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Neural network-assisted body weight prediction of goat kids using morphometric measurements in various growth phases

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ABSTRACT

Body weight (BW) measurement of animals is an essential farm activity to monitor their growth and welfare but weighing equipment is often inaccessible for low-income farmers. This work utilized animal morphometrics to determine BW of Black Bengal goat kids using artificial neural networks. Over four months, 130 observations per growth phase (pre-weaning and post-weaning) were collected for morphometric measurements and BW. Twelve different body morphometric measures were taken, and correlated with BW. Various combinations of training algorithms (LM and GDX) with LOGSIG and TANSIG transfer functions were tested across 5 to 30 hidden layer neurons (HLNs). Results showed higher accuracy for BW prediction using heart girth and height at back (HAB) for the pre-weaning phase. However, the corpus length (CL) and HAB showed better model accuracy for post-weaning and combined growth phase. The selected ANN model showed superior results than the non-linear and linear regression models. ANN may therefore be used to predict BW of goat kids in place of other regression methods.

Keywords: Algorithm, Goat kids, Machine learning, Morphometry, Post-weaning, Pre-weaning

India is home to the world's largest livestock inventory, with approximately 536.76 million animals, including 148.88 million goats, making it the second-largest animal population after cattle (DAHD 2019). The Black Bengal goat, a popular dwarf breed, is predominantly distributed in Bangladesh and the northeastern and eastern regions of India (Rakib *et al.* 2022). Body weight (BW) is a critical metric that reflects general health and productivity of goats (Mebratie *et al.* 2022) and therefore, accurate and timely prediction of BW is necessary for efficient management and improvement of goat farming. Goat body morphometric measurements are essential for meeting breed standards (Rakib *et al.* 2022) and are strongly correlated with the animal's live BW, which is used to set selection criteria, breed standards, and goat valuation (Rahman *et al.* 2019). Goat BW is an essential parameter for breeding, selection, feeding, and health care (Abraham *et al.* 2018). Predicting BW and its correlations with additional bodily characteristics provides valuable information for enhancing breeding strategies aimed at increasing meat yield per animal (Iqbal *et al.* 2022). As a result, gaining knowledge to determine body weight is vital for producers, as it affects both economic and managerial aspects of goat rearing, business, and management. However, due to lack of access to weighing scales, this essential information is usually unavailable to persons working in the goat farming sector, resulting in errors in decision-making processes.

In animals, BW is influenced by genetics, nutrition, production, reproduction, and health status (Micheal *et al.* 2019). Regression models have been used to create equations based on specific body morphological characteristics to predict body weight patterns in cattle (Siddiqui *et al.* 2015), sheep (Cam *et al.* 2010), and goats (Adhianto *et al.* 2020). The linear relationship between the dependent variable and a set of independent factors is examined by the multiple linear regression model (MLR) (Raja *et al.* 2012). However, occasionally this relationship may be complex or nonlinear, potentially leading to biased estimates from MLR. MLR is also susceptible to multicollinearity, which occurs when independent variables have a high correlation (Iqbal *et al.* 2013). The standard regression methods are

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unable to detect multicollinearity among independent variables, thus resulting in biased results (Ruhil et al., 2013). Therefore, the most effective and best solution would be to fit statistical models for underlying data using methods that incorporate both linear and non-linear models.

Artificial Neural Networks (ANNs) utilize mathematical models and training methods designed to replicate the way the human brain interprets and processes information. As a result, ANNs are commonly employed to handle intricate and non-linear data or events. In challenging environments, such as hilly terrain, ANNs offer a promising alternative to traditional methods for predicting birth weight (BW) in goat kids. Additionally, different studies suggested that ANN models have a greater degree of accuracy in predicting BW with less bias when utilizing data on body morphometric measurements than different regression procedures in animals (Vaidya *et al.* 2018; Haldar *et al.* 2023). Using several linear body measurements have been found to increase the precision in estimating BW by ANN in growing piglets in different classes of age (Preethi *et al.* 2023).

