they are sold. In the lambing season, lambs were weighed within 12 to 24 hours of birth and ear-tagged for identification. Birth weight, sex, birth type and dam age of the lambs were recorded. To determine the marketing weight of the lambs, they were weighed at an average age of 90 and 120 days. The 30th and 60th day weights of the lambs were calculated by linear interpolation using the birth weight and 90th day live weight variables.

A statistical description of growth traits is given in Table 1. The categorical variables, such as sex with two categories (male:1 and female:0) and birth type with two categories (single:1 and twin: 2) were converted into a numerical format using dummy variables. One of the categories (female for sex and single for birth type) was excluded from the models to avoid multicollinearity.

The dataset was split into 75% training and 25% testing. The training data set (n= 4374) was used to create the model, while the unseen test data set (n= 1461) was used to qualify the performance of the models. The n-fold cross-validation, a method used to evaluate machine learning models, divides the data set into n-folds and in each iteration, one is used as the test set and the rest as the training set. Until the entire data set has been examined, these processes are repeated. Using this technique makes it possible to determine whether the predictions made by the models are unique to the given data set and to provide more trustworthy results (Barut and Altuntaş, 2023).

In this study, a 5-fold cross-validation resampling technique was repeated five times to improve the accuracy of the estimated generalization error. Performance metrics in machine learning regression models are used to compare the predictions of the trained model with the actual (observed) data from the testing data set (Plevris *et al*., 2022). Models used in this study were compared based on mean absolute error (MAE), root mean squared error (RMSE) and mean absolute percent error (MAPE) performance metrics (Çakmakçı, 2022; Coşkun *et al.*, 2023).

Random forest (RF), support vector machines with radial basis function kernel (SVMR), classification and regression trees (CART) and artificial neural networks (ANN) algorithms for estimation of the marketing weight were performed using the caret R package. The ggstatsplot R package compared the live weight means estimated by machine learning models. The R programming language (version 4.1.2) was used for all analyses (RCoreTeam, 2023).

RESULTS AND DISCUSSION

A correlation matrix was created to describe the relationships between the traits. Regarding the correlation matrix of the training dataset (Fig 1), while the marketing live weight of lambs (D120) had the highest correlation (r=+0.79, P<0.05) with the 90th-day weaning weight, it showed very low and insignificant correlations with dam age and birth weight. At the same time, D120 showed significant correlations with D30 (r=+0.72, P<0.05) and D60 (r=+0.78, P<0.05) (Fig 1a). However, D30 and D60 predictors were excluded from the data set as they were highly correlated variables (Fig 1b).

Correlation matrices and a boruta algorithm based on random forests identified the study's most significant variables. This was done to avoid multicollinearity and reduce the variables needed for optimal forecasting

Table 1: Statistical description for growth traits in Morkaraman lambs (kg).

Traits	No	Mean ± SE
Birth weight	5835	4.17±0.01
30th-day live weight	5835	10.70±0.02
60th-day live weight	5835	17.20±0.03
90th-day live weight	5835	23.71±0.04
120th-day live weight	5835	34.97±0.07

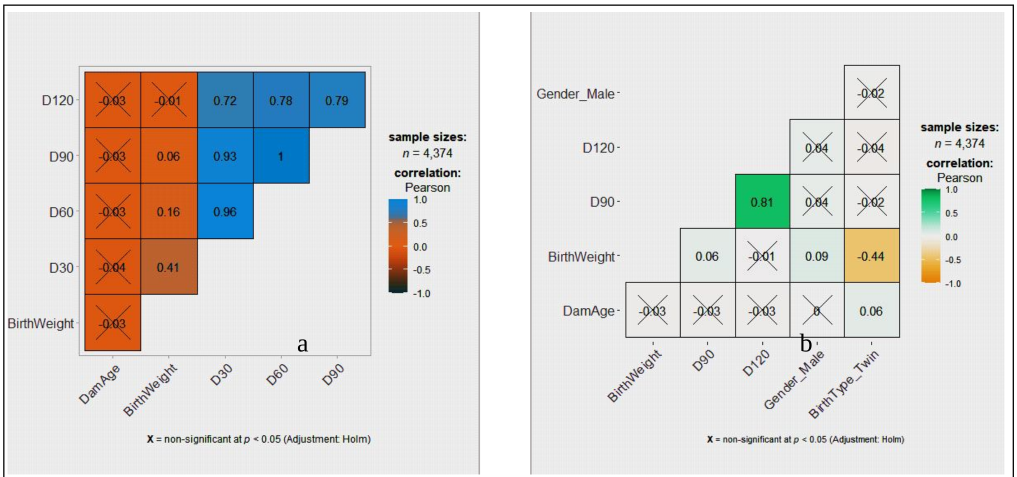
SE: Standard error.

