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Evaluation of chest circumference in 3D lateral images of dairy cattle farming for body mass prediction

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Abstract. The advancement of precision livestock farming has underscored the importance of developing innovative and non-invasive methods for monitoring animal health and productivity. In this context, this study evaluated the application of computer vision to estimate the body mass (BM) of Holstein-Friesian dairy cows using 3D images captured laterally with the Intel RealSense D435i depth camera. The methodology involved correlating chest circumference (CC) measurements obtained in the field with those derived from lateral 3D images. A total of 250 animals were analyzed, with BM ranging from 420 to 855 kg, and the relationship between CC and BM was modeled using regression techniques. The results indicated a coefficient of determination ($R^2 = 0.88$) and a mean absolute percentage error (MAPE) of 3.94% for CC measured in the field. For CC derived from 3D images, R^2 was 0.847, with an MAPE of 5.29%. Although the 3D image-based method showed a slight reduction in accuracy, it demonstrated significant potential as a non-invasive and efficient alternative for estimating BM in dairy cows. Furthermore, the study highlights the role of 3D imaging technologies in acquiring detailed morphological data, enabling a more comprehensive understanding of body composition dynamics over time. These findings reinforce the potential of integrating digital technologies into dairy farming, promoting sustainable, precise, and labor-efficient management practices.

Key words: 3D images, computer vision, dairy cattle farming, non-invasive body mass estimation.

INTRODUCTION

Precision livestock farming has gained prominence in modern agriculture, offering innovative solutions for the efficient and sustainable management of herds. However, the diversity of production environments still poses a significant challenge to the implementation of intelligent systems for monitoring animal conditions (Qiao et al., 2023). In this context, the use of automation and sensor-based systems has proven to be a promising tool, enabling real-time individualized monitoring of cows. These systems also allow for the implementation of early warning alerts, facilitating managerial decision-making to mitigate anomalies and improve productivity. One of the key parameters in this monitoring process is body mass (BM), which plays a crucial role in assessing herd health status (Gebreyesus et al., 2023).

Measuring the body dimensions of cattle is a useful method for assessing their health and growth (Weales et al., 2021), and monitoring BM plays a crucial role in tracking productivity while providing insights into the energy balance of individual lactating cows (Mäntysaari & Mäntysaari, 2015).

Traditional methods, such as weighing with scales, while accurate, often require the physical restraint of animals, leading to stress and associated risks for both cattle and operators (Xavier et al., 2022). Additionally, weighing devices may present issues related to calibration accuracy or proper functioning due to environmental conditions and the need for a dedicated team to organize and oversee the weighing process (Tasdemir et al., 2011). Moreover, these scales are relatively expensive, and their electronic components are susceptible to damage in the harsh environment, which is exposed to manure and urine and in direct contact with cows (Dickinson et al., 2013).

In this context, computer vision technologies emerge as an innovative alternative, enabling data acquisition in a less invasive manner and with higher frequency, allowing for more dynamic and efficient herd management (Le Cozler et al., 2019). Unlike conventional methods, such as manual weighing that relies on physical systems, computer vision can be applied continuously without the need for direct interaction with animals, reducing stress and improving animal welfare.

With the advancement of computer vision technologies, new approaches have been developed to capture and analyze the morphological characteristics of cattle in an automated and precise manner. These technologies can measure parameters such as chest circumference (CC), which, among other variables, stands out as one of the most reliable indicators of BM (Heinrichs et al., 1992; Martins et al., 2020).

This reliability of CC as a predictor has been reinforced since the study by Davis, Swett, and Harvey (1961), who analyzed 46 studies available up to that time and found that, in 35 of them, CC was identified as the best predictor of BM in cattle, being even used as the sole variable in several models. The authors also highlighted that adding other variables to CC-based models did not result in significant improvements in estimation accuracy, and the reported correlation coefficients often exceeded 0.95, indicating a highly robust statistical relationship with BM. This level of precision was so remarkable that it led to the development of specific measuring tapes designed for direct weight estimation based on CC.

The relevance of CC as a predictor of BM remains widely accepted in the current literature and is still employed in several studies that assess cattle body weight through indirect methods. In addition to its accuracy, CC stands out for being an easily measurable variable with practical applicability in production systems, especially on farms that lack scales or animal restraint structures. It is speculated that this strong correlation is due to anatomical and physiological factors, since the thoracic region houses large-volume organs such as the rumen, lungs, and heart, and also represents an area of significant muscular development and structural stability, as also reported by Heinrichs et al. (1992).