Extensive literature, survey indicates a lack of sufficient studies focused on body weight prediction in pre-weaning and post-weaning growing kids using ANN models, which is essential in monitoring the growth and welfare of goat kids. Furthermore, the comparison of non-linear and linear models versus ANN models for predicting BW in pre- and post-weaned kids is yet to be explored. Therefore, the objective of this study was to develop an ANN-based model for predicting the BW of Black Bengal goat kids at various growth stages using body measurements collected under intensive farm conditions.

MATERIALS AND METHODS

Experimental location: The research was carried out at the Experimental Shed, ICAR-National Dairy Research Institute (NDRI), Eastern Regional Station (ERS), Kalyani, West Bengal, India. Kalyani is positioned at a longitude of 88°26’04”E and latitude of 22°58’30”N in the Nadia District of West Bengal, within the Lower Gangetic Plains during January to May, 2022 duration .

Data collection: Data on BW and morphometric measurements were collected from thirteen Black Bengal goat kids across two distinct growth stages of their lives such as pre-weaning (0-60 days), and post-weaning (61-120 days) an interval of seven days (1 week) over a period of four months. A total of 260 observations were collected for BW and each of the morphometric traits. Specifically, there were 130 observations each obtained during the pre and post-weaning phase. After the kids were properly restrained, a measuring tape (150 cm) was used to measure 12 morphometric measurements such as height at wither (HAW), height at back (HAB), body length (BL), rear girth (RG), heart girth (HG), corpus length (CL), head width (HD), head length (HL), hip width (HW), neck circumference (NC), tail length (TL) and ear length (EL). The BW was recorded using electronic weighing machine (KiloMaxx KM-21, India).

Housing and management of animals: All the experimental kids were housed in an intensive housing system. The shed had a concrete floor surface and an asbestos roof along with an open paddock. Kids were allowed unrestricted access to suckling until weaning at 60 days of age. During the pre-weaning phase, kids were offered a concentrate mixture and green fodders (maize, mustard, oats, berseem, and para grass) as per the availability. During the post-weaning period, the young animals were provided with concentrate feed along with seasonal green forages such as maize, para grass and oat greens. Fresh drinking water was made available at all times in water containers, which were refilled with fresh water twice daily at 09:00 and 15:00 hours.

Neural network modeling: Neural network analysis was carried out using an Artificial Neural Network (ANN) approach by loading a dataset with body morphometric traits (inputs) and their respective body weights (outputs) into MATLAB software. An ANN framework was constructed using the Variable Learning Rate Backpropagation (GDX) and Levenberg-Marquardt (LM) training function (TRAINGDX and TRAINLM) from MATLAB’s neural network toolbox as suggested by Singh *et al.* (2025). This setup was designed to demonstrate the relationship between the body morphometric measurements of the kids and their body weight. The ANN architecture included an input layer, one or multiple hidden layer, and an output layer.

The complete dataset was randomly split into two portions, with 70% allocated for training and the remaining 30% set aside for testing. The weight and bias vectors were initialized randomly within the range of -1 to +1. To compute the output, the hidden layer (HL) summed the weighted inputs using TANSIG and LOGSIG functions, and the PURELIN function was employed at the output layer to derive the network’s response. To predict body weight during the pre-weaning, post-weaning, and combined phases of the kids, the ANN models were developed using their corresponding training datasets. The ANN model was programmed to stop training after 1000 iterations per epoch or upon attaining a training error of 10^{-6}, whichever condition was satisfied first. Using the available data sets, the ANN models were trained to estimate the BW in pre-weaned, post-weaned, and combined periods of kids. Multiple configurations of hidden layers (HL) with varying numbers of nodes or neurons (5 to 30), two algorithms (LM and GDX), and two transfer functions (TANSIG and LOGSIG) were used to train the network. Three separate training sessions were conducted for each model to predict body weight, and the outputs were saved in the MATLAB workspace. Within the ANN framework, comprising of‘n’ input neurons and one neuron in the hidden layer (HLN), the hidden layer input (HI) is calculated as presented in equation (1). Here, b_1 is the bias term for the hidden layer, I_i represents the i^{th} input neuron, and ω_{i1} is the weight associated with the connection from the i_{th} input neuron to the hidden layer neuron.

$$H_I = (\sum_{(i=1)}^{n} I_i \omega_{1i}) + b_1 \quad (1)$$

R² and MSE were calculated for each iteration and parameter combination, and the model with the best performance (lowest MSE and highest R²) was selected for the respective traits during pre-weaning, post-weaning, and combined phases.

