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RESEARCH ARTICLE

Performance of Machine Learning Algorithms in Predicting Sheep Weight Based on Morphometric Measurements

Desempenho de Algoritmos de Machine Learning na Predição do Peso de Ovinos com Base em Medidas Morfométricas

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Abstract: Body weight estimation is an important activity in sheep management; however, direct weighing using scales may be limited by cost and operational constraints, making it necessary to seek feasible alternatives for this process. In this context, this article presents one of the first systematic comparisons of *Machine Learning* algorithms for predicting the body weight of Santa Inês ewes based on morphometric measurements collected manually under field conditions. Data from 80 females evaluated in Campo Verde, Mato Grosso, Brazil, were analyzed. A formal variable selection pipeline was conducted by combining Pearson correlation analysis and the Variance Inflation Factor (VIF), which revealed severe multicollinearity among all morphometric variables (VIF ranging from 148 to 1,434), supporting the selection of thoracic circumference as the primary predictor (r = 0.92). Modeling was conducted in Python, and five regression models — Linear Regression, Random Forest, XGBoost, SVR, and MLP — were evaluated using K-Fold cross-validation (k = 10), with hyperparameter tuning performed through *GridSearchCV*. Results are reported as mean $\pm$ standard deviation across folds. Linear Regression achieved the best performance (R^2 = 77.44% ± 13.47%, MAE = 3.021 kg), outperforming SVR, MLP, *Random Forest*, and *XGBoost*, suggesting a predominance of linear relationships in the sample. As a practical contribution, a simple estimation equation was derived: $Weight(kg) = 1.298 ThoracicCircumference(cm) - 64.547$, enabling producers to estimate body weight using only a measuring tape, without the need for conventional scales.
Keywords: artificial intelligence — precision livestock farming — predictive modeling — zootechnical monitoring — cross-validation

Resumo: A estimativa do peso corporal é uma atividade relevante no manejo de ovinos, mas a pesagem direta por balanças pode ser limitada por custo e operação, tornando necessária a busca por alternativas viáveis para esse processo. Diante desse contexto, este artigo apresenta uma das primeiras comparações sistemáticas de algoritmos de *Machine Learning* para predição do peso corporal de ovelhas Santa Inês a partir de medidas morfométricas coletadas manualmente em condições de campo. Foram analisados dados de 80 fêmeas avaliadas em Campo Verde (MT). Um pipeline formal de seleção de variável foi conduzido combinando análise de correlação de Pearson e Fator de Inflação da Variância (VIF), que revelou multicolinearidade severa entre todas as variáveis morfométricas (VIF variando de 148 a 1.434), justificando formalmente a seleção da circunferência torácica como preditor primário (r = 0,92). A modelagem foi conduzida em Python e cinco modelos de regressão — Regressão Linear, Random Forest, XGBoost, SVR e MLP — foram avaliados por validação cruzada K-Fold (k = 10), com ajuste de hiperparâmetros via *GridSearchCV*. Os resultados são reportados como média $\pm$ desvio padrão entre os *folds.* A Regressão Linear obteve o melhor desempenho (R^2 = 77,44% ± 13,47%, MAE = 3,021 kg), superando SVR, MLP, *Random Forest* e *XGBoost*, sugerindo predominância de relações lineares na amostra considerada. Como contribuição prática, foi derivada uma equação simples de estimativa: Peso (kg) = 1,298 × Circunferência Torácica (cm) 64,547, permitindo ao produtor estimar o peso corporal com o uso de uma simples fita métrica, sem necessidade de equipamentos de pesagem convencionais.
Palavras-Chave: inteligência artificial — pecuária de precisão — modelagem preditiva — monitoramento zootécnico — validação cruzada

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1. Introduction

Brazilian livestock production is driven mainly by cattle farming, in addition to the strong production of poultry and swine [1]. Leading this national scenario, Mato Grosso has consolidated itself as the largest cattle-producing state in the country, with a herd of 34 million animals.

Despite this predominance, sheep farming reached a historic level in Brazil in 2023, totaling 21.8 million animals — a 4% increase compared with the previous year [2]. This growth is driven mainly by the Northeast region, which accounts for 71.2% of the national herd. In contrast to the national trend, Mato Grosso showed a significant decline, with the state herd recording a reduction of 15.3%.

Although the state does not prioritize this activity, studies indicate that sheep farming has high profitability potential [3]. A determining factor for profitability is strict control of production costs, especially those related to feeding. Efficient management of these costs depends on monitoring herd weight gain, which highlights the challenge of traditional management for weighing animals [4]. In this context, methods derived from precision livestock farming emerge as alternatives capable of making this process faster, safer, and more reliable.

Periodic weighing is an essential management practice, as it provides critical data for decision-making by enabling adequate adjustments in feeding and supplementation, directly contributing to the maintenance of the herd's nutritional status and, consequently, to improvements in reproductive efficiency, wool production, and carcass yield [5].

However, monitoring animal body weight faces significant obstacles, such as the high cost of weighing equipment and its limited mobility. These limitations lead producers to adopt inadequate practices, such as improvising with cattle scales, a method that compromises measurement accuracy [6].

In this context, body weight estimation through morphometric measurements emerges as an accessible and practical alternative. The use of simple instruments, such as a measuring tape, allows body measurements to be obtained and used in zootechnical monitoring even in the absence of weighing equipment [6]. Studies indicate that variables such as thoracic circumference show a strong correlation with live weight in small ruminants, with values between 0.59 and 0.95 reported in the literature [7], suggesting that predictive models based on these measurements can provide reliable estimates to support management decisions.

Although consolidated studies exist on morphometric variables and linear models applied to weight prediction in sheep, an important gap remains in the literature: investigations that systematically compare multiple *Machine Learning* algorithms applied specifically to the Santa Inês breed are scarce. Most studies remain limited to traditional linear approaches, whereas modern methods — such as *Random Forest*, *Support Vector Regression*, *XGBoost*, and Neural Networks — have the potential to capture nonlinear relationships between morphometric variables and body weight, especially in hardy, hair, and genetically heterogeneous breeds such as Santa Inês, which is widely adapted to Brazilian tropical conditions [8, 9].

