Journal of Animal & Plant Sciences, 33(4): 2023, Page: 829-839
ISSN (print): 1018-7081; ISSN (online): 2309-8694
https://doi.org/10.36899/JAPS.2023.4.0676

ARTIFICIAL NEURAL NETWORK MODEL APPROACH TO PREDICT BODY WEIGHT IN SOUTHERN ANATOLIAN RED CATTLE

H. Hizli

Ministry of Agriculture and Forestry, Eastern Mediterranean Agriculture Research Institute, Adana, Türkiye
Corresponding Author's email: haticehizli@gmail.com
Author's ORCID: Hatice HIZLI: 000-0002-5451-1397

ABSTRACT

For sustainable animal breeding, body weight and morphological measurements are taken. In this study, a multi-layer feed-forward neural network model was created utilizing several morphological measures to estimate body weight in Southern Anatolian Red Cattle. The withers height, body length, chest girth, and rump width were defined as inputs while body weight was defined as a single output in the feed-forward neural network architecture. Network training was performed using Levenberg-Marquardt, Scaled Conjugate Gradient, and Bayesian Regularization algorithms. The linear function at the output and the hyperbolic tangent sigmoid function at the input of the hidden layer were both maintained constant, and the number of neurons in the hidden layer was varied to search for the optimal geometry for each transfer function. Feed-forward neural network optimization was performed using MSE and R^2 performance criteria. The performance metrics RMSE, MAE, MAPE%, and VAF% were used to compare the optimized feed-forward neural network models and predict the best model. The neural network models model created with the Bayesian Regularization algorithm was confirmed to be the best model. All morphological measurements as predictors had a high correlation ($r < 0.8$) with body weight estimation, with the greatest correlation among the morphological measurements being 0.947 between chest girth and withers height ($p < 0.001$). As a result, the optimum feed-forward neural network model was determined to be the Bayesian Regularization back-propagation algorithm. The proposed feed-forward neural network model has been proven to accurately predict body weight in Southern Anatolian Red Cattle (SAR) using input and output variables within the study's data range.

Keywords: Back-propagation algorithm, bayesian regularization, feed-forward neural network, Cattle, Türkiye

Published first online April 15, 2023 Published final August 04, 2023

INTRODUCTION

For sustainable animal breeding and herd management, measurements of body weight and morphological characteristics are conducted in livestock. Regression algorithms are widely used for forecasting. Today, the use of artificial neural networks (ANN) and machine learning technologies are also increasing. ANNs are computer-like information processing systems inspired by the organization of the organic nervous system and coupled by weighted connections. Because ANN models can represent both linear and non-linear datasets, pattern recognition, time series estimation, regression analysis, function approximation operations, and forecast estimates, they are being employed in a wide range of applications (Abraham, 2005; Haykin, 2009).

The information gathered from the review of the literature and a few animal husbandry related investigations utilizing ANN models is presented below. The partial lactation records and the first lactation records of hybrid dairy cattle were used to compare the estimation of 305-day lactation yield with multiple linear regression and ANN techniques (Salehi *et al.,*1998; Grzesiak *et al.*, 2003). The radial-based function neural network model, the back-propagation neural network model, and multiple linear regression (MLR) analysis methods were compared for their ability to accurately predict 305-day milk outputs from the first lactation data of Karan Fries dairy cows (Sharma *et al.*, 2006). The effects of lactation time, calving age and service period on lactation yield in Holstein were compared with ANN and MLR analysis methods (Takma *et al.*, 2012). ANN and MLR approaches were used to compare the impact of morphological measurements on the body weights of hair goats (Akkol *et al.*, 2017). Regression trees, chi-square automatic interaction detectors, multilayer detectors, dataset mining algorithms, and other techniques were presented to estimate body weight from different morphological measurements (Eyduran *et al.*, 2017). Pig eating patterns were estimated using an feed-forward neural network model (FFNN) model (Cross *et al.*, 2018). ANN was used to assess the reproductive values of the milk characteristic on body weight in 6-month-old

Kermani sheep (Pour-Hamidi *et al*., 2017; Ghotbaldini *et al.*, 2019). An ANN model developed using the photogrammetric approach was used to estimate the live weight of cows (Taşdemir and Özkan, 2019). The accuracy of body weight calculation using dromedary camel body measurements at birth and 240 days of age were compared using seven Machine Learning algorithms (Asadzadeh *et al.*, 2021).

Due to their effectiveness and dependability, ANN models can be commonly applied in assessing crucial aspects of livestock research. Furthermore, no studies on Southern Anatolian Red Cattle (SAR) have been reported using the ANN model. Therefore, in this study, a FFNN algorithm model was developed to estimate body weight using a dataset of morphological measurements collected from domestic cattle breeds SAR cattle, and the developed ANN model were tried to be revealed efficiency and reliability.

MATERIALS AND METHODS

Animal material: This study used data from 409 female SAR cattle raised at the Eastern Mediterranean Agricultural Research Institute between 1995 and 2020, which included morphological measurements and body weight. Measurements were made at ages at birth, three months, six months, twelve months, eighteen months, twenty-four months, and forty-eight months age. Withers height (WH), body length (BL), chest girth (CG), rump width (RW), and body weight (BW) were taken from each animal as described by FAO (2012). The data of BW was obtained using a digital scale (kg), and the data of WH, BL, RH, and CG were obtained using a measuring stick (cm) and tape measure Otogether. In the network model, WH, BL, CG, and RW are defined as input neurons, and body weight is an output neuron. Thus, the descriptive statistics of the input and output neurons in ANN model are given in Table 1.

