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Cattle Weight Estimation Using Linear Regression and Random Forest Regressor

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Abstract

The global cattle farming industry has benefits as a food source, livelihood, economic contribution, land environmental restoration, and energy source. The importance of predicting cow weight for farmers is to monitor animal development. Meanwhile, for traders, knowing the animal's weight makes it easier to calculate the price of the animal meat they buy. The authors propose estimating cattle weighting linear regression and random forest regression. Linear regression can interpret the linear relationship between dependent and independent variables, and random forest regression can generalize the data well. The dataset used in this study consisted of ten variables: live body weight, withers height, sacrum height, chest depth, chest width, maclocks width, hip joint width, oblique body length, oblique back length, and chest circumference. To find out the model that produces the smallest MAE value. The results show that the linear regression algorithm can produce estimated weight values for cattle with the best performance. This model produces a mean absolute error (MAE) of 0.35 kg, a mean absolute percentage error (MAPE) of 0.07%, a root mean square error (RMSE) of 0.5 kg, and an R^2 of 0.99. Each variable has excellent correlation performance results and contributes to computer vision and machine learning.

Keywords: *cattle; machine learning; linear regression; random forest regressor; prediction model*

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1. Introduction

The world's cattle farming industry still needs to improve its beef production. Currently, 78% of beef production is obtained domestically; 5% is imported from beef, and 17% from live cattle [1]. The cattle farming industry has benefits as a food source, livelihood, economic contribution, environmental land restoration, and energy source [2]. Cattle are an essential resource that contributes to agricultural practices, supports biodiversity conservation, facilitates research, and has cultural significance [3].

Cow health parameters such as body weight, body temperature, pulse rate, respiration, body condition, and milk production can be used to monitor animal growth and health [4]. Beef quality is closely related to the age and body weight of the cow [5]. The highest beef production based on market value is at prime age, namely between 18 months and 24 months, and has reached optimal weight, and beef muscle mass has developed. In the context of the livestock buying and selling business, it is to help farmers make better decisions regarding selling, purchasing livestock, managing feed, health services, and efficient livestock maintenance [3]. The need for sacrificial animals for Eid al-Adha 2023 is estimated to reach 1.7 million. The number of cattle is in second place after goats, namely 650,282, 743,672 goats, 332,770 sheep, and 16,327 buffalo. The Institute for Demographic and Poverty Studies (IDEAS) also estimates the need for sacrificial animals for Eid al-Adha 2023 to be 1.78 million. This number consists of 505,000 cows and buffaloes and 1.23 million goats and sheep. From this amount, 103,000 tons of sacrificial meat can be obtained.

The importance of determining whether beef is suitable for consumption is meat quality, cleanliness, animal health, storage, transportation, and labeling in meeting food safety and quality standards [6]. Cow weight gain is determined by measuring body height, length, and chest circumference [7]. Predicting animal weight is very important for farmers to monitor animal development. Meanwhile, for traders, knowing the

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importance of these animals makes it easier to calculate the price of the meat they buy. Several studies have applied machine learning (ML) and deep learning (DL) to predict animal weights as a form of technological innovation. This research shows cow weights using two machine-learning models.

The two models examined in this research are linear regression and random forest regressor (RFR). The advantage of using a random forest regressor (RFR) is that this model can generalize the data well [8]. Random forests can produce accurate models for classification and regression [9]. The random forest technique is robust to data complexity. It is based on ensemble learning, using many randomly generated decision trees to produce accurate predictions. The strength of Random Forest lies in its capacity to reduce overfitting, increase model stability, and offer practical solutions in various classification and prediction scenarios [9]. Many industries involving random forest techniques in advanced data processing, including bioinformatics, finance, health, and others, have effectively used this approach [3]. Random forests can offer new perspectives in the investigation of predictive models, support the reliability of research, and offer reliable answers to problems posed by the complexity of modern data [8]. As a result, this research has the potential to significantly contribute to advancing data analysis techniques and expanding knowledge regarding the capabilities and constraints of Random Forests.

