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# Estimation of Bali Cattle Body Weight Based on Morphological Measurements by Machine Learning Algorithms: Random Forest, Support Vector, K-Neighbors, and Extra Tree Regression

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***Abstract***

*To forecast and model the weight of cattle, several techniques are used. Nonetheless, no machine algorithm has been utilized to estimate the weight of Bali cattle. This article examines the use of machine learning regression to create models for Bali cattle's body weight prediction. The response variables consist of body weight as the dependent variable and body length, girth circumference, and height at wither of 228 male and 211 female cattle of similar ages (285 days). The descriptive statistics of female Bali cattle in our investigation revealed that the morphological measurements were similar to those documented by other researchers. To predict body weight based on different characteristics, machine learning models such as Random Forest, Support Vector, K-Neighbors, and Extra Tree regressions have been used. Additionally, linear regression was utilized to estimate the body weight for comparison with the traditional approach. The assessment standards used included the determination coefficient, the root mean square error, the average absolute error, and the average absolute percentage error as measures of evaluation efficiency. We found that Linear Regression performs the best among all the regressors for female cattle. Similarly for males, it is about the same as extra tree regression. The machine learning algorithm (MLA) was discovered to furnish a more precise estimate of the weight of the body of cattle, surpassing the conventional algorithm.*

**Keywords:** *Bali Cattle, Machine Learning Algorithm Random Forest, Support Vector, K-Neighbors, and Extra Tree Regression.*

## 1. Introduction

The Bali cattle, also known as Balinese cattle, are a domesticated species of cattle that originated from the Banteng (Bos javanicus). Bali cattles are one of many Indonesians local cattle that play an important role in beef production. Breeding better beef has become more crucial, with a focus on enhancing growth attributes such as weaning and yearling cattle weight. The feasible growth characteristics are impacted by other supervisors, ecological circumstances, and commercial nourishment situations. As evidenced by Agung et al. (2018); Gunawan & Jakaria (2010) inquiries have been conducted regarding this issue, and they have revealed that the findings are subject to the influence of other managers, ecological circumstances, and corporate nourishment. Investigations have been undertaken on this subject., see for example Agung et al. (2018), Gunawan & Jakaria (2010), Hafid (2020), Astiti et al. (2021).

The evaluation of livestock appearance and performance heavily relies on the measurement of their body dimensions. Various dimensions, which are indicative of the animal's size, are critical factors in livestock selection and breeding. Additionally, body measurements can be applied to estimate the weight of the animal. The height at withers and hip width are other popular morphometric measurements. The metrics are selected and applied as characteristics for conventional regression models refer to, for instance Ashwini (2019), Gruber et al. (2018); Gunawan & Jakaria (2010), and Hafid (2020). This method was also applied to other species such as camel, pig, chicken, etc. (Franco et al., 2017; RA et al., 2018; Topal & Macit, 2004). The traditional method has also been applied to the body weight prediction of Bali cattle (Agung et al., 2018; Ashwini, 2019; Gunawan & Jakaria, 2010; Hafid, 2020; Astiti et al., 2021).

Linear regression to predict animal weight has been used in several previous investigations using a conventional approach. However, it is deemed insufficient to use such existing methods for prediction in case all assumptions such as correlations, distribution, or multicollinearity are violated (Bzdok et al., 2018). Lately, several scholars have effectively utilized diverse machine-learning techniques to anticipate the actual body weight of cattle by utilizing morphological measurements. (Borges Oliveira et al., 2021; Gjergji et al., 2020a, 2020b; Huma & Iqbal, 2019; Lee et al., 2020; Ruchay et al., 2021; Shahinfar et al., 2020; Wang et al., 2021b). These studies have demonstrated that machine learning algorithms can effectively forecast the non-linear correlation between animal weight and morphological characteristics (Alonso et al., 2013; Bezsonov et al., 2021; Biase et al., 2022a; Çakmakçı, 2022; Franco et al., 2017; Goopy et al., 2018; Wang et al., 2021a). With the more advanced methods of collecting data, the application of computer vision has also been increased recently (Bezen et al., 2020; Dohmen et al., 2022; Wang et al., 2021a).