Table 1. The descriptive statistics of input and output neurons in the ANN model

	Unit of		Properties of data set used in network topology				
Variables	**Variables**	**ANN parameters**	**Min.**	**Max.**	**Mean**	**SD**	**SE**
BW	kg	Output	15	700	120	147	7
WH	cm	Input	53	173	88	25	1
BL	cm	Input	16	189	83	31	2
CG	cm	Input	12	212	97	39	2
RH	cm	Input	10	71	23	10	1

SD: Standart deviation; SE: Standart error

The dataset was divided into three sections for the Levenberg-Marquardt (LM) and Scaled Conjugate Gradient (SCG) algorithms: training, testing, and validation, as 70%, 15%, and 15%, respectively. As a result, the number of cattle in the subdivisions of the LM and SCG algorithms was obtained as 287, 61, and 61, respectively. The subsections of the Bayesian Regularization (BR) algorithm were divided into two, 80% training and 20% testing, so that in the subdivisions 326 and 83 cattle were used for training and testing, respectively.

Method: An ANN is a mathematical model that uses a learning algorithm to explore the complex linear and nonlinear correlations between input and output data (Haykin, 2009). The network architecture, training algorithm, and activation functions must all be specified before creating a basic ANN architecture for whichever system. The simplest processing component in each ANN design, known as an artificial neuron, imitates the behavior and functions of real neurons in the human brain and allows for the simultaneous storage and processing of massive volumes of data (Dawson and Wilby, 1998; Akıllı and Atıl, 2014; Rachmad *et al.*, 2018; Zador, 2019). The basic building block of an ANN architecture is a collection of synthetic neurons that resemble biological neurons. Different numbers of neurons make up the input and output layers of an ANN, which are coupled to one another via one or more hidden layers. The most well-known ANN architecture is the feed-forward neural network (FFNN), which has three layers: an input layer, a hidden layer (or layers), and an output layer (Aladağ *et al.*, 2010; Asteris *et al.*, 2017; Anitha and Chakravarthy, 2018). The FFNN architecture employed in this research article is shown in Figure 1 to demonstrate a basic FFNN topology.

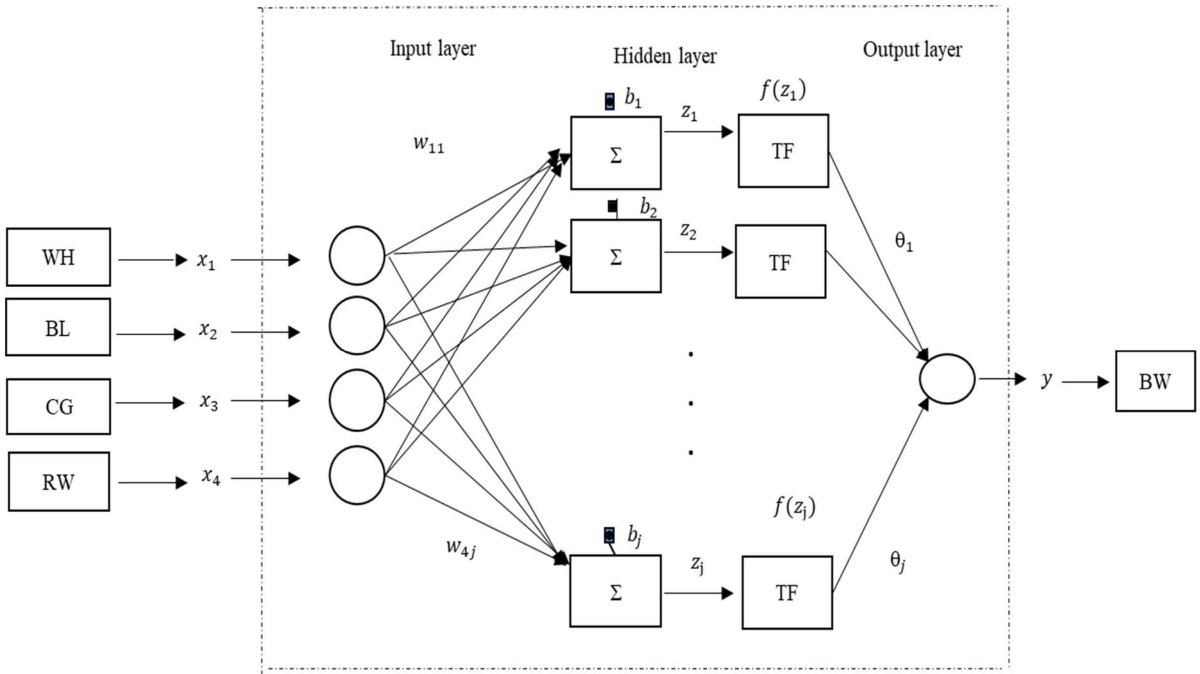

Figure 1. The architecture structure of FFNN developed for the prediction of BW

The input values $X(i = 1, \ldots, n)$ are information entering the cell from other cells or external environments in the first layer. These are WH, BL, CG and RW and are coded as x_1, x_2, x_3, and x_4. Information enters the cell through w_{ij} represents weight values that the interconnection is multiplied by x_i in the sum function for each neuron in the network (Asteris *et al.*, 2017). After that, z_j, named the weighted sum of the input dataset, as follows expressed by Equation (1) :

$z_j = \sum_{i=1}^{n} w_{ij} x_i + b_j$ (1)

where, z_j is treated with an activation function of $f(z_j)$, network can have a threshold input (b) with a value of +1 that increases the net input or -1 that decreases it, as the input neuron, and the output of the network y represents the estimated output values (Zhang and You, 2015) and as expressed by as follows Equation (2):

$y = \sum_{i=1}^{n} \theta_j f(z_j)$ (2)

where, θ_j is called the interconnection weight of nodes from hidden layer to output layer. In order to produce accurate prediction results, the training algorithm should be defined while designing an ANN model. The most powerful and common training algorithm for learning is the back-propagation neural network technique and there are many algorithms developed for this purpose (Putra and Wanto, 2017; Putro *et al.*, 2022). In this research, LM, BR, and SCG algorithms from the back-propagation training algorithms are compared. In ANN models, over-fitting and memorization problems may occur during training. There is no over-fitting or memorization problem as the BR back-propagation does not need the validation dataset to validate the network (MacKay, 1992; Saini, 2008; Kayri, 2016). In MATLAB software (2016b), it is checked using a hyper-parameter called "maximum validation failures", which specifies the maximum number of self-verification that the neural network allows for validating the network model (Beal *et al.*, 2010). For this aim information detailed in the developed model, the hyper-parameter values as learning rate, momentum factor (μ), maximum validation performance, and the number of epochs were set to 0.01, 0.001, 1000, and 1000, respectively in the FFNN model.

