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ANIMAL PRODUCTION

Birth weight in Alpine kids using body measurements: a comparison of artificial neural network and multiple linear regression models

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ABSTRACT: The present study was conducted to estimate the body weights of Alpine kids using somebody measurements with artificial neural network (ANN) and multiple linear regression (MLR) analysis. For this purpose, the birth weight of 97 kids in total and body measurements such as withers height, rump height, chest depth, chest girth and body length were taken. The model performance criteria used to compare the neural networks and regression analysis results for the goodness of fit are coefficient of determination (R^2) and mean square error (MSE). In analyses using artificial neural networks, Levenberg-Marquardt (LM), Bayesian Regularization (BR), and Scaled Conjugate Gradient (SCG) algorithms were applied. The findings showed that the LM algorithm produced the best results and achieved the highest R^2 and lowest MSE values among the ANN training algorithms. The ANN model ($R^2 = 0.9173$; MSE = 0.0006) outperformed the MLR model ($R^2 = 0.791$; MSE = 0.101) in predicting the birth weight of Alpine kids.

Key words: goat production, Türkiye, machine learning, predictive modelling.

Estimativa do peso ao nascer em cabritos alpinos usando medidas corporais: uma comparação entre redes neurais artificiais e modelos de regressão linear múltipla

RESUMO: O presente estudo foi conduzido para estimar o peso corporal de cabritos alpinos, tomando algumas medidas corporais por meio de rede neural artificial (RNA) e análise de regressão linear múltipla (RLM). Para tanto, foram coletados o peso total ao nascer de 97 cabritos, além de medidas corporais como altura da cernelha, altura da garupa, profundidade do peito, perímetro torácico e comprimento do corpo. Os critérios de desempenho do modelo usados para comparar redes neurais e os resultados de ajuste da análise de regressão são os coeficiente de determinação (R^2) e o Erro Quadrático Médio (EEM). Nas análises usando redes neurais artificiais, foram aplicados os algoritmos Levenberg–Marquardt (LM), Regularização Bayesiana (RB) e Gradiente Conjugado Escalonado (GCE). Os resultados mostraram que o algoritmo LM produziu os melhores resultados, alcançando os maiores valores de R^2 e os menores valores de EEM entre os algoritmos de treinamento de RNA. O modelo RNA (R^2 = 0.9173; EEM = 0.0006) superou o modelo RLM (R^2 = 0.791; EEM = 0.101) na previsão do peso ao nascer de cabritos da raça Alpine.

Palavras-chave: produção caprina, Turquia, aprendizado de máquina, modelagem preditiva.

INTRODUCTION

Goats (*Capra hircus*) are one of the oldest animal species, domesticated more than 10,000 years ago in the Zagros Mountains and Eastern Anatolia, playing an important cultural and economic role by providing humans with meat, milk and leather (KICHAMU et al., 2024). As small ruminants, goats are widely raised in many parts of the world, particularly in rural and mountainous regions, due to their durable constitution, low maintenance requirements, high adaptability to harsh environmental conditions, and ability to graze easily in rugged, rocky areas (NAIR et al., 2021). Goats are also highly valued for their productivity, adaptability, and resistance to diseases (DASKIRAN et al., 2018; KOLUMAN et al., 2024). According to the Food and Agriculture Organization (FAO) data, the global goat population is 1,002 billion, with the largest populations being in Asia (57.7%) and Africa (35.7%) (ANTUNOVIĆ et al., 2025). Türkiye is one of the leading countries in the world in terms of goat population and production (DASKIRAN et al., 2018), and an increase in the goat population in Türkiye has been observed in recent years (SERT & DURMUS, 2024; SERT & DURMUS, 2025). Goat farming in Türkiye is carried out by small-scale farmers living in rural areas and is a significant animal production activity for both meat and milk (TOPLU & ALTINEL, 2008). The Alpine goat, a

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high-yielding breed used in this farming activity, holds significant economic value for breeders, particularly due to its high milk yield and fertility.

