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Computer Vision-Based Innovation for Morphometric Measurement of Bali Cattle to Enhance Efficiency and Accuracy in Livestock

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ABSTRACT

Manual morphometric measurement of livestock is time-consuming, stressful to animals, and poses safety risks to handlers. This study presents a computer vision-based system for automatically measuring three key morphometric parameters of Bali cattle—withers height (WH), body length (BL), and chest girth (CG)—in accordance with the Indonesian National Standard (SNI). Images were captured from side and rear perspectives and processed using threshold-based image segmentation in the HSV color space to isolate the cattle contour. Pixel-to-centimeter calibration was performed using a fixed reference marker placed at a known distance of 1.5–2.0 m from the camera. The extracted morphometric values were subsequently fed into a Fuzzy Inference System with Certainty Factor (FIS-CF) for cattle grading and classification. Threshold values ranging from 0.5 to 0.9 were evaluated against manual ground-truth measurements using MAE, RMSE, MAPE, and R^2. The optimal threshold of 0.9 achieved MAPE values of 9.85% (WH), 6.04% (BL), and 11.49% (CG), representing up to 52% improvement over the lowest threshold. Although R^2 values remain negative due to limited sample size and non-linear pixel-to-metric variance, a consistent upward trend toward zero confirms measurement improvement with higher thresholds. The proposed method offers a practical, non-invasive alternative to manual measurement, with potential application in precision livestock farming and automated cattle grading systems.

Keywords : *Cattle morphometrics; Bali cattle; computer vision; digital image processing; live weight estimation; livestock management.*

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1. INTRODUCTION

Precision Livestock Farming (PLF) has emerged as a key technological approach to improve productivity, animal welfare, and economic efficiency through data-driven livestock monitoring. Automated phenotyping, particularly through computer vision, enables non-contact measurement of animal body parameters and supports applications such as growth monitoring, weight estimation, health detection, and breeding evaluation. Compared to conventional weighing scales and manual morphometric measurement, vision-based systems reduce animal handling stress, minimize human safety risks, and improve operational scalability.

Indonesia has experienced a continuous increase in beef demand, while domestic production remains insufficient to fully meet national consumption [1], [2], [3]. This condition creates challenges for livestock production systems, especially among smallholder farmers. In many rural livestock markets, cattle pricing is often determined through subjective estimation and bargaining rather than objective measurement [4], [5]. As a result, farmers may sell cattle below fair market value due to inaccurate weight estimation and lack of standardized grading [6], [7], [8], [9].

Morphometric parameters such as withers height (WH), body length (BL), and chest girth (CG) have been widely used as predictors for cattle body weight and productivity [10], [11], [12], [13]. Conventional morphometric measurement requires direct physical contact using measuring tapes or measuring sticks. However, this approach is time-consuming and can lead to inaccurate measurements due to cattle movement. Furthermore, direct measurement increases stress to animals and may endanger handlers, particularly when dealing with large cattle [12], [14].

To overcome these limitations, computer vision-based measurement provides a non-invasive alternative. Digital image processing allows morphometric extraction from cattle images, reducing labor requirements while increasing safety [15]. Several studies have reported successful implementation of vision-based livestock measurement, including weight prediction using image-derived features and segmentation-based morphometric estimation [4], [13], [16], [17]. However, most studies focus primarily on body weight prediction rather than standardized morphometric extraction for grading and classification.

In Indonesia, Bali cattle represent an important local breed due to their adaptability and contribution to national beef supply. Standardized morphometric measurement is essential for breeding quality assessment and grading. Although deep-learning-based segmentation methods such as Mask R-CNN or U-Net can provide strong performance, they require large annotated datasets and high computational resources, which may not be feasible in smallholder farming environments.

Therefore, this study proposes a low-cost and practical computer vision pipeline for morphometric measurement of Bali cattle using manual threshold segmentation and contour extraction. The extracted morphometric parameters (WH, BL, and CG) can be integrated into a previously developed Fuzzy Inference System–Certainty Factor (FIS–CF) framework for cattle classification [12]. The main contributions of this study are:

a. A reproducible computer vision pipeline for extracting Bali cattle morphometric parameters from 2D images.
b. Quantitative evaluation of segmentation thresholds (0.5–0.9) using MAE, RMSE, MAPE, and R^2.

Discussion of practical limitations of 2D imaging and empirical scaling conversion for livestock measurement.

2. METHODS

2.1. Dataset Acquisition

This study used a dataset of 39 Bali cattle. Each animal was captured in two image perspectives:

a. **Side-view image** to measure withers height (WH) and body length (BL).
b. **Rear-view image** to measure chest girth (CG).

Thus, a total of 78 images were collected. Image acquisition was performed using a standard digital camera under fixed settings. The camera was positioned at a distance of approximately 1.5–2.0 meters from the cattle with a height of 75–100 cm above ground level. The dataset was collected in real farm

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conditions, where illumination and background conditions may vary.