While developing an ANN model the other important point, the activation functions must be selected (Mhaskar and Micchelli, 1994). The activation functions commonly used in neural networks are sigmoid and hyperbolic tangent functions, and in the proposed ANN model, the hyperbolic tangent sigmoid function is selected for the best performance in hidden layer network training (Beal *et al.*, 2010), equation (3) is as follows.

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

The dataset was normalized in order for the network to produce successful results, by using Equation (4) (Zhang and You, 2015).

$D_N = 0.8 * [D_R - D_{min}/D_{max} - D_{min}] + 0.1$ (4)

Where, D_N, the measurements to be normalized, D_{min}, is the smallest of the available measurements, D_{max}, is the largest of the available measurements. After the network training was realized all input-output datasets were back normalized (Zhang and You, 2015), the following equation (5) has been used.

$D_R = \frac{(D_N - 0.1)}{0.8} * (D_{max} - D_{min}) + D_{min}$ (5)

The performances of the developed FFNN models were compared by the coefficient of determination (R^2), Mean Square Error (MSE), root mean squared error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE%) and Variance Accounted For (VAF%). These were represented by Equations (6), (7), (8), (9) (10) and (11), respectively (Karlik and Olgac, 2011; Erzin and Çetin, 2013).

$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}\hat{Y}_i^{\,2}}\right)$ (6)

$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2$ (7)

$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}$ (8)

$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right|$ (9)

$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right| .100$ (10)

$VAF = \left[1 - \frac{var(Y_i - \hat{Y}_i)}{var(y)}\right] .100$ (11)

Where, Y_i, $\hat{Y}_i$ represents variance measured value and the predicted value, respectively. The correlations between the input variables and the output variables are examined to determine which input variable ANN has the most impact on training performance. According to Chan (2003) and Akoğlu (2018), there was a weak correlation if $| r | < 0.2$, a moderate correlation if $0.2 < | r | < 0.8$, and a strong correlation if $| r | \geq 0.8$. In the network design and implementation of the study, the results were obtained by using the MATLAB software (2016b).

RESULTS AND DISCUSSION

In the present study, the ANN topology was developed after designing to estimate the BW. In Figure 1 shows that the architectural structure of the FFNN consists of parameters WH, BL, CG, and RW in the input layer, BW in the output layer, and a hidden layer. As seen in Table 2, network training was performed using back-propagation algorithms such as LM, BR, and SCG algorithms. In order to search for the optimum geometry in each algorithm the hyperbolic tangent sigmoid function at the input of the hidden layer and the linear function at the output were kept constant and the number of neurons in the hidden layer was tested from 1 to 13 values, and for feed-forward neural network optimization, MSE and R^2 performance criteria were used.

It can be seen that the LM and SCG training algorithms do not produce consistent results when Table 2 is reviewed by comparing the minimum MSE and maximum R^2 for the best performance in the training, testing, and validation data sets. It can be seen that the LM and SCG training algorithms do not produce consistent results when Table 2 is reviewed by comparing the minimum MSE and maximum R^2 for the best performance in the training, testing, and validation data sets. The MSE and R^2 results for the 7th neuron in the training dataset for the LM algorithm are the best; the MSE was found to be the smallest in the 3rd neuron and the R^2 to be the biggest in the 10th neuron in the testing dataset; and in the validation dataset, the first neuron had the highest R^2 and the MSE was lowest in was the 11th neuron. The MSE and R^2 results for the 12th neuron in the training dataset for the SCG algorithm are the best; in the testing dataset, the MSE was found to be the smallest in the 5th neuron and the R^2 to be the biggest in the 4th and 7th neurons; and in the validation dataset, the 5th neuron had the highest R^2 and the MSE was lowest in was the 7th neuron. On the other hand, in the BR training algorithm, both the training and testing datasets consistently produced the best performance results in the 8th neuron. When compared to other algorithms, these results are the most effective.

Akkol *et al.*, (2017) predicted body weight from body measures in hair goats using multi-layered feed-forward backpropagation algorithms, LM, BR, and SCG. According to their findings, the algorithm with the best R^2 and lowest MSE is BR. Khorshidi-Jalali *et al.*, (2019) used multi-layered feed-forward back-propagation algorithms to estimate body weight from morphological measures in Raini Cashmere goats. Researchers worked on eleven algorithms apart from the BR algorithm and discovered that the algorithm with the highest R^2 and the lowest MSE is the LM algorithm. Asadzadeh *et al.*, (2021) used dromedary camel body measurements to evaluate the accuracy of their weight prediction using seven machine learning algorithms, including bayesian regularization neural network (BRNN), extreme learning (EL), random forest (RF), support vector machine with the linear kernel (LSVM), polynomial kernel (PNLSVM), radial basis kernel (RNLSVM), and linear regression (LR). Despite the fact that they found BRNN to be the most accurate learning method among the models, they recommended the PNLSVM model based on all of the criteria they analyzed. According to Burden and Winkler (2009), the BR algorithm is more reliable than other standard optimization algorithms because it does not require validation.