Increasing the productivity of these animals and ensuring the genetic development of herds depend on accurately evaluating performance data obtained from birth (ASSAN, 2013). Weights and growth rates from birth to weaning are the primary determinants of production efficiency in livestock farming (ASSAN, 2020). In goats, birth weight varies widely due to both environmental and genetic factors, including birth season, sire age, dam age, offspring sex, year of birth, and birth type (CHALBI et al., 2022; RAMOROKA et al., 2024). It also affects basic production parameters such as birth weight, survival rate, growth rate, and milk or meat yield in goats during later periods (JAT & DATT, 2025). Therefore, birth weight is considered an important criterion for early selection and herd management in small ruminant farming (SAHIN, 2022). High mortality rates, especially among kids with low birth weight (ANDRÉS et al., 2020), make the measurement, prediction, and control of this trait critical from an economic perspective.

There are two main approaches to determine animal weight: direct measurement using weighing devices and indirect estimation using measurements taken from specific body parts (WANG et al., 2021; CAMACHO-PÉREZ et al., 2022). Direct weight measurement requires handling the animals and placing them on weighing devices. However, it has been reported that animals experience stress and increased cortisol levels during routine husbandry procedures such as milking, shearing, weighing, loading, and hoof care (YARDIMCI et al., 2013). A study with lambs indicated that stress affects their health and production performance (NAVARRO et al., 2020). Therefore, as direct interventions on animals increase, their welfare and development are negatively affected. Various methodologies, such as mathematical regression models using morphological measurements, are used for indirect weight estimation (CAMACHO-PÉREZ et al., 2022). Using such methodologies and existing data to extrapolate additional data will reduce the stress to which animals are exposed due to intervention.

Within animal production systems, estimating economically important performance metrics such as body weight, egg production, milk yield, and hair production plays a crucial role in developing future on-farm and off-farm decision support systems. Classical statistical methods and artificial intelligence-based modelling techniques are widely used today for the control, analysis, and prediction of animal production data (IKIKAT TUMER et al., 2020; SINGH et al., 2020; ELLIS, 2021; GRITSENKO et al., 2023; ERDOGAN ATAC et al., 2023; ATOUI et al., 2024; MELAK et al., 2024; MAKGOPA et al., 2024; YANG et al., 2025; GONCALVES et al., 2025). There are many studies in the literature that employ artificial neural networks and multiple linear regression, to make predictions in animal science. THIRUVENKADAN (2005), ALADE et al. (2008), RAJA et al. (2012), YILMAZ et al. (2013), AKKOL et al. (2017), KHORSHIDI-JALALI et al. (2019), GHOTBALDINI et al. (2019), ABD-ALLAH et al. (2019), ADHIANTO et al. (2020), DAKHLAN et al. (2020), IBRAHIM et al. (2021), KADER ESEN & ELMACI (2021), TYASI & CELIK (2023) estimated some body measurements in small ruminants by artificial neural network or multiple linear regression.

The multiple linear regression (MLR) model is a traditional modelling technique used to estimate the relationship between dependent and independent variables (LU et al., 2025). In recent years, artificial neural networks (ANNs) have frequently been used as an alternative to regression analysis. Various studies have shown that ANN models provide successful results in predicting traits such as milk yield, body weight gain, and birth weight (TAHMOORESPUR & AHMADI, 2012; WANG et al., 2021; RIBEIRO et al., 2021; ANGELES-HERNANDEZ et al., 2022). ANNs are an effective artificial intelligence technique that mimics the learning mechanism of the human brain and models nonlinear relationships. An artificial neuron receives information as input, processes it using mathematical formulas, and produces an output that determines the neuron's behavior (LEMONIS et al., 2022). ANNs are widely used for complex systems that are difficult to predict, especially when data are insufficient (ELMABROUK et al., 2014; SALEHUDDIN et al., 2022).

In this study, the comparative performance of ANN and MLR models was evaluated for the estimation of birth weight from various body measurements of Alpine goats. The findings are expected to contribute to early selection studies and production planning in goat breeding.