Meanwhile, linear regression can interpret the linear relationship between the dependent and independent variables [8]. Linear regression has performance capabilities in prediction, relationship analysis, variable selection, model evaluation, and causal inference [10]. The influence of the independent variable on the dependent variable can be evaluated through the use and understanding of linear regression [11]. Can investigate whether linear regression can measure the linear relationship between independent and dependent variables [12]. This approach aims to measure the extent to which changes in one variable can be associated with changes in other variables. The P value of the regression coefficient will be an essential guide in determining the relationship between variables, thereby leading to the validity of research findings [13]. By including control variables in the model, linear regression can be used as a reliable and comprehensive analysis method to increase the validity of research findings by controlling for other variables [13]. Machine learning in this research provides benefits in increasing prediction accuracy, prediction model adaptability, and time and resource efficiency [14]. In the process, machine learning can produce alternative models for predicting cow weight that are more accurate and efficient [14].

They measure cow weight predictions based on deep learning using a convolutional neural network (CNN) algorithm. Produces a top model Mean Absolute Error (MAE) value of 23.19 kg. The algorithms and data models used can still be improved [15]. Researchers found that the linear regression algorithm produced the best mean absolute error (MAE) value of 0.35 kg. They are using a model of 100 cow data, feature selection, and 50-fold cross-validation. This shows that the linear regression algorithm can outperform other models tested based on the trained model.

This research contributed to creating a method for estimating cattle weight by measuring nine-dimensional cattle factors using computer vision techniques and regression algorithms. This can be used as a helpful tactic and helps monitor cows' weight precisely and effectively. The findings of this study suggest that this method may be helpful in real-world situations, particularly in livestock management and rearing. Additionally, this research highlights how machine learning and computer vision are applied in agriculture and animal husbandry. This study also shows how linear regression can be used for predictive modeling and reliably estimating livestock weights. This study also emphasizes the importance of live weight as a predictor variable in assessing livestock dimensions to increase prediction accuracy.

Prediction of cow weight based on measurements from images of the cow area using the Random Forests algorithm provides the best performance with a mean absolute error (MAE) of 13.44 kg and a correlation coefficient of 0.75 [8]. They are predicting sheep weight based on images using a machine-learning regression algorithm. The experimental results show that the random forest regressor (RFR) method produces better error values with a mean absolute error (MAE) of 3,099 kg compared to other machines. Learning regression algorithm method [8], [16]. By using the training dataset (70%), test dataset (30%), and validation dataset (20% of the training dataset), this research uses the Stacking Regressor algorithm to produce the best performance in predicting pig weight with an MAE of 4,331 and MAPE 4,296 on the dataset testing. The researchers used a data set of 340 pigs, and the proposed model could predict pig weights in the 86 to 113 kg range.

In this experiment, the artificial neural network (ANN) method achieved impressive prediction model values, with an R2 accuracy of 0.7 and an RMSE of 42 kg. However, it should be noted that the evaluation results using 3D images of live animals and the ANN algorithm show that there is still potential to increase the R2 and RMSE values. These findings provide an exciting challenge to improve the accuracy of prediction and model optimization using 3D images and ANN algorithms in this research [17].

In the latest research regarding predictions in the context of determining the Economic Index (EI) and the Calving Interval (CI) approach in cattle, it was found that the best model for predicting EI is using the Neural Network Machine Learning Algorithm (NN MLA) with a Mean Absolute Error (MAE) of 20.72 and Root Mean Square Error (RMSE) of 29.35. Meanwhile, the best model for CI prediction uses the Gradient Boosting Machine Learning Algorithm (GB MLA) with MAE 0.79 and RMSE 1.27 [18]. However, the results of this study highlight that the data used needed to cover a sufficient number of cattle. By expanding and varying the training data set, increased prediction accuracy can be achieved. These findings show the potential for further development in optimizing predictions to increase the efficiency of economic indices and regulate calving intervals in cattle.