Comparative evaluation of ANN, linear and non-linear regression model: Linear and non-linear models were developed by selecting the most relevant combination of body morphometric measurements, identified through the ANN, across various growth stages of Black Bengal kids for predicting body weight (BW). These models were constructed using the regression tool in Microsoft Office Excel v 2007 (Microsoft Inc., Redmond, USA), found in the 'Data Analysis' tab.

The developed ANN models were evaluated against non-linear models by comparing their MSE and R² values to test the hypothesis. Furthermore, the Akaike Information Criterion (AIC) was computed to assess model complexity and goodness-of-fit. This comparative analysis aimed to assess the relative performance of ANNs in predicting the body weight (BW) of Black Bengal kids.

RESULTS AND DISCUSSION

Estimating BW at different age periods using linear morphometric measurements is beneficial particularly when weighing scales are not accessible (Jimmy *et al.* 2010). These indirect predictions enable the estimation of animal growth and body weight in practical circumstances with an acceptable level of precision (Ibrahim *et al.* 2021). A significant correlation was found between the morphometric traits and their relationship with BW at different growth stages (Table 1). The initial screening of these attributes using ANN was carried out based on specific criteria, with an emphasis on selecting the traits that have the highest correlation with BW. Only two morphometric traits having the highest correlation to BW were selected for the construction of the ANN model. During the pre-weaning period, the highest correlation was seen between BW and HG ($r = 0.953$, $p < 0.01$), with HAB closely following ($r = 0.935$, $p < 0.01$). Similarly, in the post-weaning, there was a significant association between CL and BW ($r = 0.928$, $p < 0.01$), with HAB showing the second strongest correlation ($r = 0.922$, $p < 0.01$). During the combined growth period, the HAB showed a significant relationship with BW ($r = 0.954$, $p < 0.01$), followed by the CL ($r = 0.949$, $p < 0.01$). In Raini Cashmere adult goats, Khorshidi-Jalali et al. (2019) found that the correlation between BW and height at withers (HAW) was the highest ($r = 0.75$), whereas the relationship between BW and body length was least pronounced ($r = 0.45$). They also reported heart girth and height at shoulder had the highest correlation ($r = 0.60$) across body morphometric traits, while height at shoulder and body length had the least correlation ($r = 0.35$). Similar findings have also been reported in Attappady Black goats by Raja *et al.* (2012). However, in the present study, the most significant association with BW was observed with HG during the pre-weaning phase and with CL during the post-weaning and combined period.

Table 1. Correlation of morphometric traits and body weight in different growth periods

Morphometric traits	Pre-weaning	Post-weaning	Combined
Corpus length (CL)	0.928**	0.928**	0.949**
Body length (BL)	0.900**	0.849**	0.923**
Heart girth (HG)	0.953**	0.917**	0.947**
Rear girth (RG)	0.921**	0.839**	0.922**
Height at back (HAB)	0.935**	0.922**	0.954**
Height at withers (HAW)	0.934**	0.901**	0.948**
Neck circumference (NC)	0.819**	0.885**	0.844**
Head length (HL)	0.743**	0.890**	0.890**
Head width (HW)	0.738**	0.834**	0.885**
Ear length (EL)	0.761**	0.686**	0.836**
Hip width (HW)	0.826**	0.830**	0.903**
Tail length (TL)	0.721**	0.796**	0.734**

**Correlation is significant at 1% level of significance (2-tailed).

The results indicated that during the pre-weaning period, the TRAINLM+TANSIG function exhibited the lowest MSE and highest R² value (Table 2). It outperformed other functions in predicting the body weight of pre-weaned Black Bengal kids. The findings suggest the performance

