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Weight Prediction of Landlly Pigs from Morphometric Traits in Different Age Classes Using ANN and Non-Linear Regression Models

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Abstract: The present study was undertaken to identify the best estimator(s) of body weight based on various linear morphometric measures in Landlly pigs using artificial neural network (ANN) and non-linear regression models at three life stages (4th, 6th and 8th week). Twenty-four different linear morphometric measurements were taken on 279 piglets individually at all the stages and their correlations with body weight were elucidated. The traits with high correlation ($\geq$0.8) with body weight were selected at different stages. The selected traits were categorized into 31 different combinations (single, two, three, four and five) and subjected to ANN modelling for determining the best combination of body weight predictors at each stage. The model with highest R^2 and lowest MSE was selected as best fit for a particular trait. Results revealed that the combination of heart girth (HG), body length (BL) and paunch girth (PG) was most efficient for predicting body weight of piglets at the 4th week (R^2 = 0.8697, MSE = 0.4419). The combination of neck circumference (NCR), height at back (HB), BL and HG effectively predicted body weight at 6 (R^2 = 0.8528, MSE = 0.8719) and 8 (R^2 = 0.9139, MSE = 1.2713) weeks. The two-trait combination of BL and HG exhibited notably high correlation with body weight at all stages and hence was used to develop a separate ANN model which resulted into better body weight prediction ability (R^2 = 0.9131, MSE = 1.004) as compared to age-dependent models. The results of ANN models were comparable to non-linear regression models at all the stages.

Keywords: artificial neural network; body weight; landlly pigs; MATLAB; morphometry; non-linear regression

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Citation: Preethi, A.L.; Tarafdar, A.; Ahmad, S.F.; Panda, S.; Tamilarasan, K.; Ruchay, A.; Gaur, G.K. Weight Prediction of Landlly Pigs from Morphometric Traits in Different Age Classes Using ANN and Non-Linear Regression Models. *Agriculture* **2023**, *13*, 362. https://doi.org/10.3390/agriculture13020362

Academic Editor: Roberto Alves Braga Júnior

Received: 14 November 2022
Revised: 28 January 2023
Accepted: 30 January 2023
Published: 2 February 2023

1. Introduction

India owns the heftiest inventory of livestock population across the world and is considered as one of the biodiversity hotspots. Overall, the livestock sector of India contributes up to 25.6% to the total agricultural GDP and 4.11% to the total GDP of India [1]. Among different livestock species reared in India, piggery is placed at one of the prime positions that ensures the livelihood and nutritional support to the socio-economically feeble communities of the society. Pork is also regarded as a good and cheaper source of protein all around the globe [2], that can help satisfy the demands of the increasing human population [3]. Currently, 10 well-recognized and characterized Indian pig breeds are registered with its nodal agency i.e., ICAR-NBAGR, Karnal, Haryana (India). These breeds include Agonda Goan (Goa), Doom (Assam), Ghoongroo (West Bengal), Ghurrah (Uttar Pradesh), Mali (Tripura), Niang Megha (Meghalaya), Nicobari (Andaman and Nicobar), Purnea (Bihar and Jharkhand), Tenyi Vo (Nagaland) and Zovawk (Mizoram). India is home to more than 9.06 million pigs as per the latest (20th) livestock census (BAHS, 2019). However, distribution of the pig population across the country is not homogenous; particularly a denser population of pigs is reported only in the eastern and north-eastern states. However, increased diffusion of piggery sector is seen in many northern states of India in the recent times.

Piggery possesses a significant potential and sizeable prospect to ensure optimal productivity and faster economic profitability to the farmers as they possess certain inherent traits such as enhanced feed efficiency, early maturity, shorter generation interval and improved fecundity, that makes it more suitable for intensive farming [4]. This is in contrast to other farm animal species that are reared across different nations. Despite this, the pig farming sector has remained extremely unorganized to date, with nearly 70% of the pig population being raised under less efficient and mainly extensive production systems.

Genetic progress of the pig breeds involves significant focus on strengthening the meat production with a thorough knowledge of body composition through planned and precise selection which ultimately helps in achieving an optimized production [5]. Therefore, an efficient, accurate and reliable recording of phenotype with respect to traits of economic interest is the prime need of any animal breeding and improvement program. Recording and usage of proper data on economic traits (body weight, litter size, etc.) are the foremost requisites for assessment of the production potential and profitability from piggery [5]. However, measuring live body weight of animals with considerable accuracy and reliability in farm and field conditions is tedious, as villages and hilly areas lack portable weighing balance and proficient technicians. In conditions with availability of weighbridge, body weight measurements are still considered unreliable as animals tend to move and is extremely difficult to make them stationary [6], which may lead to very high fluctuations in the readings and also, it places the animal into unnecessary stress [7] which can be risky for animal handlers as well as the animal itself [8]. Hence, methods for estimating the weight of animals comprise the use of weight band, visual appraisal and linear body measurements under such circumstances [9]. Among these methods, linear body measurements are considered to be one of the best and are used for estimating the body weight in large domestic animals [10]. It is practically difficult for most small-holding farmers (for economic reasons) to have these standard weighing scales [11]. Therefore, the dependency of farmers on readily accessible linear body measurements to indirectly predict the body weight in animals has increased [12]. There are many linear body measurement traits which have been utilized to determine the size and weight of an animal. However, more commonly, morphometric traits like height at wither, heart girth, chest depth, body length, distance between eyes, rump height, ear length, ear width, paunch girth and tail length, etc., are used for making such predictions. Different morphometric traits have also been used in the selection programs for various animal species [13–15]. Thus, morphometric traits gain significance under field and farm conditions especially when records on economic traits of interest are absent or at places where it is tough to directly measure the body weight of animals [16]. Details of morphometric traits have been employed in valuating feed utilization, growth rate, body weight, and carcass traits in farm animals [15,17,18]. It has also been reported that linear body measurements can help elucidate the body weight of an animal implicitly than customary procedures of weighing and grading [19].

Prediction of body weight using linear morphometric traits were previously based on conventional statistical methods, such as linear and logistic regression, principal component analysis, k-nearest neighbour classification, etc. [20]. For instance, there are several experiments that employed conventional methods to predict the body weight of pigs using linear morphometric measurements which include non-linear regression [21], stepwise regression [22], multiple linear regression [23] and simple linear regression [24]. Attempts to predict the body weight using such linear morphometric traits in other species have also been reported; for instance, in goats using simple and stepwise regression [25], in cattle using least squares fixed model [13], in chickens using simple linear regression [26] and in sheep using regression model analysis [27], which are all usually assumption-based; therefore, they often cannot produce the best possible results due to many limitations. Scientific studies had proved that customary regression methods may lead to biased results as they are unable to gauge the multi-collinearity between independent variables [28,29]. Hence, an ultimate and optimal choice would be to use those methodologies which club the linear and non-linear procedures while fitting statistical models on to the underlying data.

