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Digital Innovation in Predicting Live Body Weight of Female Ongole-Grade Cattle Using Pixel Area and Morphometric Analysis

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ABSTRACT

This study is the first to validate digital morphometric analysis combined with linear, quadratic, and allometric regression models for predicting body weight (BW) in Ongole-Grade cattle under smallholder field conditions, focusing on productive-age females as breeding stock. The objective was to develop and validate regression-based predictive models using digital image-derived traits and to compare their accuracy with conventional measurements and existing formulas. A total of 204 female Ongole-Grade cattle were measured manually and with ImageJ-based morphometrics. All measurements were standardized to a reference age of 12 months using an allometric adjustment. Traits assessed included BW, body length (BL), withers height (WH), chest girth (CG), chest depth (CD), rump height (RH), and rump width (RW). BW showed strong positive correlations with morphometric traits (r=0.80–0.91), with CG as the strongest predictor. Conventional and image-derived measurements were comparable for WH, BL, CG, CD, and RH (p>0.05), while RW differed significantly (p=0.01). Mean differences were small (≤0.8 cm), and the mean absolute percentage error (MAPE) ranged from 1.76% to 4.89%, confirming the reliability of digital imaging. The quadratic regression model (CG^2 + BL^2), which outperformed the linear, allometric, and pixel-area–based approaches (MAPE=4.68%; R^2=0.93). In contrast, the Schoorl formula substantially overestimated BW (MAPE=37.76%), while the pixel-area model showed only moderate accuracy (R^2=0.63). Overall, digital morphometric analysis provides a novel, non-invasive, and cost-effective tool for cattle monitoring, with refinement of pixel area-based features recommended.

Keywords: body weight; image analysis; morphometrics; Ongole-grade

INTRODUCTION

Preserving the genetic diversity of indigenous cattle breeds is essential for sustainable livestock development, particularly in tropical settings such as Indonesia. Breeds such as Bali, Madura, and Ongole-Grade have developed adaptive traits that enable them to thrive under challenging environmental conditions, including high humidity, endemic diseases, and inconsistent feed availability (Adinata *et al.*, 2023; Mohan *et al.*, 2025). These traits—including disease resilience, reproductive efficiency, and environmental adaptability—are critical for food security and the livelihoods of rural communities. Despite their importance, uncontrolled crossbreeding and introgression with exotic *Bos taurus* breeds—driven by market preferences and limited enforcement of breeding regulations—continue to threaten the genetic integrity of local populations (Mohan *et al.*, 2025).

In response, the Indonesian Ministry of Agriculture has implemented a series of conservation efforts that emphasize breed identification and structured improvement programs based on field-applicable phenotypic and morphometric data (Azis *et al.*, 2023; Hartatik *et al.*, 2018). Among native breeds, Ongole-Grade cattle have been prioritized due to their high meat quality and ability to adapt to low-input farming systems (Maharani *et al.*, 2018). However, uptake at scale remains limited by practical constraints at the smallholder level. Many farmers operate under resource-scarce conditions where conventional livestock monitoring tools such as weighing scales and manual morphometry are either unavailable or labor-intensive. These methods may also cause stress to animals, especially in remote or underdeveloped areas lacking technical personnel, and can increase handling stress (Putra *et al.*, 2025; Ünal *et al.*, 2025).

Emerging digital tools for livestock phenotyping offer a promising path forward. Recent studies have demonstrated the utility of image-based morphometric analysis for estimating body dimensions using open-source software such as ImageJ, providing low-cost, non-invasive assessments. This approach minimizes animal handling and operator bias, and allows standardized data capture even in field conditions. When paired with machine learning models such as LightGBM and XGBoost, image-derived body traits have achieved high predictive accuracy in estimating live body weight (Herrera-Camacho *et al.,* 2025). RGB-D imaging and deep learning further enhance precision and scalability (Gritsenko *et al.,* 2023; Ruchay *et al.,* 2022). Key body traits like chest girth, body length, and withers height consistently correlate with body weight and are frequently used in both conventional and digital measurement systems (Haq *et al.,* 2020; Tutkun, 2019). Multivariate approaches such as Principal Component Analysis (PCA) and allometric modeling can further improve predictive performance when appropriately validated (Azis *et al.,* 2023; Kuswati *et al.,* 2022; Silva *et al.,* 2024).

Although these digital approaches have been successfully applied in *Bos taurus* and *Bos indicus* cattle under controlled conditions (Bousbia *et al.,* 2021; Cappai *et al.,* 2019; Firdaus *et al.,* 2024), their validation in Indonesian indigenous breeds, particularly the Ongole-Grade, remains limited under smallholder-relevant field conditions. Previous studies often overlooked the breed-specific, environmental, and management challenges typical of smallholder systems. Moreover, pixel area–based models have shown lower accuracy than morphometric-based models, but their comparative performance in Ongole-Grade cattle under field conditions remains insufficiently characterized.

To our knowledge, this study is among the first to integrate digital morphometric analysis using ImageJ with multiple regression approaches—including quadratic models—for predicting the live body weight of Ongole-Grade cattle under real smallholder farming conditions, addressing the limited validation in Indonesian indigenous breeds. The novelty of this research lies in the use of productive-age female cattle, which dominate smallholder herds and play a central role in breeding and household economies, combined with the development of breed-specific, low-cost, and non-invasive predictive models tailored for rural settings and supported by a standardized field imaging protocol. The objective of this study was to develop and validate regression-based predictive models (linear, allometric, and quadratic) for estimating live body weight in female Ongole-Grade cattle using digital morphometric analysis, and to compare the accuracy of these models with conventional measurements.