Given this gap, the present study is one of the first to conduct a systematic comparison of *Machine Learning* algorithms for predicting body weight in Santa Inês ewes based on morphometric variables collected under field conditions. As contributions, the study: (i) positions itself as a reference *benchmark* for small-scale applications in this breed; (ii) identifies thoracic circumference as the primary predictor of live weight; and (iii) proposes an equation that is easy to apply in practice, reducing dependence on conventional weighing equipment in production systems with operational constraints.

Thus, this paper is structured into five sections, including this introduction. Section 2 presents the theoretical background of this research, and Section 3 describes the methodology used. Section 4 then presents the results and discussions regarding the *Machine Learning* models. Finally, Section 5 addresses the final considerations.

2. Theoretical Background

This section presents the foundations necessary to understand this study, organized into four axes: (i) Precision Livestock Farming; (ii) morphometric variables as predictors of body weight; (iii) characteristics of the Santa Inês breed; and (iv) the *Machine Learning* models and evaluation metrics used in the comparison.

2.1 Precision Livestock Farming

Precision Livestock Farming is a concept that has been gaining prominence in the agricultural sector due to the growing need to efficiently monitor and control the processes involved in animal production [10].

According to Berckmans [11], Precision Livestock Farming is fundamentally defined as a management system based on continuous, automatic, and real-time monitoring and control of production, reproduction, health, and animal welfare at different points of the production chain. In this sense, the field has begun to incorporate different intelligent systems, either already available or under development, aimed at process automation, control, and continuous monitoring of animals and their environments [10].

Such systems are multidisciplinary in nature and require intense collaboration among professionals from several areas, including animal scientists, veterinarians, engineers, and Information Technology specialists [10]. In this context, one of the simplest and most accessible approaches for generating useful management information is the use of body measurements, which can serve as a basis for estimating animal performance and supporting decision-making.

2.2 Morphometric Variables

Given this scenario, the use of tools capable of providing reliable estimates of animal performance becomes necessary, especially in production systems that require frequent monitoring. Although the scale is the most accurate method for determining body weight, its acquisition and use are not always feasible for small and medium-sized producers due to high cost and operational limitations.

Thus, body weight prediction based on morphometric variables emerges as an accessible, practical, and widely applicable alternative. The use of simple instruments, such as a measuring tape, allows body measurements to be obtained and used in zootechnical monitoring and in the evaluation of animal development, even in the absence of weighing equipment [6].

In the study by Grandis [6], different morphometric variables were used to analyze the correlation and prediction of body weight, with emphasis on: (i) thoracic perimeter (chest circumference); (ii) body length; (iii) withers height (defined as the distance between the highest point of the interscapular region and the ground); and (iv) scrotal circumference, used only in males.

The correlation between a morphological measurement (X) and body weight (Y) can be calculated by Equation 1:

$$r = \frac{\sum(X-\bar{X})(Y-\bar{Y})}{\sqrt{\sum(X-\bar{X})^2\sum(Y-\bar{Y})^2}} \tag{1}$$

High values of r indicate a strong linear association, suggesting that the morphological measurement has high potential for estimating body weight. In the study by Grandis [6], thoracic perimeter showed the highest correlations with live weight, corroborating the results of other national and international studies that identify this measurement as one of the main biometric predictors in small ruminants [12]. In a complementary manner, Yakubu [7] reported correlations between body weight and thoracic perimeter ranging from 0.59 to 0.95 in males and from 0.61 to 0.92 in females.

Based on these relationships, Artificial Intelligence techniques especially *Machine Learning* can be employed to learn patterns in the data and improve the accuracy of body weight estimation.

Although body measurements are effective in estimating live weight, the accuracy of these models is strongly associated with the specific characteristics of each breed. Therefore, before advancing to the predictive analysis, it is necessary to understand the role and particularities of Santa Inês sheep in the national and regional production context. The next section discusses the importance of this breed and supports its selection for this study.

2.3 Santa Inês Breed

The Santa Inês breed, which originated in the Northeast region of Brazil, was formed through crossbreeding among different genetic groups, including wool sheep of the Crioulo type, African hair sheep, the Italian Bergamasca breed, and, more recently, the Brazilian Somali and Suffolk breeds [13]. The result of this selection process is a hair sheep breed, highly adapted to tropical conditions and capable of good productive performance even in high-temperature environments.

Thanks to its hardiness and productive capacity, especially in semiarid regions, Santa Inês occupies a central position in Brazilian sheep farming [14]. It is the most widely distributed breed in the country, with estimates of more than 3,400 registered herds [15].

Regarding meat production, Santa Inês has characteristics that meet consumer market requirements [14]. For this reason, it is widely used as a maternal breed in industrial crossbreeding programs. Studies show that Santa Inês lambs raised exclusively on pasture can reach slaughter weight at six months of age, even without concentrate supplementation.

Considered the native breed with the greatest productive potential in Brazil, Santa Inês combines attributes such as body size, growth rate, broad adaptability, and good reproductive capacity. Nevertheless, the sector still makes limited use of this potential due to the low incorporation of science and technology into management practices [14].

To expand the incorporation of science and technology in sheep farming, it is essential to adopt appropriate management practices, including periodic animal weighing. Weighing is an essential procedure for monitoring growth and productive performance, identifying developmental deviations early, and defining the appropriate time for commercialization or slaughter.

However, on many farms, direct weighing may be infeasible due to the absence of scales or operational limitations. In such cases, body weight estimation based on morphometric variables constitutes a viable and low-cost alternative. In addition, the use of Machine Learning techniques can help increase the accuracy of these estimates by modeling nonlinear relationships between body traits and animal body weight.