The results of Table 2 are also similar to Figure 2, revealing that the BR algorithm perform effectively best in the 8th neuron and the 165th period. Figure 2 demonstrates that the best training performance is 0.00036 in the 165th epoch when the ANN model at 8 hidden neurons and the lowest MSE value is trained. Akkol *et al.* (2017) evaluated three alternative back-propagation algorithms for numbers ranging from three to ten neurons and revealed that the BR approach performed best with three neurons. They also stated The LM and SCG algorithms also have successful neuron counts of five and ten, respectively.

The residual of the created ANN model, which was derived using the BR algorithm, is depicted in Figure 3 as a histogram graph. The residual represents the difference between the measured and anticipated BW values. The residuals range from -0.1401 to 0.1254, and they are very modest.

Table 2. Comparison of performance parameters of different backpropagation algorithms and different network models of different neurons.

Training algorithms	Number of hidden neurons	Number of epochs	Training		Testing		Validation	
			MSE	R^2	MSE	R^2	MSE	R^2
LM	1	45	0.0009	0.964	0.00109	0.962	0.0016	**0.978**
LM	2	171	0.00091	0.966	0.0011	0.955	0.00148	0.956
LM	3	16	0.00088	0.97	**0.00045**	**0.974**	0.00091	0.976
LM	4	21	0.00067	0.976	0.0015	0.925	0.0081	0.974
LM	5	5	0.00088	0.968	0.00106	0.956	0.0013	0.958
LM	6	5	0.00087	0.97	0.00082	0.964	0.00082	0.968
LM	**7**	**9**	**0.00058**	**0.976**	0.0035	0.904	0.00093	0.97
LM	8	7	0.00086	0.97	0.00081	0.956	0.00105	0.964
LM	9	4	0.00081	0.97	0.0019	0.945	0.00106	0.96
LM	10	5	0.00094	0.968	0.00059	0.98	0.00092	0.955
LM	11	3	0.00088	0.97	0.00049	**0.974**	**0.00078**	0.97
LM	12	3	0.00085	0.966	0.0056	0.956	0.0011	0.97
LM	13	9	0.00082	0.97	0.0013	0.955	0.0012	0.956
BR	1	14	0.00103	0.962	0.00093	0.966		
BR	2	27	0.0008	0.972	0.0021	0.953		
BR	3	54	0.00079	0.972	0.00097	0.958		
BR	4	62	0.00065	0.974	0.0017	0.951		
BR	5	144	0.00064	0.976	0.00091	0.927		
BR	6	75	0.00054	0.810	0.00077	0.966		
BR	7	68	0.00067	0.974	0.00092	0.97		
BR	**8**	**165**	**0.00036**	**0.984**	**0.00071**	**0.974**		
BR	9	98	0.00087	0.968	0.0012	0.943		
BR	10	423	0.00083	0.968	0.0017	0.964		
BR	11	62	0.00061	0.978	0.0017	0.937		
BR	12	70	0.00074	0.974	0.0011	0.955		
BR	13	44	0.00076	0.972	0.0012	0.956		
SCG	1	27	0.0011	0.955	0.0015	0.943	0.0012	0.966
SCG	2	41	0.001	0.964	0.0015	0.955	0.00084	0.955
SCG	3	30	0.0011	0.955	0.0019	0.953	0.00081	0.974
SCG	4	38	0.0019	0.955	0.0009	**0.974**	0.0008	0.964
SCG	5	43	0.0012	0.956	0.0004	0.972	0.0048	**0.98**
SCG	6	19	0.0011	0.96	**0.00072**	0.964	0.00089	0.976
SCG	7	37	0.001	0.96	0.001	**0.974**	**0.00062**	0.968
SCG	8	33	0.001	0.96	0.0015	0.953	0.0012	0.943
SCG	9	55	0.00088	0.97	0.0015	0.945	0.0012	0.935
SCG	10	90	0.00083	0.97	0.0016	0.927	0.0007	0.974
SCG	11	45	0.0009	0.966	0.0009	0.966	0.0007	0.962
SCG	**12**	**29**	**0.0007**	**0.97**	0.0027	0.935	0.0009	0.955
SCG	13	27	0.0011	0.922	0.0017	0.867	0.00092	0.925

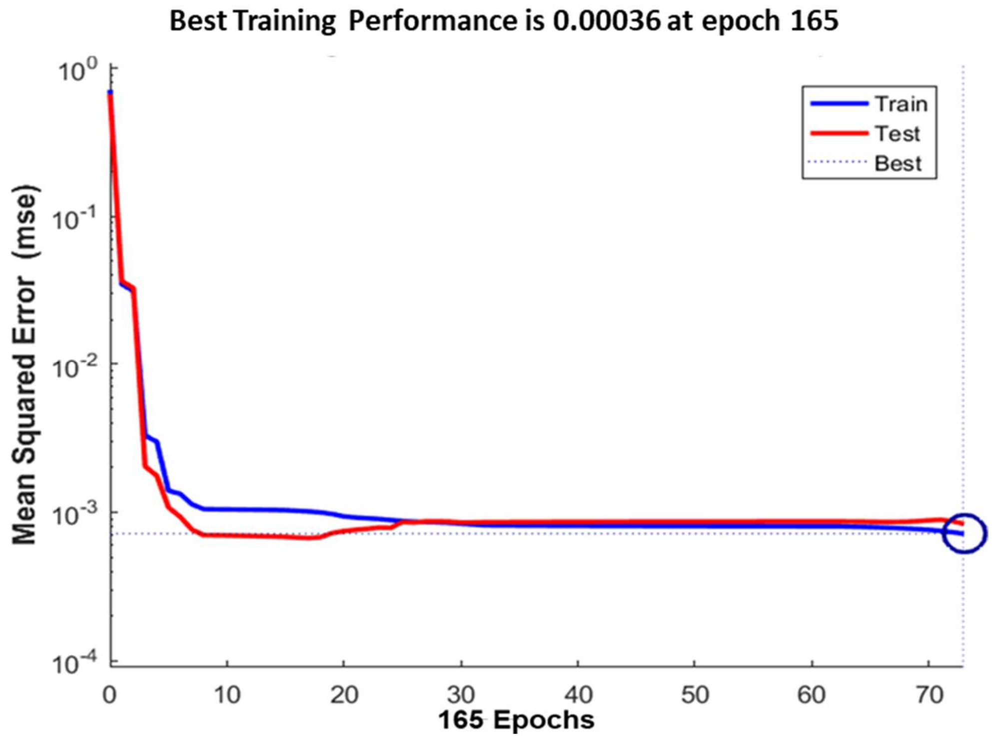

Figure 2. Mean squared error (MSE) on the best training performance of developed FFNN model