MATERIALS AND METHODS

Location and animal care

The present study was conducted on 97 kids obtained from the Alpine goats raised at

Cukurova University, Faculty of Agriculture, Dairy Goat and Sheep Breeding Research and Application Unit, Adana, Türkiye. Animals are reared under semi-intensive conditions in a semi-open system. The province of Adana carried in the study is in the Mediterranean Region at 37º north parallel, 35º east longitude, and 40 m above sea level. This region is hot and dry in summer and warm and rainy in winter. The average humidity is around 66%, and the north-south wind prevails. During pregnancy, roughage (alfalfa hay, corn silage) and concentrated feed were given to the Alpine goats.

Data set

Growth in goats is determined by taking certain body measurements, primarily body weight. For this purpose, measurements are taken to predict future growth, particularly musculoskeletal development. These early measurements are used effectively in allocating kids for breeding. Therefore, body weight (BW) and body measurements such as withers height (WH), rump height (RH), chest depth (CD), chest girth (CG), and body length (BL) from kids were taken at one day of age shortly after birth. In the current study, body measurements were taken for all offspring without considering factors such as gender, birth type, and age of the mother. When the gender and birth type of the born kids were taken into consideration, 53 were male and 44 were female; 8 were single, 52 were twins and 37 were triplets. A digital scale with a 5 g sensitivity was used to assess the kids' birth weights, and a tape measure was used to measure their chest girths and other body measurements.

The measurements taken from the kids are described below. Wither height (cm) - vertical distance between the highest point of the withers and the base level; rump height (cm) - vertical distance between the highest point of the rump and the base level; chest depth (cm) - vertical distance between the highest point of the withers and the sternum; chest girth (cm) - the length of the 360° circumference taken by passing over sternum bone, behind the withers; body length (cm) - distance between the shoulder tip and the seat bump.

Statistical analyses

The variables in the data sets used in data mining have different scales and units (WU & WANG, 2022). Attributes having large or small values and ranges in the dataset will cause instability in the ANN training process (MAARIF et al., 2022). Therefore, data normalization, which is a technique in data preprocessing, should be done. The most used data normalization is minimum/maximum normalization, which uses the minimum and maximum values of each attribute (SINSOMBOONTHONG, 2022). The minimum/maximum normalization used in this study is given by equation 1.

$$X_{nor} = \frac{X_i - X_{min}}{X_{max} - X_{min}} \quad (1)$$

In which X_{nor} is normalized imput, X_i is original value, X_{min} is minimum value of data to be normalized, and X_{max} is maksimum value of data to be normalized (CHO et al., 2022).

Artificial neural network (ANN)

In the analysis of Artificial Neural Networks (ANN), the Multi-Layer Perceptron (MLP), one of the most commonly used architectures, consists of an input layer, an output layer and one or more hidden layers of neurons (WIJAYANINGRUM et al., 2021). Feedforward neural networks (FNNs), one of the main categories of neural networks that connect neurons across layers (IMRAN & ALSUHAIBANI, 2019), connect the input to the hidden layer and the hidden layer to the output layer in a single direction (OBITE et al., 2020).

Each input from the input layer is given a certain weight. The weights indicated the importance of incoming information. The summation function is used to calculate the total input in a cell. The weighted sum, the most frequently used summation function, is calculated by multiplying and summing the inputs and the weights (CELIK & ALTUNAYDIN, 2018). The sum of the weighted inputs and the bias forms the input to the transfer function. A transfer function processes this sum and produces the output (AHMADI, 2015).

Transfer functions are used to initiate data transmission from the input or hidden layer and configure the calculated output (FENG & LU, 2019; MAKOMERE et al., 2023). The most used transfer functions are tansig and logsig function and make the ANNs a universal function approximator given a sufficient number of hidden neuron (PANDEY et al., 2016). The purelin, tansig and logsig transfer functions are given by equations (2-4) (YOGITHA & MATHIVANAN, 2018).

$$f(x)=x \quad (2)$$

$$f(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \quad (3)$$

$$f(x) = \frac{1}{1+e^{-x}} \quad (4)$$

In which f(x) is the output value from the function (output), x is the input value to the function (input), e is Euler's number (e ≈ 2.71828).

