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The Use of Artificial Neural Networks for the Prediction of Cattle Models

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***Abstract*:**
This research focuses on using an ANN algorithm to predict cow weight, which can lead to improved results with a decreased RMSE. The cattle farming business could enhance the efficiency of beef production. The timely slaughter of cattle and the dissemination of technological knowledge about livestock activities are crucial for developing more accurate weight predictions. Therefore, we must enhance cattle weight forecasts to make them more precise and reliable. This is achieved by employing the ANN technique, which is capable of simulating non-linear and interactive relationships between variables. The ANN method worked best in the experiment that tried to guess the weight of cows. It had an MSE of 0.019 kg, an RMSE of 0.14 kg, and an R-squared value of 0.99. This innovation has the potential to make cow farming more environmentally friendly and efficient, which would lead to less wasteful meat production.

***Keyword*:**
Artificial Neural Network;
Cattle Weight;
Mean Absolute Error;
Root Mean Square Error;
R-Square;

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1. INTRODUCTION

Ruminant animals, including cows, are vital to agriculture and the livestock industry [1]. Cows are an essential source of food and protein for people, since they are raised for milk, meat, and hide. The advancement of technology that precisely assesses cow body condition can improve animal welfare and livestock production efficiency [3]. Precise weight assessments allow farmers to more effectively manage the nutrition and feed of their cattle [2]. The technology is explicitly engineered to monitor the progression of cattle over time [4]. The weight of a cow significantly affects its market price. Typically, larger animals possess a greater market worth [5]. Estimating cattle weight provides critical insights for livestock management, including monitoring growth and health, planning nutrition, regulating reproduction, and evaluating performance [1].

This study introduces a novel approach for precise, non-invasive assessment of cow weight, using Artificial Neural Networks (ANNs) to use multi-dimensional data derived from nine body measures of calves. The primary advantage of ANNs in animal biometrics is its computational design, which can reflect intricate non-linear relationships between body measurements (e.g., chest circumference and body length) and live weight. Artificial Neural Networks naturally surpass the constraints of linearity and simplistic interaction assumptions that restrict traditional regression models. This capability is essential, as biological interactions among variables in live animals are often non-linear and dynamic, allowing ANNs to estimate weight with significantly greater precision—an advantage substantiated by empirical evidence, thereby revolutionizing livestock nutrition, health, and value management practices [6].

This research rigorously assesses and establishes a novel benchmark for cattle weight estimate, using an Artificial Neural Network (ANN) with the primary aim of significantly reducing the Root Mean Square Error (RMSE) as an indicator of methodological excellence. This predictive model, optimized by the Adam algorithm, iterated to the 800th epoch, and validated through 100-fold cross-validation for robust generalization, demonstrates its superiority with exceptional results: a root mean square error (RMSE) of 0.14 kg and a coefficient of determination (R^2) value of 0.99. This exceptional precision illustrates that ANN provides a more advanced and cost-effective technological alternative to electronic scales, significantly enhancing the monitoring process. The created approach enhances livestock quality and production while offering accurate prediction data to support farmers and livestock selection programs in strategic decision-making.

The efficacy of liveweight prediction in cattle exhibits considerable variability depending on the approach used and the species involved. Preliminary investigations using 3D data alongside an Artificial Neural Network (ANN) yielded subpar outcomes in cattle, shown by an RMSE of 42 kg and an R2 of just 0.7 [2], indicating much potential for improvement in non-linear modeling. A follow-up investigation [7] revealed a pronounced difference, as a Neural Network Multi-Layer Architecture (NN MLA) model exhibited markedly superior accuracy for cattle, attaining a notably reduced RMSE of 29.35 kg, emphasizing optimization according to the economic index (EI). Simultaneously, the use of a Random Forest Regressor (RFR) in sheep demonstrated reduced absolute error rates, with Mean Absolute Error (MAE) varying from 3.099 kg [4] to 3.375 kg [8] in Balochi sheep. This variation highlights the necessity for species-specific algorithm modification and demonstrates that while RFR yields numerically lower MAEs in sheep, the significantly greater challenge of predicting cattle weights (as indicated by RMSE comparisons) necessitates more sophisticated and optimized neural network architectures to attain field-applicable predictive accuracy.

Despite advancements in livestock weight prediction, notable discrepancies in accuracy persist across various species and methodologies. A Stacking Regressor model for pigs attained a Mean Absolute Error (MAE) of 4.331 kg and a Mean Absolute Percentage Error (MAPE) of 4.296% [9]. However, contemporary object detection technologies, such as R-CNN applied to pig images, have demonstrated the capacity for significantly enhanced accuracy, achieving an MAE of merely 0.644 kg [10], thereby critically undermining the efficacy of traditional regressor models. In contrast to this sophistication, a conventional linear regression model representing sheep weight (BW = -56.522 + 0.509BL + 0.843CG) [14] exhibits an insufficient simplicity to encapsulate the intricacies of non-linear biometrics.