This research utilizes a sophisticated deep-learning algorithm to estimate the pig's body weight by utilizing images of the pig's back taken from an upper angle. The algorithm combines R-CNN object detection speed with regression neural network innovation, producing weight estimates with a Mean Absolute Error (MAE) of 0.644 kg and a relative error of 0.374%. This algorithm can identify and localize the pig's position and accurately predict the pig's body weight even if the image's overlapping area is less than 30%. However, variations in pig body posture can affect the accuracy of body weight estimation. With the addition of training data, overall accuracy can be improved, opening up opportunities for implementing a more efficient non-contact pig weighing system [19].

Based on the background and literature, they are explained above. However, for the training data and previous research models that could still be improved, linear regression and random forest regressor (RFR) methods were used to predict cow weight in this research. This model produces a mean absolute error (MAE) of 0.35 kg, a mean absolute percentage error (MAPE) of 0.07%, a root mean square error (RMSE) of 0.5 kg, and an R^2 of 0.99. This research aims to improve the results of smaller MAE values and contribute to studying computer vision and machine learning. This research consists of four chapters, after which the research method will be explained, followed by a discussion of the research results. The final section will close with conclusions.

2. Research Methods

2.1 Research Workflow

The research flow stages are shown in Figure 1, divided into four stages: data collection, preprocessing, machine learning scenarios, and evaluation. In the first stage, the full-cow-promer dataset obtained from Kaggle is used. The second stage is preprocessing, where the processes carried out are data reduction, cleaning, labeling, normalization, feature selection, and 50-fold ross-validation. The third stage is a machine learning scenario, where a design is created to determine the best accuracy using data balancing with a linear regression algorithm and a random forest regressor. Finally, the fourth stage is evaluation and analysis, which includes evaluating the results, conducting research, and drawing conclusions based on the experiments.

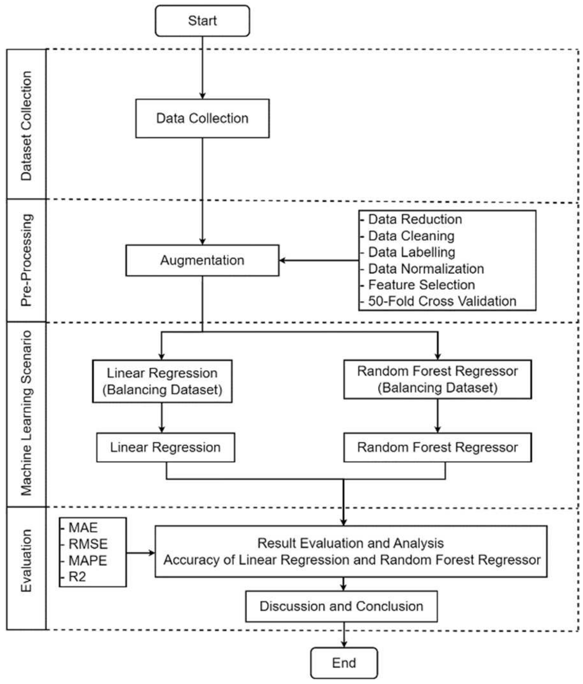

Figure 1. Research Flow Diagram

2.2 Dataset Collection

The Full Cow Promer (FCP) dataset derived from Kaggle data is a cattle dataset from private farms in the Nizhny Novgorod region of Russia, which will be used in this research [19]. The dataset consists of 100 pieces of data divided into ten variables: live weight, withers height, sacrum height, chest depth, chest width, width in maclocks, hip joint width, oblique body length, oblique hind length, and chest girth. The dataset is cow body measurement data, carried out manually using a measuring tape and recorded in centimeters [11].

2.3 Data Preprocessing

Data reduction is carried out to reduce the complexity and size of the data collected. The decline aims to eliminate irrelevant cow data. By reducing the amount of cattle data analyzed, researchers can focus on the most critical and relevant data [8].

Data cleaning is carried out to ensure data quality. The aim is to remove invalid, incomplete, and irrelevant data. It also provides accurate and reliable research results [3].