Artificial neural networking (ANN) is one such procedure which involves the combined fitting of both linear and non-linear models on the underlying data [30,31]. It includes the training algorithms and mathematical models which can imitate the data processing expertise, as analogous to the human brain; hence, they are mainly employed to process non-linear and complex data/situations. On that account, it is possible to apply ANNs, instead of customary procedures for predicting the body weight in pigs reared under harsh field conditions with rough terrains. The technical gap that existed in the application of ANN is currently getting reduced as it is gaining pace in the world of animal and veterinary sciences for its improved prediction accuracies in terms of better R^2 estimates. Some notable studies applying ANN in animal sciences encompass prediction of milk yield, fat and protein composition in milk [32], somatic cell count, fat and protein concentration in milk and milk production [33]. These studies using ANN had revealed higher coefficient of determination (R^2) and Pearson correlation coefficient and lower values of standard deviation and mean square error (MSE) in contrast with multiple regression models, asserting better predictability of ANN which were close enough to the actual weights. Furthermore, the use of a greater number of measurements is reported to increase the precision of predicted body weight in animals [24]. Therefore, it is better to record and use more related measurements so that ANN algorithms will be able to predict the desirable results with greater efficiency and accuracy. Furthermore, studies reveal that ANN models have better ability to precisely predict body weight with lower bias using the data on morphometric traits as compared to multiple regression models in animals [21,34–37]. Despite extensive literature search and the best of our knowledge, no study on the prediction of body weight in pigs/piglets using neural network models has been reported yet. Though, studies based on linear regression models for the prediction of body weight has been carried out in Landlly piglets [38]; however, the application of non-linear regression models for the same has not been reported . Furthermore, the comparison of non-linear models with ANN models for the body weight prediction in pigs has not been explored. Hence, the aim of this investigation was to develop an ANN model to predict the body weight of Landlly piglets at different life stages based on the linear body measurements under organized farm and tropical climatic conditions and also to compare it with non-linear regression models.

2. Materials and Methods

2.1. Population, Data Collection and Management

The current research was performed on piglets maintained at the Swine Production Farm, Livestock Production and Management Section, ICAR—Indian Veterinary Research Institute, Izatnagar, Uttar Pradesh, India which is a centre of ICAR—All India Coordinated Research Project on Pigs (AICRP). The centre is situated in a semi-arid region of northern India with latitude and longitude of 28° N and 79° E, respectively. The current study was based on the Landlly pigs, a crossbred variety of pig developed after crossing Landrace boars with Ghurrah sows. The final inheritance is stabilized with 75% exotic inheritance (Landrace) and 25% local inheritance (Ghurrah) after backcrossing of F_1 (half-bred) animals with Landrace boars (Figure 1). The Landlly pigs have been reported to exhibit better growth characteristics and adaptation traits under harsh conditions of climate and poor nutritional support. The animals experience harsh climate with hot dry to hot humid summers and cold winters with temperatures ranging from 5 °C to 40 °C with 21 °C as the mean annual temperature. The animals are maintained under organized farm conditions, especially pertaining to feeding, healthcare and management. The pigs are fed based on their physiological status and age group. The lactating sows are given concentrate feed at the rate of 4–5 kg/day and housed separately while the piglets are provided creep ration that is rich in protein and energy. Weaning is done at 6 weeks of age.

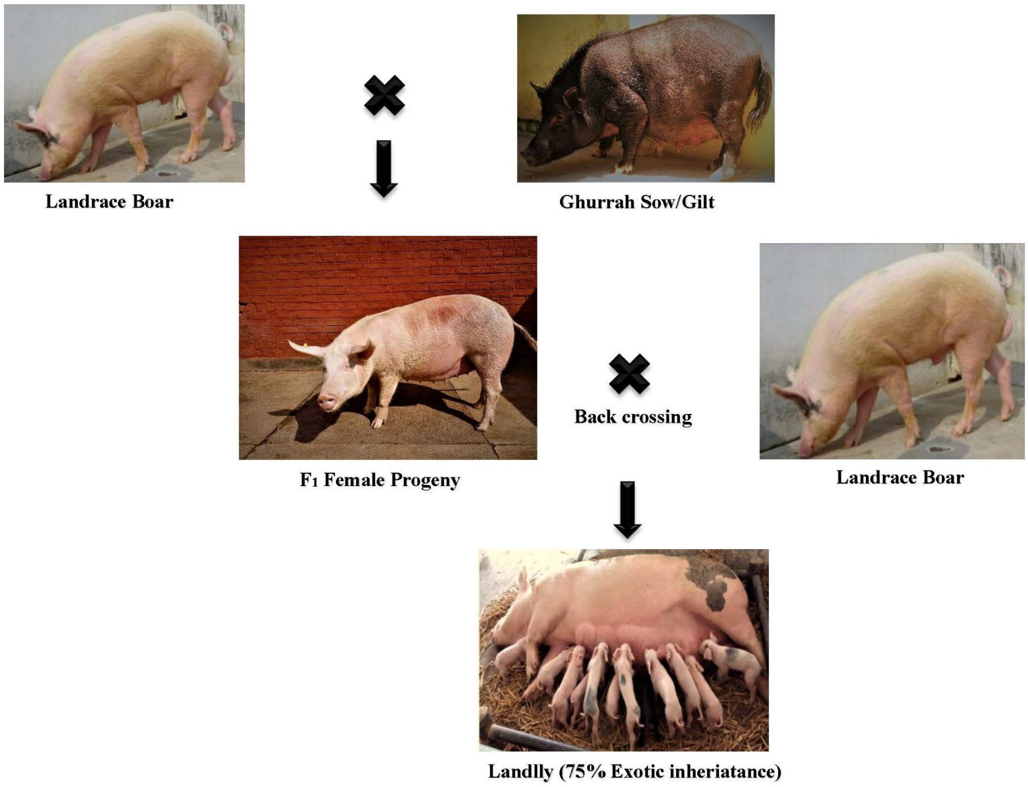


Figure 1. Landlly pigs developed from cross breeding of Landrace (Exotic breed) and Ghurrah (Indigenous/Local breed).