Performance on large-scale cattle ranged from a subpar baseline artificial neural network (ANN) with a root mean square error (RMSE) of 42 kg and a coefficient of determination R2 of 0.7 [2], to an improved multi-layer perceptron neural network (MLA NN) optimization with an RMSE of 29.35 kg [7], alongside a more consistent performance from the Random Forest Regressor (RFR) on sheep, exhibiting a mean absolute error (MAE) of about 3-3.3 kg [4, 8]. The findings together affirm that achieving great precision in large-scale livestock necessitates a meticulously tuned non-linear architecture. This study justifies its emphasis on creating a cattle weight prediction algorithm drawing from advanced and contextual data to explicitly reduce RMSE values to unprecedented levels, thereby enhancing the precision of machine learning and establishing a foundational decision-making framework for improving the quality and productivity of the livestock industry.

2. METHOD

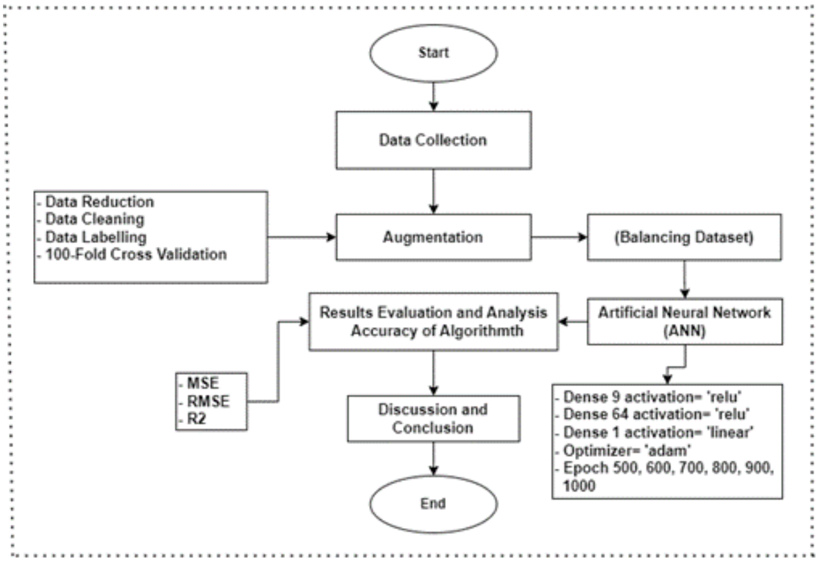

Figure 1. Research Flow Diagram

With a scientific need to reduce the Root Mean Square Error (RMSE) of cattle weight using Artificial Neural Network (ANN) optimization, this research used a rigorous data-driven experimental technique, as shown in the Flowchart (Figure 1). In order to minimize the bias associated with initial measurement errors, the method started with controlled field data acquisition, where experts employed measuring tapes to guarantee consistent body dimension measurements (in centimeters). After that, this raw data was sent through a crucial pre-processing framework, where multicollinearity of predictor variables was addressed by data reduction, dataset integrity was ensured by data cleaning, and verified response variables were accurately labeled. Above all, k-fold cross-validation was applied precisely, which is an essential step in evaluating model generalization and avoiding overfitting, which is a prevalent ANN phenomenon. Together, these steps made sure that high-quality data was produced, which was then used as the foundation for the Algorithmic Modeling Scenario, which pitted several ANN configurations against one another. The scientific understanding of the predictive efficacy of AI in livestock biometrics has been greatly advanced by this paper, which is devoted to a thorough analysis that critically examines the comparative performance of ANN models against a specified RMSE threshold in addition to descriptively comparing their functionalities.

1.1. Compilation of Collection

A cattle dataset published to GitHub has 150 entries of 18-month-old cattle from Chelyabinsk, Russia, providing a substantial resource for predictive modeling, as it includes Live Weight and nine detailed skeleton biometric parameters [11]. The uniformity of cattle age (18 months) and the geographic specificity of the data enhance the model's accuracy for this target population; however, a significant concern arises regarding measurement precision [3]. Recordings rounded to the nearest centimeter may introduce quantization errors, potentially compromising the fine-grained precision of the regression coefficients and restricting the model's applicability to various breeds, ages, or farming environments.