Training is the process of optimizing the connection weights (CHAKRABORTY & GOSWAMI, 2017). The training algorithms used in this study, namely the Levenberg-Marquardt (LM) algorithm, Bayesian Regularization (BR) algorithm and Scaled Conjugate Gradient (SCG) algorithm, are given by equations (5-7).

$$x_{k+1} = x_k - [J^T J + uI]^{-1} J^T e \quad (5)$$

In which I is a identity matrix, e is the error vector, J is a Jacobian matrix, X_k is the weight at epoch K, and u is a damping factor (MARKOVA, 2019; HUANG et al., 2021).

$$F(w) = \alpha E_w + \beta E_D \quad (6)$$

In which E_D is the sum of squared network errors, E_W is the sum of squared network weights and α and β are the function parameters (YUE et al., 2011; HUANG et al., 2021).

$$x_{k+1} = x_k + n_k d_k \quad (7)$$

In which x_k is weight parameters, n_k is the learning rate and d_k is a descent search direction (BULUT et al., 2021).

Number of hidden layers, number of neurons in hidden layers, transfer functions (activation function), training algorithms are selected by the trial and error method (ALALOUL et al., 2018; PATIL et al., 2021). Because there is no definite method to determine these parameters.

In this study, the ANN network selected is multi-layer perceptron (MLP) and neurons in all layers are connected by a feed forward neural networks (FNNs). Input variable is BW and output variables are WH, RH, CD, CG and BL. Since these values have different units, they are normalized with the min-max method. The data applied was 70% for training the network, 15% for validation and 15% for testing. Tansig and logsig function are used in the hidden layers whereas purelin function is used in the output layer. The number of neurons was selected in a range from 2 to 20. LM, BR and SCG 1000 epoch training algorithms were applied. Models are robust in BR and no need for a separate validation set (BURDEN & WINKLER, 2008). The ANN design, which demonstrates the relationship between the input and output layers, is given in figure 1.

Multiple linear regression (MLR)

The MLR is used to model the relationship between a dependent variable and more than one independent variable (ZARE ABYANEH, 2014). The general model of multiple linear regression is given by Eq. (8) (MONTGOMERY et al., 2001).

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k X_{ik} + \varepsilon_i \quad (8)$$

In which y_i is i-th observation in the dependent variable, β_0 is the intercept, β_j is the regression coefficient, X_i is the independent variables, k is the number of the independent variable, and εi is the random error term.

Evaluation criteria for ANN and MLR prediction

The performance of the model was assessed by the coefficient of determination (R^2) and mean square error (MSE). The calculation of R^2 and MSE is performed using equations (9-10) (ZHANG et al., 2022).

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y})^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} * 100 \quad (9)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{N}(y_i - \hat{y})^2 \quad (10)$$

In which n is number of observations, y_i is observed value, $\hat{y}$ is predicted value. The higher R^2 values represent the greater fit between the observed and predicted values. The lower MSE represents a trained model with higher accuracy (HUANG et al., 2021). MATLAB 2021a version software was used for ANN and MLR modeling and analysis.

RESULTS AND DISCUSSION

Descriptive statistics of body weight and some body measurements taken from 97 heads of Alpine kids are shown in table 1. In this study, the average body weight at birth was 4.166 kg. DE MENEZES et al. (2007) reported the average body weight of Alpine kids at birth as 3.61 kg, and MAKSIMOVIĆ et al. (2015) reported birth weight as 2.73 kg. KUME & HAJNO (2010) also found birth weights of 3.11-3.15 kg. Compared to other studies in the literature, the significantly higher offspring body weights detected in our current study are most likely related to the characteristics of the mothers in our experimental groups. In particular, the advanced age of the breeding mothers used in our study and their average body weight (average 60 kg) form the basis of this difference.