performance. This approach reduces time and effort by allowing variable selection to determine important variables, removing unnecessary measurements (Çakmakçı, 2022). The Boruta method has been proven effective in determining the optimal subset of traits to build a high-accuracy prediction model (Cao, 2019). The findings of Wolc *et al.* (2011), who found that the correlation between live weights of sheep of various ages increased with increasing days of age, were consistent with the high correlations between live weights at 30, 60, 90 and 120 days of age determined in this study. On the other hand, in the study conducted by Tırınk *et al.* (2023b) on romane lambs, only relatively high correlations between weaning weight and suckling weight (0.79) and low-to-moderate correlations between final weight and birth weight, suckling weight and weaning weight (0.29, 0.42, 0.52, respectively) were determined.

The importance scores of the variables are given in Table 2. Initially, the data set was cleared of highly correlated predictors. The boruta algorithm was then used to apply variable selection processes to the remaining predictors. The ML models were trained by selecting important predictors. The result of boruta analysis showed that dam age, birth weight, 90-day weight, and birth type were the variables confirmed to be significant as final predictors. However, the predictor sex was excluded from the dataset because it was insignificant. Herd, sex, birth type, dam age, birth weight, live weight at 60 days and weaning weight (90 days) were used by ANN to predict marketing weight (120 days) of hair goat kids, but only herd, sex, birth type and dam age with significant effects (P<0.05) were included in the model (Erdoğan Ataç *et al.*, 2022).

One of the most popular data resampling techniques to estimate the generalizability of a predictive model and to avoid overfitting is cross-validation (Berrar, 2019). Repeated (5 times) 5-fold cross-validation was used to evaluate the performance of each model in the study. The results of repeated 5 times 5-fold cross-validation resampling for datasets across models are given in Table 3. In various studies where the live weight of sheep was estimated with different machine learning algorithms, the best n value was obtained by the cross-validation method and the n value was selected as 5 (Sant'Ana *et al.*, 2021; Coşkun *et al.*, 2023) or 10 (Huma and Iqbal, 2019; Camacho-Perez *et al.*, 2022; Hamadani and Ganai, 2023).

The CART model was the fastest, taking only 4.52064 seconds. The ANN algorithm processed the same dataset in 15.05579 minutes, while the RF algorithm took 8.421965 minutes and the SVMR algorithm only needed 5.769735 minutes of runtime. The ANN model was the most time-consuming but had the highest prediction accuracy using



D30: 30th day weight, D60: 60th day weight, D90: 90th day weight, D120: 120th day weight.

Fig 1: Correlation matrix showing the correlation coefficients a) between the traits in the training dataset and b) between traits after removing the predictors with an absolute pairwise correlation of 0.75 or higher in the training dataset.

Table 2: Variable importance scores.

Variables	mean Imp	median Imp	min Imp	max Imp	norm Hits	Decision
Dam age	5.8295	5.3999	3.3849	8.8441	1.0000	Confirmed
Birth weight	20.6534	20.3798	17.1549	23.2021	1.0000	Confirmed
D90	313.7638	314.6368	298.1898	328.5909	1.0000	Confirmed
Sex	-1.1041	-1.0015	-5.7105	2.3602	0.0588	Rejected
Birth type	15.9706	16.2453	12.7312	17.9290	1.0000	Confirmed

D90: 90th day weight.

the test dataset. It outperformed all other models with the lowest RMSE and MAPE values. The MAE values for the ANN, CART, SVMR and RF datasets were 2.504, 2.567, 2.498 and 2.589, respectively. Training a machine learning model usually requires significant time and space (Yang and Shami, 2020). The runtime performance of the models in this study was like the study's findings that applied the same models to a smaller dataset (Çakmakçı, 2022). Reporting that the models' processing time was a factor to consider, Sant'Ana *et al*. (2021) found that the extreme gradient boost regressor (XGBR) was the fastest at 0.435 seconds, while the random forest regressor (RFR) was the most time-consuming at 5.950 s.