Data labeling is carried out to provide classifications for each cow's data. The goal is to identify and differentiate data based on specific attributes. Labeling data in this research is essential for more focused and relevant grouping, modeling, and statistical analysis [20].

Data normalization is carried out to convert data into a standard form, making it easier to process and analyze cattle data. Data normalization aims to eliminate scale differences to ensure that each attribute has a balanced contribution to obtaining more accurate research results [16].

Feature selection aims to identify the most relevant and significant subset of features in the cattle dataset. Feature selection aims to reduce data dimensions, increase computational efficiency, eliminate redundant components, and improve the performance of prediction models [3].

K-fold cross-validation is carried out to test model performance more accurately and reliably by dividing the data into k subsets of the same size. The purpose of k-fold cross-validation is also to help evaluate the stability and generalization of the model on never-before-seen cow data [8].

2.4 Machine Learning Scenario

This research predicts cow weight using two machine-learning models. The two models examined in this research are random forest regressor (RFR) and linear regression. The importance of splitting the data set using 50-fold cross-validation can balance computational efficiency and reliable performance estimation. Applying data normalization can avoid bias in the model and ensure that each feature has a balanced contribution to the learning process [20]. This research uses random forest because this model can generalize data with good performance [8]. Random forests can produce accurate models when carrying out classification and regression [9]. Random forests can reduce model overfitting, increase efficient computing time, balance data weights, and select relevant features. Estimation is essential in selecting the most relevant parts to improve the performance of a more accurate cow weight prediction model [3].

RFR can process large amounts of data with efficient computing time [21]. Random forests are robust to outlier noise, handle high-dimensional data effectively, capture non-linear relationships, and provide estimates of feature importance [9]. RFR can provide better cow weight prediction results with high accuracy [3]

Random Forest can handle missing values well [21]. Random Forest training can be easily parallelized, allowing efficient and accelerated use of computing resources [9]. Random Forest is obtained from the most results from each decision tree [9] for RF, which consists of Z trees, where Y is the indicator function, and an is the tree of the RF, defined as Equation 1.

$$l(y) = ar\ gmax_c(\sum_{z=1}^{Z} Y_{an(y)=c}) \tag{1}$$

The advantage of linear regression compared to other methods is that it can interpret the linear relationship between dependent and independent variables [4]. Has performance capabilities in prediction, relationship analysis, variable selection, model evaluation, and causal inference [6]. In feature selection, linear regression can be used by analyzing the significance of coefficients to test the assumptions of linearity, independence, homoscedasticity, and normality of residuals [8]. Linear regression tends to be stable and can provide exemplary performance in cases where the relationship between the independent and dependent variables is linear [8]. Linear regression provides a good overview of the linear relationship between variables. If the relationship is linear, linear regression can provide accurate estimates [14].

As a more complex machine learning algorithm model, it provides an interpretable benchmark against which to compare the performance of other models. Machine learning in this research offers benefits in increasing prediction accuracy, adaptability of prediction models, and time and resource efficiency [14]. In the process, machine learning can produce alternative models for predicting cow weights that are more accurate and efficient. The multiple linear regression algorithm can provide performance for finding the best prediction line [22]. There are several components, including A, the dependent variable or predicted value; b, a constant; Z, the independent variable; and c, the regression coefficient. From this equation, a line can be drawn to predict the dependent variable based on the independent variable, namely Equation 2.

$$A = b + b_1 Z_1 + c_2 Z_2 + .. + c_n Z_n \tag{2}$$

2.5 Model Evaluation

In this research, model performance evaluation was carried out to determine the best model from the two models that have been built, namely linear regression and random forest regression. Model performance is measured by the mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), and R2 values, which are the methods used to measure the accuracy of predictions made by the two models. The modeling that was successfully created in the previous stage will then be evaluated, which is defined as Equations 3, 4, 5, and 6.

$$MAE = \frac{\sum_{i=1}^{n} |xi - yi|}{n} \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (xi - yi)^2}{n}} \tag{4}$$

$$MAPE = \frac{100\%}{n} \sum \left| \frac{y - \hat{y}}{y} \right| \tag{5}$$

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \tag{6}$$

3. Results and Discussions

Data on cattle belonging to private farms in the Nizhny Novgorod region, Russia. Data collection of all selected cows was collected in the pen for manual body measurements [11]. The nine body measurements shown in Figure 2 were taken manually by an expert using a measuring tape and recorded in centimeters.

