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Research Article

Prediction of Marketing Live Weights in Hair Goat Kids Using Artificial Neural Network

Funda ERDOĞAN ATAÇ [1 (*)] Çiğdem TAKMA [1] Yakut GEVREKÇİ [1]
Şeniz ÖZİŞ ALTINÇEKİÇ [2]

[1] Ege University, Faculty of Agriculture, Department of Animal Science, TR-35100 İzmir - TÜRKİYE

[2] Bursa Uludag University, Faculty of Agriculture, Department of Animal Science, TR-16059 Bursa - TÜRKİYE

ORCIDs: F.E.A. 0000-0002-6681-212X; Ç.T. 0000-0001-8561-8333; Y.G. 0000-0002-4915-2238; Ş.Ö.A. 0000-0001-9044-8092

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Abstract: In this study, marketing live weights (120th day) were predicted using artificial neural network model according to the herd, gender, birth type, maternal age, birth weight, body weight at 60th day and weaning weight (90th day) measurements of 12983 hair goat kids born between 2018-2021 years. Artificial neural networks (ANN) have been frequently used as an alternative to classical regression analysis in recent years, especially in future estimation studies in the field of livestock, and also in many different fields. In this study, it was aimed to predict the marketing weights of hair goats according to the holding, gender, birth type, maternal age, birth, 60th day and weaning weights with the ANN model. For this purpose, the multi-layer feed-forward backpropagation algorithm the ANN model, in which the number of hidden layers is one and the numbers of hidden neurons are three, was used. This model performance metrics were obtained for training set as 0.98, 0.62 and 0.55; for validation set as 0.97, 0.62 and 0.55, respectively. According to these results, it was determined that ANN can be used successfully in terms of estimation of marketing live weight in Hair goat kids. Estimating the marketing weight will enable the economic cost calculations to be obtained from kids to be evaluated both based on Turkey and on the farm basis, and to reveal future projections.

Keywords: *Artificial neural network, Marketing live weight, Weight prediction, Hair goat kid*

Kıl Keçisi Oğlaklarında Pazarlama Canlı Ağırlığının Yapay Sinir Ağları Kullanılarak Tahminlenmesi

Öz: Bu çalışmada 2018-2021 yılları arasında doğan 12983 baş Kıl keçisi oğlaklarının sürü, cinsiyet, doğum tipi, ana yaşı, doğum ağırlığı, 60. gün canlı ağırlık ve sütten kesim canlı ağırlık (90. gün ağırlığı) ölçümlerinin dikkate alındığı yapay sinir ağları modelinde pazarlama canlı ağırlıkları (120. gün ağırlığı) tahminlenmiştir. Yapay sinir ağları (YSA) pek çok farklı alanda olduğu gibi son yıllarda hayvancılık alanında özellikle de geleceğe yönelik tahminleme çalışmalarında klasik regresyon analizine alternatif olarak sıklıkla kullanılmaya başlanan bir veri madenciliği yöntemidir. Çalışmada işletme, cinsiyet, doğum tipi, anne yaşı, doğum, 60. gün ve sütten kesim ağırlıklarına göre kıl keçisi pazarlama ağırlıklarının YSA modeli ile tahmin edilmesi amaçlanmıştır. Bu amaçla, gizli katman sayısının bir ve gizli nöron sayısının üç olduğu çok katmanlı ileri beslemeli geri yayılım algoritması YSA modeli kullanılmıştır. Bu model performans kriter değerleri eğitim seti için sırasıyla 0.98, 0.62 ve 0.55 ve doğrulama seti için 0.97, 0.62 ve 0.55 olarak elde edilmiştir. Bu sonuçlara göre, Kıl keçisi oğlaklarında pazarlama canlı ağırlığının tahmini bakımından YSA yönteminin başarıyla kullanılabileceği belirlenmiştir. Pazarlama ağırlığının tahmin edilebilmesi, oğlaklardan elde edilecek ekonomik maliyet hesaplarının hem Türkiye hem de çiftlik bazında önceden değerlendirilmesine ve geleceğe yönelik projeksiyonların ortaya çıkarılmasına olanak sağlayacaktır.