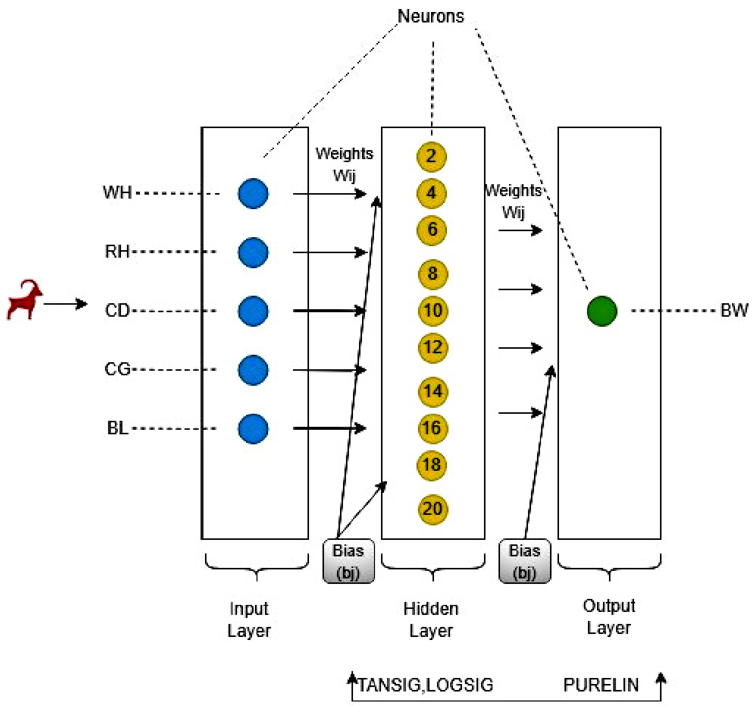

Figure 1 - Developed ANN model design.

WH = withers height; RH = rump height; CD = chest depth; CG = chest girth; BL = body length; BW = body weight; ANN = artificial neural network.

The MLR analysis results are shown in table 2. The most reliable predictors of the equation are the variables CG and BL, with $P < 0.001$. Although, the other variables (WH, RH, CD) contribute to the model, they are not considered statistically significant on their own.

Through the MLR model, the direction of effect (positive or negative coefficient) and

Table 1 - Descriptive statistics of birth weight and some body measurements.

Variables	Min	Max	Mean	SE	CV (%)
BW (kg)	2.63	6.12	4.166	0.060	14.275
WH (cm)	33.50	43.00	39.051	0.181	4.577
RH (cm)	33.00	43.50	38.948	0.177	4.498
CD (cm)	10.50	15.50	12.762	0.101	7.796
CG (cm)	29.50	42.00	36.974	0.188	5.012
BL (cm)	26.50	35.50	31.041	0.175	5.554

BW = body weight; WH = withers height; RH = rump height; CD = chest depth; CG = chest girth; BL = body length; Min = minimum value; Max = maximum value; SE = standard error of the mean; CV (%) = coefficient of variation.

Table 2 - The MLR model summaries for prediction of BW.

Variables	Coefficient	Standard Error	T value	Pr (> |t|)
Constant	-6.577	1.034	-6.358	P < 0.001
WH (cm)	0.092	0.092	0.998	0.322
RH (cm)	-0.059	0.088	-0.667	0.508
CD (cm)	-0.048	0.058	-0.824	0.413
CG (cm)	0.149	0.039	3.868	P < 0.001
BL (cm)	0.146	0.031	4.760	P < 0.001

MLR = multiple linear regression; BW = body weight; WH = withers height; RH = rump height; CD = chest depth; CG = chest girth; BL = body length.

the magnitude (coefficient value) of each body measurement on the birth weight estimation are clearly visible. If the coefficient values in table 2 are substituted, the final equation for BW estimation is as follows:

$$BW = -6.557 + 0.092WH - 0.059RH - 0.048CD + 0.149CG + 0.146BL$$

The network structure selection was made based on the mean square error (MSE) (LORENC et al., 2021). The modelling results of three training algorithms (LM, BR and SCG algorithm) are given in table 3, table 4, and table 5.

When the ANN model's predictive performance is examined, as shown in figure 2, the

Table 3 - Results of LM training algorithm of ANN model.