In Figure 2, you can see each cow's dimensions such as: (1) withers height, (2) hip height, (3) chest depth, (4) heart girth, (5) ilium width, (6) hip joint width, (7) oblique body length, (8) hip length, (9) chest width.

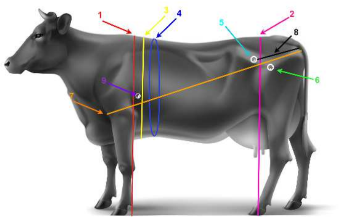

Figure 2. Nine dimensions of the cow's body

Markers were made on the cow's body using white paint during manual measurements. Then, the automatic system uses the cow's body parameters using anatomical features. Bone protrusions and depressions on the surface of the cow's body can be measured as anatomical markers [23].

The researcher's main objective is to find a suitable model to apply cow weight predictions and find the model that produces the minor mean absolute error (MAE) error value using the liner regression and random forest regressor methods.

Table 1 shows the abbreviations and definitions for the estimated body size of cattle.

Table 1. Abbreviations and definitions of cow body size

Abbreviation	Definition
Withers height (WH)	Vertical distance from the highest point on the withers to the highest point on the bottom of the toe
Hip height (HH)	The vertical distance from the highest point, the hip bone, to the lowest point, the ground at the level of the hind legs
Chest depth (CD)	The vertical distance from the back to the base of the father in the farthest-reaching section of the father
Heart girth (HG)	Body circumference at a point just posterior to the front leg and shoulder and perpendicular to the body axis
Ilium width (IW)	Distance between the outermost points of the ilium bone perpendicular to the base.
Hip joint width (HJW)	Comparison of two hip joint points that aren't moving forward quickly
Oblique body length (OBL)	From the internal posterior ischium to the anterior humerus' extremity
Hip length (HL)	From the posterior extreme of the internal ischium to the outermost point of the ilium
Chest width (CW)	Posterior shoulder perpendicular to the back distance between corner points

Table 1 shows nine definitions and abbreviations for the results of cow body measurements, which are the variable values in this study.

3.1 Linear Regression Algorithm

Figure 3 shows performance metrics results with nine variables and 50-fold cross-validation using the linear regression algorithm.

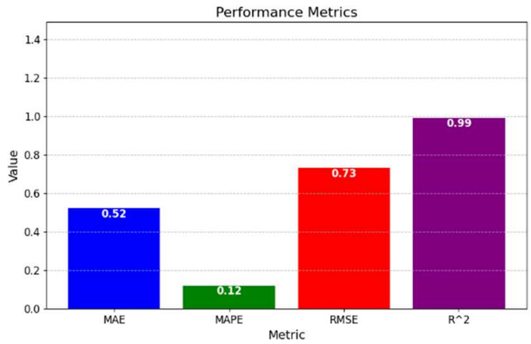

Figure 3. Performance Metrics Linear Regression Algorithm with Nine Variables and 50-fold Cross Validation

Figure 3 shows that the linear regression algorithm is known to have an accuracy level of MAE values of 0.52 kg, MAPE of 0.12%, RMSE of 0.73 kg, and R-square of 0.99.

Figure 4 shows performance metrics results with eight variables and 50-fold cross-validation using the linear regression algorithm.