Table 2. Performance evaluation of different training and transfer function with highest coefficient of determination (R2) for body weight prediction

Training and transfer function of network	Pre-weaning (HG-HAB)			Post-weaning (CL-HAB)			Combined (CL-HAB)		
	HLN	Overall-R²	MSE	HLN	Overall-R²	MSE	HLN	Overall-R²	MSE
TRAINLM + TANSIG	15	0.9675	0.0562	10	0.9256	0.1539	10	0.9496	0.1450
TRAINLM + LOGSIG	10	0.9605	0.0526	20	0.9171	0.1379	10	0.9566	0.1564
TRAINGDX + TANSIG	10	0.9562	0.0902	15	0.9187	0.1402	15	0.9502	0.1974
TRAINGDX+ LOGSIG	15	0.9576	0.0897	15	0.9130	0.2045	30	0.9447	0.1768

HG: Heart girth, HAB: Height at back, CL: Corpus length; HLN: Hidden layer neuron; LM: Levenberg-Marquardt, GDX: Variable Learning Rate; TANSIG: Tansigmoidal, LOGSIG: Logsigmoidal metrics of the ANN model are significantly affected by the number of neurons added to the hidden layer. Among the various combinations that were tested, the best performance was seen by the model with 15 neurons in the hidden layer. This configuration also resulted in a greater overall-R^2 value, showing a good capacity to predict and generalize the body weight distribution. The model achieved an overall-R^2 of 0.9675 and an MSE of 0.0562 (Table 2). Models with fewer hidden layer neurons, specifically 5 and 10 neurons, had lower MSE values. However, they also displayed lesser R^2 values for both the training and testing datasets. Furthermore, when the number of neurons was increased beyond 15, specifically to 20, 25, and 30 neurons, there were no improvements in MSE whereas there was a decrease in R^2 values. The results indicated that the ANN model, consisting of 15 neurons in the HL, provided an optimal choice between complexity and performance. This model provided the most precise predictions for body weight in pre-weaned Black Bengal kids.

The findings for post-weaning kids indicated that the TRAINLM+TANSIG function exhibited the best R^2 and the lowest MSE value. This function was superior to other functions in predicting the post-weaning body weight of kids. Further, the model with 10 HLNs in the hidden layer performed best, with a high overall-R^2 value of 0.9256 (Table 2). This ANN configuration also resulted in a satisfactory MSE value of 0.1539, which suggests a high capacity to make accurate predictions. On the basis an extensive evaluation of the entire neuro solution, the ANN model with a single hidden layer consisting of 10 nodes was selected as the best model.

The results from the analysis of both pre- and post-weaning (combined) datasets revealed that the TRAINLM+LOGSIG combination showed lowest MSE and the highest R^2 value (Table 2). It exhibited superior performance compared to other functions in predicting the BW of kids. Among the configurations investigated, the model with 10 nodes in the hidden layer showed the highest overall-R^2 value (0.9566) and the lowest MSE (0.1564), suggesting superior predictive accuracy overall. Nevertheless, as the number of neurons exceeded 10, there was a noticeable reduction in the model's performance, as seen by the decrease in R^2 values and increase in MSE. Models including 15, 20, 25, and 30 neurons had greater MSE, suggesting a decrease in predictive accuracy.

