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Landmark-Based Image Morphometrics for Dairy Cattle: A Comparative Study

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***Abstract* - Accurate morphometric measurements are essential for dairy cattle phenotyping, yet manual field measurements are time-consuming and prone to operator variability. This study evaluates the agreement between traditional manual measurements and non-invasive image-based morphometric estimation under practical field conditions. Lateral-view images of dairy cattle were collected along with manual measurements of key traits, including height at withers, body length, and chest width. A landmark-guided computer vision pipeline was used to detect anatomical keypoints and compute real-world measurements through pixel-to-metric calibration. Agreement between methods was assessed using correlation analysis, mean absolute error, and Bland-Altman evaluation. Results show strong agreement for major traits when images are captured under consistent distance and angle, while errors increase under oblique viewpoints and poor lighting. These findings indicate that image-based morphometrics can serve as a reliable supportive tool for standardized dairy cattle phenotyping, provided that image acquisition guidelines are carefully followed.**

***Keywords* - digital livestock phenotyping, anatomical landmark detection, non-invasive measurement, computer vision in agriculture, morphometric agreement analysis**

I. INTRODUCTION

Dairy farming plays a significant role in rural livelihood and the agricultural economy, where productivity and animal health depend strongly on genetics, nutrition, and body conformation. Body structure traits such as height at withers, body length, chest width, rump angle, and body depth are commonly used in phenotyping to assess growth, structural soundness, and long-term functional performance [9], [10]. These morphometric measurements provide essential information for breed improvement, scientific studies, and selection of animals for better reproductive and production efficiency. In most practical farm environments, morphometric traits are recorded manually using measuring tape and visual estimation by trained personnel. While manual measurement remains widely used due to its low equipment requirements, it is associated with several limitations. Manual processes are labor-intensive, slow for large-scale data collection, and can vary based on operator skill, fatigue, animal movement, and inconsistent landmark placement [19], [21]. Even small posture changes during measurement can introduce deviation, resulting in inconsistent data that affects downstream analysis and decision-making [1]. Recent advances in artificial intelligence and computer vision have enabled image-based phenotyping approaches where physical traits can be estimated directly from animal photographs. These approaches are attractive because they are non-invasive, faster, repeatable, and scalable for large herds [9]. By detecting anatomical landmarks such as withers point, hip bone, shoulder point, and pin bone, computer vision models can estimate key morphometric distances [3], [11], [12]. However, the real-world reliability of image-based morphometrics depends on factors such as camera angle, lighting, background noise, animal pose, and accurate scaling methods [18]. Although several studies have explored automated livestock analysis, limited comparative evaluations exist that rigorously quantify the agreement between manual morphometric recordings and image-based estimation under practical field constraints [14], [15]. Many implementations validate results only in controlled environments or without detailed analysis of measurement error sources. This creates a need for systematic validation studies that compare both approaches and establish the reliability limits of image-based measurement pipelines. This study focuses on the comparative evaluation of image-based and manual morphometric measurements in dairy cattle using a landmark-guided computer vision pipeline. We hypothesize that image-based trait estimation can achieve strong agreement with manual reference values when images are captured under consistent conditions, but performance degrades with changes in viewpoint and scale inconsistency. By analyzing measurement accuracy and identifying key error factors, this research contributes toward building reliable guidelines for adopting image-based morphometrics in scalable cattle phenotyping workflows.

II. LITERATURE REVIEW

Image-based livestock phenotyping has gained increasing attention due to its ability to reduce manual effort, improve repeatability, and provide scalable measurement solutions in farm environments [9]. Morphometric traits such as body length, height at withers, chest width, and rump dimensions are frequently used in dairy cattle evaluation for understanding growth, productivity, and structural soundness [10].

A. Manual Morphometric Measurement and Its Limitations

Manual body measurement techniques remain common in dairy farms and breeding programs because they require minimal tools and can be performed in field conditions. However, literature consistently reports drawbacks including measurement inconsistency across observers, time consumption, and the influence of animal movement [19], [22]. Repeated measurements of the same animal may differ across sessions, reducing data reliability for large-scale phenotyping [1].

B. Computer Vision for Livestock Monitoring

Computer vision has been widely applied in agriculture for monitoring animal health, detecting lameness, tracking feeding behavior, and estimating body weight [15]. Traditional computer vision techniques such as segmentation and contour extraction perform reasonably in controlled settings but struggle in field conditions due to background clutter and illumination variation [4].