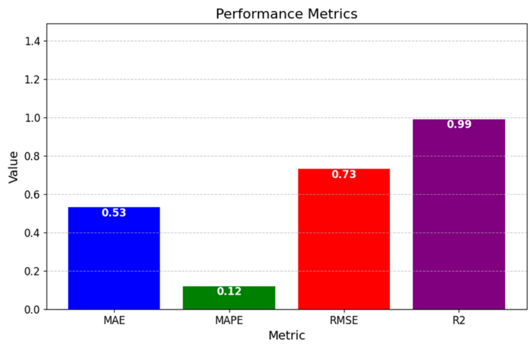

Figure 4. Performance Metrics Linear Regression Algorithm with Eight Variables and 50-fold Cross Validation

Figure 4 shows that the linear regression algorithm is known to have an accuracy level of MAE values of 0.53 kg, MAPE of 0.12%, RMSE of 0.73 kg, and R-square of 0.99.

Figure 5 shows performance metrics results with seven variables and 50-fold cross-validation using the linear regression algorithm.

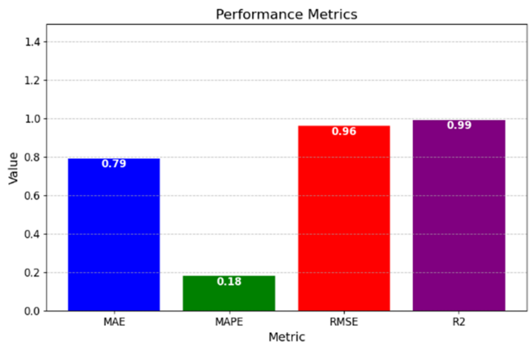

Figure 5. Performance Metrics Linear Regression Algorithm with Seven Variables and 50-fold Cross Validation

Figure 5 shows that the linear regression algorithm is known to have an accuracy level of MAE values of 0.79

kg, MAPE of 0.18%, RMSE of 0.96 kg, and R-square of 0.99.

Figure 6 shows performance metrics results with six variables and 50-fold cross-validation using the linear regression algorithm.

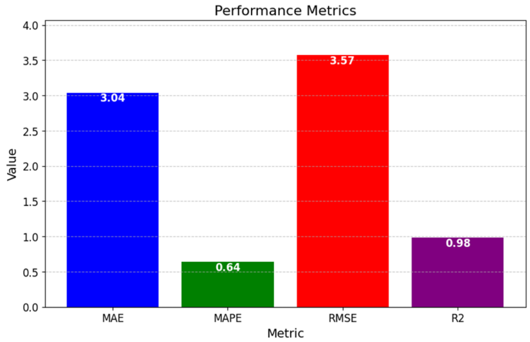

Figure 6. Performance Metrics Linear Regression Algorithm with Six Variables and 50-fold Cross Validation

Figure 6 shows that the linear regression algorithm is known to have an accuracy level of MAE values of 3.04 kg, MAPE of 0.64%, RMSE of 3.57 kg, and R-square of 0.98.

Figure 7 shows performance metrics results with five variables and 50-fold cross-validation using the linear regression algorithm.

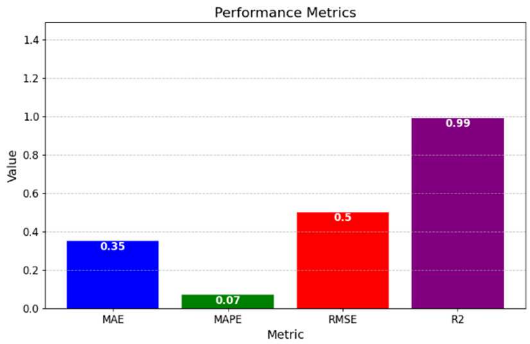

Figure 7. Performance Metrics Linear Regression Algorithm with Five Variables and 50-fold Cross Validation

Figure 7 shows that the linear regression algorithm is known to have an accuracy level of MAE values of 0.35 kg, MAPE of 0.07%, RMSE of 0.5 kg, and R-square of 0.99.

3.2 Random Forest Regressor Algorithm

Figure 8 shows performance metrics results with nine variables and 50-fold cross-validation using the random forest regressor algorithm.

Figure 8 shows that the random forest regressor algorithm is known to have an accuracy level of MAE values of 2.4 kg, MAPE of 0.54%, RMSE of 3.1 kg, and R-square of 0.99.