MATERIALS AND METHODS

Study Area and Sample

The research was conducted at two distinct sites: the Village Breeding Center in Napis Village, Tambakrejo District, Bojonegoro Regency, East Java (-7.3320318 S, 111.5643664 E) with 108 head of cattle, and the Technical Unit for Animal Breeding and Forage Development in Tuban, East Java, Indonesia (-6.9056977 S, 112.0550822 E) with 96 head of cattle. Napis Village is located in the hill area of the Kendeng Mountains with varied topography, whereas the UPT in Tuban is situated on relatively flat land with more stable environmental conditions. Despite these topographical differences, all sampled cattle at both sites were raised under the same intensive management system. In total, 204 female Ongole-Grade cattle aged 12 to 36 months were observed. The focus on female cattle was chosen because they are more relevant for phenotypic selection as breeding stock, given that females are prioritized as prospective dams (Gunawan & Putera, 2016). Accordingly, body weight and morphometric traits were measured to evaluate their potential as breeding animals. The samples were selected using purposive sampling with the criteria that the cattle were non-pregnant and had one to three pairs of permanent incisors (PI). The age of the cattle was further verified through farmer interviews and examination of permanent incisors. Breed identification was conducted visually in accordance with the Indonesian National Standard (SNI) 7651-5:2020, which defines the distinctive characteristics of Ongole-Grade cattle as predominantly white to grayish coat color, long dewlap, prominent hump, short neck, elongated horned head, and black pigmentation around the eyes, muzzle, ears, and tail switch.

Morphometric measurements of Ongole-Grade cattle were conducted using the tuberosities, processes, and articulations of the observed Ongole-Grade cattle (Figure 1). Morphometric measurements are body weight (BW), body length (BL), withers height (WH), chest girth (CG), chest depth (CD), rump height (RH), and rump width (RW) (Ali *et al.,* 2024; Kuswati *et al.,* 2022). The measurement results were recorded in a form. A 300 dpi camera was used to capture the images, with the cattle positioned upright and in the flat area so that the resulting photo is accurately centered within the photo frame. A comparative scale was placed on the cattle's body as a means to calibrate the size during

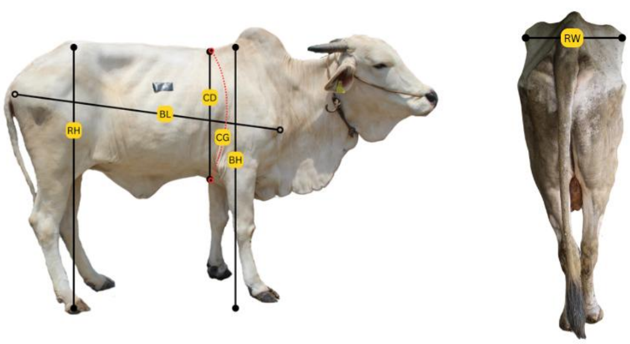

Figure 1. Morphometric measurement of the observed Ongole-Grade cattle. BL: Measured from the tuber humerus to the tuber ischium; CG: Measured using a measuring tape encircling the chest just behind the forelegs; CD: Measured vertically from the dorsal to the ventral side, immediately behind the os scapula; WH: Measured vertically from the dorsal point just behind the os scapula to the ground; RH: Measured vertically from the os coxae (tuber coxae) to the ground; RW: The distance across the hips; and BW: Measured using a cattle scale with a maximum capacity of 1,500 kg.

image processing. The illustration of the image capture process can be seen in Figure 2. The images of the cattle were analyzed using the ImageJ application (Brito *et al.*, 2022; Cortivo *et al.*, 2016).

All images were analyzed using ImageJ software (https://imagej.nih.gov) (Rueden *et al.*, 2017). First, the images were converted into digital format and imported into the software. A calibration step was performed by selecting a reference object of known dimensions (a ruler measuring 48 mm × 100 mm) placed in the image. The scale was set by marking the two ends of the ruler, allowing ImageJ to convert pixel distances into real-world units (centimeters). After calibration, the appropriate measurement tool from the ImageJ toolbar was used to define the start and end points of each measurement (body length, chest girth, and related morphological traits). The software displayed the results in pixels, which were subsequently converted into centimeters using the calibration scale ratio. An illustration of the image pixel extraction and conversion process is presented in Figure 3.

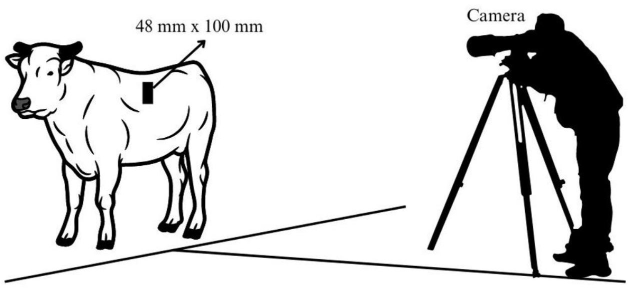

Figure 2. The schema for capturing Ongole Grade cattle images and the placement of the comparative scale. Image capture setup for Ongole Grade cattle with placement of a 48 × 100 mm scale as a size reference. Photos were taken using a Canon 500D digital camera.