2.4 Machine Learning

Machine Learning is a subfield of Artificial Intelligence (AI) that enables computational systems to identify patterns and improve their performance on a given task based on data, without relying on explicit instructions [16, 17]. In this study, supervised learning models are used, in which the objective is to learn a mapping between the input morphometric variables and body weight as a continuous output variable [18, 19].

Applied to sheep farming, *Machine Learning* enables the construction of predictive models capable of estimating live weight based on morphometric variables obtained under field conditions, offering a practical alternative for situations in which direct weighing is limited by cost, infrastructure, or management. Thus, machine learning allows the model to learn from real examples, capturing both predominantly linear and nonlinear relationships between variables.

Based on this understanding of the behavior of supervised models, it becomes possible to discuss the regression models used to capture the relationship between morphometric measurements and animal body weight.

2.5 Regression Models

In a regression problem, the goal is to model the relationship between a continuous target variable and a set of input variables [18]. In this study, five algorithms were selected, as described in the following sections:

2.5.1 Linear Regression

Linear Regression is one of the most fundamental statistical methods for predictive modeling, as it establishes a linear relationship between a dependent variable and one or more independent variables [16]. In this study, it serves as a baseline reference model due to its interpretability and suitability for predominantly linear relationships [18]. Studies with sheep indicate that morphometric variables show an approximately linear relationship with live weight [20, 21], allowing a coherent initial reference before evaluating more flexible models.

2.5.2 Random Forest

Random Forest is an *ensemble* method that combines multiple Decision Trees trained through *bootstrap*, producing more robust predictions by averaging the individual results [22]. It is particularly advantageous in scenarios with nonlinear patterns and complex interactions among variables [16], and was included in this study to evaluate whether there is a predictive gain compared with Linear Regression.

2.5.3 Kernel-Based Models

Support Vector Regression (SVR) is an adaptation of *Support Vector Machine* that estimates a function within an ε-tolerance margin, using the *kernel trick* to model nonlinear relationships without increasing computational cost [23]. It is particularly useful when relationships among variables show high curvature or complex nonlinear behavior [24].

2.5.4 Artificial Neural Networks

The *Multilayer Perceptron* (MLP) is a universal function approximator capable of modeling complex nonlinear relationships among variables through hidden layers with nonlinear activation functions [25, 18]. In regression tasks, it transforms an input vector into a continuous output, making it a promising alternative for body weight estimation based on morphometric variables [24].

2.5.5 XGBoost

XGBoost is a *gradient boosting* algorithm that combines multiple decision trees trained sequentially, incorporating explicit regularization to control overfitting [26]. Unlike *Random Forest*, which uses *bagging*, *XGBoost* simultaneously reduces bias and variance and has high predictive capacity in datasets with nonlinear relationships and complex interactions among variables.

2.6 Evaluation Metrics

Evaluating the performance of regression models is necessary to determine their generalization capacity and the accuracy of the estimates produced [16, 25]. In this study, five complementary metrics widely recommended in the Machine Learning literature were used:

Coefficient of Determination (R^2): measures the proportion of variability in the dependent variable explained by the model, with values between 0 and 1, where higher values indicate greater explanatory capacity [18, 19].

Mean Absolute Error (MAE): represents the average of the absolute errors between the actual and predicted weight, expressed in the same unit as the target variable (kg), and is easy to interpret in practical terms [16].

Mean Squared Error (MSE): penalizes larger errors more strongly and is widely used as a cost function in gradient-based models [25].

Root Mean Squared Error (RMSE): is the square root of the MSE and expresses the average error in the same unit as the target variable, facilitating its interpretation in relation to the magnitude of the observed data [25].

Mean Absolute Percentage Error (MAPE): expresses the average error in percentage terms and is widely used in zootechnical analyses because it facilitates producers' understanding of the results [27].

2.7 Related Work

The Santa Inês breed plays a central role in Brazilian sheep farming, which explains the large number of studies dedicated to its growth and morphometric characteristics. Studies such as those by Teixeira Neto et al. [12], Costa Júnior et al. [28], and Souza et al. [21] show that variables such as body length, height, and thoracic perimeter have a strong relationship with weight development, directly reflecting animal productive performance. Silva et al. [20] specifically demonstrated that thoracic perimeter is an efficient predictor of live weight in Santa Inês sheep, obtaining an R^2 close to 0.89 in simple linear models.

In the international context, Hamadani and Ganai [8] compared multiple *Machine Learning* algorithms for weight prediction in sheep, demonstrating that the choice of the most appropriate algorithm strongly depends on the characteristics of the dataset and the breed studied. Ninahuanca et al. [9], when evaluating weight prediction in Andean ewes based on morphometric measurements, concluded that linear models show competitive performance compared with more complex methods in small-scale datasets, reinforcing the importance of balancing accuracy, interpretability, and stability.

These studies show that, although weight prediction through morphometric variables is a consolidated topic, the systematic comparison of multiple *Machine Learning* algorithms applied specifically to the Santa Inês breed under Brazilian field conditions remains underexplored, motivating the present study.

3. Materials and Methods

All procedures were conducted in accordance with the guidelines established by the Institutional Ethics Committee of the Federal University of Mato Grosso (UFMT), process No. 23108.083252/2024-49.

3.1 Data Source

The data used in this study were collected from 80 Santa Inês ewes on a farm located in the municipality of Campo Verde, state of Mato Grosso.

The sample group consisted of two productive categories: ewe lambs and adult ewes (Figure 1). The ewe lambs (young ewes), aged between 6 and 12 months, totaled 31 animals, of which 20 were pregnant and 11 were nonpregnant. The adult ewes, aged between 16 and 17 months, totaled 49 individuals, of which 40 were pregnant and 9 were nonpregnant. This classification made it possible to characterize the herd according to the physiological status and age range of the evaluated breeding females.

During data collection, the animals were guided in single file through the handling paddock to the commercial scale, which was properly calibrated and had an area of 1.35 m² (Figure 2), where each individual was weighed and had its morphometric variables recorded.