Considerable research on the prediction of BM in cows has been conducted, achieving promising results through innovative approaches. These studies can be divided into two main categories: methods based on traditional morphometric measurements and technologies involving computer vision and machine learning. Traditional methods utilize physical variables such as chest circumference (CC), body length (BL), and hip height (HH), applied in statistical models to estimate BM. While widely validated, these methods have limitations due to the need for direct contact with the animals, as seen in the following studies (Heinrichs et al., 1992; Kashoma et al., 2011; Dickinson et al., 2013; Mäntysaari & Mäntysaari, 2015; Lukuyu et al., 2016; Heinrichs et al., 2017). On the other hand, computer vision technologies enable the extraction of morphological features through images captured by RGB cameras, depth cameras, and drones, integrating this information into machine learning models for improved prediction accuracy, as demonstrated in studies such as (Tasdemir et al., 2011; Song et al., 2018; Xavier et al., 2022; Gebreyesus et al., 2023). By combining established methods with technological innovations, these approaches have significantly contributed to the advancement of digital and precision livestock farming.

The 3D imaging technologies have solidified their position as promising tools in the morphological analysis of cattle, enabling significant advancements in the precision and richness of the data collected. By utilizing depth cameras, it is possible to capture detailed information about body structure and its variations over time, supporting a dynamic and integrated approach to precision livestock farming (Ferreira et al., 2022). This ability to record high-resolution three-dimensional data not only enhances BM estimation but also opens new possibilities for continuous monitoring of body composition, such as changes in energy reserves, growth, and gastrointestinal tract filling, providing a broader and more detailed view of animal physiology at different production stages (Xavier et al., 2022).

Over the last decade, and more recently, various non-invasive approaches have been proposed for predicting BM in cattle, with particular emphasis on methods based on digital imaging. Tasdemir et al. (2011) used 2D photographs taken from different angles to extract morphometric measurements and estimate the body weight of Holstein cows using linear regressions. However, their method required multiple cameras, a controlled lighting environment, and calibration procedures, which may hinder large-scale adoption. Advancing to the use of depth sensors, Kuzuhara et al. (2015) applied a 3D camera to capture dorsal images and estimated weight based on geodesic measurements of the back, achieving promising results. Although effective, this approach did not directly incorporate conventional morphometric measures such as CC, which is widely recognized in the literature as one of the most robust predictors of BM. Similarly, Na et al. (2022) proposed an automated system using RGB-D images captured from a top view and machine learning techniques, extracting descriptors such as body area and volume. While efficient, the method also did not consider variables traditionally used in precision livestock farming, such as CC. In light of this, the present study proposes an alternative approach based on laterally captured 3D images, aiming to combine the reliability of classical morphometric methods with the technological advances of computer vision, offering a more practical, accurate, and production-compatible solution.

Building upon the advancements in computer vision applications for bovine morphometry, Peng et al. (2024) proposed a method to estimate CC based on RGB-D lateral images captured by a ZED2i camera. By utilizing keypoint detection with the YOLOv8-Pose model and mirroring symmetry, the authors reconstructed the thoracic shape to estimate CC, achieving promising results. However, the methodology requires precise anatomical labeling and computationally complex steps. In contrast, the present study proposes a more direct approach, based on the extraction of CC from 3D images captured laterally in a production environment. Although the current step still relies on manual annotations, the adopted strategy demonstrates potential for future automation of the process, combining operational simplicity and practical applicability with accuracy in predicting BM.

Despite the recognition of CC as a robust predictor of BM, studies validating its estimation from 3D images captured laterally in field conditions remain scarce. This limitation highlights an important gap in the use of computer vision applied to automated morphometric measurement of bovines, particularly regarding the integration of scientific accuracy and practical applicability. Therefore, this study aims to assess the application of computer vision in estimating the BM of Holstein-Friesian dairy cows, using 3D images captured laterally with the Intel RealSense D435i depth camera. From a scientific perspective, the goal is to validate the efficiency of estimating CC from 3D images, analyzing its correlation with the actual BM of the animals, and contributing to the advancement of non-invasive techniques in precision livestock management. From a practical standpoint, the work proposes a viable, lower-cost alternative that can be applied in the field for the automatic measurement of BM, reducing the need for animal containment and optimizing management in modern dairy systems.