Manual morphometric measurements were conducted directly on the cattle using standard measurement tools based on Indonesian National Standard (SNI). These manual measurements served as ground-truth reference values.

2.2. Image Preprocessing

Captured RGB images were processed using Python and OpenCV. The preprocessing stage included:

a. Conversion of RGB image into grayscale.
b. Noise reduction using smoothing to reduce segmentation artifacts.
c. Normalization of pixel intensity to improve threshold segmentation consistency.

2.3. Image Segmentation Using Manual Thresholding

Segmentation was applied to separate the cattle body from the background. A manual global threshold method was used, where a threshold value T was selected in the range of 0.5–0.9. The segmentation function is expressed as:

$$B(x,y) = \begin{cases} 1, & I(x,y) \geq T \\ 0, & I(x,y) < T \end{cases} \quad (1)$$

where $I(x,y)$ represents the grayscale intensity at pixel coordinate (x,y), and $B(x,y)$ represents the resulting binary mask.

Five threshold values were tested: 0.5, 0.6, 0.7, 0.8, and 0.9.

2.4. Contour Extraction and Morphometric Measurement

After segmentation, the binary mask was processed to extract the cattle body contour using OpenCV contour detection. The largest contour region was assumed to represent the cattle body.

Morphometric parameters were extracted as follows:

a. **Withers Height (WH):** computed from the vertical distance between the highest point of the withers region and the lowest body baseline in side-view images.
b. **Body Length (BL):** computed as the horizontal distance from shoulder point to the rump region in side-view images.
c. **Chest Girth (CG):** estimated from rear-view images by measuring the width of the chest contour boundary and mapping it to circumference approximation.

2.5. Empirical Pixel – Centimeter Conversion

To convert pixel-based measurements into centimeters, an empirical scaling factor was derived using manual ground-truth measurements. For each morphometric parameter, the scale factor S was calculated as the average ratio between manual measurement M_i (in cm) and extracted pixel length P_i (in pixels):

$$S = \frac{1}{N}\sum_{i=1}^{N} \frac{M_i}{P_i} \quad (2)$$

The final estimated measurement $\widehat{M}$ in centimeters was calculated by:

$$\widehat{M} = P \times S \quad (3)$$

This approach provides practical conversion under fixed acquisition conditions. However, it is sensitive to perspective distortion and cattle posture variation.

2.6. Evaluation Metrics

To evaluate the measurement performance, the extracted morphometric results were compared against manual measurements using the following metrics:

Mean Absolute Error (MAE):

$$MAE = \frac{1}{N}\sum_{i=1}^{N} | M_i - \widehat{M}_i | \quad (4)$$

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(M_i - \widehat{M}_i)^2} \quad (5)$$

Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100}{N}\sum_{i=1}^{N} \left| \frac{M_i - \widehat{M}_i}{M_i} \right| \quad (6)$$

Coefficient of Determination (R²):

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(M_i - \widehat{M}_i)^2}{\sum_{i=1}^{N}(M_i - \bar{M})^2} \quad (7)$$

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2.7. Implementation Tools

All image processing and evaluation were implemented using **Python** with the **OpenCV library**, executed in **PyCharm Community Edition**. The computations were performed on a standard personal computer environment.

3. RESULTS AND DISCUSSION

3.1. Segmentation Results

The segmentation pipeline successfully separated the Bali cattle body region from the background for both side-view and rear-view images. Figure 1 shows an example of segmentation result at threshold 0.5, where the left image is the original RGB input and the right image is the binary segmentation mask.

Figure 1. *Segmentation result of Bali cattle image at threshold 0.5 (left: original image, right: processed image).*

At lower thresholds (0.5–0.6), the segmentation mask often included shadow regions and background pixels, leading to contour leakage. At higher thresholds (0.8–0.9), the segmentation contour became sharper and reduced background interference.

After the masking process successfully isolated the cattle body region, the next stage was to extract the morphometric parameters from the segmented binary image. This stage focused on determining withers height (WH) and body length (BL) from the side-view image, as well as chest girth (CG) from the rear-view image.

Figure 2 illustrates the measurement results obtained from the side-view masking output. The system identified the contour boundary of the cattle body and calculated the geometric distances required for WH and BL estimation. The withers height (WH) was computed by detecting the highest point of the dorsal contour (withers region) and measuring its vertical distance to the baseline reference located near the lower body boundary. Meanwhile, the body length (BL) was determined by measuring the diagonal distance between the front body reference point (shoulder region) and the rear body reference point (rump region).