Four algorithms, namely Extra Trees Regression (ET), Random Forest (RF) Regression, K-Neighbors Regression (KN), Support Vector Regression (SV) were selected as machine learning algorithm used to estimate the body weight (BW) of Bali. The four models as reported by (Natekin & Knoll, 2013; Ruchay et al., 2021b; Wang et al., 2021a) have shown a consistent performance compared to other models evaluated by root mean square error (RMSE). This study aimed to determine the best machine learning algorithm to predict the body weight of Bali cattle using different morphological characteristics, that is body weight as a dependent variable and body length, girth circumference, and height at wither, all cm as independent variables. Additionally, in the framework of our machine learning methodology, we have used this idea to divide data into training sets, tests and validations to determine a precise approach for modeling and predicting. The model is taught by means of a training regimen that normally contains 80% to 90% of the data. After that, the parameters of the model are manually tuned using a validation set, which is typically a subset of the training set consisting of at least 20% of the data. Finally, the model's actual predictive ability is assessed using a separate testing set.

In this research, we utilized the technique of machine learning regression as mentioned above to establish a framework for anticipating the weight of Bali cattle. As far as we are aware, no prior investigations have been conducted on forecasting the body weight of Bali cattle using machine learning algorithms. To predict the weight of Bali cattle using diverse physical characteristics, this research has been aimed at finding the most effective machine learning regression algorithm.

## 2. Materials And Methods

### Material and measurement

This research was carried out at BPTU-HPT Denpasar located in Pangyangan Village, Pekutatan, Jembrana Regency. April-May 2022 period. Linear body measurements were taken for each cattle after being weighed to obtain weight in kg, body weight (BW) as the response variable and body length (BL), girth circumference (GC), height at wither (WH), all in cm as input variables. The data collection was conducted in accordance with Animal Care and it is supervised by the Bali Superior Livestock Breeding Center. The collection of data sets and all other procedures carried out in this investigation were conducted without confining the cattle. BW was measured by weighing the animal in a kilogram scale perpendicular to the surface. BL were obtained by measuring the distance between the shoulder joint (later humerus) to the edge of the pelvis. WH was obtained from measurement of the distance from the edge to the surface through the perpendicular parameters. WH and BL were measured using a stick tool (Hauptner, Germany) on a 1 cm scale.

**Ethical Considerations**

This study was conducted in accordance with the guidelines given by the Animal Care of BPTU-HPT Denpasar situated in Pangyangan Village, Pekutatan, Jembrana Regency. The collection of information and all other techniques utilized in this research were carried out without restraining the livestock. This research, which precludes ecological monitoring or livestock science studies from obtaining approval, is not required to be approved by the Animal Care and Use Committee.

**Machine Learning Algorithm**

Regression in machine learning is a type of supervised learning algorithm used for predicting continuous numerical values based on input features. It aims to establish a relationship between the independent variables (input features) and the dependent variable (output or target variable). The goal of regression is to build a mathematical model that can accurately predict the output value for new, unseen input data points. It assumes that there is a functional relationship between the input variables and the output variable, and the task is to learn this relationship from the training data. In our study, we utilize the standard regression algorithm from the SciKit-Learn (SKlearn): Linear Regression (LR), Extra Trees Regression (ET), Random Forest (RF) Regression, K-Neighbors Regression (KN), Support Vector Regression (SV). The primary aim of these algorithms is to establish the most suitable line or curve among the data points for precise prediction.

LR is a commonly used technique for predicting numerical values, such as the body weight of cattle, based on input features, such as age, breed, gender, measurements (such as height or body length), and other characteristics (Agung et al., 2018; Ashwini, 2019; Bhagat et al., 2016; Gunawan & Jakaria, 2010; Hafid, 2020; Haq et al., 2020; Ni Made Ayu Gemuh Rasa Astiti et al., 2021; Prihandini et al., 2020). LR equations can be applied to predict cattle's body weight. Extra Trees Regression has several advantages in predicting the body weight of cattle. It can handle both numerical and categorical features, can capture non-linear relationships, and requires less computational resources compared to some other complex regression algorithms (Biase et al., 2022b; Wang et al., 2021a; Weber et al., 2020)

RF regression uses a large number of decision trees constructed using random subsets of the training data. Each decision tree is built by selecting a random subset of features at each split. To predict the body weight of cattle using RF regression, a training dataset is required, which includes input features (such as age, breed, gender, and measurements) and the corresponding body weight values for a set of cattle. The algorithm learns the relationship between the input features and the body weight by constructing an ensemble of decision trees (Hossain et al., 2022; Modaresi et al., 2018).