Transfer functions	Number of neurons	----------Performance Criteria----------				
		MSE	----------R----------			
			Training	Validation	Test	All
Tansig	2	0.00868	0.8540	0.7184	0.8525	0.8364
	4	0.00477	0.8368	0.8377	0.8116	0.8252
	6	0.00337	0.8979	0.8827	0.8411	0.8783
	8	0.00207	0.8950	0.9530	0.7509	0.8523
	10	0.00428	0.8705	0.8652	0.7464	0.8512
	12	0.00296	0.9030	0.6646	0.8202	0.8631
	14	0.00211	0.7604	0.8728	0.8538	0.7834
	16	0.00366	0.7975	0.6553	0.5577	0.7479
	18	0.00426	0.8689	0.8909	0.8526	0.8618
	20	0.00063	0.9102	0.9718	0.9578	0.9333
Logsig	2	0.00766	0.8528	0.8667	0.8308	0.8443
	4	0.00367	0.9048	0.8696	0.7977	0.8691
	6	0.00457	0.8909	0.9325	0.7214	0.8737
	8	0.00276	0.9174	0.5987	0.8817	0.8721
	10	0.00406	0.8542	0.6357	0.8054	0.8290
	12	0.00288	0.8910	0.8313	0.8009	0.8697
	14	0.00194	0.9447	0.6461	0.7830	0.8777
	16	0.00218	0.915	0.7630	0.7148	0.8521
	18	0.00240	0.9056	0.9450	0.8160	0.9034
	20	0.00269	0.8475	0.7192	0.7336	0.8114

LM = levenberg-marquardt algorithm; ANN = artificial neural network; MSE = mean square error; R = correlation coefficient.

Table 4 - Results of BR training algorithm of ANN model.

Transfer functions	Number of neurons	------------------------------------Performance Criteria------------------------------------			
		MSE	------------------------------------R------------------------------------		
			Training	Test	All
Tansig	2	0.0073	0.8469	0.8686	0.8513
	4	0.0061	0.8904	0.8202	0.8846
	6	0.0077	0.8462	0.8601	0.8434
	8	0.0078	0.8484	0.8268	0.8430
	10	0.0039	0.8267	0.9133	0.8418
	12	0.0085	0.8442	0.8520	0.8416
	14	0.0076	0.8456	0.8120	0.8422
	16	0.0083	0.8485	0.8307	0.8452
	18	0.0084	0.8250	0.9303	0.8445
	20	0.0066	0.8679	0.7336	0.8445
Logsig	2	0.0055	0.9007	0.6313	0.8599
	4	0.0066	0.8790	0.9266	0.8855
	6	0.0073	0.8535	0.9132	0.8615
	8	0.0058	0.8853	0.8502	0.8776
	10	0.0084	0.8517	0.8476	0.8439
	12	0.0075	0.8477	0.8366	0.8417
	14	0.0067	0.8873	0.5486	0.8697
	16	0.0081	0.8474	0.7993	0.8454
	18	0.0086	0.8319	0.9021	0.8440
	20	0.0085	0.8491	0.8901	0.8454

BR = bayesian regularization algorithm; ANN = artificial neural network; MSE = mean square error; R = correlation coefficient.

R correlation coefficient is very high at 0.95789, even on the test data set, which is the most critical success metric. The R = 0.97189 value on the validation set demonstrates that the model is not overfitting and possesses high generalization capability. These high correlation values demonstrate that the ANN model produces highly reliable and accurate results for birth weight prediction in Alpine goats.

When the ability of BR, LM and SCG neural network training algorithms to estimate body weight was investigated, the LM algorithm provided the best result (Table 6). MARKOVA (2019) stated that among LM, BR and SCG algorithms, the LM algorithm performed better in its predictions. GUZEL (2018), XEZONAKIS et al. (2024), DENIZHAN (2024) reported that both LM and BR algorithms outperformed the SCG algorithm.