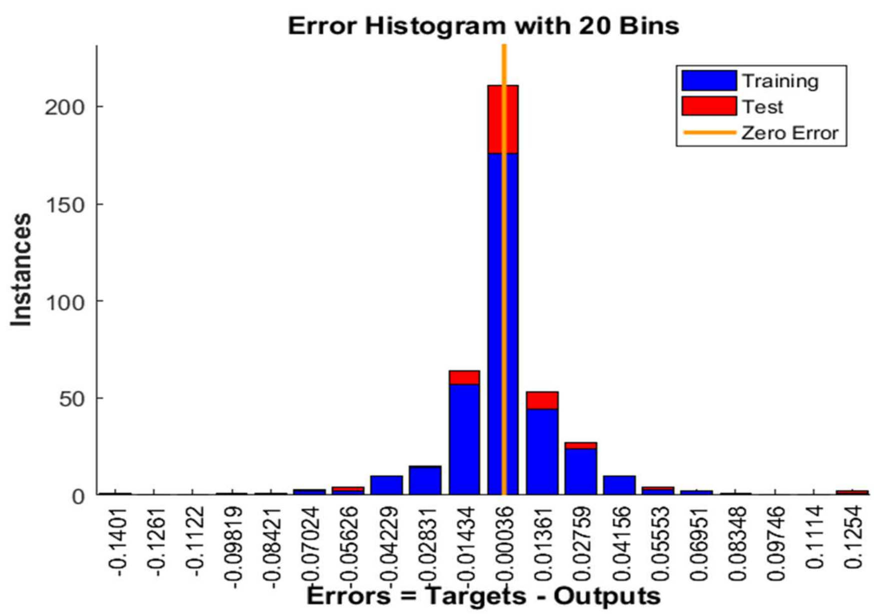

Figure 3. Residuals, the difference between measured and predicted BW values of developed FFNN model

For the best FFNN model in Figure 3, the residues exhibit a normal distribution with mean 0, variance 1, and the difference between measured and predicted BW values.

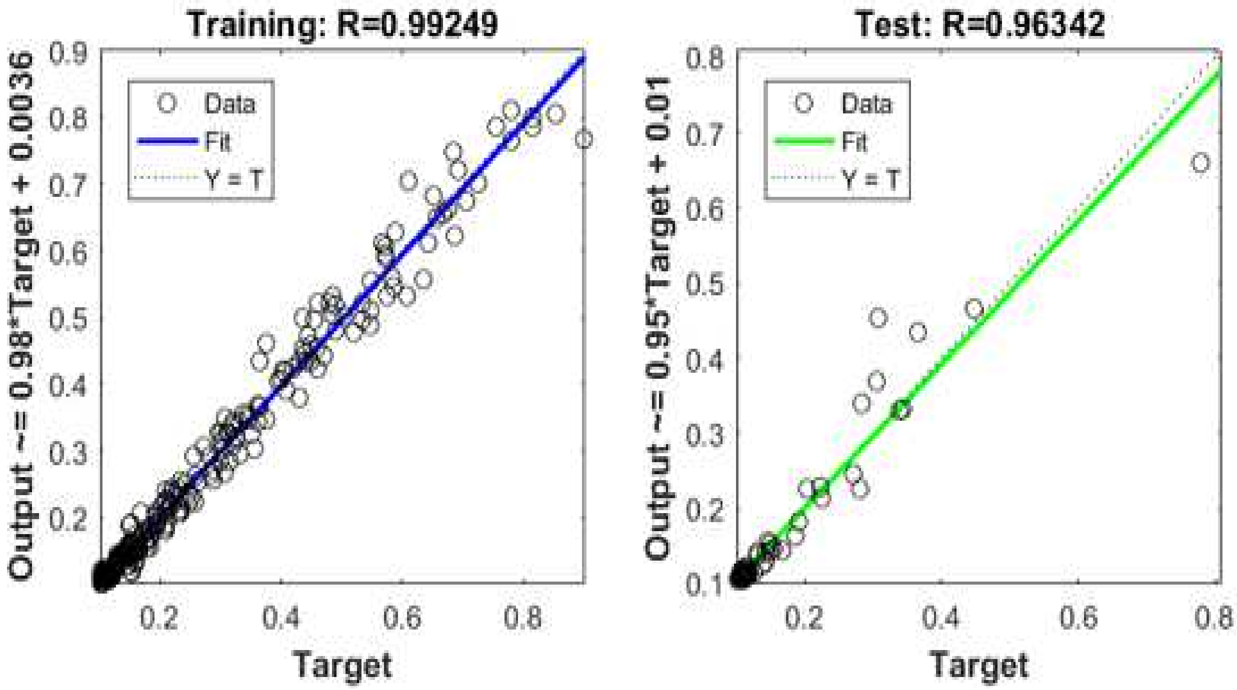

Figure 4. Regression plot for the best FFNN model developed

Figure 4 shows the regression graphs of the actual and estimated BW values for the training and test data sets for the developed FFNN model. Figure 4 and Table 2 results overlap. The R values for training and test data are 0.99249 and 0.96342, respectively, in Figure 4. Table 2 displays the same results as R^2 in training and test datasets. Figure 4 shows R values that are very close to 1. The linear least-squares fitting line on the regression plot is almost certainly distributed uniformly across the training and test data. As a result, assuming the values of WH, BL, CG, and RW are known, high performance results in neuron network training show that the FFNN model can estimate BW.