Anahtar sözcükler: *Yapay sinir ağları, Pazarlama ağırlığı, Ağırlık tahmini, Kıl Keçisi oğlağı*

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(*) Corresponding Author
Tel: +90 232 311 4466 Fax: +90 232 388 1867
E-mail: funda.erdogan.atac@ege.edu.tr (F. Erdoğan Ataç)

Introduction

Hair goat is the dominant goat breed, which has adapted to almost all regions in Turkey and is resistant to adverse environmental conditions [1-3]. According to TUIK data, in 2021, the number of Hair goats was 12.051.957 which establish 99% of total goat population. Hair goats, which are the socio-economic and cultural richness of Turkey, are mostly raised in forests and villages, in village herds, on highland or nomads [4]. It constitutes an important source of food and livelihood for low-income families in rural and forested areas [5]. In the Aegean region, it is primarily consumed as kid meat. Hair goats, 40-45 kg live weight of mature, have low fertility and relatively low production of milk [1]. There are 1.248.977 head goats, of which approximately 11% and approximately 18% of the Aegean Region is in İzmir [4]. Especially in the Aegean Region, in recent years, it is seen that there is a tendency towards intensive or semi-intensive breeding in order to increase the production of kid meat or to make more income for the breeders. These transitions affect the physiology of the animal according to the breeding system of the goats and may have some consequences in human nutrition and health as a result of their consumption as a final product. This distinction may have a genetic aspect as well as a relationship with the feeding regimen. On the other hand, with the right relationship between increasing population and nutritional needs, domestic production remains insufficient, especially for red meat. Habits in animal feeding are changing and as a result, differences in yield and quality of red meat emerge among animal products obtained according to production systems. Therefore, hair goats are important for Turkey in terms of closing the red meat deficit and offering natural and healthy animal products as their nutrition is based on pasture. As a matter of fact, the average meat production per goat is 19.26 kg, and the milk yield is around 105 kg [6]. Since free breeding is generally applied in the herds held by the public and the oestrus is not synchronized, pregnant, giving birth, pregnant for the first and large and small kids can be found in the herd in the same period. This situation also creates problems for the breeders who make their living by putting their kids on the market. When the breeders market their kids without knowing the slaughter weight of their kids, they make a loss before they reach the slaughter age. However, the covid epidemic in the world and in Turkey and the accompanying economic problems have put goat breeding in a bottleneck. In this context, estimating the marketing weight of kids in the early period is important for breeding. Whereas the heritability of meat yield is low-medium. However, in estimating the adult live weight, the 120-day-old body weight has a higher heritability than the birth weight and weaning age weight [2]. Since the marketing weight can be determined in the early period with artificial neural networks, it will be possible to select the breeder for animal breeding in the earlier period. Important economic values that can be measured for the development of small ruminant breeding and increasing meat production are growth characteristics such as birth weight, live weight at 3 months, live weight at 6 months, live weight at 9 months and live weight at 12 months. The live weight at the age of 3 months, where weaning is frequently performed, is considered as one of the most important production characteristics in lambs. The decrease in maternal effects on lamb live weight at the age of 3 months has a high share in this. For this reason, 3-month age is accepted as one of the important selection criteria for lambs [7]. It is possible to determine the marketing weight in the early period with the measurements taken before 120 days and with various mathematical approaches including the relevant environmental factors, and thus the breeder selection can be made in the earlier period. However, knowing the body weight of the sheep in various periods is very important for determining the amount of feed to be given to the animal, the drug dose to be applied and the marketing weight [8]. Moreover, body weight (BW) values, which is one of the most important measurements used to describe the variation among animals and to reveal their growth characteristics, are frequently used criteria for both scientific research and selection applications. BW estimation, which is an important measure of animal performance, not only provides informative measures for animal nutrition, health care, selection, but also provides important information for research on economic growth, reproductive efficiency and meat production per animal [9,10]. In other words, the estimation of BW for successful breeding is indispensable for both increasing the reproductive performance of animals and thus both meat production per animal and obtaining superior offspring [11,12].