The data on morphometric characteristics (linear body measurements) were collected on a total of 279 Landlly piglets at three different life stages, i.e., pre-weaning (4th week), weaning (6th week) and post-weaning (8th week). A total of 24 morphometric traits i.e., body length (BL), height at wither (HW), heart girth (HG), ear length (EL), ear width (EW), head length (HL), chest width (CW), rump height (RH), rump width (RW), rump length (RL), front body depth (FBD), back body depth (BBD), paunch girth (PG), height at shoulder (HS), height at back (HB), height at fore leg (HF), height at hind leg (HHL), thigh length (THL), thigh circumference (TCR), snout length (SL), snout circumference (SCR), neck circumference (NCR), inner orbital width (IO) and tail length (TL) were measured individually on each animal using measuring tape, subsequent to their proper restraining. Each morphometric trait was measured on centimetre unit scale (Figure 2).

Out of the 24 morphometric traits, the most correlated traits with the body weight (BW) were selected/screened using artificial neural networks. The ANN infrastructure used for trait screening consisted of 1 hidden layer neuron with tan-sigmoidal (TANSIG) transfer function in the hidden layer and linear approximation function (PURELIN) in the output layer. The selected traits were used for further analysis and model development.

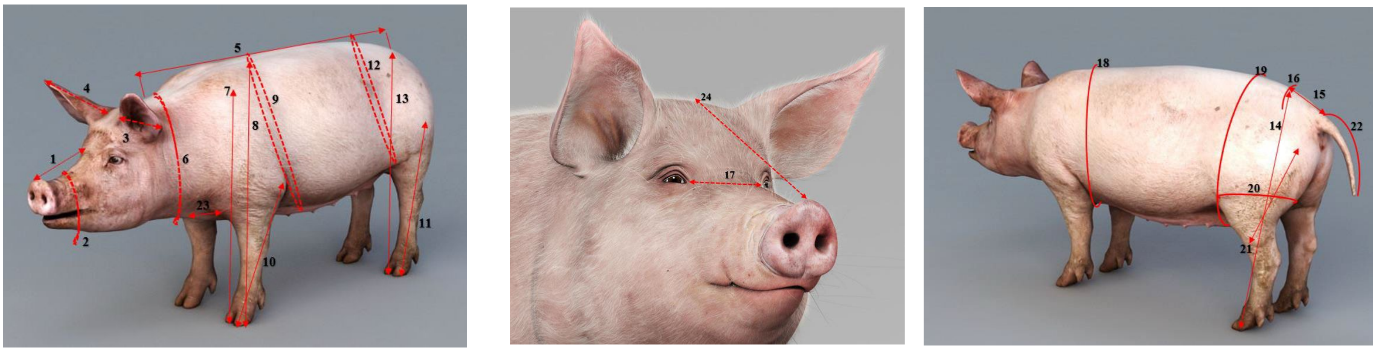


Figure 2. Linear morphometric measures in pig: 1. SL—snout length, 2. SCR-snout circumference, 3. EW—ear width, 4. EL—ear length, 5. BL—body length, 6. NCR—neck circumference, 7. HS—height at shoulder, 8. BH—body height, 9. FBD—front body depth, 10. HF—height at front leg, 11.HHL—height at hind leg, 12. BBD—back body depth, 13. HB—height at back, 14. RH—rump height, 15. RL—rump length, 16. RW—rump width, 17. IOL—inner orbital length, 18. HG—heart girth, 19. PG—paunch girth, 20. TCR—thigh circumference, 21. THL—thigh length, 22. TL—tail length, 23. CW—chest width, 24. HL-head length.

2.2. Data Modelling

2.2.1. Artificial Neural Network Models

The data consisting of the morphometric traits (input) and their corresponding weight (output) were imported to the MATLABv.2012 interface (MathWorks Inc., Natick, Massachusetts, USA) for ANN modelling. An ANN infrastructure was built with the Bayesian Regularization Backpropagation training function (TRAINBR) using the neural network tool box of MATLAB to model the relationship between the linear body measures and BW of pigs. The ANN infrastructure consisted of a single input layer with nodes or neurons representing a combination (single trait, two-trait, three-trait, etc.) of the traits screened previously; a hidden layer and, an output layer with 1 neuron each.

The entire dataset was randomly divided into two subsets viz, the training subset (consisting of 70% of data from the original dataset) and test subset (comprising of remaining 30% of the data). The weights and bias matrices were randomly initialized between −1 to +1. A TANSIG transfer function was used to compute the output from summation of weighted inputs of neurons in the hidden layer while a PURELIN function was used at the output layer for getting the network response. To ensure fine training of the ANN model, the learning rate was set at 0.01 and the momentum factor was set as low as 0.001. The model termination criterion was set as 1000 epochs/iterations or a training error of 10^{-6}, whichever was attained earlier. Each model was trained thrice for predicting the BW and the results were saved in the MATLAB workspace. For an ANN infrastructure with n input neurons and 1 hidden layer neuron (HLN), the input signal to the hidden layer (H_I) can be expressed as Equation (1), where I_i is the i^{th} input neuron, w_{i1} is the network weight of the i^{th} neuron in the input layer to the HLN and b_1 is the hidden layer bias.

$$H_I = \left(\sum_{i=1}^{n} I_i w_{i1} \right) + b_1 \quad (1)$$

The output of the hidden layer (H_O) can then be written as Equation (2) while the input signal to the output layer (O_I) can be written as Equation (3) where v_{11} is the net-work.

$$H_O = \frac{1 - e^{-2\{(\sum_{i=1}^{n} I_i w_{i1}) + b_1\}}}{1 + e^{-2\{(\sum_{i=1}^{n} I_i w_{i1}) + b_1\}}} \quad (2)$$

$$O_I = v_{11} H_O + b_2 = v_{11} \left(\frac{1 - e^{-2\{(\sum_{i=1}^{n} I_i w_{i1}) + b_1\}}}{1 + e^{-2\{(\sum_{i=1}^{n} I_i w_{i1}) + b_1\}}} \right) + b_2 \quad (3)$$

The final model response is a linear approximation of the input signal to the output layer ($O_O \sim O_I$).The R^2 and MSE were determined for each run and each combination of traits. Prediction accuracy was used as the criterion for judging the models' performance in order to investigate the research hypotheses. The model with highest R^2 and lowest MSE were selected as best fit for a particular trait at different stages (4th, 6th and 8th weeks).