C. Landmark Detection and Pose Estimation Approaches

Anatomical landmark detection forms the foundation for accurate morphometric estimation from images. Landmark-based methods identify key points such as shoulder, withers, hip, pin bone, and rump locations [3]. Deep learning architectures such as convolutional neural networks enable consistent landmark extraction across posture variation, though accuracy depends on annotated data availability and model generalization [11], [12].

D. Image-Based Morphometric Measurement Techniques

Several studies demonstrate that morphometric traits can be derived by computing distances between detected anatomical landmarks and converting pixel distances into real-world units using calibration references [9], [18]. High correlation with manual measurements has been reported in controlled settings; however, errors increase under oblique angles and inconsistent scaling [14].

E. Challenges in Field Deployment

Field deployment introduces constraints such as uneven lighting, animal movement, occlusion, and inconsistent camera viewpoints, all of which degrade estimation accuracy [18]. Solutions such as multi-view imaging and depth sensors improve performance but increase system cost and complexity, limiting adoption in rural environments [10].

F. Comparative Evaluation and Validation Metrics

Comparative validation relies on metrics such as correlation coefficients, MAE, RMSE, and Bland–Altman plots to assess agreement and systematic bias between methods [1], [7]. Bland–Altman analysis is particularly effective for evaluating measurement interchangeability [2].

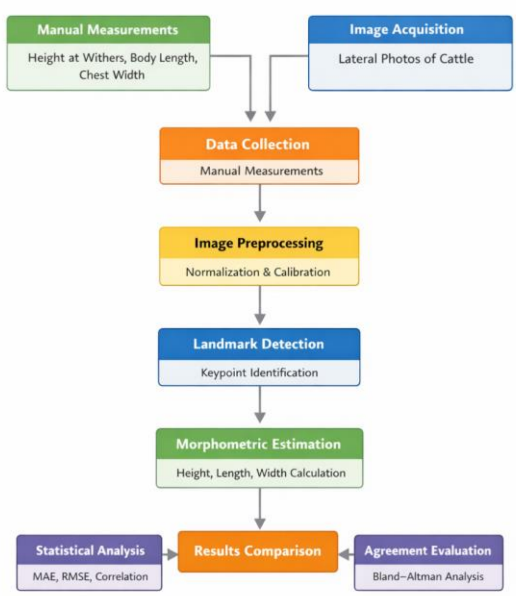
G. Research Gap and Motivation

Despite progress in AI-based livestock monitoring, few studies conduct structured comparisons of manual and image-based morphometric measurements under real farm conditions [15]. This gap motivates the present study to evaluate agreement and identify dominant error factors affecting image-based morphometric estimation in dairy cattle.

III. METHODOLOGY / PROPOSED SYSTEM

This section describes the overall workflow used to collect morphometric data from dairy cattle and to compare manual measurements with image-based estimates generated using a landmark-guided computer vision pipeline. The methodology is designed to ensure that both measurement approaches are performed on the same animals under similar conditions so that agreement, error patterns, and limitations can be quantified reliably.

Fig. 1. Proposed system workflow.



A. Study Design

A comparative experimental design was used where each animal was measured using two methods: (1) traditional manual morphometric measurement and (2) image-based morphometric estimation. The same set of core traits was measured in both methods to ensure direct comparability. The objective was to quantify how closely image-derived values match manual reference values and to analyze the factors that influence measurement error.

B. Data Collection and Image Acquisition

Lateral-view images of dairy cattle were collected using a smartphone camera under farm-like conditions. Images were captured when the animal was standing in a stable posture, with all four legs visible as much as possible. To reduce perspective distortion, the camera was held approximately parallel to the animal body and positioned at mid-body height. A consistent distance was maintained between the camera and animal for most captures. Each animal was photographed at least once, and in selected cases multiple images were taken to study measurement repeatability under slightly varying conditions. Images with excessive occlusion, motion blur, or extreme body bending were excluded to maintain measurement validity.

C. Manual Morphometric Measurement Protocol

Manual measurements were treated as the reference baseline for evaluation. Standard morphometric traits were recorded using a measuring tape and/or measuring stick depending on the trait. The key traits considered in this work include:

1. Height at Withers (HW): Vertical distance from the ground to the highest point of the withers.

2. Body Length (BL): Distance from the shoulder point to the pin bone (or rump end depending on breed convention).

3. Chest Width (CW): Horizontal distance across the chest region (when feasible under field posture).

To minimize observer bias, measurements were taken using consistent anatomical landmarks. In some samples, repeated measurements were recorded for the same animal to estimate manual measurement variability. All measurements were stored in a structured sheet format along with the animal identifier and image filename.