However, classical methods such as simple linear regression or multiple linear regression analysis were used in these estimation studies. In these studies, it was emphasized that when the effects of many factors on body weight should be examined simultaneously, multicollinearity problems may arise between the factors and the effect of the features affecting the estimated parameter with the body weight estimates could not be interpreted correctly [10,13-15]. On the other hand, it is reported that data mining algorithms are not affected by the current multi-collinearity problem [10,16,17]. In addition, data mining techniques can process fast, accurate, low-cost and also non-linear complex data, which is not possible using traditional techniques [18]. Many researchers [15,19-24] used the artificial neural network method in sheep, goat and cattle breeding, and they reported that artificial neural networks had a lower error rate than classical statistical methods.

In this study, the estimation efficiency of Hair goat marketing weights was investigated with the artificial neural network model, which takes into account the farm, sex, birth type, maternal age, birth, 60th day and weaning weights, which are known to be effective on live weight.

Material and Methods

Material

The total of 12983 kids born in 28 goat farms from 2018 to 2021 years in İzmir province were used as material. In general, semi-intensive breeding system is applied in an extensive part of the herds in the farm. The herd capacities of the farms vary between about 150-1000 heads. İzmir provience is under the influence of Mediterranean climate, population density is 369/ km^2. In this study, herd, gender (male or female), birth type (single or twin), age of dam (1-10 year) factors, and birth, 60th day, and weaning weights were considered for predicting marketing live weights of kids.

The mean and standard deviation values of the 60th day, weaning and marketing body weights and frequencies of the herd, gender, birth type, age of dam effects together with the percentages were given in *Table 1*.

Method

ANN of many neurons in its structure work similarly to biological neurons. The main components of an artificial neuron are inputs, weights, transfer function, activation function and output [25]. Artificial neural networks consist of artificial neurons that systematically join in each of the input layer, hidden layer, and output layer [25-27].

The task of ANN is to produce an output as given in *Fig. 1* in response to the information given to it as an input set. In order to do this, input information and output

Table 1. *The description of the data set*

Herd	Frequency	Percent	Gender	Frequency	Percent
1	481	3.7	Male	6455	49.7
2	274	2.1	Female	6528	50.3
3	516	4.0			
4	274	2.1			
5	608	4.7	**Birth Type**	**Frequency**	**Percent**
6	256	2.0	Single	11446	88.2
7	288	2.2	Twin	1537	11.8
8	646	5.0			
9	780	6.0			
10	604	4.7			
11	308	2.4	**Age of Dam (Year)**	**Frequency**	**Percent**
12	662	5.1	1	181	1.4
13	178	1.4	2	746	5.7
14	234	1.8	3	1450	11.2
15	1059	8.2	4	1606	12.4
16	149	1.1	5	2167	16.7
17	652	5.0	6	1831	14.1
18	535	4.1	7	2405	18.5
19	266	2.0	8	1465	11.3
20	273	2.1	9	811	6.2
21	391	3.0	10	321	2.5
22	494	3.8			
23	649	5.0			
24	829	6.4			
25	656	5.1	**Weights**	**Mean**	**Std. Deviation**
26	240	1.8	Weight at 60th Day	11.34	2.32
27	323	2.5	Weaning Weight	15.00	2.85
28	358	2.8	Marketing Weight	18.74	3.84