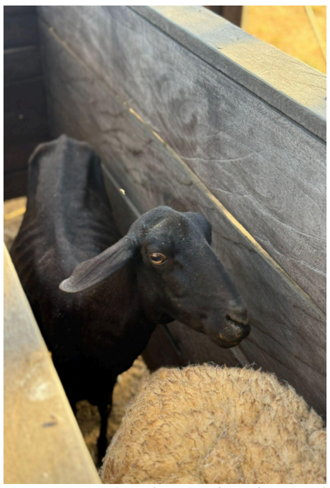

Figure 1. Ewes in single file for weighing

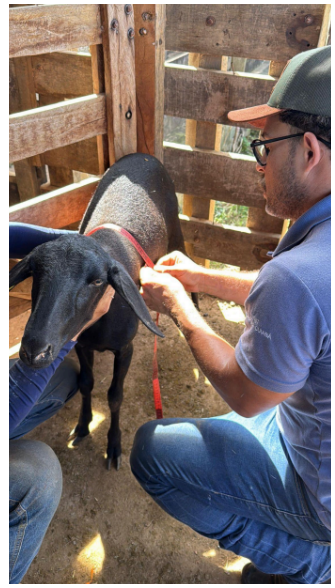

Figure 2. Collecting the ewe's body measurements

Body weight was determined by direct reading on a commercial scale. The morphometric variables, namely body length, thoracic circumference, chest height, withers height, rump width, rump height, and age, were manually collected by the animal scientist responsible, as illustrated in Figure 2.

To ensure individual control of each sheep during the experimental procedure, an exclusive numerical identification system was adopted. After data collection, all generated data were gathered and separated into specific directories to facilitate access and avoid information loss. The measurements obtained were subsequently transferred to electronic spreadsheets created in Microsoft Excel®, where each animal was associated with its respective numerical code, forming the organized database for data processing and analysis.

3.2 Data Preprocessing

The first step consisted of exploratory analysis and data cleaning (*Data Cleaning*), performed with the objective of verifying the consistency of the biological information and ensuring that there were no typing errors, values incompatible with reality, or blank cells. Although the original dataset contained information on physiological status (pregnant and nonpregnant), no distinction was made between these categories, as the purpose was to evaluate model performance considering the real variation observed under field conditions, simulating practical situations in which physiological information is not always available to the producer.

For processing and storage, Google Colab integrated with Google Drive was used as the repository. The steps were implemented in Python, using the Pandas, NumPy, Matplotlib, Seaborn, SciPy, scikit-learn, and *XGBoost* libraries, in addition to integration with the Google Drive API for file access.

During the cleaning step, *outliers* were detected using the *Z-Score* method, which made it possible to identify values that were excessively distant from the mean in terms of standard deviations and could compromise the consistency and quality of subsequent analyses.

After cleaning, a multicollinearity analysis was conducted using the Variance Inflation Factor (VIF) to verify redundancy among the morphometric variables. VIF values greater than 10 indicate severe multicollinearity, compromising model stability and the interpretability of coefficients [26]. The results revealed severe multicollinearity in all variables, with values ranging from 148 to 1,434, confirming that the morphometric variables share redundant information among themselves. Therefore, a formal variable selection pipeline was adopted based on two complementary criteria: (i) the highest Pearson correlation with body weight; and (ii) the lowest relative VIF among the variables with the highest correlations. Thoracic Circumference was selected based on the criterion of the highest correlation with body weight (r = 0.92), with the redundancy of the remaining variables confirmed by VIF values, all far above the critical threshold of 10.

The models were evaluated using Cross-Validation (*Cross-Validation*) to ensure greater statistical reliability [19, 24]. The *K-Fold* procedure with $k = 10$ was used, in which the dataset is partitioned into 10 subsets of approximately equal size. In each iteration, one of the subsets is used for validation, whereas the others compose the training set, and the process is repeated until all subsets have been used for validation [16, 18, 19]. Given the small sample size (n = 80), the cross-validation strategy without a prior split into a separate test set was chosen. This approach is recommended for small samples because it maximizes the use of available data, ensuring that each animal is evaluated independently of training [26, 18]. The results presented in Table 5 are reported as mean ± standard deviation of the metrics obtained across the 10 *folds*, allowing both the average performance and the stability of each model to be evaluated.

To prevent data leakage (*data leakage*), all preprocessing was applied within the cross-validation pipeline, ensuring that normalization was fitted exclusively on the training data of each *fold*. Scaling using *StandardScaler* was applied only to models sensitive to data scale, as described in Table 1.

Table 1. Preprocessing applied by model

Model	Scaling	Justification
Linear Regression	No	Scale-invariant
Random Forest	No	Tree-based
XGBoost	No	Tree-based
SVR	Yes	Scale-sensitive
MLP	Yes	Scale-sensitive

3.3 Models Used

In the initial modeling stage, a Pearson correlation analysis was performed between the morphometric variables and body weight in order to understand the strength and direction of the linear relationships present in the dataset. Next, VIF analysis was conducted to verify redundancy among the predictors, as described in the previous section.

Five regression models were trained: Linear Regression, *Random Forest* Regressor, *Support Vector Regression* (SVR), *XGBoost*, and *Multilayer Perceptron* (MLP). For each algorithm, a hyperparameter grid was defined (Table 2), and the selection of the best configuration was performed using *GridSearchCV* together with K-Fold cross-validation ($k = 10$) on the training set. Finally, the hyperparameter set that achieved the best average performance in cross-validation was used for the final model fitting.

Regarding the MLP, a two-hidden-layer architecture (100 and 50 neurons, respectively) was adopted, selected via *GridSearchCV* as the best-performing configuration in cross validation. Although this architecture is more complex relative to the sample size, the risk of overfitting was controlled through three complementary strategies: (i) L2 regularization via the `alpha` parameter; (ii) a maximum number of iterations fixed at 3,000; (iii) evaluation through K-Fold cross-validation, ensuring that performance was measured exclusively on data not seen during training.