MATERIALS AND METHODS

This research followed all experimental procedures approved by the Animal Ethics Committee (CEUA) of the Federal University of Lavras, in accordance with Protocol Number 8093310125.

The study was conducted on an experimental dairy cattle farm located in the municipality of Ijaci, in the state of Minas Gerais, Brazil, at coordinates 21°09'40.1"S 44°55'45.3"W (Fig. 1), involving lactating Holstein-Friesian cows. A total of 250 records were used for analysis. The cows were housed in a Tie-stall system, with individual sand beds and continuous mechanical ventilation operating 24 hours a day. Fan speed was automatically adjusted by ambient temperature sensors to ensure adequate thermal comfort. Additionally, sprinklers were manually activated during the day, generally between 7 a.m. and 5 p.m., in intermittent cycles, especially on hot days, such as those recorded during the experimental period.

Figure 1. Farm location.

The cows had continuous access to water on demand, with one water trough available for every two stalls, regulated by a float valve. Additional water troughs were available in both the holding pen and the milking parlor. Feeding was carried out using a Total Mixed Ration (TMR). During the data collection period, due to concurrent nutritional experiments conducted on the farm, wooden dividers were used to individually control each cow's access to feed. Outside of these periods, feeding is carried out in groups.

Although the study involved occasional animal restraint procedures to obtain actual BM and CC measurements using a measuring tape - which served as reference values for model validation - these practices were already part of the farm's routine, especially during data collection for other nutritional and zootechnical experiments. All management procedures followed animal welfare principles, ensuring comfort, access to water and feed, as well as appropriate environmental conditions. It is also worth noting that the approach proposed in this study, based on computer vision, aims precisely to provide a less invasive and more efficient alternative, with the potential to replace manual procedures requiring physical restraint in future field applications.

After milking, the cows were managed towards an Intel® RealSense™ Depth Camera D435i to capture 3D images, located near the entrance to the weighing area where there was a Tru-Test digital scale, model EziWeigh5, with a 5 kg resolution for the collection of their BM. The camera was positioned 1.5 meters from the animal, along the path to the scale, at a height of 1 meter from the ground, to capture lateral videos of the cows using the Intel RealSense Viewer software (version 2.54.1), as shown in Fig. 2. The camera was used with its default settings, without additional calibration adjustments. The reliability of the depth estimates was verified in a practical manner by comparing them with objects of known dimensions placed at varying distances. This visual verification ensured that the captured images accurately reflected the animals body structure in the field environment.

Figure 2. Camera installed to capture side images.

This handling procedure took place after the cows exited the first milking of the day, which started at 5:00 a.m. As the animals approached the camera, a video capture was initiated to collect a sequence of images, from which a frame could later be selected that best displayed the full lateral body of the animal. An example of one of the captures made by the RGB and depth cameras can be seen in Fig. 3.

Recording videos with a depth camera allows for the capture of dynamic and continuous information about animal movement, enhancing data accuracy and representativeness. Additionally, it facilitates the extraction of specific frames for analysis. This video capture methodology, instead of isolated photos, has been widely recommended in the literature and has been used by authors such as Hansen et al. (2018), Wu et al. (2021), and Qiao et al. (2023).

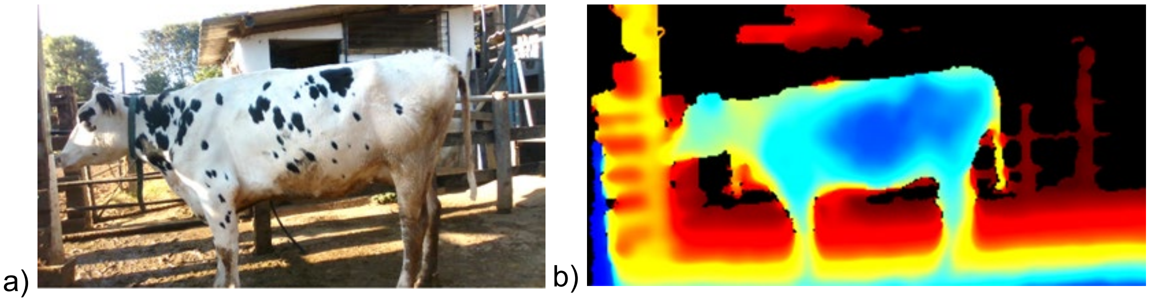

Figure 3. Image capture: a) RGB image; b) depth image.