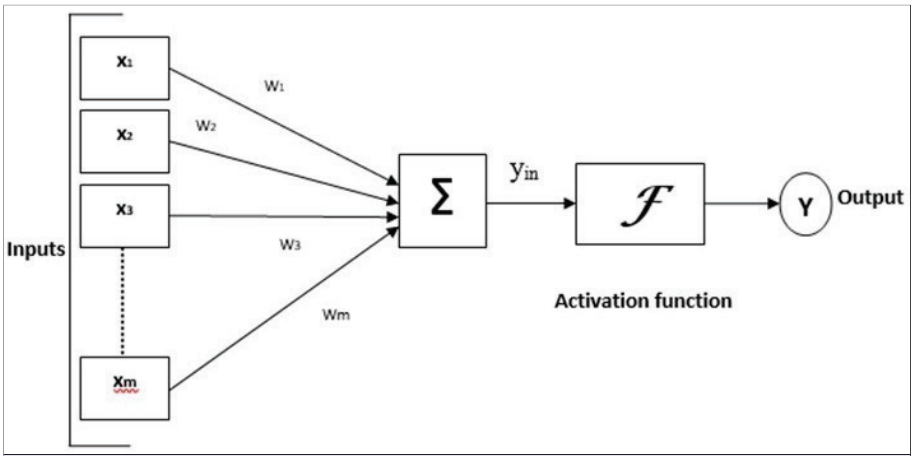

Fig 1. The architecture of artificial neural network

information corresponding to the inputs are given to the ANN, and the network is provided to learn the relationship between input-output, thus training the network. Then, the network reaches the level where it can generalize and decide, and determine the outputs with this acquired ability [27-30].

Artificial neural networks operate differently from the calculations of traditional processors. While a computer's processor (CPU) does the task assigned to it within the framework of a certain algorithm, each artificial neural network processes only a small part of a major problem nonlinearly and achieves a result [25,31].

Some goodess of fit criteria such as The Adjusted coefficient of determination (R^2_{adj}), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) are used to determine performance of ANN models and even compare with different model predictions [29,32,33]. According to these criteria, the model that provides the highest R^2_{adj} and the lowest RMSE, and MAE values is accepted as the most suitable. The mainly used equations and their definitions were given in the *Table 2*. In equations y_i denotes observed data, $\hat{y}_i$ is predicted data, n is the number of observations and p is the numbers of independent variables.

In this study, preliminary analysis with the general linear model was carried out for the effects of herd, gender, birth type and age of dam, which are thought to be effective in estimating the marketing age. Finally, these effects were found to be statistically significant (P<0.05). Therefore, these effects were used in the ANN model.

Moreover, marketing live weigths were predicted using a multi-layer feed-forward backpropagation algorithm ANN architecture. In this architecture, 7 variables as farm, gender, birth type, maternal age, birth weight, 60th day body weight and weaning weights were used as input data, and marketing weight was used as output data set. The data set was randomly divided into two groups by 70% training and 30% as the validating set. Therefore, artificial neural networks were modeled with different number of hidden layers and neurons training algorithms on (n=9088) training and (n=3894) validation sets. Hyperbolic Tangent activation function was used between layers. The convergence criterion was 1.10-6, the maximum number of iterations was 50, and 20 epochs were taken at the termination of the algorithm in each run. JMP Pro 16.0.0 program was used in all analyzes.

Table 2. *Definition and equation of criteria for model evaluation*

Definition	Equation
Adjusted coefficient of determination The coefficient of how well the values fit compared to the original values	$R^2_{adj} = 1 - \left[(1 - R^2).\left(\frac{n-1}{n-p-1}\right)\right]$
Root Mean Square Error The difference between the original and predicted values extracted by squared the average difference over the data set	$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}$
Mean Absolute Error The difference between the original and predicted values extracted by averaged the absolute difference over the data set	$MAE = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert$

Results

In this research, the aim was to predict marketing live weight of Hair goat kids using an artificial neural network. Based on this aim the most suitable hidden layer number in the designed artificial neural network was found to be "1" and the neuron number in this layer was found as '3' (*Fig. 2*).