To ensure reproducibility, all steps involving randomness (K-Fold and MLP initialization) were executed with a fixed seed (`random_state = 42`).

Table 2. Hyperparameters evaluated in the Grid Search (k-fold, $k = 10$).

Model	Parameter	Tested values
Random Forest	`n_estimators`	100, 200
	`max_depth`	None, 10
	`min_samples_leaf`	1, 2
XGBoost	`n_estimators`	100, 200
	`max_depth`	3, 5
	`learning_rate`	0.05, 0.1
	`subsample`	0.8, 1.0
	`colsample_bytree`	0.8, 1.0
SVR	`C`	10, 100
	`epsilon`	0.05, 0.1
	`gamma`	`scale`, `auto`
MLP	`hidden_layer_sizes`	(100, 50)
	`alpha`	0.0001, 0.001
	`learning_rate_init`	0.001, 0.01

Once the modeling stage was completed, it became possible to analyze the performance of each algorithm and identify which techniques were most suitable for the proposed problem. The following section presents the results obtained, as well as their implications for body weight prediction.

4. Results and Discussion

Based on the configured models and the previously validated data, this section presents the results obtained during the experiments, highlighting the performance of each method in predicting the body weight of ewes from morphometric variables. The analysis was divided into two stages: (i) data treatment and organization; and (ii) application and evaluation of the regression models.

4.1 Data Treatment and Organization

Before the tests began, it is important to highlight that, during the data validation stage, application of the *Z-Score* method did not identify any outlier outside the acceptable range of variation, as can be seen in Figure 3.

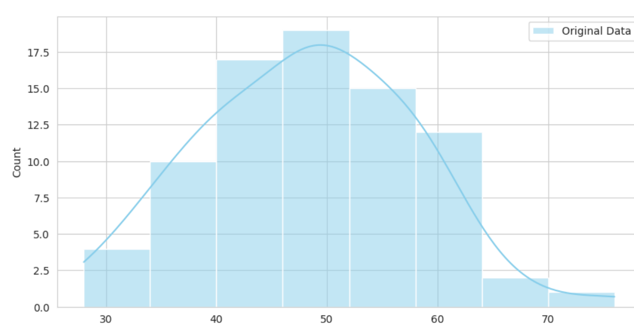

Figure 3. Weight Distribution (Outlier Detection)

The exploratory analysis considered the 80 observations in the dataset and identified a mean weight of 46.10 kg, with a standard deviation of 8.53 kg.

With the data organized, the Pearson correlation between weight and the morphometric variables was calculated (Figure 4).

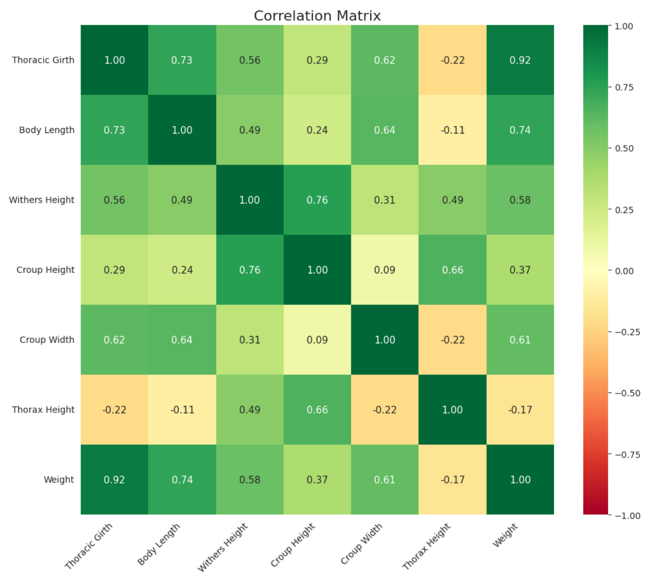

Figure 4. Correlation Matrix: Morphometric Variables vs. Body Weight

The results shown in Figure 4 indicate that the variables Thoracic Circumference (r = 0.92) and Body Length (r = 0.74) have the highest correlations with weight, demonstrating their strong influence on the variation in body mass. The variables Rump Height and Chest Height showed lower correlations (r = 0.37 and r = -0.17, respectively), indicating a weaker linear relationship with weight. This pattern is consistent with the literature, since Thoracic Circumference and Body Length are measurements directly associated with body volume and the animal's structural development [6, 7]. Table 3 presents the complete ranking of correlations with weight.

Table 3. Ranking of variable influence on body weight

Variable	Correlation with weight
THORACIC CIRC.	0.92
BODY LENGTH	0.74
RUMP WIDTH	0.61
WITHERS HEIGHT	0.58
RUMP HEIGHT	0.37
CHEST HEIGHT	-0.17

Next, a multicollinearity analysis was conducted using the Variance Inflation Factor (VIF), whose results are presented in Table 4. The values revealed severe multicollinearity in all morphometric variables, with VIF ranging from 148.57 to 1,434.37 — far above the critical threshold of 10 [26]. This result confirms that the morphometric measurements share highly redundant information with one another, which is biologically expected, since they all reflect the animal's overall size.

Table 4. Variance Inflation Factor (VIF) of the morphometric variables

Variable	VIF
WITHERS HEIGHT	1,434.37
RUMP HEIGHT	1,021.09
THORACIC CIRC.	634.41
BODY LENGTH	485.12
CHEST HEIGHT	255.24
RUMP WIDTH	148.57

Given these results, predictor variable selection was conducted based on two complementary criteria: (i) the highest Pearson correlation with body weight; and (ii) confirmation of redundancy among the remaining variables via VIF. Thoracic Circumference met both criteria, presenting a correlation of 0.92 with body weight, and was selected as the sole predictor for the subsequent models. This relationship is illustrated in Figure 5.