Figure 9 shows performance metrics results with eight variables and 50-fold cross-validation using the random forest regressor algorithm.

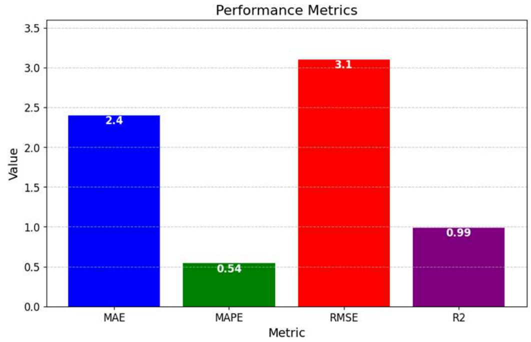

Figure 8. Performance Metrics Random Forest Regressor Algorithm with Nine Variables and 50-fold Cross Validation

Figure 9 shows that the random forest regressor algorithm is known to have an accuracy level of MAE values of 4.5 kg, MAPE of 1.02%, RMSE of 5.2 kg, and R-square of 0.96.

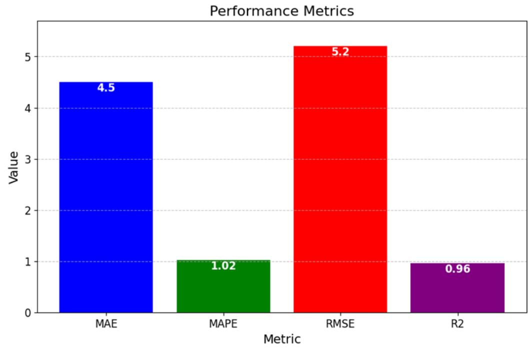

Figure 9. Performance Metrics Random Forest Regressor Algorithm with Eight Variables and 50-fold Cross Validation

Figure 10 shows performance metrics results with seven variables and 50-fold cross-validation using the random forest regressor algorithm.

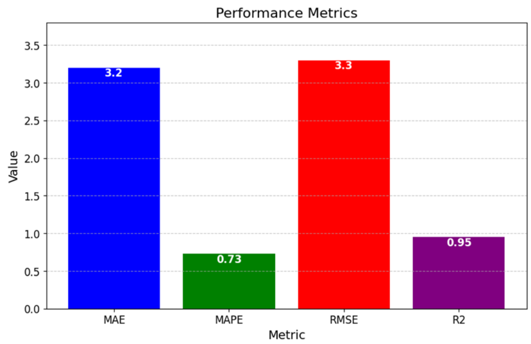

Figure 10. Performance Metrics Random Forest Regressor Algorithm with Seven Variables and 50-fold Cross Validation

Figure 10 shows that the random forest regressor algorithm is known to have an accuracy level of MAE values of 3.2 kg, MAPE of 0.73%, RMSE of 3.3 kg, and R-square of 0.95.

Figure 11 shows performance metrics results with six variables and 50-fold cross-validation using the random forest regressor algorithm.

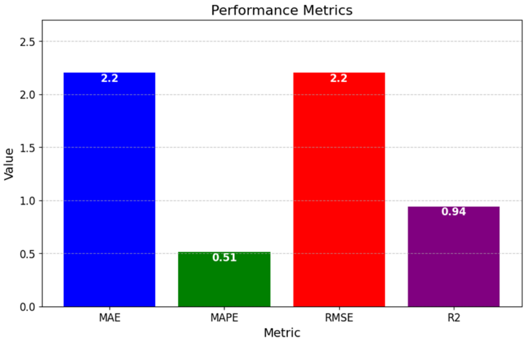

Figure 11. Performance Metrics Random Forest Regressor Algorithm with Six Variables and 50-fold Cross Validation

Figure 11 shows that the random forest regressor algorithm is known to have an accuracy level of MAE values of 2.2 kg, MAPE of 0.51%, RMSE of 2.2 kg, and R-square of 0.94.