2.2.2. Non-Linear Regression Models

ANNs in general are highly non-linear models that exhibit excellent data pattern recognition ability. However, ANNs may not be always the best suitable model for certain data patterns which could otherwise be mapped using general non-linear models [39]. To test this premise, the obtained ANN models were compared to the corresponding non-linear models based on R^2 and MSE to evaluate their relative performance in prediction of the piglet body weight.

The second order non-linear regression models were developed taking the best combination of morphometric traits (screened using ANN) at different stages of Landlly piglets. The said models were developed in MS Excel v.2007 (Microsoft Inc., Redmond, Washington, DC, USA) using the 'Regression' function under 'Data Analysis' tab.

3. Results and Discussion

Predicting body weight at a particular stage using linear morphometric traits is desirable where there is unavailability of weighing scales [38]. Such indirect predictions enable one to predict the growth of an animal [26] and body weight in field conditions with fair accuracy. Based on this premise, the data on 24 linear morphometric traits collected on a total of 279 Landlly piglets at three different stages (4, 6 and 8 weeks) and analysed using different models. The ANN-based preliminary screening of these traits was done assuming the two specific criteria. Minimum correlation value must be $\gtrsim$ 0.80 and the selected trait must be common at all the stages of life. HG, BL, NCR, PG, HB were identified as the top five traits which satisfied the set criteria (Figure 3, Table 1) and were therefore, used further as inputs (in combinations) for developing the ANN model for predicting the body weight. The correlation between different traits was also established to gain more insight into the association between the morphometric traits at different stages of growth (Table 2).

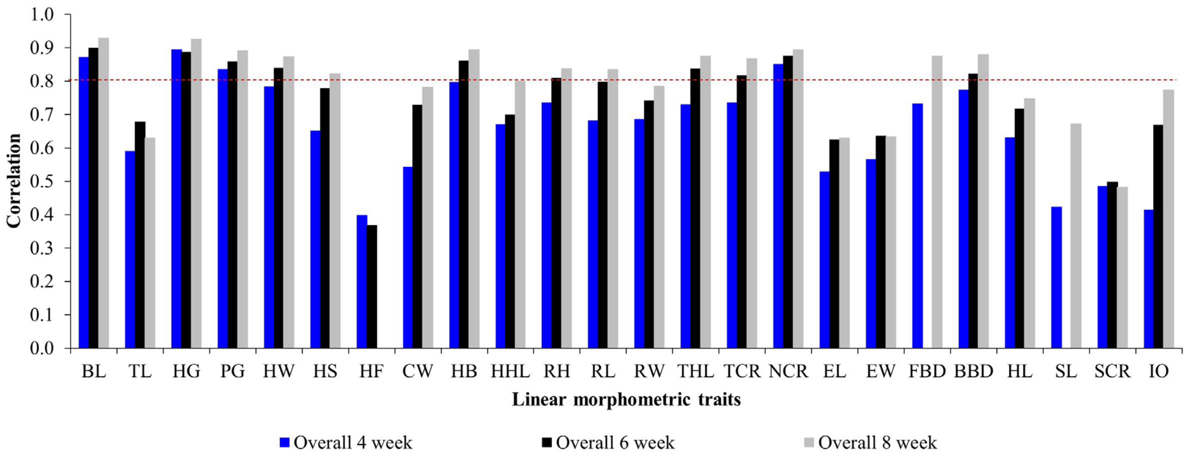


Figure 3. Correlation of morphometric traits with body weight with a cut-off of 0.8 (dotted line).

Table 1. ANN based correlation of morphological traits with body weight.

Age	Trait *	R^2
4 weeks	HG	0.8001
	BL	0.7616
	NCR	0.7244
	PG	0.7002
	HB	0.6344
6 weeks	BL	0.8111
	HG	0.7871
	NCR	0.7679
	PG	0.7429
	HB	0.7382
8 weeks	HG	0.8641
	BL	0.8601
	HB	0.8008
	NCR	0.7971
	PG	0.7753

* HG: Heart Girth; BL: Body Length; NCR: Neck Circumference; PG: Paunch Girth; HB: Height at Back.

Table 2. Correlation between different traits at different growth stages of Landlly piglets.

Correlation	4 Week	6 Week	8 Week
HG-BL	0.87 ± 0.03	0.92 ± 0.05	0.90 ± 0.03
BL-NCR	0.83 ± 0.03	0.87 ± 0.05	0.87 ± 0.03
NCR-PG	0.85 ± 0.03	0.89 ± 0.04	0.88 ± 0.03
PG-HB	0.75 ± 0.04	0.83 ± 0.03	0.86 ± 0.03
HB-HG	0.83 ± 0.03	0.87 ± 0.04	0.90 ± 0.03
HG-NCR	0.89 ± 0.03	0.91 ± 0.05	0.91 ± 0.03
HG-PG	0.91 ± 0.02	0.95 ± 0.04	0.93 ± 0.02
BL-PG	0.81 ± 0.04	0.89 ± 0.04	0.87 ± 0.03
NCR-HB	0.75 ± 0.04	0.83 ± 0.05	0.84 ± 0.03
BL-HB	0.83 ± 0.03	0.90 ± 0.04	0.91 ± 0.03

It was revealed from the analysis that at 4th week, three of the ten two-trait combinations, viz., HG-BL, HG-NCR and HG-PG performed better (Adj-R^2 = 0.806–0.864) than individual traits (R^2 = 0.634–0.800) for predicting the BW (Table 3). Seven of the ten three-trait combinations performed better than individual traits while HG-BL-PG exhibited adj-R^2 comparable but slightly higher than the best two-trait combination. Out of the five four-trait combinations, four performed better than single trait prediction while BL-HG-PG-NCR showed a comparable adj-R^2 than the best two-trait and three-trait combinations. In contrast, the five-trait combination showed a drop in adj-R^2 as compared to the other best combinations but was still higher than the BW prediction using a single trait.

On analysing and fitting the data on BW of piglets at the 6th week, among ten two-trait combinations, eight were found to show better R^2 ($\geq$0.80) when compared with the single traits (0.73–0.81). Among these eight combinations, BL-HG, BL-NCR, NCR-HB showed higher adj-R^2 (0.827–0.842). Inclusion of additional traits (three-trait and four-trait combinations) proclaimed ascendancy and signified better prediction accuracy. However, the four-trait combination, BL-HG-HB-NCR had set up modest supremacy over the five-trait combination in terms of prediction accuracy. Similar to the 4th week results, the five-trait combination did not produce any significant change in prediction ability in the 6th weeks' BW.