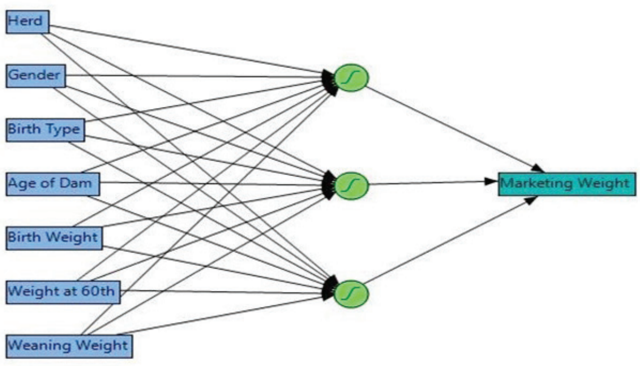

Fig 2. The diagram of the ANN for prediction of marketing weigh

In this study, R^2_{adj} and the RMSE, and MAE were adopted to evaluate the quality of fit for ANN in terms of the distance of the predictors from the actual training points and the results of model performance metrics were shown in *Table 3*. This model performance metrics were obtained for training set as 0.98, 0.62 and 0.55; for validation set as 0.97, 0.62 and 0.55, respectively. As can be seen, the validation set gave the same results as the training set.

***Table 3.** The results of model performance metrics*

Metrics	Training Set	Validation Set
Adj. R^2	0.975	0.973
RMSE	0.623	0.618
MAE	0.546	0.553

The actual and residual by predicted marketing live weight plots of the best ANN model for training and validation sets were visualized in *Fig. 3* and *Fig. 4*, respectively.

As can be seen from *Fig. 3* and *Fig. 4*, the preditcs were very well adapted to the observations and the error levels were found to be quite low.

According to these results, it was determined that ANN has a good fit and can be used successfully. It has been revealed also, the 7-input, single-output and single-layer 3-hidden node network structure can be used safely in estimating the marketing live weight for Hair goats.