In order to find out which input variable has a how-relationship with the output variable, correlation coefficients were calculated in Table 3 and the calculated r values were tried to be explained with the suggestions made by Chan (2003) and Akoğlu (2018). Correlation values of WH, BL, CG, RW with BW were 0.930, 0.914, 0.935 and 0.840, respectively, all of them have strong relationship and were significant ($p < 0.001$). These results show that all inputs and output variables contribute to successful training performance results. Therefore, the relationship between the WH, BL, CG, RW, and BW variables used in ANN may be an important reason for successful performance results found in network training. The good performance results found in the ANN training show that the ANN model can predict BW if the WH, BL, CG, and RW values are known.

Table 3. Pearson correlation coefficients for morphological measurements

	Pearson Correlation				
	BW	WH	BL	CG	RH
BW	1				
WH	0.930**	1			
BL	0.914**	0.946**	1		
CG	0.935**	0.947**	0.924**	1	
RH	0.840**	0.852**	0.841**	0.863**	1

*: Correlation is significant at the 0.05 level (2-tailed); **: Correlation is significant at the 0.01 level (2-tailed).

Ünalan and Işık (2007) reported that the same correlation value results for SAR cattle among birth weight and all other measurements. Koç and Akman, (2007) reported that the estimation of body measurements of Holstein-Friesian bulls at different periods and live weight prediction from body measurements and reported that using CG alone would be sufficient to predict BW. Turini *et al.* (2021) reported that among the traits, the highest and the lowest correlations results in the same live weight prediction from body measurements for Holstein-Friesian.

In Table 4, the best ANN model results obtained with the best neuron numbers from three different training algorithms back-propagation to predict body weight from morphological measurement for SAR cattle are presented to compare. RMSE, MAE, MAPE% and VAF% were used as performance criteria. In LM and SCG algorithms, the data set was divided into three subgroups: training, testing, and validity. But since there is no need for a set of validity in the BR back-propagation, it was divided into only training and test subgroups. As a result, apart from the BR algorithm, LM and SCG algorithms also calculated performance criteria for training, testing, and validity, respectively.

Table 4. Performance criteria of developed FFNN models

Training Alg.	Data set	N	RMSE	MAE	MAPE%	VAF%
LM	Training	287	0.0241	0.0142	5.7	97.930
	Testing	61	0.0592	0.0255	10.4	92.428
	Validation	61	0.0305	0.0181	7.1	96.631
BR	Training	327	0.0212	0.0134	5.5	98.147
	Testing	82	0.0266	0.0155	6.2	97.443
SCG	Training	287	0.027	0.016	6.3	97.453
	Testing	61	0.052	0.023	10.6	95.636
	Validation	61	0.03	0.017	6.5	96.841

Therefore, the model with the lowest RMSE, MAE, and highest VAF% performance criterion was anticipated to have the best fit. Lewis (1982) defined "very good" MAPE (%) values as less than 10%, "good" MAPE (%) values as 10% to 20%, "acceptable" MAPE (%) values as 20% to 50%, and "wrong or faulty" MAPE (%) values as more than 50%. Given that the results are fewer than 10%, it is reasonable to draw the conclusion that the model developed is "very good" when the MAPE (%) values discovered by the BR method are examined using this categorization. The BR method beat other algorithms in terms of performance criteria in both training and test datasets. It was determined that the network model created using the BR method was the most accurate predictor of body weight in SAR cattle in the study. The study's results showed that the network model created using the BR algorithm was the most accurate predictor of body weight in SAR cattle.

Similar outcomes to those of this study were discovered, and it was noted that the BR algorithm produced superior outcomes. Akkol *et al.* (2017) reported that the "Bayesian Regularization " algorithm is the best estimation model among the three different back-propagation algorithms for estimating body weight in hair goats. Joy *et al.* (2022) reported that they studied infrared thermography (IRT) and machine learning techniques that can predict sheep rectal temperature when subjected to heat stress, and ANN developed by applying the BR algorithm showed the highest accuracy and performance for predicting rectal temperature using IRT. Furthermore, significant investigations have also been done comparing artificial neural networks and regression models to the outcomes of the ANN technique. Comparing artificial neural network model and regression models, Favaro *et al*. (2014) in goat kids, Salawu *et al*. (2014) in rabbits, Szyndler-Nędza *et al*. (2016) in pigs, and Khorshidi-Jalali *et al*. (2019) in Raini Cashmere goats revealed that the findings of ANN were better and more accurate.

Conclusion: Although artificial neural networks have recently been widely used because they allow experimental problems to be modelled accurately in all disciplines, they are not enough used in animal husbandry studies. For this aim, an FFNN model was designed and developed to estimate the effect of morphological measurements of SAR cattle on body weight to be compared to these models. The Bayesian Regularization back-propagation algorithm was found to be the best FFNN model topology with the smallest MSE, the largest R^2, and the most appropriate regression estimation in both the training dataset and the test dataset. The best network models developed are compared to find the best model estimate based on RMSE, Mean MAE, MAPE%, and VAF% performance criteria. It was found that body weight predictive values were in good agreement with all morphological measurements for the ANN model. As a result, it has been shown that the proposed FFNN model is the best model, can be used effectively to predict body weight with all morphological measurements, and has a very good agreement with body weight in terms of robustness and reliability.