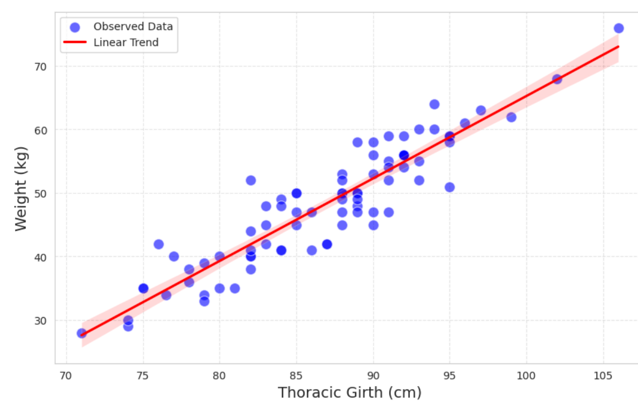

Figure 5. Morphometric Relationship: Thoracic Circumference vs. Live Weight

4.2 Applied Regression Techniques

Table 5 presents the performance of five models applied to body weight estimation in Santa Inês ewes. Performance was measured using the R^2, MAE, MAPE, MSE, and RMSE metrics, reported as mean ± standard deviation across the 10 *folds* of cross-validation, allowing both the average performance and the stability of each model to be evaluated.

It can be observed that the models showed relatively similar performances, which reflects the predominantly linear nature of the relationships between morphometric measurements and body weight previously evidenced by the correlation matrix and confirmed by the VIF analysis. Variability among the *folds* was high for all models, with standard deviations of R^2 ranging from ±12.08% (SVR) to ±17.42% (XGBoost), an

Table 5. Performance of regression models for body weight prediction (mean ± SD)

Model	R^2 (%)	R^2 SD	MAE (kg)	MAPE (%)	MSE	RMSE (kg)
Linear Regression	77.44	±13.47	3.021	6.55	14.257	3.627
Neural Network	74.67	±15.11	3.225	7.08	15.867	3.854
SVR	74.50	±12.08	3.327	7.31	16.588	3.974
Random Forest	69.67	±17.00	3.512	7.54	18.684	4.226
XGBoost	69.07	±17.42	3.544	7.53	19.063	4.279

expected behavior in small-scale datasets where each test *fold* contains only 8 animals [26, 18].

The superiority of Linear Regression in this dataset corroborates previous studies on weight prediction using morphometric variables, in which linear models show high performance when biometric variables have a strong correlation with weight [8, 9, 6, 12]. In reduced-size datasets, complex methods such as *ensembles* do not ensure gains in accuracy and may even show inferior performance [9]. The fact that no nonlinear model outperformed Linear Regression constitutes empirical evidence of the predominance of linear relationships in the data — if relevant nonlinear patterns were present, models such as Random Forest and XGBoost, designed to capture them, would have shown superior performance.

Next, the Neural Network (74.67% ± 15.11%) and SVR (74.50% ± 12.08%) stand out, both with very similar R^2 values and superior to the other tree-based models. Although more sophisticated, *Random Forest* (69.67% ± 17.00%) and *XGBoost* (69.07% ± 17.42%) showed the lowest R^2 values, indicating lower explanatory capacity compared with the other approaches.

Linear Regression. The superior performance of Linear Regression (Figure 6) — both in R^2 and RMSE — reinforces what was identified during the exploratory analysis: the relationships between morphometric measurements and body weight are mostly linear, which favors models based on this assumption.

Despite being the simplest model, its interpretability represents a relevant practical advantage. The estimated coefficients make it possible to directly quantify the impact of the morphometric variable on body weight, favoring applied zootechnical analyses and evidence-based decision-making. According to Bishop [18], linear models tend to present lower variance when compared with more flexible methods, especially in datasets with limited size.

The coefficient of determination obtained in this study (R^2 = 77.44% ± 13.47%) indicates that approximately 77% of the variability in body weight was explained by Thoracic Circumference. Although lower than the value reported by Silva et al. [20], who observed an R^2 close to 0.89 in the relationship between thoracic perimeter and live weight in Santa Inês sheep, both studies converge in demonstrating that the relationship between morphometric variables and live weight in the Santa Inês breed can be adequately described by linear models.

The final equation obtained by the Linear Regression model, based on the analysis of 80 animals, was:

$$\text{Weight (kg)} = 1.298 \times \text{Thoracic Circumference (cm)} - 64.547 \tag{2}$$

As a practical application example, an ewe with a thoracic circumference of 80 cm would have an estimated weight of approximately 39.27 kg. This equation allows rural producers to estimate the animal's body weight using a simple measuring tape, without the need for weighing equipment, representing a low-cost and easy-to-apply tool for herd management.

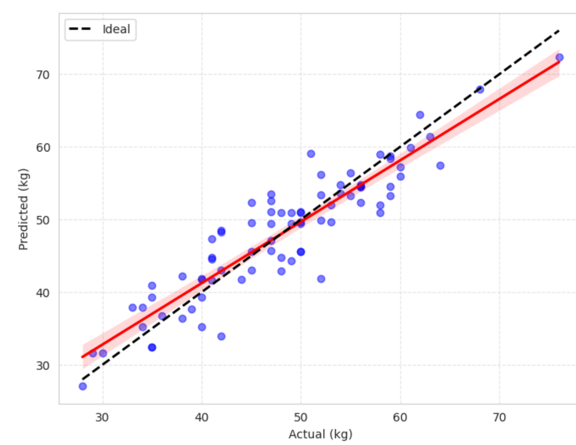

Figure 6. Linear Regression R^2: 77.44% — MAE: 3.021 kg

Random Forest and XGBoost. The tree-based models showed the lowest R^2 values and the highest squared errors (Figures 7 and 8), in addition to the greatest variability among *folds* — Random Forest (±17.00%) and XGBoost (±17.42%). This behavior is associated with two main factors: (i) the relatively small sample size (n = 80), which makes it difficult to learn complex relationships; and (ii) the predominance of linear relationships, which does not favor *ensemble* models [16, 24].