In a study, Vaidya *et al.* (2018) had investigated the correlation between independent factors including heart girths, height at withers, and body length, and the dependent variable, body weight (BW). This investigation utilized a multilayer feedforward ANN incorporating backpropagation of error learning mechanism and Bayesian regularization (TRAINBR) techniques. The findings revealed that the model achieved the optimal fitting in goats (adj-R^2 = 0.93) and sheep (adj-R^2 = 0.82). In another investigation, Khorshidi-Jalali *et al.* (2019) had used multiple regression analysis (MRA) alongside a Multilayer Perceptron model consisting of a single hidden layer and neurons to predict the BW of Raini Cashmere goats. The input variables used for this prediction were heart girths (HG), height at withers (HAW), and body length (BL). Among all the morphometric characteristics, the height at withers exhibited a higher correlation value of 0.65. The comparison between the two models indicated that the ANN model exhibited greater accuracy with an R^2 value of 0.86, compared to 0.76 for MRA. Hence, in the present investigation encompassing 12 body morphometric traits being utilized to estimate body weight across different growth phases, it was found that the most appropriate trait for predicting the pre-weaning BW of kids was the combination of HG-HAB. The finding was based on its higher overall-R^2 and lowest MSE. CL-HAB was selected for the development of the ANN model due to its greater overall-R^2 and lowest MSE in predicting post-weaning and combined body weight of kids.

The ANN models were validated through simulation by applying a randomly generated set of input variables to assess their predictive performance. The models accurately accounted for 96.04% and 91.03% of the BW datasets in pre-weaned and post-weaned kids, respectively (Table 3). In addition, the comprehensive model, which included both periods combined, accounted for 94.93% of the BW datasets. Furthermore, the variations in model error showed a random distribution, suggesting an enhanced linear component within the developed ANN models. Similarly, Vaidya et al. (2018) had also observed that using the ANN model to estimate goat body weight based on morphometric traits resulted in a model accuracy of 94.21% with an error of 2.35 kg, whereas in sheep, the accuracy was 85.29% with an error of 3.48 kg. Roush *et al.* (2006) found that ANN modeling predicted broiler body weight with the lowest bias compared to Gompertz non-linear regression.

In this study, two input variables were employed to predict the body weight (BW) of kids at different growth phases. Additionally, the coefficient of variation (CV) for the pre-weaning BW of kids was found to be 31.97%, while the estimation for post-weaning BW had a CV of 22.59%.

The CV estimations reinforced the need for a limited number of variables to accurately predict the body weight (BW) of Black Bengal kids. This suggested that there is variation of genetic regulation of BW at various stages of development, suggesting that the genes responsible for controlling BW during early stages may differ from those involved in later stages.

The higher R^2 values indicated that the model provided accurate predictions of body weight at an acceptable level for each growth phase of the kids. Along with the ANN models, second-order non-linear and linear models were also developed to estimate the BW of Black Bengal goat kids (Table 4). The non-linear regression models exhibited R^2 values of 0.9478, 0.9005, and 0.9439 for predicting the BW of kids in the pre-weaning, post-weaning, and combined phases, respectively. The ANN produced higher values of R^2 and the lowest MSE for predicting body weight across the pre-weaning, post-weaning, and combined phases in

Table 3. ANN simulations for prediction of kids' body weights and corresponding error variation at different growth periods

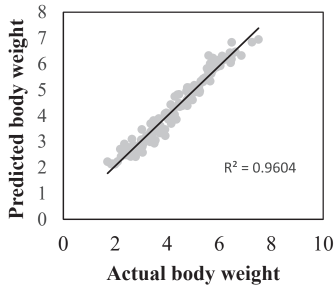
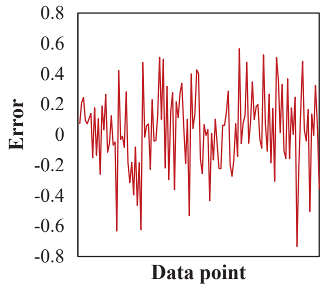
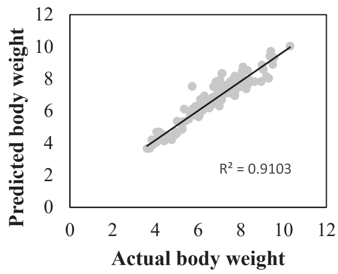
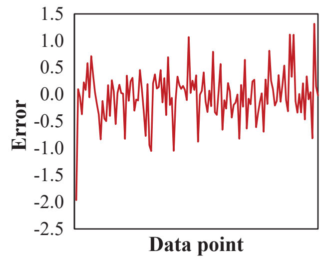
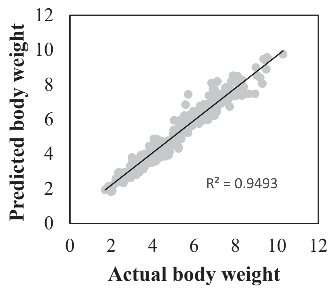
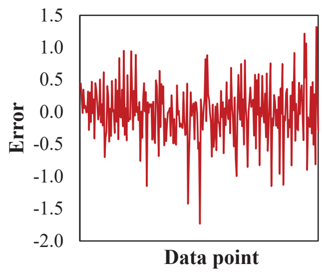
Growth periods	Prediction model	Error variation
Pre-weaning		
Post-weaning		
Combined		