Data Analysis

The stages to determine the most suitable variables for predicting BW in Ongole-Grade cattle were conducted using the stepwise selection method. This method helps select independent variables that have the most significant impact on predicting the dependent variable (BW) by involving relevant and significant variables. Prior to model selection, all morphometric traits were adjusted to a standard age of 12 months using size-correction based on allometric scaling (Klingenberg, 2016; Lleonart *et al.*, 2000).

$$Y_{std12} = Y_{Obs}\left(\frac{Age_{12}}{Age_{obs}}\right)^{b}$$

Y_{obs} was the observed morphometric measurement, Age_{ref} was the reference age (12 months), Age_{obs} was the actual observed age of the animal (in months), and b was the allometric growth exponent (BW= 0.46; WH= 0.09; BL= 0.15; CG= 0.16; CD= 0.17; RH= 0.08; RW= 0.24).

By using this method, the most significant and relevant variables that influence the BW of Ongole-Grade cattle can be identified. The estimation analysis of BW in this study employed simple linear regression (1), multiple linear regression (2), quadratic linear regression (3), allometry (4) (Vanvanhossou *et al.*, 2018), and the Schoorl formula (5).

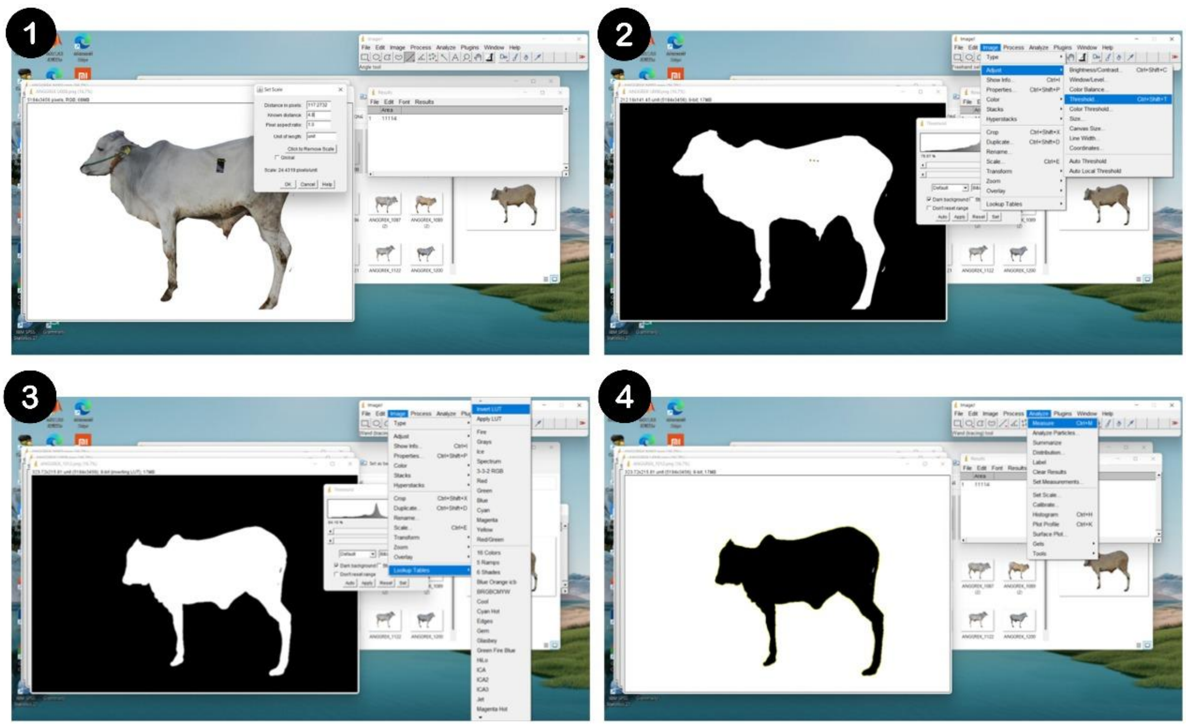

Figure 3. ImageJ steps for pixel area analysis of the observed Ongole-Grade cattle. (1) Prepare cattle image with background removed and calibrate using known scale; click Set Scale to calibrate the image using the 48 × 100 mm reference ruler; (2) Convert to 8-bit grayscale to standardize pixel intensities and adjust Threshold to isolate the animal silhouette; (3) Invert LUT to turn image black; and (4) Measure pixel area of the selected region.

$$\mathrm{BW} = \mathrm{b_0} + \mathrm{b_1X} + \varepsilon_0 \quad (1)$$

$$\mathrm{BW} = \mathrm{b_0} + \mathrm{b_1X_1} + \mathrm{b_2X_2} + \cdots + \mathrm{b_iX_i} + \varepsilon_0 \quad (2)$$

$$\mathrm{BW} = \mathrm{b_0} + \mathrm{b_1X^2} + \mathrm{b_2X} + \varepsilon_0 \quad (3)$$

$$\mathrm{BW} = \mathrm{aX^b} + \varepsilon_0 \quad (4)$$

$$\mathrm{BW} = {(\mathrm{CG_{cm}} + 22)^2}/{100} \quad (5)$$

Where BW was the live body weight of the cattle; X_1 to X_i was the body measurement; b_0 was the intercept or the allometric coefficient; b_1 to b_i was the regression coefficients of body weight on X, or the allometric exponent; and ε0 was the residual error.

To evaluate the prediction quality of regression models and compare various models to find the most suitable one for the given data, the following formulas are used: root mean square error (RMSE) (1), mean absolute percentage error (MAPE) (2), and correlation coefficient. The lower the values of RMSE and MAPE and the closer the value of the correlation coefficient is to 1, the better the predictive performance of the regression model. We performed the Student's t-test hypothesis test with a significance level of 0.05.

$$RMSE = \sqrt{\sum \frac{(Y'-Y)^2}{n}} \quad (1)$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \frac{|\hat{Y}_t - Y_t|}{Y_t} x100 \quad (2)$$

where Y′ was the predicted value, Y was the true value (actual value), and n was the number of data (sample size).