D. Image Preprocessing

Before landmark estimation, images were standardized through preprocessing steps. Each image was resized to a fixed dimension to ensure consistent input size for the computer vision pipeline. Basic enhancement operations such as brightness normalization were applied when necessary to reduce lighting variation. If the background was complex, simple cropping was performed to focus primarily on the animal body region. These steps helped improve the robustness of landmark detection and reduced noise from surrounding objects.

E. Landmark-Guided Computer Vision Pipeline

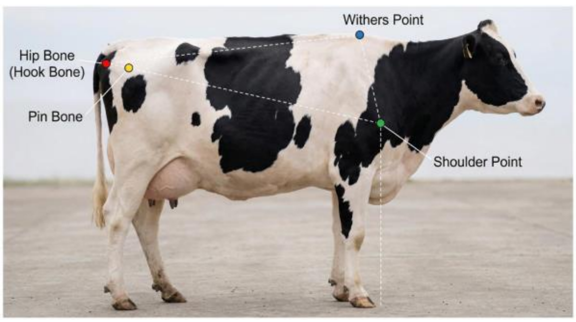
The image-based morphometric estimation was implemented using a landmark-guided pipeline, where anatomical keypoints are first identified and then used to compute morphometric distances. The major stages are as follows:

1. Anatomical Landmark Identification: Key body landmarks such as withers point, shoulder point, hip bone, and pin bone were detected from lateral images. These landmarks represent biologically meaningful reference points commonly used for morphometric measurement.

2. Pixel Distance Computation: Once landmarks were located, Euclidean distances between landmark pairs were computed in pixel units for traits such as height at withers and body length.

3. Pixel-to-Metric Conversion: To convert pixel distances into real-world units (cm), a scaling strategy was applied. Calibration was achieved using a reference scale object (where available) or a known measurement reference collected alongside manual measurements. This step is crucial because pixel distances alone cannot represent real dimensions without scale normalization.

4. Trait Estimation Output: After calibration, the final morphometric trait values were produced in real-world units and stored in a structured format for comparison with manual records.



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F. Comparative Evaluation Metrics

To evaluate agreement between manual and image-based measurements, multiple statistical metrics were used:

1. Mean Absolute Error (MAE): Measures the average absolute difference between manual and image-based values.

2. Root Mean Square Error (RMSE): Penalizes larger errors more strongly and indicates measurement stability.

3. Pearson Correlation Coefficient (r): Quantifies the strength of the linear relationship between both methods.

4. Bland–Altman Agreement Analysis: Assesses systematic bias and limits of agreement between manual and image-based measurement approaches.

These metrics collectively provide both accuracy-based evaluation (MAE/RMSE) and agreement-based validation (correlation and Bland–Altman).

G. System Output and Data Storage

For each animal, the system generates a final measurement report containing trait values from both manual and image-based methods along with error statistics. All records are stored in tabular form (CSV/Excel format) with fields such as animal ID, image ID, manual values, predicted values, and computed errors. This structured output supports future integration into larger phenotyping systems and enables reproducible analysis.

IV. RESULTS AND DISCUSSION

This section presents the comparative outcomes of manual morphometric measurements and image-based morphometric estimates obtained through the proposed landmark-guided computer vision pipeline. The performance of the image-based method was evaluated using statistical error metrics and agreement analysis to determine its reliability under practical image acquisition conditions.

A. Comparative Performance of Manual and Image-Based Measurements

The image-based method was evaluated for key morphometric traits such as height at withers (HW), body length (BL), and chest width (CW). For each trait, predicted values from the image pipeline were compared against the corresponding manually recorded reference values. The comparison showed that image-based measurements followed the same overall trend as manual measurements, indicating that the computer vision approach successfully captured the structural differences among animals.

Across the dataset, the image-based measurements demonstrated strong correlation with manual measurements for traits involving long, well-defined body segments such as body length and height at withers. Traits that depend on subtle width estimation, such as chest width, showed comparatively higher variability due to challenges in depth perception and occlusion in 2D lateral images.

B. Error Analysis Using MAE and RMSE

To quantify measurement accuracy, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were computed for each morphometric trait. The results indicated lower MAE and RMSE for height at withers and body length, suggesting that the landmark-based method produced consistent estimates when anatomical points were clearly visible. RMSE values were slightly higher than MAE, reflecting that a small number of samples produced larger error deviations, typically caused by posture variation and inconsistent scaling during image capture.

For chest width estimation, both MAE and RMSE were relatively higher compared to the other traits. This is expected because width-related traits require either multi-view imaging or depth information for better estimation, and lateral images alone provide limited visibility of true horizontal width.