Table 4. Comparison of body weight prediction for different growth periods of Black Bengal goat kids using linear, non-linear and ANN models.

Model	Pre-weaning			Post-weaning			Combined		
	R^2	MSE	AIC	R^2	MSE	AIC	R^2	MSE	AIC
Linear regression	0.9371	0.1181	-88.45	0.8991	0.2486	-81.63	0.9305	0.2570	-58.22
Non-linear regression	0.9478	0.1002	-91.15	0.9005	0.2510	-92.91	0.9439	0.2100	-65.78
ANN	0.9675	0.0562	-104.26	0.9256	0.1539	-101.34	0.9566	0.1564	-77.65

comparison to non-linear and linear regression models (Table 4). Furthermore, AIC values were determined to compare the models' relative effectiveness, with the ANN model achieving the lowest AIC across all three models for the kids' different growth periods (Table 4).

The present study found that HG, HAB, and CL had the most significant influence on predicting body weight (BW) during various growth phases. A regression equation that included both the heart girth (HG) and the body length (BL) accurately predicted the live body weight of Black Bengal goats (Habib *et al.* 2019). In previous studies, particular linear morphometric characteristics were used to formulate regression equations using stepwise regression methods to predict the fluctuations in BW across various goat breeds (Adhianto *et al.* 2020; Sun *et al.* 2020). However, conventional regression techniques often fail to adequately evaluate the presence of multicollinearity among independent variables, potentially resulting in biased results (Ruhil *et al.* 2013). Khorshidi-Jalali *et al.* (2019) and Raja *et al.* (2012) predicted body weight in adult goats based on body measurements by using multiple regression and ANN methods. Based on their findings, the ANN demonstrated superior performance over multiple regression models in terms of R^2 values and MSE. Their conclusion asserted the superiority of the ANN model over multiple regression models in predicting BW in adult goats, which is similar to the results seen in the current study for Black Bengal goat kids in different growth phases. Behzadi and Aslaminejad (2010) used six nonlinear regression models, including Logistic, Gompertz, von Bertalanffy, Brody, Richards, and ANN, to predict BW of Baluchi sheep. They found that the ANN produced the most precise predictions and marginally superior descriptive curves of sheep growth than nonlinear models. Comparable findings were reported for the BW prediction in pigs (Preethi *et al.* 2023), goats (Raja *et al.* 2012; Vaidya *et al.* 2018; Akkol *et al.* 2017), and in 6-month-old Kermani sheep regarding the breeding values prediction for the BW (Ghotbaldini *et al.* 2019).

This study successfully predicted the body weight of Black Bengal goat kids across various growth phases using ANN models and subsequently evaluated their ability to make accurate predictions. The presence of a significant association between different body morphometric measurements and BW indicated potential for model development and further investigations. The ANN models provided higher prediction accuracy as compared to regression models in different growth phases of Black Bengal kid's development. The ANN model, showed low MSE and high R^2, validated the reliability of HG, CL, and HAB in accurately predicting the body weight (BW) of kids across different growth phases. The incorporation of HG and HAB improved the validation of the ANN model to predict the BW of kids during the pre-weaning period. Furthermore, the addition of CL and HAB increased the accuracy of BW prediction during post-weaning and combined growth phases. Therefore, neural networks could be regarded as the preferred method for predicting the BW of Black Bengal kids using body morphometric measurement data.

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