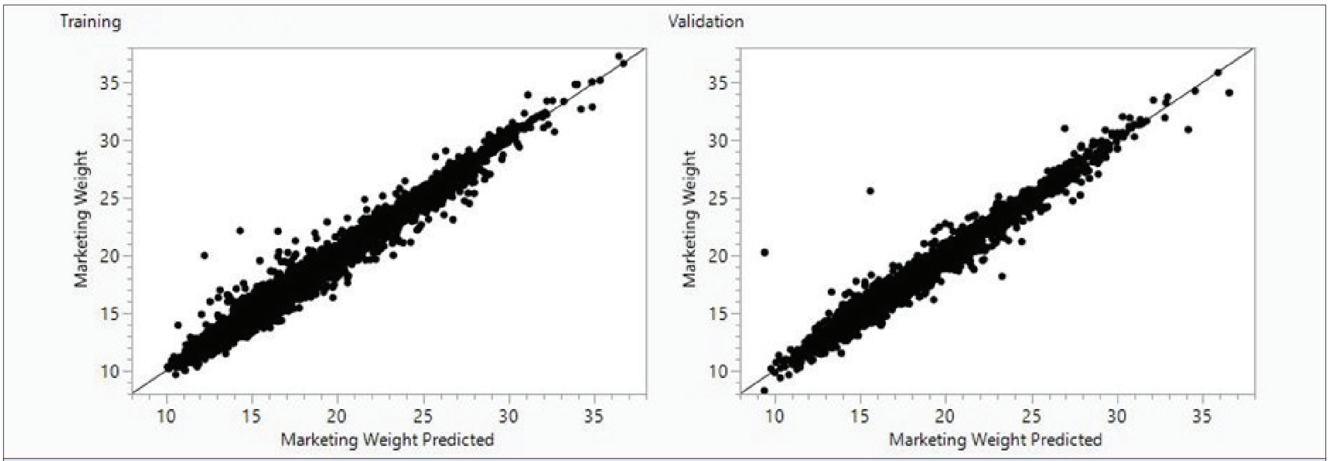

Fig 3. Actual by predicted marketing live weight of the best ANN model

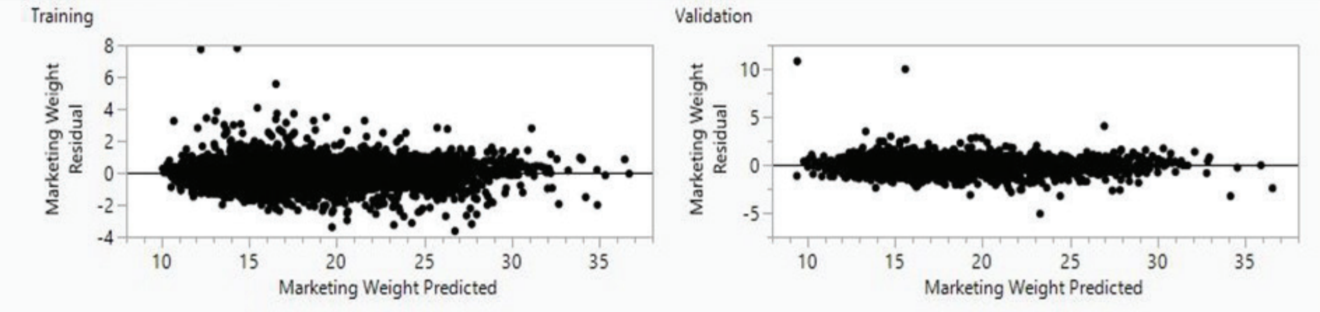

Fig 4. Residual by predicted marketing live weight of the best ANN model

Discussion

Taşdemir and Özkan [34] used ANN modeling, which includes 4 inputs and 1 output, to estimate body weight in cattle using body measurements, and they found the correlation coefficient between the estimated body weight values and the body weight values determined from the scale as 0.995. As a result of their studies, researchers reported that ANN can be used successfully in body weight estimation. Tırınk [35] showed that artificial neural network algorithms can be successfully applied in estimating BW based on measured values in estimating body weight in Thalli sheep breed. However, the R^2 value obtained from the ANN algorithm was found to be lower than the values obtained in this study.

Race and assessed traits may account for these differences. Behzadi and Aslaminejad [36] reported that in estimating the growth characteristics of Baluchi sheep, ANN provides the most accurate estimation by creating a better descriptive sheep growth curve compared to nonlinear models. They reported an MSE of 0.06 for the artificial neural network, which is similar to our research results. They also stated that ANN is a valuable tool in estimating body weight in lambs. Ali et al.[37] compared artificial neural networks and other methods in estimating weaning body weight of lambs with the help of some morphological features in Harnai sheep. The correlation coefficient for actual and estimated body weight with ANN was determined as 0.91, MAE value as 0.0594, and RMSE value as 1.589. However, in their study of data mining algorithms, they suggested that the SD ratio of the algorithm applied should be lower than 0.40 for a good prediction performance. Norouzian and Vakili Alavijeh [38] compared ANN and multiple regression models for tail fat estimation by using birth weight and weaning weights in Balouchi sheep and found that ANN had higher R^2 value (0.93) and lower MSE (0.51) value compared to multiple regression model. The same values were reported as 0.81 and 1.24 in the multiple regression model, respectively. As a result of the study, the researchers revealed that the ANN model gave more accurate predictions than the multiple regression model in estimating the tail fat weight in sheep. Lactation milk yield was estimated by ANN model in terms of province, number of sheep, total amount of feed, veterinary costs, total labor costs, amount of salt, grazing period, lambing month, age of ewe, lactation length and number of milking factors in Akkaraman sheep [39]. As a result of the study, they determined R^2, MAE and RMSE in the ANN model as 0.791, 14.360, and 18.78, respectively. Ghotbaldini et al.[21] estimated the body weight of Kermani sheep at 6 months of age with ANN. For this purpose, they used the records of 867 lambs including lamb gender, maternal age, birth weight, weaning weight and 3-month live weight. They found the correlation coefficient as 0.864 and MSE=0.015 in the multilayer ANN model with nine input variables and seven neurons. As a result of the study, they reported that ANN has a good ability to predict the growth characteristics of sheep with an acceptable speed and accuracy. It has been reported that ANN can be used successfully as an alternative method to linear regression in estimating the effect of herd, lambing month and lactation period on lactation milk yields [40]. In addition, it has been stated that ANN provides valuable contributions to animal husbandry studies in terms of estimating body weight from testicular measurements and defining body weight in sheep [41].