The t-test statistic is used to test the difference in the mean values of a variable between two groups, one using digital images and the other using conventional measurements. The t-test formula, according to Pituch & Stevens (2016), is as follows:

$$t = \frac{\bar{X_1} - \bar{X}_2}{\sqrt{\frac{(n_1-1)S_1^2 + (n_2-1)S_2^2}{n_1+n_2-2}\left(\frac{1}{n_1}+\frac{1}{n_2}\right)}}$$

where X_1 is the mean value of conventional measurements, X_2 is the mean value of digital image measurements, and n is the group size (number of cattle in the group).

RESULTS

This study assessed the feasibility of using digital image-based morphometric analysis for predicting live body weight (BW) and body dimensions in female Ongole-Grade cattle. The findings are presented in three parts: correlations between BW and morphometric traits, comparison of conventional and digital measurements, and performance of various prediction models.

Correlation between BW and Morphometric Traits

To further investigate the association between live body weight (BW) and morphometric traits, a correlation analysis was undertaken. This analysis elucidates the magnitude and direction of the relationships among the examined variables, thereby delineating which morphometric dimensions represent the most robust predictors of BW. The corresponding results are presented in Table 1.

Table 1 presents the correlation matrix between body weight (BW) and morphometric traits of female Ongole-Grade cattle. BW showed strong positive correlations with all morphometric variables. The highest correlation was observed between BW and chest girth (CG; r=0.91), followed by body length (BL; r=0.89), rump width (RW; r=0.86), chest depth (CD; r=0.84), and withers height (WH; r=0.84). BW also showed a moderately high correlation with rump height (RH; r=0.80). Among morphometric traits, WH and RH exhibited the strongest inter-trait correlation (r=0.94), while other variables also demonstrated strong positive associations (r=0.70–0.87).

These findings highlight that chest girth and body length are the most reliable predictors of BW in Ongole-Grade female cattle, suggesting their potential use as practical indicators for on-field body weight estimation. The overall strong correlations among morphometric traits further indicate their interdependence in determining growth and body development patterns (Table 1).

Comparison of Conventional and Digital Measurements

To evaluate the reliability of digital morphometric techniques, a comparative analysis was conducted between conventional manual measurements and those derived from digital image–based methods. This comparison was designed to assess the degree of agreement and potential discrepancies between the two approaches, thereby validating the applicability of digital morphometry for predicting body weight. The results of this comparison are presented in Table 2.

Table 2 shows the comparison between conventional measurements and computer vision-based predictions of morphometric traits in female Ongole-Grade cattle. The mean values of withers height (WH), body length (BL), chest girth (CG), chest depth (CD), and rump height (RH) obtained by computer vision were not significantly different from the conventional measurements (p>0.05). The mean absolute percentage

Table 1. Matrix correlation based on body weight and morphometric Ongole-Grade female cattle

Variables	BW	WH	BL	CG	CD	RH	RW
BW	1.00						
WH	0.84	1.00					
BL	0.89	0.87	1.00				
CG	0.91	0.76	0.76	1.00			
CD	0.84	0.82	0.86	0.81	1.00		
RH	0.80	0.94	0.84	0.70	0.77	1.00	
RW	0.86	0.74	0.80	0.85	0.80	0.65	1.00

Note: BW = body weight, BL = body length, WH = withers height, CG = chest girth, CD = chest depth, RH = rump height, RW = rump width.

Table 2. Comparison of body size values of cattle Ongole-Grade conventional measurement and digital image

Variables	Conventional method		Computer vision		MAPE (%)	RMSE	MAE	p-value (p<0.05)
	Mean ± SD	SEM	Mean ± SD	SEM				
WH	114.8 ± 7.47	0.52	114.8 ± 7.94	0.56	1.76	3.09	2.02	0.96
BL	111.9 ± 9.61	0.67	112.9 ± 9.65	0.68	3.44	5.14	3.77	0.12
CG	138.0 ± 10.31	0.72	137.5 ± 11.81	0.83	3.67	6.89	5.07	0.62
CD	54.2 ± 5.35	0.38	54.6 ± 5.38	0.38	3.36	2.83	1.80	0.36
RH	121.0 ± 8.25	0.58	120.4 ± 8.54	0.60	2.25	3.99	2.71	0.40
RW	32.0 ± 3.38^{a}	0.24	32.8 ± 3.59^{b}	0.25	4.89	2.61	1.54	0.01

Note: a,b Means in the same column with different superscript differ significantly p<0.05; SEM = standard error of mean; SD = standard deviation; MAPE = mean absolute percentage error; RMSE = root mean square error; MAE = mean absolute error; BL = body length, WH = withers height, CG = chest girth, CD = chest depth, RH = rump height, RW = rump width.

error (MAPE) values for these traits ranged from 1.76% (WH) to 3.67% (CG), with root mean square error (RMSE) between 2.83 and 6.89, and mean absolute error (MAE) between 1.80 and 5.07. These results indicate good agreement between conventional and computer vision-derived measurements.

In contrast, rump width (RW) showed a significant difference between conventional and computer vision methods ($p<0.05$), although the error values (MAPE=4.89%, RMSE=2.61, MAE=1.54) remained within an acceptable range. These findings confirm that most morphometric traits can be accurately predicted using computer vision, except RW, which requires further refinement of measurement techniques (Table 2).