In particular, the inferior performance of XGBoost (R^2 = 69.07% ± 17.42%) compared with Random Forest (R^2 = 69.67% ± 17.00%) suggests that the sequential *boosting* strategy, although efficient in datasets with complex patterns and large data volumes, did not provide an advantage in this scenario. The iterative residual error correction mechanism of XGBoost assumes the existence of nonlinear patterns to be progressively captured — a condition not observed in this dataset, where relationships are predominantly linear [26].

As discussed by Goodfellow et al. [25] and Aggarwal [24], algorithms with greater capacity tend to perform better when the underlying mechanism is structurally complex. When the relationship between variables is mostly linear, simpler models may show equivalent or superior performance, as observed in this study.

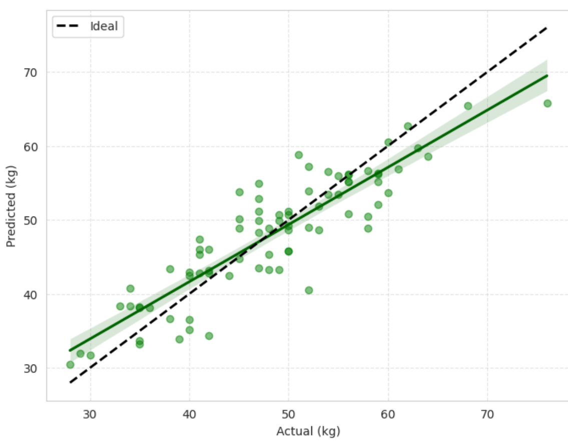

Figure 7. Random Forest R^2: 69.67% — MAE: 3.512 kg

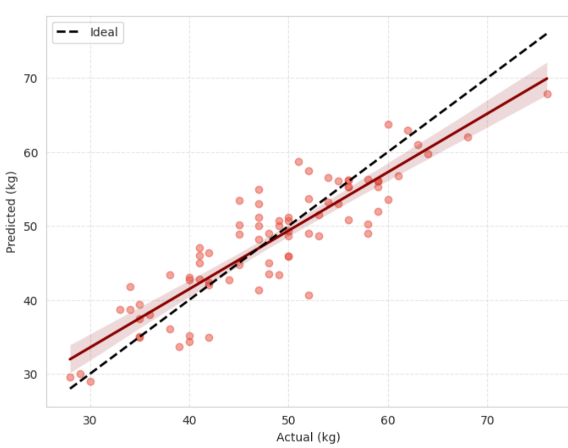

Figure 8. XGBoost R^2: 69.07% — MAE: 3.544 kg

Support Vector Regression (SVR). SVR (Figure 9) showed intermediate performance, with an R^2 of 74.50% ± 12.08% — the lowest standard deviation among all evaluated models, indicating greater stability across *folds*. Although it did not outperform Linear Regression, it showed statistical performance close to that of the Neural Network.

From a structural perspective, SVR with an RBF kernel introduces a nonlinear transformation into the feature space, allowing complex relationships among variables to be modeled [23]. However, when the underlying mechanism presents linear predominance, this additional flexibility may not result in a substantial gain in explained variance. In small-scale datasets, the model's greater fitting capacity may increase its sensitivity to sample-specific characteristics, reducing its practical advantage over linear approaches [18, 26].

The performance similar to that of Linear Regression indicates that the data structure did not require highly nonlinear modeling, reinforcing the conclusion that the relationships between Thoracic Circumference and body weight are predominantly linear in this dataset.

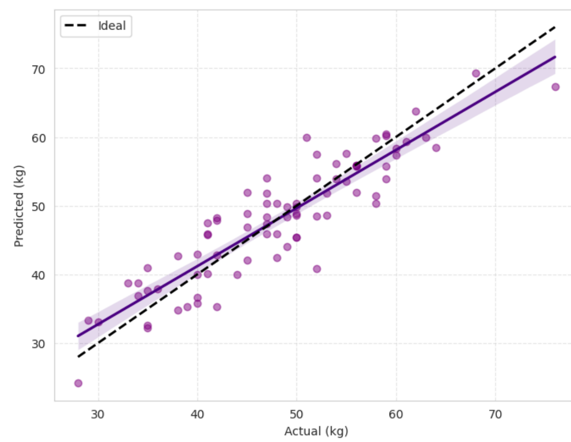

Figure 9. SVR R^2: 74.50% — MAE: 3.327 kg

Artificial Neural Network (MLP). The Neural Network (Figure 10) was the second-best model in terms of R^2 (74.67% ± 15.11%) and showed the second-lowest MAE among all evaluated models (3.225 kg), indicating good accuracy in individual estimates and a slight advantage in capturing small variations among animals.

However, the fact that the Neural Network did not outperform Linear Regression in terms of R^2 suggests that the structure of the dataset did not require high functional complexity, in line with the principle that simpler models tend to be preferable when they adequately capture the structure of the data [18, 26].

From a structural perspective, the MLP is a universal function approximator and has a high capacity to model nonlinear interactions among variables [25]. However, when the relationships between morphometric variables and body weight show predominantly linear behavior, this additional flexibility may not translate into a substantial gain in generalization [19, 18]. Similar to the other models, the MLP was also conditioned by the limited sample size (n = 80), which may have restricted the full use of its representational capacity. To control the risk of overfitting in this scenario, L2 regularization strategies through the `alpha` parameter and evaluation by K-Fold cross-validation were adopted, ensuring that performance was measured on data not seen by the model [26].