Table 3. Correlation between different combinations of linear morphometric traits and the actual body weight of pigs predicted using artificial neural networks.

4 Weeks			6 Weeks			8 Weeks		
Combinations	**Train MSE**	**Adj-R^2**	**Combinations**	**Train MSE**	**Adj-R^2**	**Combinations**	**Train MSE**	**Adj-R^2**
BL-HG-PG-HB-NCR	0.3788	0.829	BL-HG-PG-HB-NCR	0.9927	0.849	BL-HG-PG-HB-NCR	1.3915	0.909
BL-HB	0.6017	0.788	BL-HB	1.1551	0.821	BL-HB	1.8428	0.877
BL-HB-NCR	0.4978	0.850	BL-HB-NCR	0.8957	0.849	BL-HB-NCR	1.5035	0.899
BL-HG	0.4512	0.864	BL-HG	0.9626	0.830	BL-HG	1.4511	0.905
BL-HG-HB	0.4361	0.823	BL-HG-HB	1.0488	0.836	BL-HG-HB	1.3856	0.906
BL-HG-HB-NCR	0.4207	0.833	BL-HG-HB-NCR	0.8719	0.849	BL-HG-HB-NCR	1.2713	0.911
BL-HG-NCR	0.4475	0.862	BL-HG-NCR	0.9909	0.845	BL-HG-NCR	1.3438	0.909
BL-HG-PG	0.4419	0.867	BL-HG-PG	1.0231	0.830	BL-HG-PG	1.4508	0.904
BL-HG-PG-HB	0.3635	0.724	BL-HG-PG-HB	1.0001	0.835	BL-HG-PG-HB	1.2949	0.905
BL-HG-PG-NCR	0.446	0.867	BL-HG-PG-NCR	1.0037	0.843	BL-HG-PG-NCR	1.3149	0.908
BL-NCR	0.4898	0.778	BL-NCR	0.9779	0.842	BL-NCR	1.6412	0.894
BL-PG	0.4698	0.750	BL-PG	1.0477	0.823	BL-PG	1.6500	0.886
BL-PG-HB	0.489	0.804	BL-PG-HB	0.9311	0.837	BL-PG-HB	1.6124	0.891
BL-PG-HB-NCR	0.4699	0.857	BL-PG-HB-NCR	0.8993	0.848	BL-PG-HB-NCR	1.5419	0.902
BL-PG-NCR	0.4799	0.836	BL-PG-NCR	0.9789	0.843	BL-PG-NCR	1.5384	0.898
HB-NCR	0.5525	0.774	HB-NCR	1.0786	0.827	HB-NCR	1.9607	0.868
HG-HB	0.4074	0.756	HG-HB	1.1194	0.820	HG-HB	1.6972	0.883
HG-HB-NCR	0.9094	0.776	HG-HB-NCR	0.9789	0.838	HG-HB-NCR	1.5852	0.890
HG-NCR	0.5011	0.826	HG-NCR	1.2344	0.811	HG-NCR	1.7502	0.875
HG-PG	0.4984	0.806	HG-PG	1.3421	0.788	HG-PG	2.0297	0.864
HG-PG-HB	0.5001	0.843	HG-PG-HB	1.1056	0.822	HG-PG-HB	1.7812	0.883
HG-PG-HB-NCR	0.4473	0.813	HG-PG-HB-NCR	1.0774	0.836	HG-PG-HB-NCR	1.58000	0.891
HG-PG-NCR	0.5038	0.839	HG-PG-NCR	1.1990	0.811	HG-PG-NCR	1.725	0.875
PG-HB	0.6504	0.796	PG-HB	1.1592	0.807	PG-HB	2.2244	0.852
PG-HB-NCR	0.8982	0.759	PG-HB-NCR	0.9818	0.833	PG-HB-NCR	1.9429	0.877
PG-NCR	0.5695	0.704	PG-NCR	1.2357	0.793	PG-NCR	2.2363	0.844

On fitting the BW data of Landlly piglets at 8th week, it was revealed that all of the two trait combinations exhibited a higher adj-R^2 ($\geq$0.844) than individual traits (R^2 = 0.77–0.86). Of all the two-trait combinations, BL-HG displayed the highest adj-R^2 (0.905) when compared with other two stages. The four-trait combination of BL-HG-HB-NCR exhibited a comparable but slightly higher BW prediction ability (adj-R^2 = 0.911) followed by the five trait (adj-R^2 = 0.909) and three-trait combination (adj-R^2 = 0.909). Indicated that although inclusion of supplementary traits beyond 'two' enabled notably higher prediction accuracy, it did not drastically impact the BW prediction capability. This result was in congruence to the observations made for the 6th week BW data. Further, it was confirmed that the five-trait combination did not generate any significant improvement in the prediction of BW of Landlly piglets at any of the stages. The least R^2 estimates were exhibited by PG-NCR for 4th week, HG-PG for 6th week and, PG-NCR for 8th week (Table 3). This shows that the impact of paunch girth in predicting BW is hindered to some extent when associated with other morphometric traits. This effect was also observed and reported by Banik and co-workers for Ghungroo pigs where they observed that paunch girth has an indirect negative effect on the BW via height at hindleg [40]. Likewise, the highest MSE estimates were recorded for HG-HB-NCR, HG-PG and PG-NCR combination for the 4th, 6th and 8th week, respectively.

Among all 31 combinations employed for fitting the BW data at three different stages, it was established that the three-trait combination of BL-HG-PG was most suitable for predicting the 4th week BW on account of its higher adj-R^2 and low MSE (comparable to four-trait combination). For predicting the 6th and 8th week BW, BL-HG-HB-NCR exhibited higher adj-R^2 with lowest MSE and was therefore, selected for ANN model development. Figure 4 shows the ANN infrastructure used for model development at all life stages. The final ANN model equations with higher BW prediction capability for 4, 6 and 8 weeks were determined and have been represented as Equations (4)–(6), respectively.

$$O_{O4} \cong O_I = \frac{1 - e^{-2(I1 \times 0.323 + I2 \times 0.447 + I3 \times 0.049 - 0.151)}}{1 + e^{-2(I1 \times 0.323 + I2 \times 0.447 + I3 \times 0.049 - 0.151)}} \times 1.313 + 0.031 \quad (4)$$

$$O_{O6} \cong O_I = -\frac{1 - e^{-2(-I1 \times 0.346 + I2 \times -0.134 - I3 \times 0.151 - I4 \times 0.249 + 0.086)}}{1 + e^{-2(-I1 \times 0.346 + I2 \times -0.134 - I3 \times 0.151 - I4 \times 0.249 + 0.086)}} \times 1.292 + 0.044 \quad (5)$$

$$O_{O8} \cong O_I = \frac{1 - e^{-2(I1 \times 0.467 + I2 \times 0.345 + I3 \times 0.069 + I4 \times 0.143 - 0.154)}}{1 + e^{-2(I1 \times 0.467 + I2 \times 0.345 + I3 \times 0.06914 + I4 \times 0.143 - 0.154)}} \times 1.131 + 0.075 \quad (6)$$