Model Performance for Body Weight Prediction

To rigorously evaluate the predictive capacity of various statistical approaches, multiple models were developed to estimate live body weight using selected morphometric traits. The performance of these models was assessed through established indicators of accuracy and reliability, thereby facilitating a critical comparison of their effectiveness under field conditions. The results of this evaluation are presented in Table 3.

Table 3 presents the body weight (BW) of female Ongole-Grade cattle estimated using different predictive models. The mean conventional BW was 191.5 ± 49.7 kg. Predictions based on pixel area and chest girth (CG) alone showed relatively higher errors, with MAPE values of 12.86% and 9.29%, respectively. The linear model using only CG (MAPE=10.25%) provided moderate accuracy, while combining CG and body length (BL) improved the performance substantially (MAPE=5.76%, RMSE=15.30, MAE=10.86, R^2=0.91).

The quadratic model of CG yielded a similar level of accuracy to the allometric model, whereas the quadratic model incorporating both CG and BL (CG^2+BL^2) demonstrated the highest predictive accuracy (MAPE=4.68%, RMSE=13.21, MAE=9.23, R^2=0.93). In contrast, the Schoorl formula resulted in a significant overestimation of BW (255.4 ± 36.6 kg, $p<0.01$), with the highest error indices (MAPE=37.76%, RMSE=69.05, MAE=64.74). These results indicate that prediction models combining CG and BL, particularly the quadratic model, provide the most reliable estimates of cattle BW, while the Schoorl formula is less suitable for Ongole-Grade cattle (Table 3).

DISCUSSION

The present study highlights the potential of digital image-based morphometric analysis as a practical and reliable approach for estimating live body weight (BW) in female Ongole-Grade cattle. As shown in Table 1, BW exhibits strong correlations with key morphometric traits—most notably chest girth (CG), body length (BL), and rump width (RW)—which is consistent with prior evidence in *Bos indicus* and crossbred populations that linear morphometrics are robust, biologically meaningful predictors of BW (Haq *et al.*, 2020; Tutkun, 2019). The very high inter-trait associations (WH–RH) also suggest potential multicollinearity, indicating that future work should complement regression with

Table 3. Measurements of cattle's body weight using different methods

Methods	Formula models	BW (Kg)				
		Mean ± SD	MAPE (%)	RMSE	MAE	R2
BW	-	191.5 ± 49.7^{a}	-	-	-	-
Pixels area	Y = 13.179 + 0.02052X	191.5 ± 39.2^{a}	12.86	30.18	23.99	0.63
Allometry (CG)	$Y = 0.000459CG^{2.625}$	190.1 ± 41.5^{a}	9.29	23.95	18.47	0.77
Linear model CG	Y = -330.069 + 3.799CG	191.5 ± 43.2^{a}	10.25	24.74	19.83	0.75
Linear model CG + BL	Y = -443.918 + 2.629CG + 2.476BL	191.5 ± 47.3^{a}	5.76	15.3	10.86	0.91
Linear model CG^2	$Y = 411.017 + (-6.990CG) + 0.038998CG^2$	191.5 ± 43.8^{a}	9.38	23.6	18.56	0.77
Linear model $CG^2 + BL^2$	$Y = 438.541 + (-6.022CG) + 0.031266CG^2 + (-2.651BL) + 0.02264BL^2$	191.5 ± 48.0^{a}	4.68	13.21	9.23	0.93
Schoorl formula	BW = ((CG + 22)2)/100	255.4 ± 36.6^{b}	37.76	69.05	64.74	

Note: a,b Means in the same row with different superscript differ significantly ($p<0.01$); SD = standard deviation; MAPE = mean absolute percentage error; RMSE = root mean square error; BW = body weight; BL = body length; CG = chest girth.

dimensionality-reduction (PCA) or regularization (e.g., ridge/LASSO) and report variance inflation factors (VIF) to quantify collinearity to stabilize coefficient estimates when predictors are strongly collinear (Silva, *et al.*, 2024; Kuswati *et al.*, 2022).

Agreement between manual and image-derived measurements was generally high (Table 2). Beyond summary statistics, two mechanistic factors explain this convergence. First, traits such as WH and BL are predominantly captured in planes that minimize foreshortening in a standardized lateral view; consequently, modest pose deviations introduce limited perspective error. Second, the single trait that differed significantly—RW—depends on pelvic landmarks that are more susceptible to out-of-plane rotation and self-occlusion, making it inherently sensitive to camera angle and animal stance. This pattern mirrors prior validations showing that image-based morphometrics can reproduce tape measures when capture geometry is controlled, whereas landmarks affected by yaw/roll or parallax are more error-prone (Guimarães *et al.*, 2020; Pugliesi *et al.*, 2024; Tasdemir *et al.*, 2011; Zhang *et al.*, 2018). Methodological reviews likewise emphasize that 2D pipelines cannot directly encode three-dimensional quantities (circumferences) and are vulnerable to pose-dependent distortions, underscoring the need to standardize calibration markers/scales, camera distance and height, and animal alignment to reduce bias and improve reproducibility (Ma *et al.*, 2024) and thus require conventional measures or 3D proxies for circumferential traits. To strengthen reproducibility in future work, agreement should be reported using Bland–Altman bias and limits of agreement and Lin's concordance correlation coefficient (CCC), alongside explicit documentation of fixed camera distance/height, scale markers, and animal alignment. In practice, posture-aware capture and the use of depth or 3D modalities (or multi-view reconstruction) can further enhance robustness and downstream BW-estimation accuracy (Hou *et al.*, 2023; Ruchay *et al.*, 2022; Xiong *et al.*, 2023).