When the internal structure of the ANN model was examined, it was determined that among the body measurements used in birth weight estimation, CG had the greatest mathematical weight compared to all other inputs. The RH was determined as the second most influential input. This finding from the ANN model closely parallels the results of the MLR model. In the MLR analysis, CG had the highest positive coefficient and the highest statistical significance ($P < 0.001$), indicating that both models, based on two fundamentally different mathematical principles, confirmed chest girth as the most reliable biological determinant of birth weight in Alpine goats. Although, although it was statistically insignificant in the MLR ($P > 0.05$), the RH variable was identified as the second most significant variable in the ANN model. This result demonstrated the ability of the

Table 5 - Results of SCG training algorithm of ANN model.

Transfer functions	Number of neurons	Performance Criteria				
		MSE	R			
			Training	Validation	Test	All
Tansig	2	0.0077	0.8289	0.8474	0.8884	0.8359
	4	0.0110	0.7856	0.9188	0.6362	0.7815
	6	0.0091	0.7817	0.8066	0.7846	0.7812
	8	0.0100	0.5616	0.7799	0.4147	0.5734
	10	0.0100	0.6833	0.8224	0.4298	0.6507
	12	0.0100	0.7789	0.9215	0.7487	0.7902
	14	0.0077	0.7835	0.8874	0.8252	0.8265
	16	0.0074	0.8257	0.7451	0.4940	0.7759
	18	0.0064	0.8699	0.7877	0.7765	0.8410
	20	0.0073	0.8273	0.8789	0.6295	0.7990
Logsig	2	0.0088	0.7989	0.9165	0.7712	0.8066
	4	0.0077	0.7368	0.6455	0.6659	0.7127
	6	0.0075	0.8486	0.8492	0.8941	0.8561
	8	0.0071	0.8616	0.9041	0.8272	0.8601
	10	0.0073	0.7974	0.8176	0.8556	0.8099
	12	0.0076	0.6423	0.5643	0.7236	0.6335
	14	0.0073	0.8750	0.8332	0.7745	0.8599
	16	0.0062	0.8859	0.7726	0.8687	0.8647
	18	0.0090	0.7916	0.7822	0.6779	0.7763
	20	0.0092	0.8107	0.9039	0.7959	0.8192

SCG = scaled conjugate gradient algorithm; ANN = artificial neural network; MSE = mean square error; R = correlation coefficient.

ANN to capture complex nonlinear relationships. This suggests that the effect of RH on birth weight is mediated through complex interactions and synergies with other morphological measurements, rather than a simple linear relationship.

While the MSE of the ANN model (0.0006) was lower than that of the MLR (0.101), the coefficient of determination ($R^2 = 0.9173$) was higher than that of the MLR (0.791) in Alpine kids (Table 7). Therefore, it was concluded that the ANN model is a more reliable and accurate tool for estimating the body weight of Alpine kids. AKKOL et al. (2017) estimated body weight from chest width, rump height, withers height, back height, chest depth, chest girth and body length in Hair goats; KHORSHIDI-JALALI et al. (2019) estimated from body length, withers height, chest girth in Raini Cashmere goats; RAJA et al. (2012) estimated from body circumference, body length and withers height in Attappady Black goats; TYASI & CELIK (2023) estimated from body length, heart girth, withers height, rump height, rump length, ear length and head width in Boer goats. It has been proven that the ANN model has better performance than the MLR model because it has higher R^2 and the lowest MSE.

CONCLUSION

Artificial neural networks and multiple linear regression models were compared to identify the best model for predicting the birth weight of Alpine kids. The results indicated that artificial neural network model is more robust and can predict birth weight from certain body measurements of Alpine kids more accurately than multiple linear regression model. The findings also show that chest girth is the