1.2. Data Preparation

This study utilized 150 entries of 18-month-old cattle from a farm in Chelyabinsk, Russia, obtained from GitHub; nevertheless, the external validity of the findings is significantly compromised due to the limited dataset size and geographic constraints of the population. The dataset used in this study is a secondary dataset obtained from a GitHub repository maintained by the original data provider. According to the source documentation, cattle weights were obtained from direct measurements using livestock scales on commercial farms. Manual collection methods degrade data quality, with precision restricted to increments of one centimeter [3], resulting in quantization error that can significantly obscure critical variations in ten crucial variables, including Live Weight and nine biometric measurements [11]. The preprocessing phase, encompassing data reduction and cleaning [1, 4] as well as data labeling [12], is essential for model fidelity; yet, it may introduce selection bias if the rules for excluding "irrelevant" data are not clearly articulated.

The fully connected Artificial Neural Network model employed featuring Dense 9 and Dense 64 hidden layer architectures with ReLU activation functions, and a Linear output layer for regression constitutes a robust standard configuration; however, the selection of neuron counts (9 and 64) seems inadequately justified and potentially suboptimal. The efficacy of k-fold cross-validation in enhancing the robustness of the model's generalization assessment on novel cattle data is contingent upon the judicious selection of k. Ultimately, the optimization techniques utilizing Adam [16] and epoch-based training [17] are considered best practices; however, without revealing the employed loss function, the early stopping criterion, and the ideal number of epochs, it is challenging to evaluate whether the model attains effective convergence or is prone to overfitting.

1.3. Artificial Neural Network (ANN)

Artificial Neural Network (ANN) algorithms are structurally and functionally inspired by biological neurons in the brain's central nervous system [18]. The primary objective is to emulate the brain's essential functions of information processing, learning, and pattern recognition. The fundamental component of an artificial neural network, known as a synthetic neuron, is engineered to actively assimilate information [19]. The absorption is dual: the neuron acquires raw input from the external world (the Input Layer) and also obtains processed signals from other synthetic neurons in the preceding layer. The incoming signals are subjected to a weighted sum computation, which is modulated by the neuron's own synaptic weights. The aggregated signal subsequently traverses an activation function that serves as a gatekeeper. A neuron generates an output signal just when the weighted sum over a non-linear threshold established by the activation function, contingent upon appropriate environmental circumstances. The singular output signal is subsequently triggered and transmitted as input to all other interconnected artificial neurons in the subsequent layer, facilitating intricate information flow and processing within the network architecture.

Each artificial neuron in an Artificial Neural Network functions by a sequence of computer procedures that emulate the fundamental role of a biological synapse. It consolidates incoming signals from several links by computing their net input signal based on corresponding weights [20]. These weights may possess positive or negative values, serving as a vital mechanism to either stimulate (enhance) or inhibit (diminish) the input at any specific connection. The consolidated and diminished net signal is subsequently input into an activation function [20]. This activation function serves as a non-linear thresholding mechanism, processing the net input signal to determine the output signal of the artificial neuron. To activate a synthetic neuron, so enabling it to generate an output and transmit its signal to other neurons, the activation function must be adhered to, guaranteeing that only signals over a processing threshold can advance throughout the network.

The principal objective of developing and training Artificial Neural Networks (ANNs) is to imbue them with computational abilities and behaviors that emulate human cognitive functions, including learning and pattern recognition. Each synthetic neuron fundamentally functions as a signal aggregator, absorbing numerous inputs either raw external data or processed signals from preceding neurons while generating a singular output, which may serve as either the end product or a precursor for additional processing units. Artificial Neural Networks (ANNs) are systematically arranged into three distinct layers: the Input Layer, which merely links the network to external data sources and transmits data to the subsequent layer without processing; the Hidden Layer, where the principal non-linear data transformations take place, with a highly adaptable quantity that can range from one to multiple or none; and the Output Layer, which generates the model's response or prediction. While the description indicates that this layer employs a sigmoid function, the selection of the activation function (sigmoid, ReLU, or linear) must be meticulously customized to the specific task assigned to the network (e.g., sigmoid for binary classification, linear for regression).

1.4. Assessment of Models

The evaluation of model performance is essential to confirm that the devised Artificial Neural Network (ANN) approach attains optimality, utilizing three principal metrics: Mean Square Error (MSE), Root Mean Square Error (RMSE), and the Coefficient of Determination R^2 value. Error measures, including MSE (Equation 1) and RMSE (Equation 2), quantify the average discrepancy between anticipated and actual values. MSE imposes a significant penalty on big errors, whereas RMSE, sharing the same units as the target variable, facilitates interpretation; both metrics should be reduced. Conversely, the R^2 Value (Equation 3) assesses the model's predictive capacity by quantifying the proportion of variance in the dependent variable explicable by the model, with the aim of maximizing this value (approaching 1) to signify a superior fit; thus, the assessment of model predictions necessitates attaining both low MSE/RMSE and high R^2 concurrently.