Regarding predictive performance (Table 3), models with quadratic terms in CG^2+BL^2 provided the best overall accuracy (R^2=0.93), outperforming linear and allometric alternatives. This superiority is mechanistically coherent with geometric scaling: CG approximates thoracic circumference, so cross-sectional area scales with CG^2, while mass is linked to body volume (area × length). Quadratic forms thus capture curvature introduced by size-related (allometric) variation across ages and management conditions (Klingenberg, 2016; Lleonart *et al.*, 2000). By contrast, the Schoorl formula overestimated BW, which aligns with reports that classical single-measure tape formulas—calibrated in different populations—can be biased when applied to Indonesian cattle, including Bali and crossbred types (Azis *et al.*, 2023). The pixel-area model yielded only moderate accuracy, which is expected because 2D area lacks depth information and is highly sensitive to pose, perspective, and occlusion; multiple studies show that integrating depth- or 3D-based features, or volumetric proxies, improves performance beyond 2D area alone (Hou *et al.*, 2023; Ruchay *et al.*, 2022; Wang *et al.*, 2021; Xiong *et al.*, 2023). Notably, the quadratic specification achieves this improvement with a parsimonious two-predictor structure, facilitating field deployment. Consistent with this evidence, refining pixel-based approaches via higher-resolution imaging, standardized capture, and machine-learning frameworks (e.g., tree boosting) is a reasonable next step (Herrera-Camacho *et al.*, 2025; Vázquez-Martínez *et al.*, 2024).

Beyond accuracy, the workflow offers clear practical advantages: it is non-invasive, reduces handling stress and logistical constraints, and leverages accessible tools (consumer-grade cameras and open-source software such as ImageJ), aligning with smallholder realities (Maharani *et al.*, 2018). With targeted training and simple capture checklists, farmers and field technicians can implement routine growth monitoring to inform selection, feeding, and health decisions.

Finally, our findings reinforce that, while pixel area alone is insufficient for precise BW prediction, morphometric models—especially those combining CG and BL—are reliable for Ongole-Grade cattle (Firdaus *et al.*, 2024; Lukuyu *et al.*, 2016; Vanvanhossou *et al.*, 2018). To our knowledge, this is the first study to directly compare conventional tape-based and image-derived morphometrics for BW prediction in this breed, and the pattern we observe accords with broader literature showing CG (alone or with BL) among the most informative linear predictors, whereas single two-dimensional (2D) area metrics are typically surpassed by multivariate morphometrics or depth-/volume-based imaging features (Cominotte *et al.*, 2023; Kamchen *et al.*, 2021; Xiong *et al.*, 2023). Future work should therefore prioritize protocol standardization, data collection across wider populations and production systems, and benchmarking of learning-based models under cross-site validation to ensure reproducibility and generalizability (Herrera-Camacho *et al.*, 2025; Wang *et al.*, 2021).

CONCLUSION

Body weight in productive-age female Ongole-Grade cattle can be estimated reliably from a small set of morphometric traits. A quadratic model based on chest girth and body length offers the most practical and accurate solution and can be implemented with image-based measurements. Routine use should include basic age standardization and standardized imaging procedures. This approach is suitable for smallholder decision-making and provides a foundation for scalable digital phenotyping in livestock.

CONFLICT OF INTEREST

The authors declare that they have no financial, personal, or other conflicts of interest with any individuals or organizations that could inappropriately influence or bias the content of this manuscript.

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DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the authors used Grammarly to refine sentence structure and Elicit to assist literature searches. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

REFERENCES

Adinata, Y., Noor, R. R., Priyanto, R., Cyrilla, L., & Sudrajad, P. (2023). Morphometric and physical characteristics of Indonesian beef cattle. Archives Animal Breeding, 66(2), 153–161. https://doi.org/10.5194/aab-66-153-2023

Ali, M. I., Atmaja, B. M., Hidayatulloh, R., Herviyanto, D., & Kuswati. (2024). Sustainability strategy and development of village breeding center: Evaluation of morphometric characteristics of female Peranakan Ongole cattle in Napis village. Journal of Tropical Animal Production, 25(2), 117–130. https://doi.org/10.21776/ub.jtapro.2024.025.02.3

Azis, R., Ciptadi, G., Wahjuningsih, S., Hariyono, D. N. H., Tribudi, Y. A., & Nurgiartiningsih, V. M. A. (2023). Prediction of body weight from body measurements in Bali cattle of Indonesia using regression analysis. Advances in Animal and Veterinary Sciences, 11(9), 1486–1491. https://doi.org/10.17582/journal.aavs/2023/11.9.1486.1491

Bousbia, A., Boudalia, S., Gueroui, Y., Hadded, K., Bouzaoui, A., Kiboub, D., & Symeon, G. (2021). Use of multivariate analysis as a tool in the morphological characterization of the main indigenous bovine ecotypes in northeastern Algeria. PLOS ONE, 16(7), e0255153. https://doi.org/10.1371/journal.pone.0255153

Brito, L. S., Cavalcante, A. K. D. S., Rodrigues, A. S., Ferraz, P. A., Bittencourt, R. F., Junior, L. D. P. M., Vasconcelos, I. C., Carôso, B. S. S., Lents, M. P., Loiola, M. V. G., Madrigal-Valverde, M., Bastos, M. C. B. B., De Brito, O. S., & Filho, A. D. L. R. (2022). Evaluation of ImageJ software in ultrasonic image analysis: follicular and luteal morphological characteristics of cattle. Animal Reproduction Science, 236, 106907. https://doi.org/10.1016/j.anireprosci.2021.106907