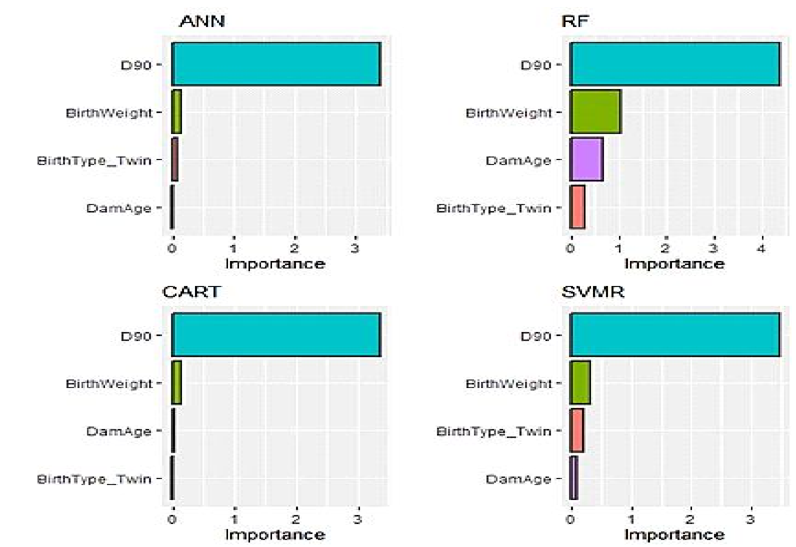
The cross-validation results were analyzed and after extracting all the metrics, the mean statistical value of each metric (MAE, RMSE, and MAPE) was calculated. Accuracy metrics are commonly used to assess machine learning predictions. The sensitivity of the seven accuracy measures was listed as MSE > SMAPE = MAPE > MAE > RMSE > R2 > R (Jierula *et al*., 2021). On the other hand, Camacho-Perez *et al*. (2022) reported that the expected errors in predictions and experimental measurements were errors of low magnitude and that RMSE was a suitable indicator to evaluate the algorithm's performance. In this study, the ANN model with the lowest RMSE (3.181) and MAPE (0.076) values had the best predictive performance in terms of prediction accuracy on the test dataset (Table 3). The order of superiority of the algorithms in prediction accuracy was found as ANN > CART > SVMR > RF. Similarly, it was determined that marketing live weight of hair goat kids (Erdoğan Ataç *et al*., 2022) and the growth of baluchi lambs (Behzadi and Aslaminejad, 2010) could be predicted successfully by ANN. However, according to the goodness of fit criteria, CART was the best model in estimating the ideal final weight at 4 months of age in Romane male and female breeding lambs (Tırınk *et al*., 2023b). In contrast to the study findings, RF performed better in predicting the live weight of different sheep breeds, as it had the lowest values of the accuracy metrics (Huma and Iqbal, 2019, Sant'Ana *et al*., 2021; Çakmakçı, 2022).

Fig 2 shows the variable importance scores based on permutation. Including the minimum possible number of predictors that give acceptable results can reduce the data acquisition cost or improve the software's efficiency

Table 3: Results of the regression models on train and test datasets.

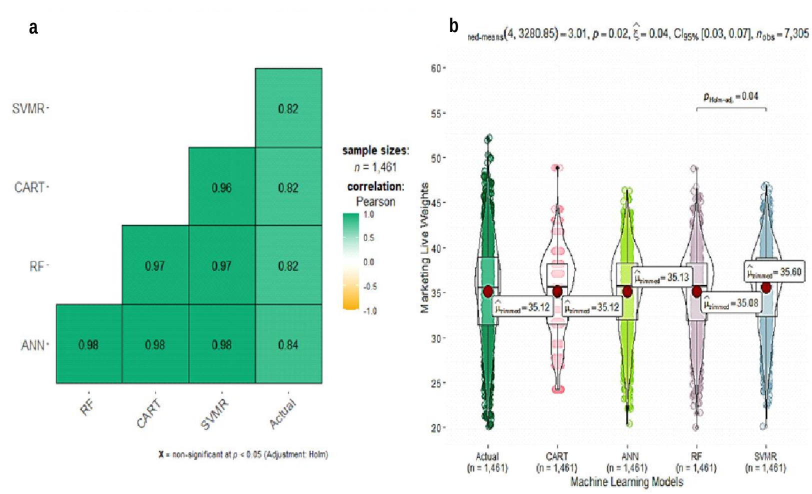
Model	Train					Test		
	MAE	RMSE	MAPE	Runtime	Tuning parameters	MAE	RMSE	MAPE
ANN	2.447	3.159	0.073	15.05579 mins	Size = 5, Decay = 0.01	2.504	3.181	0.076
CART	2.526	3.247	0.074	4.52064 secs	cp = 0.001	2.567	3.275	0.078
SVMR	2.426	3.257	0.071	5.769735 mins	Sigma = 0.4 and C = 1	2.498	3.351	0.079
RF	2.542	3.287	0.043	8.421965 mins	mtry = 2	2.589	3.317	0.079

MAE: Mean absolute error, RMSE: Root mean squared error and MAPE: Mean absolute percent error. ANN: Artificial neural networks, CART: Classification and regression trees, RF: Random forest, SVMR: Support vector machines with radial basis function kernel.