Figure 12 shows performance metrics results with five variables and 50-fold cross-validation using the random forest regressor algorithm.

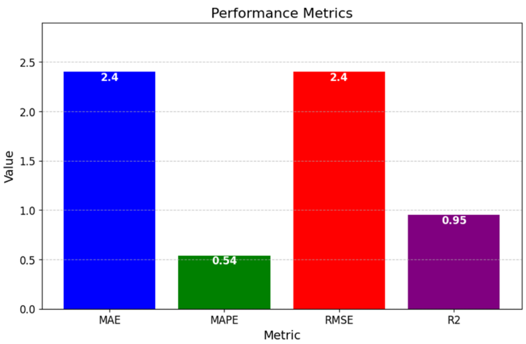

Figure 12. Performance Metrics Random Forest Regressor Algorithm with Five Variables and 50-fold Cross Validation

Figure 12 shows that the random forest regressor algorithm is known to have an accuracy level of MAE values of 2.4 kg, MAPE of 0.54%, RMSE of 2.4 kg, and R-square of 0.95.

3.3 Relationship Between Variables

Figure 13 shows a pattern of positive relationships between the nine variables and the live weight variable.

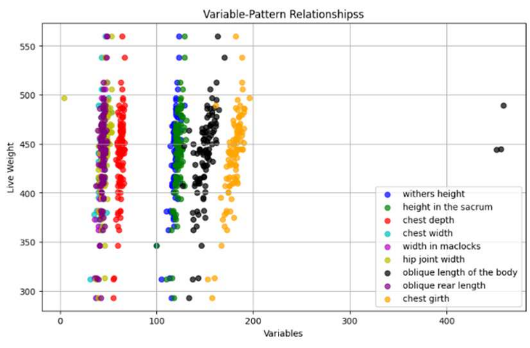

Figure 13. Variable-Pattern Relationships

It can be seen from Figure 13 that the relationship between the variables (1) withers height, (2) hip height, (3) chest depth, (4) heart girth, (5) ilium width, (6) hip joint width, (7) oblique body length, (8) hip length, and (9) chest width has excellent correlation performance with different color signs to the Live Weithg variable.

3.4 Best Evaluation Model Value

Table 2 shows the results of the best evaluation model values with five variables and 50-fold cross-validation using the linear regression algorithm as follows:

Table 2. Best Evaluation Model Value

MAE	MAPE	RMSE	R-square
0.35 kg	0.07%	0.5 kg	0.99

Table 2 shows that the linear regression model is superior in predicting outcomes with striking evaluation value results. With the best MAE value of 0.35 kg, MAPE of 0.07%, RMSE of 0.5 kg, and R-square reaching 0.99, linear regression proves its accuracy compared to random forest.

This advantage is due to the simple and linear nature of linear regression, which effectively captures the relationship between input and output variables. These results are in line with the literature highlighting the usefulness of linear regression in cases where the relationships between variables tend to be linear. With a more straightforward approach, linear regression may be more agile and efficient, avoiding overfitting that may occur in more complex models such as random forests.

Although random forests have advantages in dealing with data complexity and non-linear patterns, this research shows that for specific datasets, linear regression is more suitable and provides more accurate and stable results. These findings contribute to our understanding of the contexts in which linear regression may be a superior choice in predictive modeling.

4. Conclusions

The results of the cattle weight prediction experiment using the linear regression method produced the best mean absolute error (MAE) value of 0.35 kg, mean absolute percentage error (MAPE) of 0.07%, root mean square error (RMSE) of 0.5 kg, and R-square of 0.99 compared to the random forest regressor method, and the correlation between variables is perfect in predicting cow weight. These results confirm that linear regression not only provides accurate predictions but is also stable and consistent in measuring the variability between predictions and actual data in the cattle farming industry more effectively and efficiently. This research only focuses on how to produce minor mean absolute error (MAE) error values, so model optimization has not been carried out, thus opening opportunities for further research in the future to test the model in different environmental conditions or with various cattle breeds.

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