Cappai, M. G., Gambella, F., Piccirilli, D., Rubiu, N. G., Dimauro, C., Pazzona, A. L., & Pinna, W. (2019). Integrating the RFID identification system for Charolaise breeding bulls with 3D imaging for virtual archive creation. PeerJ Computer Science, 5, e179. https://doi.org/10.7717/peerj-cs.179

Cominotte, A., Fernandes, A., Dórea, J., Rosa, G., Torres, R., Pereira, G., Baldassini, W., & Machado Neto, O. (2023). Use of biometric images to predict body weight and hot carcass weight of Nellore cattle. Animals, 13(10), 1679. https://doi.org/10.3390/ani13101679

Cortivo, P. D., Dias, E., Barcellos, J. O. J., Peripolli, V., Costa Jr., J. B. G., Dallago, B. S. L., & McManus, C. M. (2016). Use of thermographic images to detect external parasite load in cattle. Computers and Electronics in Agriculture, 127, 413–417. https://doi.org/10.1016/j.compag.2016.07.002

Firdaus, F., Atmoko, B., Ibrahim, A., Nugroho, T., Baliarti, E., & Panjono, P. (2024). A first meta-analysis study on body weight prediction method for beef cattle based on digital image processing. Journal of Advanced Veterinary and Animal Research, 11(1), 153–160. https://doi.org/10.5455/javar.2024.k760

Gritsenko, S., Ruchay, A., Kolpakov, V., Lebedev, S., Guo, H., & Pezzuolo, A. (2023). On-barn forecasting beef cattle production based on automated non-contact body measurement system. Animals, 13(4), 611. https://doi.org/10.3390/ani13040611

Guimarães, T. P., Restle, J., Moreira, K. K. G., Freitas Neto, M. D. D., Souza, L. F. N., Moraes, É. G., & Fernandes, J. J. R. (2020). Temperament and performance of Nellore bulls classified for residual feed intake in a feedlot system. Anais Da Academia Brasileira de Ciências, 92(3), e20190222. https://doi.org/10.1590/0001-3765202020190222

Gunawan, A., & Putera, B. W. (2016). Aplikasi linier ukuran tubuh untuk seleksi fenotipik bibit induk sapi PO di kabupaten Bojonegoro. Jurnal Ilmu Produksi dan Teknologi Hasil Peternakan, 4(3), 375–378. https://doi.org/10.29244/jipthp.4.3.375-378

Haq, M. S., Budisatria, I. G. S., Panjono, P., & Maharani, D. (2020). Prediction of live body weight using body measurements for Jawa Brebes (Jabres) cattle. The Journal of Animal and Plant Sciences, 30(3), 552–559. https://doi.org/10.36899/JAPS.2020.3.0065

Hartatik, T., Putra, D. E., Volkandari, S. D., Kanazawa, T., & Sumadi, S. (2018). Genotype analysis of partial growth hormone gene (GH891|MspI) in Pesisir cattle and Simmental-pesisir crossbred cattle. Journal of the Indonesian Tropical Animal Agriculture, 43(1), 1. https://doi.org/10.14710/jitaa.43.1.1-8

Herrera-Camacho, J., Tırınk, C., Parra-Cortés, R. I., Bayyurt, L., Uskenov, R., Omarova, K., Makhanbetova, A., Chekirov, K., & Chay-Canul, A. J. (2025). Body weight estimation in Holstein × *zebu* crossbred heifers: Comparative analysis of XGBoost and LightGBM algorithms. Veterinary Medicine and Science, 11(4), e70422. https://doi.org/10.1002/vms3.70422

Hou, Z., Huang, L., Zhang, Q., & Miao, Y. (2023). Body weight estimation of beef cattle with 3D deep learning model: PointNet++. Computers and Electronics in Agriculture, 213, 108184. https://doi.org/10.1016/j.compag.2023.108184

Kamchen, S. G., Santos, E. F. D., Lopes, L. B., Vendrusculo, L. G., & Condotta, I. C. F. S. (2021). Application of depth sensor to estimate body mass and morphometric assessment in Nellore heifers. Livestock Science, 245, 104442. https://doi.org/10.1016/j.livsci.2021.104442

Klingenberg, C. P. (2016). Size, shape, and form: Concepts of allometry in geometric morphometrics. Development Genes and Evolution, 226(3), 113–137. https://doi.org/10.1007/s00427-016-0539-2

Kuswati, K., Ali, M. I., & Wahyuni, R. D. (2022). Morphometric characteristics of Galekan cattle breed base on principle component analysis (PCA). Jurnal Ilmu-Ilmu Peternakan, 32(1), 1–12. https://doi.org/10.21776/ub.jiip.2022.032.01.01

Lleonart, J., Salat, J., & Torres, G. J. (2000). Removing allometric effects of body size in morphological analysis. Journal of Theoretical Biology, 205(1), 85–93. https://doi.org/10.1006/jtbi.2000.2043

Lukuyu, M. N., Gibson, J. P., Savage, D. B., Duncan, A. J., Mujibi, F. D. N., & Okeyo, A. M. (2016). Use of body linear measurements to estimate liveweight of crossbred dairy cattle in smallholder farms in Kenya. Springer Plus, 5(1), 63. https://doi.org/10.1186/s40064-016-1698-3