KN algorithm identifies the k nearest neighbors of a new data point based on a similarity metric, such as Euclidean distance or Manhattan distance. The value of k represents the number of neighbors considered. The predicted body weight of the new data point is determined by averaging the body weights of its k nearest neighbors (Biase et al., 2022b; Modaresi et al., 2018). Another machine learning algorithm that is popular used to approximate the relationship between the input features (e.g., age, breed, gender, measurements) and the body weight of cattle is SV regression. SV achieves this by mapping the input features into a higher-dimensional feature space using a kernel function. In this feature space, SV aims to find a hyperplane that best fits the training data while minimizing the prediction error (Biase et al., 2022b; Truong & Pham, 2021; Zhang & O'Donnell, 2020).

To evaluate the effectiveness of models built in this research for simulating and predicting cattle weight, different evaluation standards have been used. In this study, various common assessment measures have been taken into account. The assessment standards utilized the root mean squared error (RMSE), the mean absolute error (MAE), and the average absolute percentage error (MAPE) as indicators of evaluation efficiency. The following is the definition of these measures:

$$RMSE = \sqrt{1/N \sum_{i=1}^{N} (y_i - \hat{y}_i)^2}$$

$$MAE = 1/N \sum_{i=1}^{N} |y_i - \hat{y}_i|$$

$$MAPE = 1/N \sum_{i=1}^{N} |(y_i - \hat{y}_i)/y_i|$$

where $N$ is the number of observations or iterations used in error calculation, $\hat{y}$ is predicted to be the dependent value and $y$ shall be an actual value. The real value is the values that are input to your training model, and the predicted values are those obtained following a machine learning regression analysis.

The process of linear regression commences with the pre-processing of data. During this stage, information consisting of BW as the response variable and BL, GC, and WH as the predictor variables for a total of 228 male Bali Cattle and 211 female cattle. They are all in similar ages of 285 days. Next, a fitted model is generated. In this step variable predictors that have p-values higher than 0.05 are considered to be unnecessary, then are eliminated. The third step, locating and removing outliers. In case there are outliers within the data, they must be eliminated from the fitting process. The fourth phase involves streamlining the model, aiming to achieve a less complex version with fewer predictors but equivalent predictive precision. The objective is to search for an improved model by gradually introducing or removing one term at a time. The final step is to anticipate responses for new data.

## 3. Results and Discussion

### Body weight and morphometry

The descriptive statistics of morphometry of female Bali cattle in Pangyangan Village, Pekutatan, Jembrana Regency are presented in Table 1. The Body weight (BW) coefficient of variation parameter was higher than the other morphometric parameters. This can be interpreted that the BW parameter of Bali cattle are more diverse than the other morphometric parameters. Agung et al. (2018) reported a positive and high correlation between morphometric measurements and body weight. Furthermore, their analysis revealed a substantial correlation between chest circumference and overall body mass as indicated by the correlation coefficients. As reported by Hafid (2020) the physical structures of male and female Bali cattle from conventional animal husbandry in Southeast Sulawesi were comparatively consistent. He claimed that there were no notable disparities in the mean weight and physical dimensions between male and female Bali cattle. As well, Agung et al. (2018) reported that morphometric data follow a normal distribution indicated by a Kolmogoro-Smirnoff significance value of $\alpha$ (0.05). Table 1 contains the average values and standard deviations for the body weight and body measurements of Bali cattle. Among the morphometric data, the BW (128.84± 38.66 cm) of male Bali cattle exhibited the highest level of variability as per the findings of this study.