$$MSE = \frac{\sum_{i=1}^{n}(xi-yi)^2}{n} \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(xi-yi)^2}{n}} \quad (2)$$

$$R^2 = 1 - \frac{\sum(y_i-\hat{y}_i)^2}{\sum(y_i-\bar{y})^2} \quad (3)$$

3. RESULTS AND DISCUSSIONS

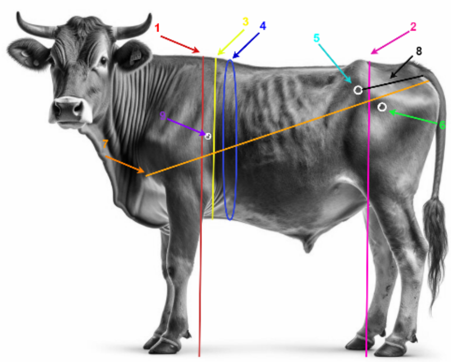

Figure 2. Nine Dimensions of the Bovine Anatomy

This study's predictive assertions rely on a dataset of 150 18-month-old cattle from Chelyabinsk [3, 11], yet its external validity is significantly undermined by the small sample size and the restricted manual measurement accuracy of 1 cm, a critical deficiency that ensures quantization error in essential biometric variables. Although preprocessing encompasses data reduction, cleaning, and labeling [1, 4, 12] to guarantee correctness, the absence of specifics of data exclusion criteria presents a danger of selection bias. The architecture of the Artificial Neural Network (ANN) employing Dense 9 and Dense 64 hidden layers with ReLU activation and Linear output is conventional; nonetheless, the random selection of neuron quantities prompts inquiries over the design's optimality. This study employed k-fold cross-validation to assert robustness and optimized training through Adam [16] and epoch [17], although it did not reveal the loss function, early stopping criterion, or number of epochs utilized, hence raising concerns over the model's vulnerability to overfitting. Thus, performance assessed via elevated R2 and diminished MSE/RMSE may indicate effective fitting on restricted and imprecise data, rather than authentic generalization capability.

The biometric data collection approach for cattle in Chelyabinsk exhibited a significant endeavor to maintain measurement consistency, with proficient practitioners performing in-situ measurements in the pen by marking essential areas on the cattle's body with white paint [22]. This visual marking specifically focused on bony indentations and prominences as anatomical landmarks, substantially reducing operator bias and guaranteeing that all nine anthropometric measures (including Heart Circumference and Ilium Width) were measured from a stable skeletal reference point. This high-precision endeavor to ascertain measurement points was ultimately hindered by the data recording protocol, which mandated rounding to the nearest centimeter, a fundamental constraint that introduced quantization error into the dataset prior to its processing by the Artificial Neural Network.

Figure 3. A Sequence of RGB-D Images of Cattle

This work aimed to get the minimal Root Mean Square Error (RMSE) for predicting cow weight, necessitating an exceptionally advanced prediction model. This endeavor encountered a paradoxical data duality: on one side, there was a tenuous ground truth of 150 entries from Chelyabinsk, vulnerable to quantization mistakes stemming from manual measurements of 1 cm, notwithstanding meticulous bone labeling. Conversely, there existed a significant technological aspiration to attain enhanced precision, exemplified by the procurement of 20 RGB frames at a resolution of 1920 × 1080 from three cameras, captured at a rapid system time of 7.3 ms, utilized for precise 3D modeling. The efficacy of this advanced 3D model for predicting BBH was likely constrained by the quality of the training and validation data; if the manual BBH data contains substantial inaccuracies, even the most intricate 3D model will be trained and validated against a less reliable reference, rendering assertions of achieving the lowest RMSE questionable, as the accuracy of the final outcome is contingent upon the precision of the fundamental manual input.

The 3D image capture system (Figure 3) was meticulously designed utilizing three Microsoft Kinect v2 cameras to capture RGB-D (color and depth) imagery. Two cameras were positioned laterally in the hallway, approximately 2 meters apart, while a third was mounted overhead at approximately 3.0 meters. Data was synchronized to a laptop via USB 3.0 for precise visual modeling. Subsequent to data collecting, the Artificial Neural Network model underwent systematic training, with parameters optimized over many training iterations spanning 500 to 1000 epochs (Figures 4 to 9), each iteration focused on minimizing the Mean Squared Error (MSE) as the loss function. The MSE results from this training set are essential as they offer direct insight into the model's comprehension and its ability to generalize effectively from the training data to the validation data.