Ma, W., Qi, X., Sun, Y., Gao, R., Ding, L., Wang, R., Peng, C., Zhang, J., Wu, J., Xu, Z., Li, M., Zhao, H., Huang, S., & Li, Q. (2024). Computer vision-based measurement techniques for livestock body dimension and weight: A review. Agriculture, 14(2), 306. https://doi.org/10.3390/agriculture14020306

Maharani, D., Fathoni, A., Sumadi, S., Hartatik, T., & Khusnudin, M. (2018). Identification of MC4R gene and its association with body weight and body size in Kebumen Ongole Grade cattle. Journal of the Indonesian Tropical Animal Agriculture, 43(2), 87–93. https://doi.org/10.14710/jitaa.43.2.87-93

Mohan, K., Kumar, P., & Kundu, A. (2025). Comparative analysis of the physical and phenotypic traits of native cattle (*Bos indicus*) in the Tarai region of north Bihar for conservation. Veterinary World, 18(1), 95–101. https://doi.org/10.14202/vetworld.2025.95-101

Pituch, K. A., & Stevens, J. P. (2016). Applied multivariate statistics for the social sciences: Analyses with SAS and IBM's SPSS (Sixth edition). Routledge, Taylor and Francis Group.

Pugliesi, G., Feltrin, I. R., Mattos, A. C. D., Silva, A. G., Morelli, K. G., Nishmura, T. K., & Sales, J. N. D. S. (2024). Evolution over the last 40 years of the assisted reproductive technologies in cattle—The Brazilian perspective for embryo transfer and resynchronization programs (part II). Animal Reproduction, 21(3), e20240058. https://doi.org/10.1590/1984-3143-ar2024-0058

Putra, W. P. B., Hartati, H., Margawati, E. T., Mariyono, M., Maulana, T., & Tyasi, T. L. (2025). Polymorphism of splicing factor 3A subunit 3/PstI gene and its association with the performance of Madura cows (*Bos indicus*). Veterinary World, 8(5), 1306–1312. https://doi.org/10.14202/vetworld.2025.1306-1312

Ruchay, A., Kober, V., Dorofeev, K., Kolpakov, V., Gladkov, A., & Guo, H. (2022). Live weight prediction of cattle based on deep regression of RGB-D images. Agriculture, 12(11), 1794. https://doi.org/10.3390/agriculture12111794

Rueden, C. T., Schindelin, J., Hiner, M. C., DeZonia, B. E., Walter, A. E., Arena, E. T., & Eliceiri, K. W. (2017). ImageJ2: ImageJ for the next generation of scientific image data. BMC Bioinformatics, 18(1), 529. https://doi.org/10.1186/s12859-017-1934-z

Silva, F. G., Carreira, E., Ramalho, J. M., Correia, T., Meira, M., Conceição, C., Silva, S. R., Pereira, A. M. F., & Cerqueira, J. L. (2024). Predicting body weight in pre-weaned Holstein–friesian calves using morphometric measurements. Animals, 14(14), 2129. https://doi.org/10.3390/ani14142129

Tasdemir, S., Urkmez, A., & Inal, S. (2011). Determination of body measurements on the Holstein cows using digital image analysis and estimation of live weight with regression analysis. Computers and Electronics in Agriculture, 76(2), 189–197. https://doi.org/10.1016/j.compag.2011.02.001

Tutkun, M. (2019). Estimation of live weight of Holstein-friesian bulls by using body linear measurements. Applied Ecology and Environmental Research, 17(2), 2257–2265. https://doi.org/10.15666/aeer/1702_22572265

Ünal, B., Güzel, B. C., Çakar, B., Aslan Kanmaz, Y., Yiğit, F., Gündemir, O., & Spataru, M.-C. (2025). Shape and size variations in the astragalus of large and small bovids. Animals, 15(3), 425. https://doi.org/10.3390/ani15030425

Vanvanhossou, S. F. U., Diogo, R. V. C., & Dossa, L. H. (2018). Estimation of live bodyweight from linear body measurements and body condition score in the West African Savannah Shorthorn cattle in North-West Benin. Cogent Food & Agriculture, 4(1), 1549767. https://doi.org/10.1080/23311932.2018.1549767

Vázquez-Martínez, I., Tirink, C., Casanova-Lugo, F., Pozo-Leyva, D., Mota-Rojas, D., Kalmagambetov, M. B., Uskenov, R., Gülboy, Ö., Garcia-Herrera, R. A., & Chay-Canul, A. J. (2024). Predicting the body weight of crossbred Holstein × Zebu dairy cows using multivariate adaptive regression splines algorithm. Journal of Dairy Research, 91(3), 267–272. https://doi.org/10.1017/S0022029924000578

Wang, Z., Shadpour, S., Chan, E., Rotondo, V., Wood, K. M., & Tulpan, D. (2021). Applications of machine learning for livestock body weight prediction from digital images. Journal of Animal Science, 99(2), skab022. https://doi.org/10.1093/jas/skab022

Xiong, Y., Condotta, I. C. F. S., Musgrave, J. A., Brown-Brandl, T. M., & Mulliniks, J. T. (2023). Estimating body weight and body condition score of mature beef cows using depth images. Translational Animal Science, 7(1), txad085. https://doi.org/10.1093/tas/txad085

Zhang, A. L. N., Wu, B. P., Jiang, C. X. H., Xuan, D. C. Z., Ma, E. Y. H., & Zhang, F. Y. A. (2018). Development and validation of a visual image analysis for monitoring the body size of sheep. Journal of Applied Animal Research, 46(1), 1004–1015. https://doi.org/10.1080/09712119.2018.1450257