**Table 1.** Mean, standard deviation (StdDev) and coefficient of variation (CoefVar in %) for body size and body weight of Bali cattle.

| Sex | Variable | Mean | | StdDev | CV (%). |
|---|---|---|---|---|---|
| Female | BodyWeight ($y$) (Kg) | 128.04 | ± | 22.31 | 17.43 |
| | WitherHeight ($x_1$) (cm) | 99.78 | ± | 4.64 | 4.65 |
| | BodyLength ($x_2$) (cm) | 95.88 | ± | 5.93 | 6.19 |
| | GirthCirc ($x_3$) (cm) | 124.34 | ± | 8.31 | 6.68 |
| Male | BodyWeight ($y$) (Kg) | 128.84 | ± | 38.66 | 30.00 |
| | WitherHeight ($x_1$) (cm) | 100.75 | ± | 7.35 | 7.29 |
| | BodyLength ($x_2$) (cm) | 95.24 | ± | 8.60 | 9.03 |
| | GirthCirc ($x_3$) (cm) | 122.56 | ± | 12.75 | 10.40 |

*Source: Primary data collect in BPTU-HPT, Pangyangan Village, Jembrana Regency.*

The findings of this investigation revealed that the morphological measurements were similar to those documented by Agung et al. (2018) where they recorded 99.78 ± 4.64 cm for wither height (WH) of female cattles, and 100.75 ± 4.64 cm 128.6 ± 7.04 cm for body length, and 128.64 ± 8.25 for chest circumference in yearling Madura cattle. However, the average weight of mature Bali cattle (237.00± 37.35kg) in Banyumulek Techno Park, West Nusa Tenggara as reported by Agung et al., (2018) was slightly lighter than that noted by Hafid (2020) which was 260 kg,

**Table 2.** Correlation matrix

| | | FEMALE | | | |
|---|---|---|---|---|---|
| | | BW | WH | BL | GC |
| M | BW | 1 | 0.660 | 0.722 | 0.840 |
| A | WH | 0.855 | 1 | 0.766 | 0.597 |
| L | BL | 0.887 | 0.921 | 1 | 0.649 |
| E | GC | 0.940 | 0.877 | 0.850 | 1 |

*Source: Primary data collect in BPTU-HPT, Pangyangan Village, Jembrana Regency*

To determine the relationship between body measurements to each other, a correlation coefficient has been used: bodyweight, height at withers, length and girth. An investigation into the relationship of biometric characteristics with body weight in different animal species is also performed using correlation coefficients. (Paputungan et al., 2013; Yanto et al., 2021). Table 2 displays the most noteworthy correlation coefficient between girth circumference (GC) and body mass (BM) (coefficient of 0.940). The other traits, except for the height at the withers (HW) of female cattle, exhibit a relatively strong correlation coefficient with body mass. Furthermore, all coefficients were significant under statistics measure ($p < 0.05$).

**Prediction of Body Weight**

Table 3 provides the body weight prediction produced by various models, applied to the complete dataset. It is seen that the evaluation criteria, RMSE, MAE, and MAPE are consistent for every algorithm. So, in our discussion, we only refer to RMSE for the evaluation of each model's performance.

**Table 3.** Evaluation models based on different performance measures

| Regression Models | Male | | | Female | | |
|---|---|---|---|---|---|---|
| | RMSE | MAE | MAPE | RMSE | MAE | MAPE |
| Linear Regression | 10.1706 | 8.1690 | 7.5796 | 9.6172 | 7.2026 | 5.6319 |
| Extra Trees | 10.0271 | 7.9731 | 6.7411 | 13.8009 | 9.9795 | 8.2882 |
| Random Forest | 9.8952 | 7.6494 | 6.5710 | 14.9789 | 10.4839 | 8.6324 |
| K-Neighbors | 12.7911 | 10.0444 | 8.3888 | 14.2447 | 11.6786 | 9.1615 |
| Support Vector | 10.1612 | 8.0902 | 7.5771 | 9.7003 | 7.2833 | 5.6628 |
| Gradient Boosting | 16.0442 | 12.7644 | 11.8235 | 14.5019 | 12.2108 | 10.1072 |

*Source: Primary data collect in BPTU-HPT, Pangyangan Village, Jembrana Regency*

Linear Regression (LR) with an RMSE of 9.6172, performs the best among all the regressors for female cattle. Similarly for males, it is about the same as ET. The goal of applying linear regression in this scenario would be to learn a linear relationship of input characteristics to the body weight of Bali cattle (Agung et al., 2018; Gunawan & Jakaria, 2010). Random Forest (RF) with an RMSE of 9.8952 performs the best among all the regressors for male cattle. However, it shows a very high RMSE of 14.9789 when it is applied to female cattle. This algorithm has been also applied to estimate the BW of cows (Ruchay et al., 2021b). Extra Trees with an RMSE of 10.0271 closely follows RF and performs well for Male cattle. Similar results were also been found by Ruchay et al. (2021b). While LR with an RMSE of 10.1706 performs reasonably well for male cattle and it performs the best among all the regressors for Female cattle. SV with an RMSE of 10.1612 performs similarly to LR for Male cattle. Similarly, SV Regression with an RMSE of 9.7003 has a slightly higher RMSE compared to LR for female cattle, see also Kavitha S et al. (2016).