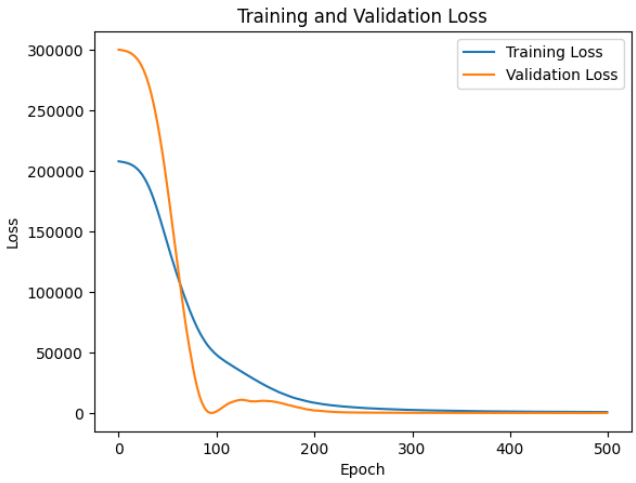

Figure 4. Training and Validation Loss MSE 500^{th} Epoch

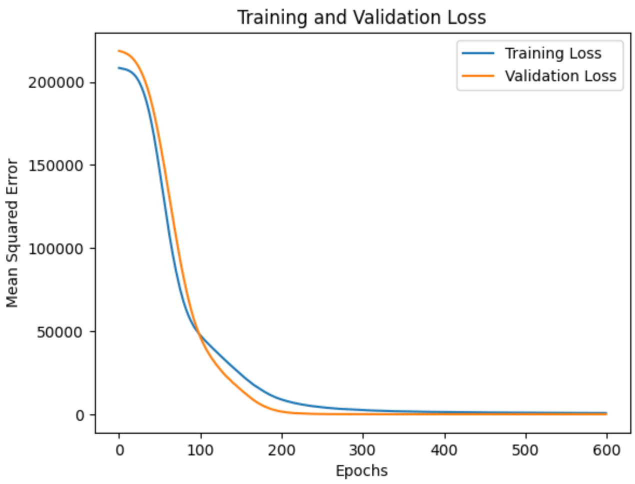

Figure 5. Training and Validation Loss MSE 600^{th} Epoch

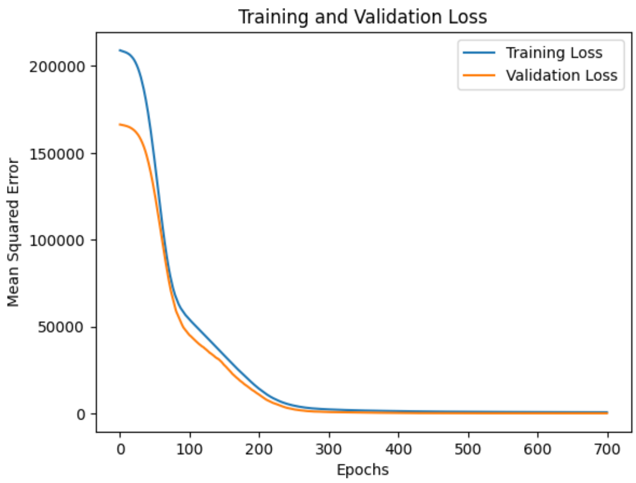

Figure 6. Training and Validation Loss MSE 700^{th} Epoch

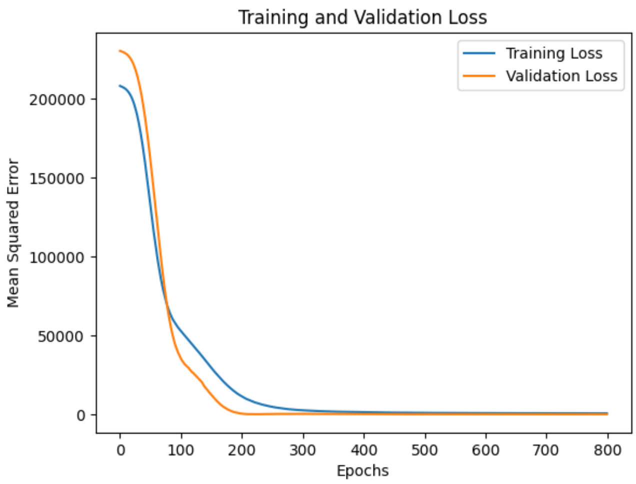

Figure 7. Training and Validation Loss MSE 800^{th} Epoch

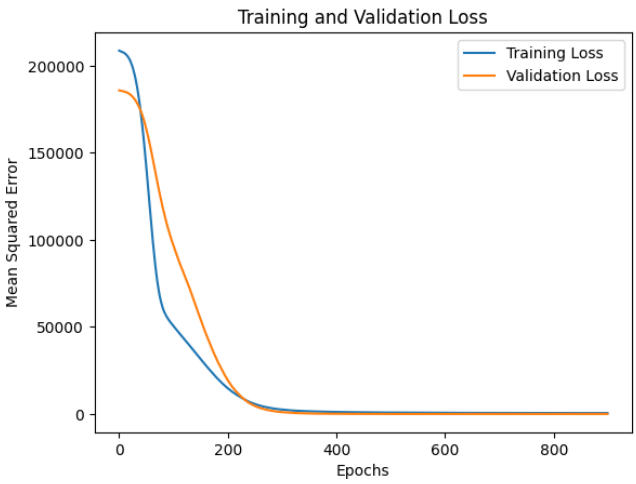

Figure 8. Training and Validation Loss MSE 900^{th} Epoch

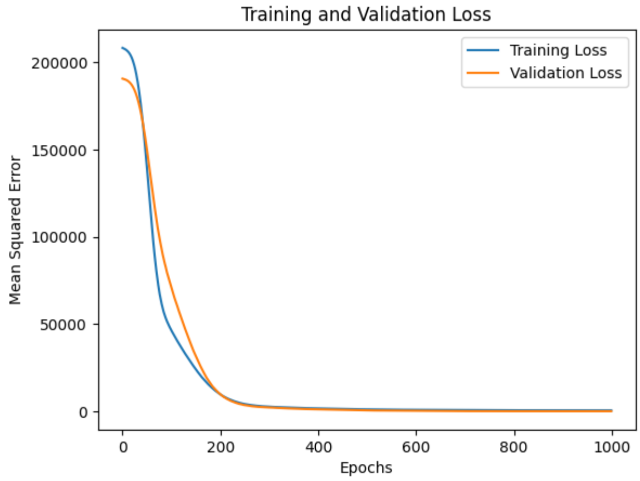

Figure 9. Training and Validation Loss MSE 1000^{th} Epoch

3.1. Model Accuracy Results

Table 1. Model of Artificial Neural Network (ANN)

Model ANN						
No	**Neuron**	**Activation Function**	**Batch Size**	**Epoch**	**K-fold cross validation**	**Optimizer**
1.	9, 64, 1	Relu, Relu, Linear	32	500	100	Adam
2.	9, 64, 1	Relu, Relu, Linear	32	600	100	Adam
3.	9, 64, 1	Relu, Relu, Linear	32	700	100	Adam
4.	9, 64, 1	Relu, Relu, Linear	32	800	100	Adam
5.	9, 64, 1	Relu, Relu, Linear	32	900	100	Adam
6.	9, 64, 1	Relu, Relu, Linear	32	1000	100	Adam

This study seeks to minimize the Root Mean Square Error (RMSE) in predicting the Live Weight (BW) of cattle, utilizing 150 entries of 18 month old calves from Chelyabinsk, incorporating nine biometric factors [11]. In this study, validation was conducted using a train-test split approach on the actual dataset measured in the field. Predicted values were directly compared with the actual weight values in the test dataset. Despite the precision of manual anthropometric measurements, facilitated by paint marking of bony prominences, being restricted to 1 cm, these measures were complemented by an advanced 3D imaging system utilizing three Kinect v2 cameras for comprehensive visual data collecting. The raw data was subsequently subjected to reduction, cleaning, and labeling [1, 4, 12] prior to testing for