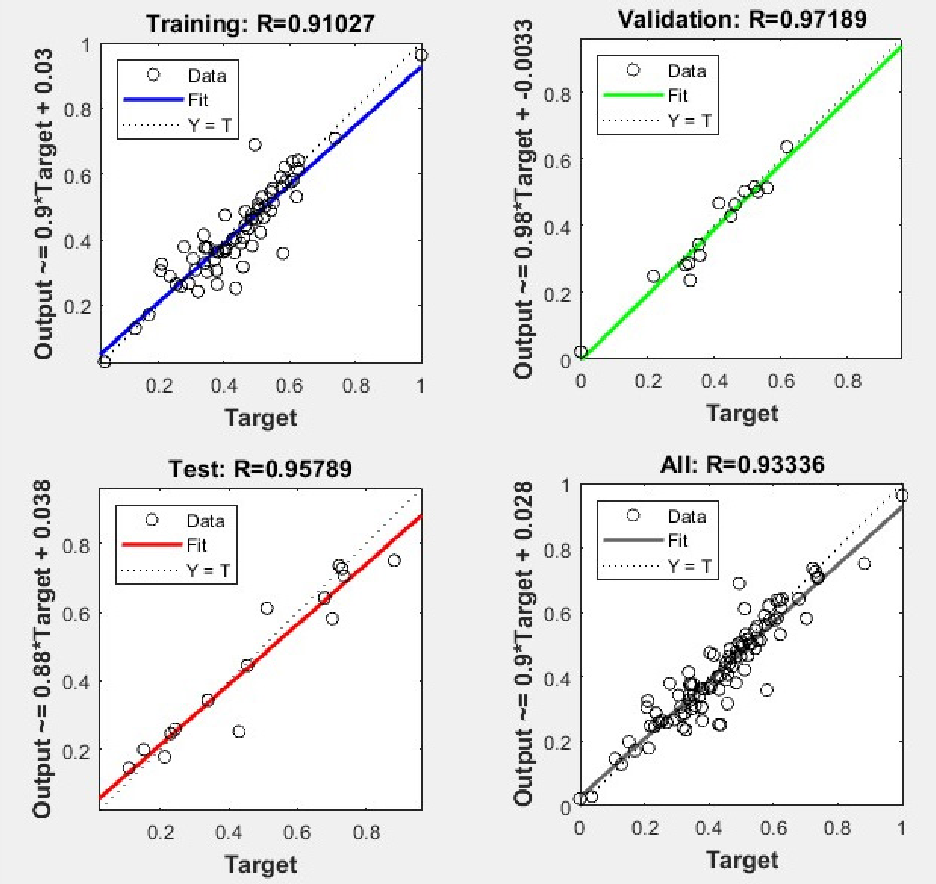

Figure 2 - The regression fit graphical representation for LM.

R = correlation coefficient; LM = levenberg-marquardt algorithm.

most reliable predictor of birth weight in kids. This morphological measurement can serve as a simple, practical, and reliable tool for estimating birth weight in the field with high accuracy and low cost. This provided farmers with a solid basis for making informed herd management and feeding decisions.

Table 6 - The best results for LM, BR and SCG training algorithms.

Training algorithm	Transfer functions	Number of neurons	MSE	R (Test)
LM	Tansig	20	0.0006	0.9578
BR	Tansig	10	0.0039	0.9133
SCG	Logsig	16	0.0062	0.8687

LM = levenberg-marquardt algorithm; BR = bayesian regularization algorithm; SCG = scaled conjugate gradient algorithm; MSE = mean square error; R = correlation coefficient.

Table 7 - Comparison of ANN and MLR.

Performance criteria	---Test data set---	
	MLR	ANN
R^2	0.791	0.9173 [$R^2 = (0.9578)^2$]
MSE	0.101	0.0006

ANN = artificial neural network; MLR = multiple linear regression; R^2 = coefficient of determination; MSE = mean square error.

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DECLARATION OF CONFLICT OF INTEREST

The author declares that there is no conflict of interest.

AUTHORS' CONTRIBUTIONS

MCG: Conceptualization, design of methodology, writing - review and editing.

BIOETHICS AND BIOSECURITY COMMITTEE APPROVAL

Cukurova University Animal Ethics Committee approved all experimental procedures for the present study (Protocol No. 2022/8).

DATA AVAILABILITY STATEMENT

The raw data is available directly with the author.

DECLARATION OF USE OF ARTIFICIAL INTELLIGENCE

No artificial intelligence was used to prepare this article.

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