D90: 90th day weight. ANN: Artificial neural networks, CART: Classification and regression trees, RF: Random forest, SVMR: Support vector machines with radial basis function kernel.

Fig 2: Variable importance scores for the predictors.



ANN: Artificial neural networks, CART: Classification and regression trees, RF: Random forest, SVMR: Support vector machines with radial basis function kernel.

Fig 3: a) Correlation matrix showing the correlation coefficients between the actual and predicted marketing live weights with different machine learning models, b) Comparing the differences between the predicted marketing weights with different machine learning models.

(Çakmakçı, 2022). According to the variable importance scores used to analyze the relative importance of the predictors, 90th day live weight was the most important predictor of marketing live weight in all models. However, birth weight, birth type (twin) and dam age were determined as predictors with low relative importance. The sensitivity analysis results for the support vector regression algorithm in the study by Tırınk *et al.* (2023b) showed that the most effective variable on final weight was the age of final weight, and the second variable was weaning weight. Sex, suckling weight, weaning age and birth weight were also found to be important while the age of suckling weight, birth type (2, 3 and 4) and the number of co-suckled lambs were the least effective variables. On the other hand, in studies in which live weight was estimated from morphological measurements, it was reported that the most important variables in predicting live weight were chest width, chest depth (Çakmakçı, 2022) and chest circumference (Tırınk *et al.*, 2023a).

According to the correlation matrix (Fig 3a), the correlation coefficients between the values estimated by the SVMR, CART, RF and ANN models and the actual marketing live weight values were determined as 0.82 (P<0.05), 0.82 (P<0.05), 0.82 (P<0.05) and 0.84 (P<0.05), respectively. Based on the ANOVA results, there was a statistically significant difference between the marketing live weight values estimated by the RF and SVMR models (P<0.05) (Fig 3b). When the performance of each model as a weight predictor was analyzed, it was found that all models used in this study had similar prediction trends. Contrary to the study findings, there was no difference between the actual live weight values and the values predicted by machine learning models in Norduz sheep (Çakmakçı, 2022).

In the study in which fat tail weight was estimated in sheep using ANN and MLR (multiple linear regression) models, the mean relative error between actual and model-predicted values was significantly (P<0.01) lower for ANN than for the MLR model and the ANN model gave a better estimation (Norouzian and Alavijeh, 2016). The mean error of the measured values compared to the actual value was reported to be less than 10% in the study, where the live weight of the sheep was estimated from biometric data (Camacho-Perez *et al*., 2022).

The optimal model identified in this study was artificial neural n etwork (ANN) with a 4-5-1 architecture, consisting of four input nodes corresponding to the predictor variables, a single hidden layer with five neurons and one output node. This configuration resulted in a total of 31 trainable parameters. The model employed a weight decay coefficient of 0.01 to mitigate overfitting.

CONCLUSION

In this study, goodness-of-fit criteria were used to select the best-fitting model. Study findings showed that machine learning algorithms can predict lambs' marketing live weight based on explanatory variables. The ANN model obtained the best prediction for the marketing live weight of Morkaraman lambs in 4th month. Using artificial neural networks to determine the marketing weight of lambs can save time and labor because of the reduced number of weighings. It may improve decisions made in flock management.

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Disclaimers

The views and conclusions expressed in this article are solely those of the author and do not necessarily represent the views of their affiliated institutions. The author is responsible for the accuracy and completeness of the information provided, but do not accept any liability for any direct or indirect losses resulting from the use of this content.

Informed consent

All animal procedures for experiments were approved by Van Yüzüncü Yil University Ethical Committee on Animal Experimentation (reference no 2023/07-24).

Conflict of interest

The author declares that there are no conflicts of interest regarding the publication of this article. No funding or sponsorship influenced the design of the study, data collection, analysis, decision to publish, or preparation of the manuscript.

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