Acknowledgements: This study was carried out by using the data of the “Southern Anatolian Red Kilis (SAR)-Sub Project” of the "National Project for Conservation of Local Genetic Resources" conducted under the coordination of the General Directorate of Agricultural Research and Policies of the Ministry of Food, Agriculture and Livestock. I would like to thank the General Directorate of Agricultural Research and Policies of the Ministry of Food, Agriculture and Livestock, the Directorate of the Eastern Mediterranean Agricultural Research Institute, and all those who contributed.

Financial Support: This research received no grant from any funding agency/sector.

Ethical Statement: This study does not require approval from the Animal Experiments Local Ethics Committee.

Conflict of Interest: The authors declared that there is no conflict of interest.

REFERENCES

Abraham, A. (2005) Artificial neural networks: Handbook of measuring system design, John Wiley and Sons, Ltd., ISBN: 0-470-02143-8, 908 p.

Akıllı, A. and H. Atıl (2014) Artificial intelligence technologies in dairy science: fuzzy logic and artificial neural network. J. Anim. Prod., 55(1): 39-45.

Akkol, S., A. Akilli, and İ. Cemal, (2017) Comparison of artificial neural network and multiple linear regression for prediction of live weight in hair goats. Yüzüncü Yil University J. Agri. Sci., 27(1): 21-29. DOI: 10.29133/yyutbd.263968

Akoğlu, H. (2018) User's guide to correlation coefficients. Turkish J. Emergency Medicine 18(3): 91-93. DOI: 10.1016/j.tjem.2018.08.001

Aladağ, C.H., E. Egrioglu, and C. Kadilar (2010) Modeling brain wave dataset by using artificial neural networks. Hacettepe J. Math. Stat., 39(1): 81-88.

Anitha, P., and T. Chakravarthy (2018) Agricultural crop yield prediction using artificial neural network with feed-forward algorithm. Intl., J. Computer Sci. & Engin., 6(11): 178-181. DOI: 10.26438/ijcse/v6i11.178181

Asadzadeh, N., M. Bitaraf Sani., E. Shams-Davodly, J. Zare-Harofte, M. Khojestehkey, S. Abbaasi, and A. Shafie-Naderi (2021). Body weight prediction of dromedary camels using the machine learning models. Iranian J. Appl. Anim. Sci., 11(3): 605-614. DOI: 20.1001.1.2251628.2021.11.3.19.5

Asteris, P.G., P.C. Roussis, and M.G. Douvika (2017) Feed-forward neural network prediction of the mechanical properties of sandcrete materials. Sensors 17: 1344 -1364 DOI: 10.3390/s17061344

Beal, M., M.T. Hagan, and H.B. Demuth (2010) Neural network toolbox™ 6 user's guide; the math works inc., Natick, MA, USA; 146-175.

Burden, F. and D. Winkler (2009) Bayesian regularization of neural networks. In D.J. Livingstone (Ed.), Artificial neural, networks: Methods and applications (pp. 23-42). Totowa, NJ: Humana Press.

Chan, Y.H. (2003) Biostatistics 104: Correlational analysis, The Singapore Medical J. 44(12): 614-619.

Cross, A.J., G.A Rohrer, T.M. Brown-Brand, J.P. Cassady, and B.N. Keel (2018) Feed-forward and generalised regression neural networks in modelling feeding behaviour of pigs in the grow-finish phase. Biosystems Engineering 173:124-133. DOI: 10.1016/j.biosystemseng.2018.02.005

Dawson, C.W. and R. Wilby (1998) An artificial neural network approach to rainfall-runoff modelling. Hydrological Sciences J. 43(1): 47-66. DOI: 10.1080/02626669809492102

Erzin, Y. and T. Çetin (2013) The prediction of the critical factor of safety of homogeneous finite slopes using neural networks and multiple regressions. Computers and Geosciences 51:305-313. DOI: 10.1016/j.cageo.2012.09.003

Eyduran, E., D. Zaborski, A. Waheed, S. Celik, K. Koksal, and W. Grzesiak (2017) Comparison of the predictive capabilities of several dataset mining algorithms and multiple linear regression in the prediction of body weight by means of body measurements in the indigenous Beetal goat of Pakistan. Pakistan J. Zoology 49(1): 257-265. DOI: 10.17582/journal.pjz/2017.49.1.257.265

FAO. (2012) Phenotypic characterization of animal genetic resources. FAO animal production and health guidelines No.11. Rome, Italy (available at http://www.fao.org/docrep/015/i2686e/i2686e00.htm).

Favaro, L., E.F. Briefer, and A.G. McElligott (2014) Artificial neural network approach for revealing individuality, group membership and age information in goat kid contact calls. Acta Acustica United with Acustica 100(4): 782-789. DOI: 10.3813/AAA.918758

Ghotbaldini, H., M. Mohammadabadi, H. Nezamabadi-Pour, O.I. Babenko, M.V. Bushtruk, and S.V. Tkachenko (2019) Predicting breeding value of body weight at 6-month age using artificial neural networks in Kermani sheep breed. Acta Scientiarum. Animal Sciences 41. DOI: 10.4025/actascianimsci.v41i1.45282

Grzesiak, W., R. Lacroix, J. Wójcik, and P.A. Blaszczyk (2003) Comparison of neural network and multiple regression predictions for 305-day lactation yield using partial lactation records. Canadian J. Animal Science 83(2): 307-310. DOI: 10.4141/A02-002

Haykin, S.S. (2009). Neural networks and learning machines/Simon Haykin. New York: Prentice Hall,. Copyright © 2009 by Pearson Education, Inc., Upper Saddle River, New Jersey 07458, ISBN-13: 978-0-13-147139-9, ISBN-10: 0-13-147139-2, 937 p.

Joy, A., Taheri, S., Dunshea, F.R., Leury, B.J., DiGiacomo, K., Osei-Amponsah, R., Brodie, G. and S.S. Chauhan (2022). Non-invasive measure of heat stress in sheep using machine learning techniques and infrared thermography. Small

Ruminant Research 207: 106592. DOI: 10.1016/j.smallrumres.2021.106592

Karlik, B. and A.V. Olgac (2011). Performance analysis of various activation functions in generalized MLP architectures of neural networks. International J. Artificial Intelligence and Expert Systems 1: 111-122.