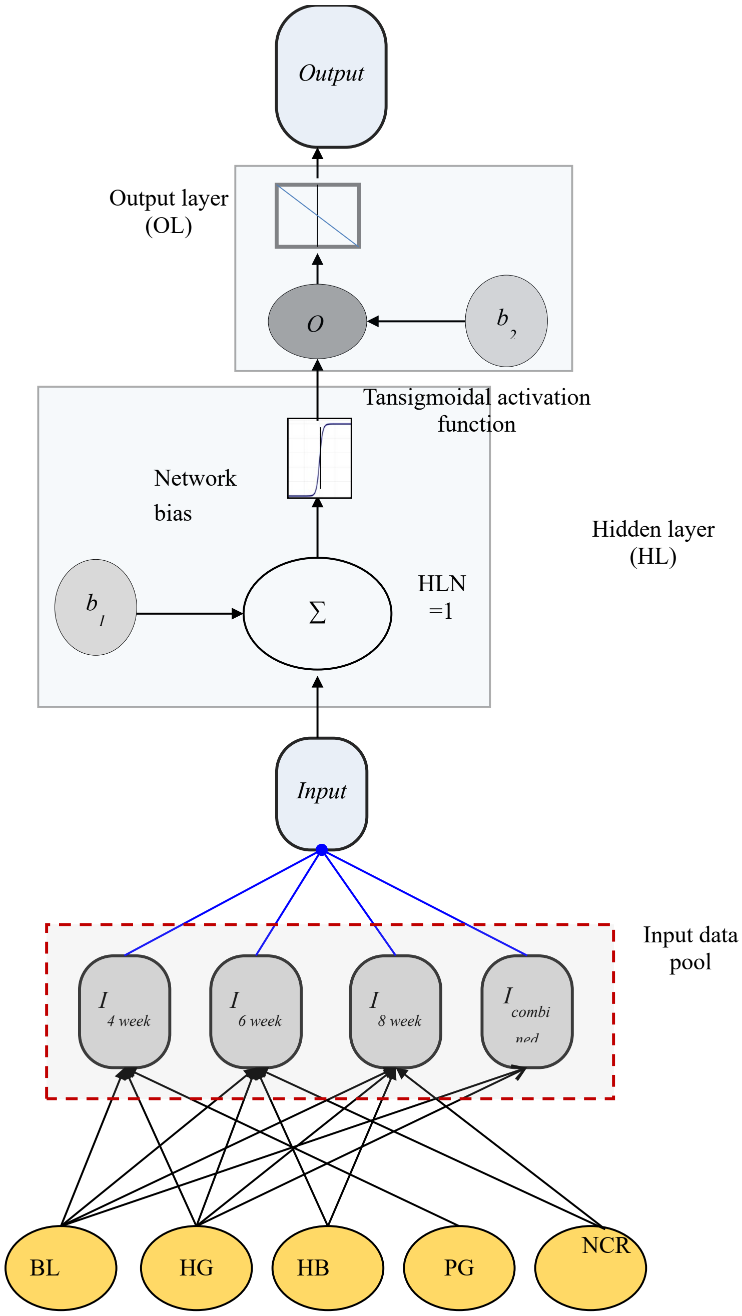


Figure 4. ANN model infrastructure for determination of body weight of Landlly piglets at different life stages. Four separate models taking I_4, I_6, I_8 and I_{combined} as input were developed.

Among different linear morphometric traits, heart girth is known to be the least affected measure irrespective of the posture of the animal [13]. Furthermore, strong correlation between body weight and heart girth had been reported in finishing pigs by Groesbeck and co-workers [41]. Similarly, the results of the current study reflected that heart girth was more correlated to the BW of Landlly piglets at 4 and 8 weeks of age. On the contrary, the 6th week results showed body length as the most correlated morphometric measure to the BW. In Landrace and Large white pigs, Sungirai and co-workers determined BW using linear body measurements and developed a model through stepwise multiple linear regression [23]. They reported that the age, body length and heart girth were useful predictors of live weight. Further, they also reported that body length contributed more to the variation in body weight than the heart girth, which is closely associated with the results of the current study for 6-week-old piglets. Birteeb and co-workers determined the relationship between linear body measurements in three selected weaning ages (4, 6, 8 weeks) and concluded that chest girth was the best predictor of BW irrespective of the age and also added that the addition of multiple traits produced higher prediction accuracies than individual traits [24]. Correspondingly, in the current investigation, the two-trait combination, BL-HG was found highly correlated to BW for 4- and 8-week old piglets; however, BL-NCR exhibited a negligible rise in prediction accuracy to BL-HG for 6 weeks old piglets. Hence, from a broader perspective, the BL-HG combination is suitable for predicting BW at all three stages of Landlly piglets with an adj-R^2 value of >0.9. Considering this, a model combining the BL-HG combination at all three stages was developed using ANN as shown in Equation (7). The combined model showed acceptable level of body weight prediction accuracy (Figure 5) which was found to be better than individual life stages in terms of higher R^2 and lower number of traits.

$$O_{Ocomb} \cong O_I = \frac{1 - e^{-2(I1 \times 0.374 + I2 \times 0.312 - 0.438)}}{1 + e^{-2(I1 \times 0.374 + I2 \times 0.312 - 0.438)}} \times 1.887 + 0.558 \quad (7)$$

Sabbioni and co-workers found that the equations calculated using HG were easier to apply under field conditions; however, they were slightly less accurate than those calculated from more body measurements [42]. Similarly, it was found that considering all the possible combinations (single trait, two-trait, three-trait, four-trait and five-trait), addition of BL and PG to HG (HG-BL-PG, HG-BL, HG-PG) predicted the BW of 4 weeks old piglets more efficiently in the current study. Likewise, addition of BL, HB and NCR to HG generated a more efficient combination (BL-HG-HB-NCR) to predict the body weight of 6 and 8 weeks old piglets.