It has been reported that the determination coefficients between the estimated and actual body weights in goats were positive and highly significant and ranged from 90.27% to 93.69%. The highest R^2 value in estimating body weight in goats using body measurements was obtained in 0-3 month-old kids [42]. However, they reported that ANN gave more successful results than multiple regression analysis in body weight estimation in all age groups. According to Eyduran et al.[33] stated that artificial neural networks and other algorithms can be successfully applied in the estimation of live weight according to various body measurements in Beetal goats and they obtained estimates that are very close to the truth. In addition, they found that the gender factor was the most determinant body weight predictor in all algorithms. It has been reported by Kaygısız and Sezgin [43] that ANN can be used safely in terms of prospective estimates of goat milk production data and their compatibility. According to Kannan et al.[44] reported that ANN models predicted responses more accurately than regression models in predicting physiological stress responses in post-transplant goats. Khorshidi-Jalali et al.[45] stated that ANN (R^2=0.86, RMSE=19.86) provides realistic data in body weight estimation using various morphological measurements in Raini goats and that it can be successfully used instead of traditional methods for this purpose.

On the other hand, Cihan et al.[46] used and compared Artificial Intelligence Methods and Immunoglobulin G prediction in lambs, ANN, multivariate adaptive regression curves (MARS), support vector regression (SVR) and fuzzy neural network (FNN) models. FNN was found to be the most successful method for estimating the IgG value. According to Ekiz et al.[47] compared chi-squared automatic interaction detection (CHAID) and ANN methods in estimating carcass tissue composition in Gokceada kids and found that the results were close to each other in estimating bone ratio, and the CHAID model gave better results in estimating subcutaneous fat and intermuscular fat ratios. They explained the reason for this as the small size of the data set in the study is a limiting factor for ANN estimation. When these studies are evaluated, it is seen that the ANN model can be used instead of multiple regression models in estimating live weight by using many different measurements in livestock, because it has a higher R^2 and correlation coefficient, a lower standard deviation, and thus performs more effectively.

In this study, the obtained results proved that the ANN can be used successfully for the prediction of marketing live weight. ANNs also have an important role because it does not need large data sets to design a quite reliable neural network. The usage of ANN modeling may be highly recommended to predict marketing live weight. With the estimation of the marketing weight, it will be possible to pre-evaluate the economic cost calculations to be obtained from the kids based on both the country and the farm, and to reveal the future projections, especially for supporting red meat production in Turkey or using it as an alternative. The importance of keeping records is seen again in this study, that proper and continuous records will increase the degree of accuracy in breeder selection and breeding for meat purposes. It is essential for the future of small cattle breeding and its contribution to the country's economy to put into operation systems that will record long-term data and monitor herd management programs. ANN will enable early selection of animals in terms of meat yield with low heritability as well as other yield characteristics.

Due to the developing technology and livestock herd management systems and parallel to the increase in the number of records, it has become necessary to evaluate large data sets with data mining methods. As long-term and large-scale data are obtained in the hands of the public with this study, it has been revealed that it is necessary to evaluate the environmental factors important in terms of agriculture at the same time and to prefer the ANN, which is an unbiased and reliable estimation method. It is necessary to continue to work on estimating marketing weights with different ANN models in larger data sets.

Availability of Data and Materıals

The authors declare that the data supporting the study findings were obtained from the corresponding author (F. Erdoğan Ataç).

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Competing Interests

The author declared that there is no conflict of interest.

Ethical Statement

In the study, there is no need for ethical approval due to the lack of blood sampling from the animals and the absence of any surgical procedures. All data were collected with the approval of the breeder.

Authors' Contributions

F.E.A and Ç.T. planned the study; F.E.A. collected datas; F.E.A., Ç.T., Ş.Ö.A., Y.G., designed the experiments and drafted manuscript; Ç.T., Y.G., analyzed all data; F.E.A., Ç.T., Ş.Ö.A. reviewed and edited the manuscript. All authors have read and agreed to the published version of the manuscript.

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