robustness by k-fold cross-validation. The predictive model utilizes a fully connected Artificial Neural Network (ANN) optimized via the Adam algorithm and trained across many epochs, featuring a hidden layer of 9 ReLU neurons, succeeded by a layer of 64 ReLU neurons, and concluding with a single neuron employing linear activation. The complete procedure is assessed using MSE as the loss function, with performance quantified through RMSE and R2, guaranteeing that the devised ANN methodology is optimal in generalization ability and predictive accuracy.

Table 2. Matrix Assessment

No	Matrix Assessment			
	Epoch	**MSE**	**RMSE**	**R2**
1.	500	1.71	1.31	0.82
2.	600	0.80	0.89	0.91
3.	700	0.12	0.35	0.98
4.	800	0.019	0.14	0.99
5.	900	4.01	2.00	0.59
6.	1000	0.16	0.40	0.98

Despite attaining near-perfect accuracy with an R2 of 0.99 and a minimal RMSE of 0.14 across 800 epochs using Adam optimization, the optimal results in Table 2 are highly questionable and merit significant scrutiny. After reviewing the data, we found that the RMSE value of 0.14 was obtained from data that had undergone a normalization process (min-max scaling). Therefore, the value is on a standardized scale (0–1), not in actual kilograms. Attaining an R2 of 0.99 on field biological data, characterized by substantial variability and intrinsic quantization error (1 cm) from hand measurements, suggests a considerable risk of overfitting. Although 100-fold cross-validation is deemed robust, its use to a little dataset (150 entries) may yield too optimistic performance estimates, as the validation subset could closely resemble the training data. A model necessitating 800 epochs for minimal convergence is likely to have learned the unique noise and artifacts resulting from the 1 cm rounding error in the Chelyabinsk dataset, rather than acquiring a generalizable relationship applicable to a wider cow population.