In addition to the 2D images captured by the Intel RealSense Viewer® software, it also allows for the acquisition of 3D images in the form of meshes and point clouds (Fig. 4). In this study, these 3D images played a central role, being used for the measurement of the CC of the cattle from lateral captures.

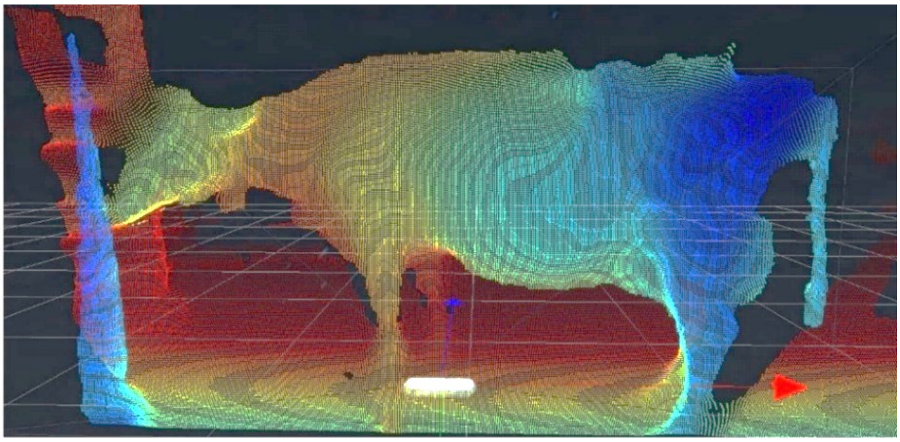

Figure 4. Representation of a 3D point cloud image in Intel RealSense Viewer® software.

The 3D images underwent preprocessing in the CloudCompare® software (version 2.13.1) to exclusively segment the region of interest, corresponding to the animal's lateral side, removing the background and other unwanted parts of the image (Fig. 5). Segmentation was performed manually in CloudCompare using the 'Segment' tool to outline the animal's side by marking multiple points, forming straight lines that define the region of interest. At this stage, parts such as the head and tail may or may not be removed, depending on the need, to facilitate the segmentation of the thoracic region. This decision is

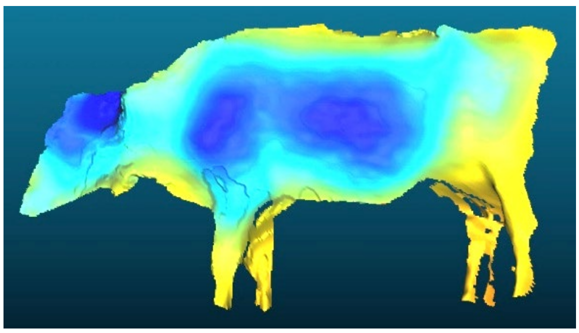

Figure 5. Segmented image in CloudCompare® software.

possible since the postural standardization had already been considered during frame selection. After segmentation, the isolated region was extracted as a new entity and, when necessary, refined with the help of the ‘Cross Section’ tool, which allows cutting residual elements based on section planes. It is important to note that the original mesh generated by the camera was kept unchanged in terms of resolution or retopology, ensuring geometric fidelity during segmentation. At the end of the process, the segmented mesh was saved in OBJ format for later analysis in the MeshInspector software (version 2.4.7.79). This process ensured greater precision and focus on the area required for the analysis.

From the segmentation, the resulting 3D meshes were imported into the MeshInspector® software, where the geodesic measurement of the CC was performed (Fig. 6). This perimeter was identified on the visible lateral portion of the 3D image and corresponds to approximately half of the total CC. In MeshInspector, the segmented mesh was loaded in the format exported from CloudCompare and initially visualized in TopView mode, which automatically positions the animal according to its movement on the horizontal plane, allowing for a clear observation of the lateral region. To perform the geodesic measurement, the Geodesic Path tool was used, accessed from the Inspect tab. To ensure greater accuracy in selecting the start and end points of the measurement, the mesh was slightly rotated along the vertical axis to clearly identify the deepest point of the lateral curvature of the thorax at each end of the 3D image. The measurement was made with only two points, positioned similarly to the traditional tape measure method: just behind the front legs and at the top of the lateral projection, simulating the thoracic arch (Fig. 6). The tool then automatically calculated the geodesic contour over the mesh surface between these two points, providing a value corresponding to approximately half of the CC. The unit was set to meters, and the values were later converted to centimeters to ensure compatibility with the physical data obtained in the field.