Kayri, M. (2016). Predictive abilities of Bayesian regularization and Levenberg-Marquardt algorithms in artificial neural networks: A comparative empirical study on social dataset. Mathematical and Computational Applications 21(2): 20-31. DOI: 10.3390/mca21020020

Khorshidi-Jalali, M., M. Mohammadabadi, A.E. Koshkooieh, A. Barazandeh, and O. Babenko (2019) Comparison of artificial neural network and regression models for prediction of body weight in Raini Cashmere goat. Iranian J. as Applied Animal Science www.ijas.ir

Koç, A. and N. Akman (2007) Body Measurements of Holstein-Friesian Bulls at Different Periods and Live Weight Prediction from Body Measurements. J. Adnan Menderes University Agricultural Faculty 2007 4(1-2): 21 – 25.

Lewis, C.D. (1982) Industrial and Business Forecasting Methods. Butterworths Publishing: London, 1982. 40 p.

MacKay, D.J. (1992) Bayesian interpolation. Neural computation; 4: 415-447. DOI: 10.1162/neco.1992.4.3.415

Matlab. (2016) R, software 2016b. Matlab R., The mathworks, Inc., United States of America. Retrieved in March, 3, 2022 from https://ch.mathworks.com/

Mhaskar, H.N. and C.A. Micchelli (1994) How to choose an activation function. Retrieved in March, 10, 2022 from https://papers.nips.cc/paper/874-how-to-choose-anactivation-function.pdf.

Pour-Hamidi, S., M.R. Mohammadabadi, M. Asadi Foozi, and H. Nezamabadi-Pour (2017) Prediction of breeding values for the milk production trait in Iranian Holstein cows applying artificial neural networks. J. Livestock Science and Technologies 5(2): 53-61. DOI: 10.22103/jlst.2017.10043.1188

Putra, S. and A. Wanto (2017) Analysis of artificial neural network accuracy using backpropagation algorithm in predicting process (forecasting). International J. Information System and Technology 1(1): 34-42. DOI: 10.30645/ijistech.v1i1.4

Putro, S.S., M.A. Syakur, E.M.S. Rochman, and A. Rachmad (2022) Comparison of back-propagation and ERNN methods in predicting corn production. Communications in Mathematical Biology and Neuroscience 17 p. DOI: 10.28919/cmbn/7082

Rachmad, A.E., M.S. Rochman, D. Kuswanto, I. Santosa, R.K. Hapsari, T. Indriyani, and E. Purwanti (2018) Comparison of the traveling salesman problem analysis using neural network method, In: International Conference on Science and Technology, Atlantis Press 1057-1061. DOI: 10.2991/icst-18.2018.213

Saini, L.M. (2008) Peak load forecasting using bayesian regularization, resilient and adaptive back-propagation learning based artificial neural networks. Electric Power Systems Research 78(7): 1302-1310. DOI: 10.1016/j.epsr.2007.11.003

Salawu, E.O., M. Abdulraheem, A. Shoyombo, A. Adepeju, S. Davies, O. Akinsola, and B. Nwagu (2014) Using artificial neural network to predict body weights of rabbits. Open J. Animal Science 4: 182-186. DOI: 10.4236/ojas.2014.44023

Salehi, F., R. Lacroix, and K.M. Wade (1998) Improving dairy yield predictions through combined record classifiers and specialized artificial neural networks. Computers and Electronics in Agriculture 20(3): 199-213. DOI: 10.1016/S0168-1699(98)00018-0

Sharma, A.K., R.K. Sharma, and H.S. Kasana (2006) Empirical comparisons of feed-forward connectionist and conventional regression models for prediction of first lactation 305-day milk yield in Karan Fries dairy cows. Neural Computing and Applications 15 (3): 359-365. DOI: 10.1007/s00521-006-0037-y

Szyndler-Nędza, M. Robert, E. Tadeusz, B. Mirosław, and P. Artur (2016) Prediction of carcass meat percentage in young pigs using linear regression models and artificial neural networks. Annals of Animal Science 16(1): 275-286. DOI: 10.1515/aoas-2015-0069

Takma, Ç., H. Atıl, and V. Aksakal. (2012) Comparison of multiple linear regression and artificial neural network models goodness of fit to lactation milk yields. J. The Faculty of Veterinary Medicine, Kafkas University 18: 941-944. DOI: 10.9775/kvfd.2012.6764

Taşdemir, Ş. and I.A. Özkan (2019) Ann approach for estimation of cow weight depending on photogrammetric body dimensions. International J. Geoscience Engineering and Technology 4 (1): 036-044. DOI: 10.26833/ijeg.427531

Turini, L., G. Conte, F. Bonelli, A. Madrigali, B. Marani, M. Sgorbini, and M. Mele (2021) Designing Statistical Models for Holstein Rearing Heifers' Weight Estimation from Birth to 15 Months Old Using Body Measurements. Animals 11(7):1846. DOI: 10.3390/ani11071846

Ünalan, A. and A. Işık (2007) A Study on Determination of Environmental Effects and Phenotypic Correlations Among Some Body Measurements of South Anatolian Red (SAR) Calves. J. Agriculture Faculty, Çukurova University 22. (2): 1-6.

Zador, A.M. (2019) A critique of pure learning and what artificial neural networks can learn from animal brains. Nature Communications 10: 3770 DOI: 10.1038/s41467-019-11786-6

Zhang, T. and X. You (2015) Improvement of the training and normalization method of artificial neural network in the prediction of indoor environment. Procedia Engineering 121: 1245-1251. DOI: 10.1016/j.proeng.2015.09.152.