The developed ANN models were simulated with a random set of input variables to determine their prediction accuracy. It was observed that the models were able to correctly explain 83.54%, 85.30% and 91.15% of the body weight data in 4, 6, 8 weeks old Landlly pigs (Table 4). Further, the holistic model (combined) taking into consideration of all stages explained 92.86% of the body weight data. Moreover, the model error variations showed a random distribution which indicated that the developed ANN models had a more prominent linear component.

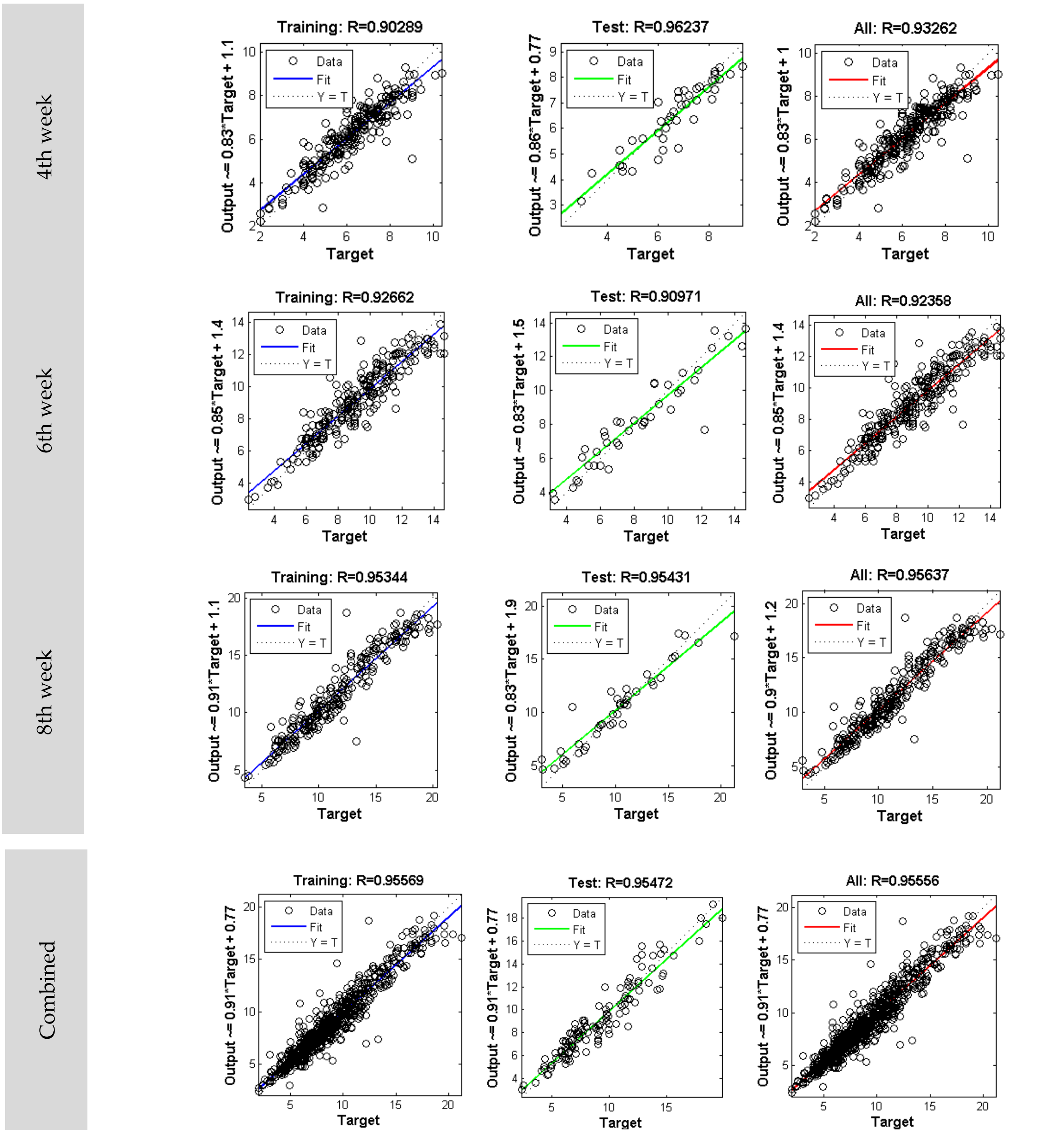
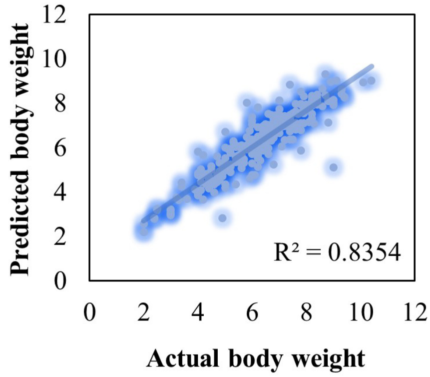
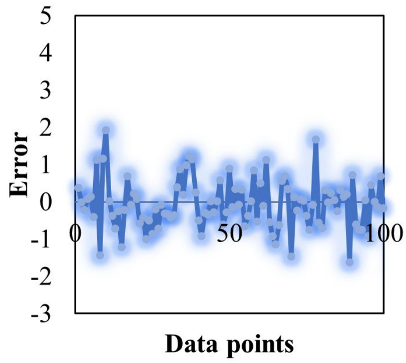
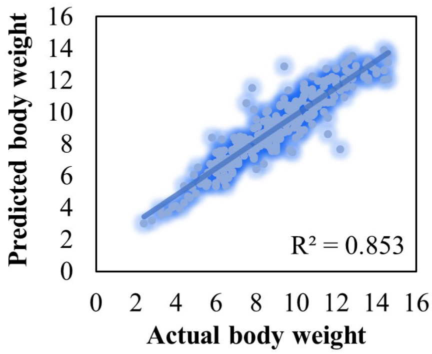
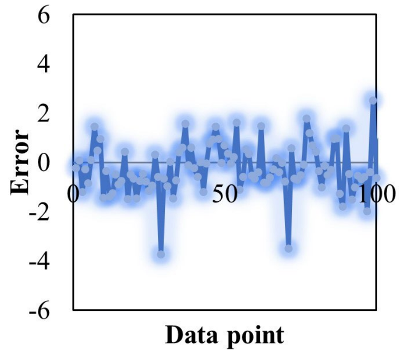
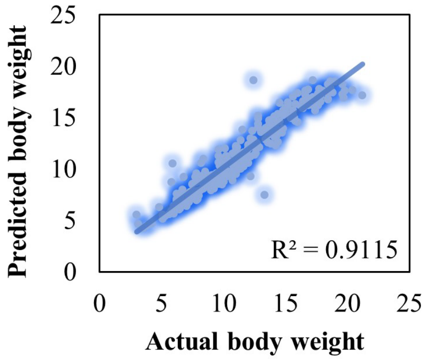
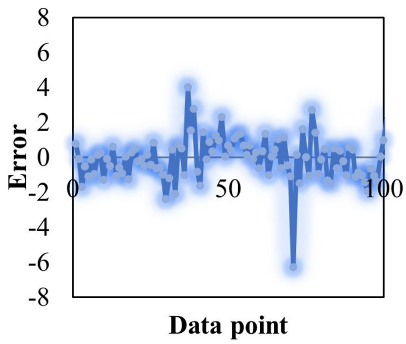
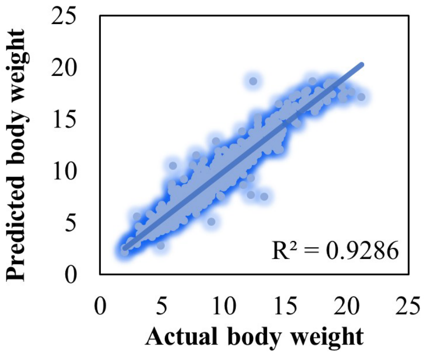
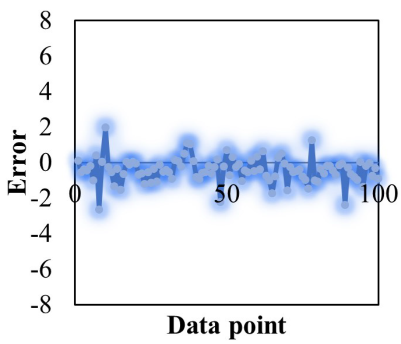