The study determined that the constructed Artificial Neural Network (ANN) model is a highly precise and reliable tool or livestock management, attaining exceptional optimal results with an almost perfect R2 of 0.99 and the minimal RMSE of 0.14 kg over 800 epochs and 100-fold cross-validation; however, this remarkable accuracy has elicited significant criticism and suggests a considerable risk of overfitting. The elevated R2 value in field biology data, characterized by inherent variability and trained on ground truth compromised by a 1 cm quantization error from hand measurements, suggests that the model has likely memorized noise and artifacts unique to the limited sample size of 150 entries from Chelyabinsk. Consequently, assertions of "entirely accurate predictions" and negligible uncertainty are untenable without comprehensive external validation on a wider and more heterogeneous livestock dataset, as the presently attained performance may only be pertinent within the confines of a restricted and less precise initial dataset.

4. CONCLUSION

The optimal outcomes from the cattle weight prediction experiment utilizing the ANN technique demonstrated an exceptional degree of accuracy, with a Mean Square Error

(MSE) of 0.019 kg, a Root Mean Square Error (RMSE) of 0.14 kg, and a coefficient of determination R2 exceeding 0.99. The nearly perfect R2 value signifies that the model accounts for almost all data variability, while the smallest RMSE of 0.14 kg verifies a minimal average prediction error in actual weight units. This study establishes a minimum RMSE value of 0.14 kg as a critical precision benchmark, intended to facilitate future research opportunities and enable further enhancement of both the ANN model architecture and the quality of the training data to attain greater accuracy.

REFERENCES

[1] Weber, V. A. M., et al. (2020). Cattle weight estimation using active contour models and regression trees Bagging. Computers and Electronics in Agriculture, 179, 105804. https://doi.org/10.1016/j.compag.2020.105804.

[2] G. A. Miller, J. J. Hyslop, D. Barclay, A. J. Edwards, W. Thomson, and C.-A. Duthie, "Using 3D imaging and machine learning to predict liveweight and carcass characteristics of live finishing beef cattle," Frontiers in Sustainable Food Systems, vol. 3, May 2019, doi: 10.3389/fsufs.2019.00030.

[3] A. Ruchay, V. Kober, K. Dorofeev, В. И. Колпаков, and С. А. Мирошников, "Accurate body measurement of live cattle using three depth cameras and non-rigid 3-D shape recovery," Computers and Electronics in Agriculture, vol. 179, p. 105821, Dec. 2020, doi: 10.1016/j.compag.2020.105821.

[4] D. A. Sant'Ana et al., "Weighing live sheep using computer vision techniques and regression machine learning," Machine Learning With Applications, vol. 5, p. 100076, Sep. 2021, doi: 10.1016/j.mlwa.2021.100076.

[5] A. Ibrahim, W. T. Artama, I. G. S. Budisatria, R. Yuniawan, B. A. Atmoko, and R. Widayanti, "Regression model analysis for prediction of body weight from body measurements in female Batur sheep of Banjarnegara District, Indonesia," Biodiversitas, vol. 22, no. 7, Jun. 2021, doi: 10.13057/biodiv/d220721.

[6] M. Gjergji et al., "Deep Learning Techniques for Beef Cattle Body Weight Prediction," In 2020 International Joint Conference on Neural Networks (IJCNN), Jul. 2020, doi: 10.1109/ijcnn48605.2020.9207624.

[7] J. Wełeszczuk, B. Kosińska-Selbi, and P. Cholewińska, "Prediction of Polish Holstein's economical index and calving interval using machine learning," Livestock Science, vol. 264, p. 105039, Oct. 2022, doi: 10.1016/j.livsci.2022.105039.

[8] Z. E. Huma and F. Iqbal, "Predicting the body weight of Balochi sheep using a machine learning approach," Turkish Journal of Veterinary & Animal Sciences, vol. 43, no. 4, pp. 500–506, Aug. 2019, doi: 10.3906/vet-1812-23.

[9] A. Ruchay et al., "A comparative study of machine learning methods for predicting live weight of Duroc, Landrace, and Yorkshire pigs," Animals, vol. 12, no. 9, p. 1152, Apr. 2022, doi: 10.3390/ani12091152.