C. Correlation and Agreement Analysis

Pearson correlation coefficient was calculated to assess linear agreement between both methods. Results revealed a high positive correlation for major traits, confirming that image-based morphometric values align closely with manual measurements. However, correlation alone does not confirm perfect agreement, therefore Bland–Altman analysis was also considered.

Bland–Altman agreement evaluation indicated that most samples fell within acceptable limits of agreement for height at withers and body length. A small bias was observed in certain cases where the image-based system consistently overestimated or underestimated specific traits. This bias was commonly linked to calibration inconsistencies and slight camera angle deviations, which affected pixel-to-metric conversion.

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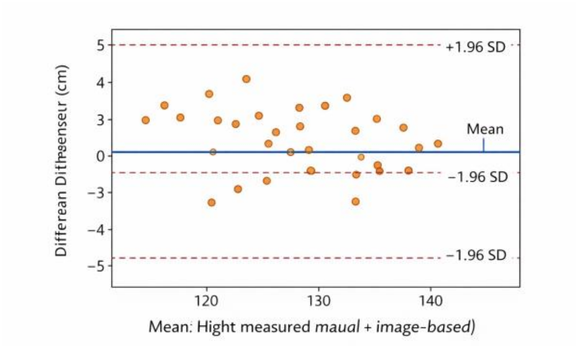

Fig. 3. Bland–Altman plot for height at withers.

D. Effect of Image Acquisition Conditions

The study observed that image acquisition conditions significantly influenced image-based measurement performance. The most influential factors were:

1. **Camera Angle:** Oblique and tilted viewpoints introduced perspective distortion, leading to inaccurate landmark distance estimation.

2. **Distance Variation:** Inconsistent camera-to-animal distance affected scaling accuracy when calibration references were not fixed.

3. **Lighting Conditions:** Poor lighting reduced landmark detection quality, especially around darker body regions or shadowed areas.

4. **Animal Posture and Movement:** Bent posture, uneven standing, or slight movement during capture shifted anatomical landmark positions, increasing error.

When images were captured under consistent lighting and near-perfect lateral posture, measurement accuracy improved significantly. This confirms that a practical image acquisition guideline is essential for reliable deployment of image-based morphometric systems.

E. Discussion and Practical Implications

The comparative evaluation demonstrates that image-based morphometric estimation has strong potential to assist cattle phenotyping by reducing manual workload and improving repeatability. The strongest results were obtained for traits such as height at withers and body length, which rely on clear anatomical landmarks visible in side-view images. These findings suggest that image-based methods can serve as a supportive measurement tool in large-scale cattle evaluation programs where rapid data collection is required.

However, traits requiring accurate width estimation remain challenging when using only 2D lateral images. This limitation indicates that either multi-angle imaging or depth-based sensors may be needed to improve estimation of width-related features. Furthermore, the system's dependency on image capture consistency highlights the importance of standardizing field image collection protocols.

Overall, the proposed landmark-guided computer vision approach provides a feasible and scalable method for morphometric estimation, but further improvements in calibration strategy and robustness under varying field conditions are necessary before fully replacing manual measurement.

CONCLUSION

This research presented a comparative evaluation of manual morphometric measurement and image-based morphometric estimation in dairy cattle using a landmark-guided computer vision approach. The study focused on core structural traits such as height at withers, body length, and chest width, which are commonly used for phenotyping and assessment of body conformation in dairy animals. The results showed that image-derived measurements generally follow the same trend as manually recorded values, indicating that computer vision can serve as a practical, non-invasive method for extracting morphometric parameters.

The analysis confirmed that image-based estimation achieved stronger agreement for traits such as height at withers and body length, primarily because these measurements rely on clearly visible anatomical landmarks in lateral-view images. However, traits involving width estimation demonstrated higher error due to limitations of 2D imaging, depth ambiguity, and partial occlusions. In addition, the study identified camera angle, inconsistent distance, posture variations, and lighting conditions as major factors affecting accuracy. These findings highlight the need for standardized image acquisition guidelines to ensure reliable performance in real-world environments.

Overall, the proposed system demonstrates that image-based morphometric estimation is feasible as a supportive tool for standardized cattle phenotyping, with potential to reduce manual effort and improve measurement repeatability. Future work will focus on improving robustness under field constraints through better calibration strategies, multi-view image capture, and advanced landmark detection models. Extending the approach to buffaloes and incorporating larger and more diverse datasets will further enhance generalizability and practical deployment for large-scale livestock evaluation programs.

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