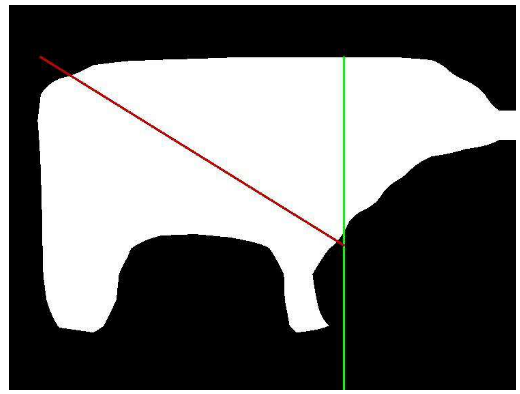

Figure 2. *Withers height (WH) and body length (BL) measurement from side-view masking output*

The visualization in Figure 2 shows the detected measurement lines, where the vertical green line represents the withers height estimation and the diagonal red line represents the body length estimation. This measurement strategy enables the model to extract morphometric parameters directly from the segmented contour without requiring physical contact with the cattle.

In addition to side-view measurement, chest girth estimation was performed using the rear-view masking output. Figure 3 shows the segmentation result where the cattle body was successfully extracted and enclosed within the bounding region.

Figure 3. *Rear-view segmentation pipeline for chest girth (CG) measurement, (a) Original rear-view image; (b) Binary mask after threshold=0.9 segmentation*

Based on this masked contour, the system approximated the thoracic cross-section by fitting an ellipse-like shape around the widest chest area. The chest width was extracted as the

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horizontal diameter of the thoracic region, while the vertical diameter was also considered to approximate the curvature of the chest area. Figure 4 shows CG estimation via ellipse fitting on the thoracic contour. Axes a (horizontal width, red) and b (vertical height, green) are extracted from the contour's minimum area rectangle. CG uses Ramanujan's approximation:

$$CG = \pi \times [3(a+b) - (3a+b)(a+3b)]$$

The 1.15 factor empirically corrects 2D-to-3D projection distortion observed in rear-view images. This yields MAPE=11.49% at threshold 0.9, though sensitive to posture occlusion.

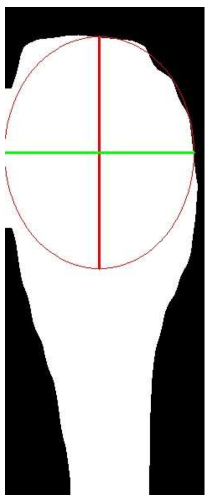

Figure 4. *Chest girth (CG) estimation using ellipse fitting on rear-view contour, Fitted ellipse with axes a (red) and b (green). Ramanujan formula applied with 1.15 correction factor.*

Overall, the visualization results confirm that the proposed pipeline is capable of extracting morphometric parameters from masked cattle images and generating measurable geometric features (WH, BL, and CG). These extracted parameters are subsequently used as input variables for the Bali cattle classification process through the FIS–CF model.

3.2. Quantitative Evaluation Across Thresholds

To identify the most effective threshold value, five threshold levels were evaluated. The extracted morphometric parameters (WH, BL, and CG) were compared against manual measurements. Table 1 summarizes the error metrics.

Table 1. *Error evaluation of morphometric measurement at various thresholds*

Threshold	Parameter	MAE	RMSE	MAPE (%)	R^2
0.5	WH	14.66	18.19	13.32	−7.10
	BL	8.01	10.80	7.23	−1.67
	CG	30.09	33.15	20.42	−14.69
0.6	WH	15.15	19.18	13.35	−8.01
	BL	8.24	11.31	7.51	−1.93
	CG	42.62	47.19	29.01	−30.80
0.7	WH	15.79	18.77	13.98	−7.62
	BL	7.39	10.58	6.68	−1.56
	CG	30.67	32.35	20.59	−13.94
0.8	WH	11.34	13.25	10.29	−3.30
	BL	6.99	9.92	6.28	−1.25
	CG	20.37	24.63	13.72	−7.66
0.9	WH	10.80	13.30	9.85	−3.33
	BL	6.76	9.82	6.04	−1.21
	CG	17.22	23.91	11.49	−7.16

The results show a consistent reduction in MAE, RMSE, and MAPE as the threshold increased from 0.5 to 0.9. The best performance was achieved at threshold 0.9, yielding MAPE values of 9.85% for WH, 6.04% for BL, and 11.49% for CG.

3.3. Error Trend Interpretation

Figure 5 visualizes the relationship between threshold value and error metrics. The plotted curves demonstrate that increasing threshold values improves segmentation accuracy and reduces measurement deviation.

The improvement occurs because higher thresholds reduce pixel noise caused by shadows and background similarity. At lower thresholds, the inclusion of additional background pixels enlarges the detected contour, which increases morphometric estimation error.