[10] Y. Cang, H. He, and Y. Qiao, "An intelligent pig weights estimate method based on deep learning in sow stall environments," IEEE Access, vol. 7, pp. 164867–164875, Jan. 2019, doi: 10.1109/access.2019.2953099.

[11] A. Ruchay, V. Kober, K. Dorofeev, В. И. Колпаков, A. Gladkov, and H. Guo, "Live weight prediction of cattle based on deep regression of RGB-D images," Agriculture, vol. 12, no. 11, p. 1794, Oct. 2022, doi: 10.3390/agriculture12111794.

[12] T. Hastie, R. Tibshirani, and J. H. Friedman, The elements of statistical learning. 2009. doi: 10.1007/978-0-387-84858-7.

[13] Y. Qiao et al., "Intelligent perception for cattle monitoring: A review for cattle identification, body condition score evaluation, and weight estimation," Computers and Electronics in Agriculture, vol. 185, p. 106143, Jun. 2021, doi: 10.1016/j.compag.2021.106143.

[14] A. Cominotte et al., "Automated computer vision system to predict body weight and average daily gain in beef cattle during growing and finishing phases," Livestock Science, vol. 232, p. 103904, Feb. 2020, doi: 10.1016/j.livsci.2019.103904.

[15] D. A. B. Oliveira, L. G. R. Pereira, T. Bresolin, R. Ferreira, and J. R. R. Dórea, "A review

of deep learning algorithms for computer vision systems in livestock," Livestock Science, vol. 253, p. 104700, Nov. 2021, doi: 10.1016/j.livsci.2021.104700.

[16] J. Han, C. Gondro, K. N. Reid, and J. P. Steibel, "Heuristic hyperparameter optimization of deep learning models for genomic prediction," G3: Genes, Genomes, Genetics, vol. 11, no. 7, Feb. 2021, doi: 10.1093/g3journal/jkab032.

[17] S. Bhardwaj, A. Tarafdar, M. Baghel, T. Dutt, and G. K. Gaur, "Determining Point of Economic Cattle Milk Production through Machine Learning and Evolutionary Algorithm for Enhancing Food Security," Journal of Food Quality, vol. 2023, pp. 1–9, Feb. 2023, doi: 10.1155/2023/7568139.

[18] C. S. Vui, G. K. Soon, C. K. On, R. Alfred, and P. Anthony, "A review of stock market prediction with Artificial neural network (ANN)," In 2013 IEEE International Conference on Control System, Computing and Engineering, Nov. 2013, doi: 10.1109/iccsce.2013.6720012.

[19] R. E. Uhrig, ''Introduction to artificial neural networks,'' Proceedings of IECON '95 - 21st Annual Conference on IEEE Industrial Electronics, Orlando, FL, USA, 1995, pp. 33-37 vol.1, doi: 10.1109/IECON.1995.483329.

[20] J. Zupan, "Introduction to Artificial Neural Network (ANN) Methods: What They Are and How to Use Them*.," Acta Chimica Slovenica, Jan. 1994, [Online]. Available: https://www2.ccc.uni-erlangen.de/publications/ANN-book/publications/ACS-41-94.pdf

[21] Setiawan, A., Utami, E., & Ariatmanto, D. (2024). Cattle Weight Estimation Using Linear Regression and Random Forest Regressor. Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi), 8(1), 1–6. https://doi.org/10.29207/resti.v8i1.5494.

[22] Setiawan, A., Utami, E., & Ariatmanto, D. (2024). Cattle body weight prediction using regression machine learning. Jurnal Teknik Informatika (JUTIF), 5(2), 509–518. https://doi.org/10.52436/1.jutif.2024.5.2.1521.

[23] Setiawan, A., & Utami, E. (2024). Predicting the Weight of Livestock Using Machine Learning. In 2024 IEEE International Conference on Artificial Intelligence and Mechatronics Systems (AIMS) (pp. 1–6). https://doi.org/10.1109/AIMS61812.2024.10512610.

[24] Herman et al., "Comparison of Artificial Neural Network and Gaussian Naïve Bayes in Recognit ion of Hand-Writ ing Number," Proc. - 2nd East Indones. Conf. Comput. Inf. Technol. Internet Things Ind. EIConCIT 2018, no. 1, pp. 276–279, 2018, doi: 10.1109/EIConCIT.2018.8878651.

[25] X. Song, E. A. M. Bokkers, S. Van Mourik, P. W. G. G. Koerkamp, and P. P. J. Van Der Tol, "Automated body condition scoring of dairy cows using 3-dimensional feature extraction from multiple body regions," Journal of Dairy Science, vol. 102, no. 5, pp. 4294–4308, May 2019, doi: 10.3168/jds.2018-15238.