KN relies on the values of neighboring data points, and its performance can be sensitive to the choice of $K$ and the distance metric. In this case, the higher RMSE suggests that KN may not be capturing the underlying patterns as effectively as the other models. KN with an RMSE of 12.7911, a higher RMSE compared to the other models for male cattle, has the highest RMSE among all the regressors for male cattle. From the comparison, we can observe that for male Bale cattle, RF and ET perform the best with the lowest RMSE values, followed closely by LR and SVR. KN has higher RMSE values, indicating poorer performance for Male cattle. For female cattle, LR and SV Regression perform the best with the lowest RMSE values. RF and KN have higher RMSE values, indicating relatively poorer performance for female cattle. ET has the highest RMSE among all the regressors for female cattle.

RF performs the best among the regressors listed when it is used to estimate the male BW. The lower RMSE suggests that RF is able to capture the underlying patterns in the data effectively and make accurate predictions. However, this is not true when it is applied to estimate the female ones. These disparities in performance between male and female Bali cattle may be because the discrepancies in the underlying patterns and relationships within the data for each gender. This underscores the significance of taking into account the distinct characteristics and qualities of the data when choosing the most suitable regression model. It is advisable to assess and contrast various models on the particular dataset to determine the optimal match for the assigned objective and target variable. This outcome does not correspond to the result reported by Hafid (2020) which shows that the physical structure of male and female Bali cattle from conventional animal feeding in Southeast Sulawesi is relatively similar.

Coşkun et al. (2023) conducted a study with the objective of comparing the performance of the Gradient Boosting (GB), RF, and Bayesian Regularization Neural Network (BRNN) data mining algorithms in predicting the final live weight of Anatolian Merino lambs at the end of the fattening period using certain body characteristics measured at the start of fattening. Their findings indicated that the GB algorithm outperformed BRNN and RF in terms of fitting accuracy, as measured by RMSE, MAPE and $R^2$ adjusted. In their analysis, Coşkun et al. (2022) primarily focused on short-term fattening performance outcomes. Furthermore, similar research also conducted by Iqbal et al. (2022) was aimed to assess the performance of various machine learning models, including GB, RT, RF, and SVR, in predicting the body weight of Beetal goats. They considered explanatory variables such as gender, BW, GC, neck length, head girth, rump height, and belly sprung. The evaluation of these models was based on MAE, MAPE, or RMSE.

The findings of their research are that the GB emerged as the most effective model for predicting the body weight of Beetal goats. Following closely, the RF algorithm was identified as the second-best performer among the models assessed. This study's results strongly indicate the reliability of RF for model fitting, even though there is no direct comparison with GB, which was the top-performing model in Iqbal et al.'s research (2022).

The study was performed on a range of machine learning algorithms in comparison with previous studies. The large variation in results is due to differences in the age of animals, as well as data methods used for previous studies. Models we used to compare our study with other studies, using the goodness-of-fit criteria, have yielded similar results. However, it is important to recommend various statistical procedures for estimating body weight using morphological measurements or biometrics to characterize both species and breeds in the meat production industry. This highlights the need for further studies on this subject.

## 4. Conclusion

In conclusion, machine learning algorithms can help farmers improve the accuracy of estimating Bali cattle body weight without worrying about the nature of the data. Moreover, BW was found to be the criterion used for establishing morphologic measurements in this study. The results suggest that machine learning may be commercially viable for weight prediction on measured body weights using a basic mean squared error criterion to choose the most suitable model. According to the findings of the current investigation, we deduce that the machine learning algorithm is suitable for the estimation of Bali cattle's body weight. Furthermore, the discoveries of this investigation can assist analysts and professionals in embracing the most recent artificial intelligence algorithms for precise anticipation of body weight by utilizing different morphological characteristics and additional variables.

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