Batch-Level Performance Analysis. In addition to the individual evaluation of predictions, a complementary analysis

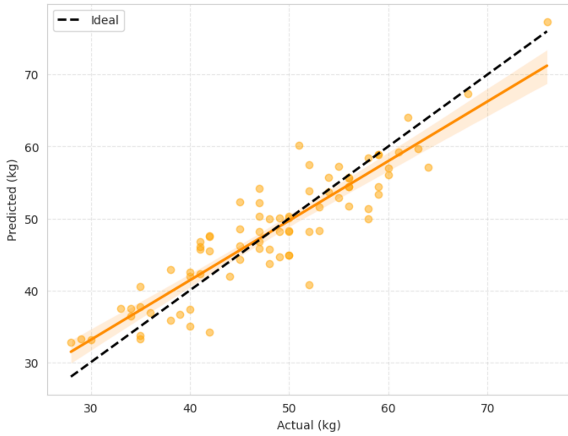

Figure 10. Neural Network R^2: 74.67% — MAE: 3.225 kg

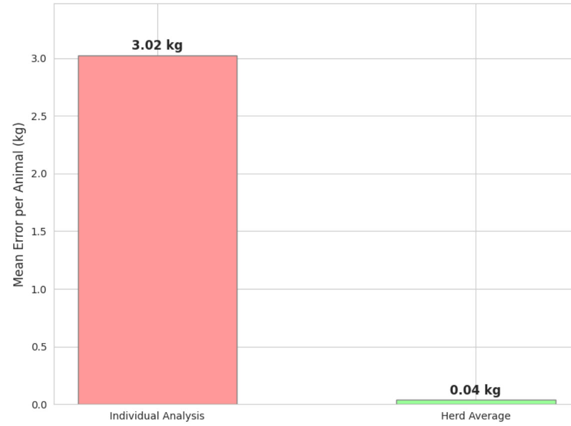

Figure 11. Error impact: Individual vs. Collective

was conducted to estimate model behavior when results are aggregated at the batch level. This analysis is relevant because management decisions in precision livestock farming frequently involve groups of animals, such as herd nutritional planning, expected production estimates, and allocation of lots for sale [10].

Figure 11 illustrates the difference between individual error and aggregate error: while the mean absolute error per animal (MAE = 3.02 kg) represents a relevant variation at the individual scale, the difference between the sum of the actual weights and the sum of the predicted weights, divided by the total number of animals, resulted in 0.04 kg. This result indicates that the model has low aggregate bias — that is, it does not have a systematic tendency to overestimate or underestimate the weight of the herd as a whole. It is important to emphasize that this value reflects the partial cancellation of positive and negative individual errors and should not be interpreted as a reduction in individual imprecision, which remains around 3.02 kg per animal [18].

This behavior is consistent with recent approaches in animal production that use group-level aggregated estimates as decision support [29]. Tu and Jørgensen [29], when estimating pig weight at the pen level using a computer vision system, observed good accuracy for the predicted average weight of the group, suggesting that aggregated estimates may be useful for management applications.

Thus, although the model shows perceptible variations at the individual scale, its low aggregate bias indicates suitability for herd-level management decisions, reinforcing the potential of *Machine Learning* models as decision-support tools in precision livestock farming, especially in scenarios with limited weighing infrastructure [10].

5. Conclusion

This study conducted a systematic comparison of *Machine Learning* algorithms for predicting the body weight of Santa Inês ewes based on morphometric variables collected under field conditions. The results indicated that linear models showed superior or equivalent performance compared with more complex methods, demonstrating that the relationship among the analyzed variables can be adequately represented by lower-complexity structures.

The multicollinearity analysis using VIF confirmed the redundancy among morphometric variables, with values ranging from 148 to 1,434, formally supporting the selection of Thoracic Circumference as the sole predictor. The equation obtained by Linear Regression:

$$\text{Weight (kg)} = 1.298 \times \text{Thoracic Circumference (cm)} - 64.547 \tag{3}$$

allows rural producers to estimate body weight using a simple measuring tape, reducing dependence on conventional scales and the operational costs associated with animal management.

From an applied perspective, the mean absolute error of approximately 3 kg per animal indicates that the model is suitable for supporting herd-level management decisions in precision livestock farming systems. The batch-level analysis revealed low aggregate bias of the model, with a mean difference of 0.04 kg between total actual weight and total predicted weight, making this result suitable for decisions involving groups of animals, such as nutritional planning and production estimates.

The limitations of the present study include: (i) a sample restricted to a single municipality (Campo Verde, MT), on a single day of data collection, which may not represent the variability of other herds and management conditions; (ii) analysis limited to females, meaning that the results cannot be directly extrapolated to males of the same breed; (iii) absence of segmentation by physiological status — pregnant and nonpregnant animals were analyzed jointly, which may have influenced the results given the impact of gestational status on body weight; and (iv) absence of external validation in independent herds, which limits the assessment of the generalization capacity of the proposed models. Therefore, extrapolation of the results to other herds, management conditions, and population profiles should be performed with caution.

As future perspectives, the following are recommended: (i) expansion of the database, including different age groups, productive categories, and management conditions; (ii) evaluation of other breeds and incorporation of additional variables, such as body condition scores or traits obtained through computer vision; (iii) investigation of the impact of physiological status and age on body weight prediction; (iv) external validation of the models in independent herds to assess their generalization capacity; and (v) exploration of feature selection strategies and hybrid *ensemble* techniques to improve the accuracy and robustness of the predictive models presented here.

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Author Contributions

Leonardo Jardim Antunes contributed the full drafting of the manuscript and conducted the analyses related to the artificial intelligence models used in the study; Ana Flavia da Guia Miranda participated in data collection as an undergraduate research fellow on the project, was responsible for organizing and tabulating the data, contributed to preliminary data analysis, and collaborated in writing and reviewing the manuscript; João Batista Gonçalves Costa Junior conceived and coordinated the research project, participated in data collection and analysis, contributed to the interpretation of results, and collaborated in the writing and critical review of the manuscript; Caroline Lima Amorim & Maria Eduarda Garcia Corrêa participated in data collection, organization, and tabulation; Adrielly Kamile Silva Bezerra, Kauane Ferreira da Silva & Shara Luzia Cavalcante Souza participated in data collection; Juliana Fonseca Antunes contributed to the review of the machine learning models.

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