Figure 5. ANN based correlation between the linear morphometric traits and the actual body weight of pigs predicted using artificial neural networks. Training, testing and overall correlation graphs have been provided (from left to right) for all the stages.

Table 4. ANN simulation results for prediction of piglet weight and corresponding error variation at different stages.

Age	Prediction Model	Error Variation
4 weeks		
6 weeks		
8 weeks		
Combined		

Overall, only three efficient predictor variables were sufficient to predict the body weight of piglets at 4 weeks of age while four predictor variables were needed to predict the body weight at the 6th and 8th week stages. Furthermore, the coefficient of variation (CV) for 4th week body weight was 25.95%, while its estimate was 27.85% for 6th week body weight, and 33.72% for 8th week body weight. The CV estimates were in line with the requirement of comparatively lesser number of predictors to predict the body weight at 4th week of age in Landlly piglets. This points out that there is differential genetic control of body weight at different stages wherein the genes controlling the body weight trait at earlier stage might be different than those controlling it at later stages. Similar findings have been reported by Chu et al. for broiler chickens [43].

In addition to ANN models, non-linear models for BW prediction were also developed. The results of second order non-linear regression models for predicting the body weight of Landlly pigs at different stages showed a R^2 of 0.842, 0.855 and 0.916 at 4, 6 and 8 weeks, respectively. Although ANN generated slightly higher R^2 for body weight prediction at 4th week, the results of ANN prediction at 6th and 8th week were comparable or marginally lower than that of the non-linear regression models (Table 5). AIC of the models was also determined to test the relative performance of the models. It was observed that for the 4th week, linear regression showed the lowest AIC exerting its dominance over non-linear and ANN models. In contrast, ANN showed better prediction performance for the 6th and 8th week as well as the combined model. Behzadi and Aslaminejad used artificial neural networks to predict the growth of Baluchi sheep and also observed that ANN were comparable to non-linear regression models [21]. However, our results did not corroborate the findings of Raja et al. (2012), who reported better prediction of body weight in Attapady goats through ANN models rather than regression models. Similar findings were also reported by Ghotbaldini and co-workers for the prediction of breeding values of body weight in 6 month old Kermani sheep, Akkol and co-workers for the prediction of body weight in hair goats [36] and Roush and co-workers for the prediction of body weight in broilers [34].

Table 5. Comparison of body weight prediction for different age classes of Landlly piglets using non-linear regression and ANN models.

Model	4th Week [a]			6th Week [b]			8th Week [b]			Combined [c]		
	R^2	MSE	AIC	R^2	MSE	AIC	R^2	MSE	AIC	R^2	MSE	AIC
Linear regression	0.834	0.436	−94.08	0.853	0.936	−0.13	0.908	1.388	47.55	0.900	1.243	83.81
Non-linear regression	0.842	0.425	−87.85	0.855	0.960	14.53	0.916	1.307	52.63	0.914	1.080	37.53
ANN	0.869	0.441	−87.20	0.852	0.871	−2.73	0.913	1.271	43.05	0.913	1.004	14.48

Note: The inputs were similar across different models, but different across ages. Inputs: [a]: BL, HG, PG; [b]: BL, HG, HB, NCR; [c]: BL, HG.

4. Conclusions

The current investigation was undertaken to predict the body weight at different stages of Landlly pigs using ANN and non-linear regression models and to compare their prediction ability. The correlation between certain linear body measures with the body weight were encouraging for the development of the model and further analysis. Such models developed and analysed with the help of ANN (based on high R^2 and low MSE) suggested that one can trust the measures of heart girth and body length in order to predict the body weight of pigs. Along with HG and BL, paunch girth needs to be included in body weight prediction models for a strong validation during the 4th week. Similarly, NCR and HB can also be added to HG and BL for a better prediction of body weight at 6th and 8th weeks of age. However, ANN models' prediction ability was comparable to non-linear regression analysis at all three stages of Landlly piglets.

Author Contributions: A.L.P.: Data curation; Formal analysis; Software; Writing—original draft, A.T. and S.F.A.: Formal analysis; Investigation; Methodology; Software; Writing—review & editing, S.P. and K.T.: Data curation; Writing—original draft, A.R.: Writing—review & editing, resources, software, G.K.G.: Conceptualization; Methodology; Formal Analysis; Supervision; Writing—review & editing. All authors have read and agreed to the published version of the manuscript.

Funding: The present work was supported by Indian Council of Agricultural Research, New Delhi, India and Indian Veterinary Research Institute, Bareilly, India through regular research grants. Alexey Ruchay thanks the Russian Science Foundation, for supporting this work via grant no. 21-76-20014.

Institutional Review Board Statement: Not applicable.

Data Availability Statement: Data will be made available on reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

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