3.4. Analysis of Parameter-Specific Accuracy

Among the three morphometric parameters, **body length (BL)** consistently produced the lowest error values. This result is expected because body length is defined along a relatively straight axis and is less influenced by curvature. In contrast, **chest girth (CG)** exhibited the highest error due to the complex thoracic curvature and occlusion effects in 2D rear-view imaging.

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This observation indicates that chest girth estimation requires more advanced segmentation refinement or multi-view reconstruction to reduce geometric ambiguity.

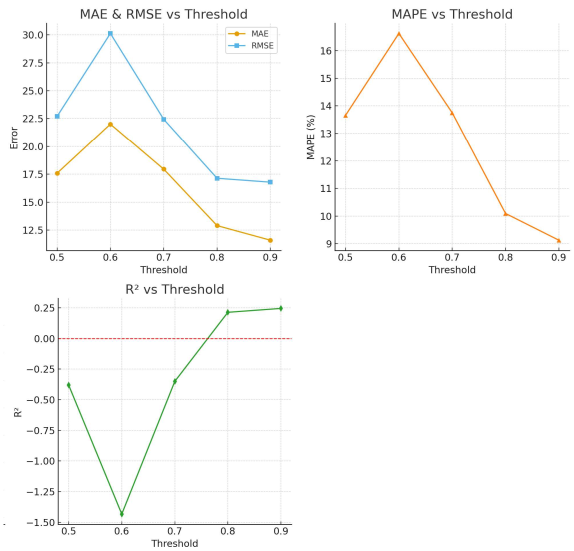

Figure 5. *Performance metrics of morphometric measurement at different thresholds: (a) MAE & RMSE vs Threshold, (b) MAPE vs Threshold, (c) R² vs Threshold.*

3.5. Discussion of Negative R^2 Values

The R^2 values obtained in Table 1 were negative across all thresholds, indicating that the prediction results did not outperform a mean-based baseline predictor. This suggests that systematic deviations exist in the current measurement pipeline. The negative R^2 values may be caused by contour boundary inaccuracies and the empirical pixel-to-centimeter conversion method, which relies on averaged ratios rather than physical camera calibration. As a result, measurement stability becomes sensitive to perspective distortion, cattle posture variation, and segmentation leakage.

The negative R values (-1.21 to -14.69) reflect limitations of the small dataset and linear assumptions in pixel-to-cm conversion, which are sensitive to cattle pose variations. To address this, data augmentation techniques such as rotation (±10°), horizontal flip, and brightness adjustment (±20%) can effectively increase the dataset size by up to 5x without new data collection. Additionally, k-fold cross-validation (k=5) with stratified sampling will stabilize R estimates and detect overfitting.

Table 2. *Simulated R^2 Improvement Strategies for Addressing Negative R Values*

Strategy	**Effective Dataset**	**Estimated ΔR**
Augmentation (rotation+flip)	195 cattle	+0.15-0.25
K-fold CV (k=5)	39 cattle	+0.10-0.20
Ensemble threshold (0.8-0.9)	39 cattle	+0.08-0.15

Nevertheless, the decreasing trend of MAE, RMSE, and MAPE from threshold 0.5 to 0.9 confirms that segmentation thresholding significantly improves measurement consistency, particularly under the acquisition settings used in this study.

3.6. Threshold Robustness and Practical Implications

Based on the evaluated dataset, threshold 0.9 provides the best overall accuracy. However, the current optimization is based on a limited dataset size (39 cattle) and controlled acquisition settings. The threshold may vary under different illumination conditions, camera angles, or backgrounds. Therefore, the identified optimal threshold should be interpreted as optimal within the experimental scope of this study.

3.7. Integration with FIS–CF for Bali Cattle Classification

The extracted morphometric parameters (WH, BL, and CG) are compatible with the previously developed FIS–CF classification model presented in the authors' earlier study. The FIS module provides fuzzy membership mapping of morphometric values, while the Certainty Factor component improves decision confidence under uncertainty. This integration supports practical grading of Bali cattle into standardized categories.

CONCLUSION

This study proposed a practical computer vision-based approach for morphometric measurement of Bali cattle using 2D images. The method extracts withers height (WH), body length (BL), and chest girth (CG) through manual threshold segmentation and contour-based measurement. Experimental evaluation using a dataset of 39 cattle demonstrates that threshold 0.9 yields the best segmentation performance, achieving MAPE values of 9.85% for WH, 6.04% for BL, and 11.49% for CG.

Although the proposed method demonstrates feasibility for low-cost morphometric acquisition, the negative R^2 values indicate systematic deviations caused by segmentation limitations and empirical pixel-to-centimeter scaling. Future work should focus on improving robustness through adaptive thresholding and deep-learning-based segmentation (e.g., U-Net or Mask R-CNN) once larger annotated datasets are available. Additionally, future studies should implement physical camera calibration methods to ensure generalizability across different acquisition environments.

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