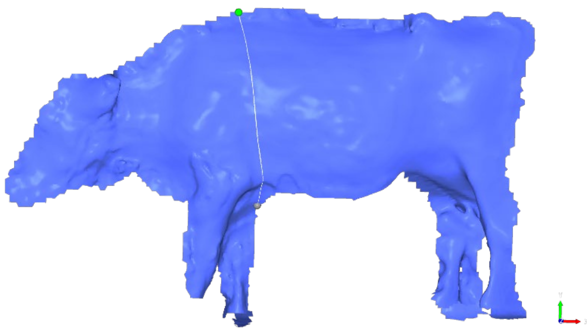

Figure 6. Geodetic measurement of CC in MeshInspector® software.

To enable comparisons with physically measured values, the obtained value was adjusted by multiplying by 2, creating an estimate of the complete CC. This approach combined advanced technologies and image processing techniques to facilitate a more detailed and robust analysis of the morphological characteristics of the cattle.

To ensure the reliability of the estimates, a careful selection of images used in the analysis was performed. Only frames with proper body posture and image quality were considered, excluding those with misalignment of the body axis (Fig. 7, a), the head turned laterally (Fig. 7, b), or visual distortions caused by light reflection on bright coat areas, which affected contour definition (Fig. 7, c). Only frames in which the animals’ front legs were approximately parallel and their heads were facing forward - simulating the conventional posture adopted in manual tape measurements - were retained. Since an individual video was recorded for each animal during the journey between the milking area and the scale, several frames were captured, allowing for the selection of the most appropriate one for analysis according to the established criteria. Thus, although only a single camera positioned laterally was used, the careful selection of frames acted as a practical control for postural standardization, contributing to the consistency of the measurements obtained.

Figure 7. Examples of images rejected for CC measurement, organized in pairs with RGB view (right) and Depth view (left): a) misalignment of the body axis; b) head turned laterally; c) visual distortion caused by light reflection.

Although estimating CC by duplicating the lateral measurement implies an assumption of bilateral symmetry, this approach was applied based on the visual quality of the selected images, aiming to minimize distortions associated with anatomical asymmetries or physiological variations, such as rumen filling, for example. Similarly, Guo et al. (2019) developed a posture normalization method based on bilateral symmetry to standardize animal poses in 3D point clouds, emphasizing that, while promising, this approach requires a series of assumptions regarding animal morphology and posture, such as standing on flat ground and presenting symmetrical body shapes. Nonetheless, it is acknowledged that, under field conditions, it is challenging to obtain situations perfectly aligned with the assumption of bilateral symmetry, given the natural variations in posture, conformation, and animal movement. Precisely for this reason lies the real challenge and contribution of this type of approach: to develop robust models capable of accurately predicting body mass even in the face of imperfections inherent to the production environment.

Additionally, it was observed that cows with predominantly white coats were more susceptible to visual distortions caused by the natural lighting of the environment. The high light reflection on these lighter regions resulted, in some cases, in the loss of definition of body contours in the images. This type of visual interference, associated with light variation, has already been reported in the literature as a factor that compromises image quality in production environments (Ramesh et al., 2023), although not directly related to coat color. In the present study, however, this effect was more evident in light-colored animals, which led to the exclusion of the affected frames to ensure the consistency of the measurements. Meng et al. (2025), in a systematic review on animal biometrics based on computer vision, highlight that variations in lighting conditions and capture angles remain critical factors for model accuracy, even with the use of 3D cameras. This reinforces the idea that, although technology is advancing, model robustness still needs to address the natural imperfections of the production environment.

After the images of each cow were collected, the animals were weighed and measured while contained on the scale. During this process, in addition to obtaining the BM data in kilograms directly from the scale, CC measurements were manually taken in centimeters using a measuring tape. In order to maintain the normal workflow on the farm and avoid delays during the milking and weighing routine, each measurement was performed only once per animal, always by the same trained evaluator, following a standardized protocol. This approach aimed to ensure the consistency of the reference measurements, even without formal repetition, reflecting common practice in dairy production systems and allowing for a proper comparison with the automated approach proposed in the present study. The measurements taken with measuring tapes, providing values in centimeters, can be used as input data for predictive equations, widely employed in estimating BM, as seen in studies like Pereira et al. (2021), where the CC predictor was included in their predictive equation for dairy cattle weight.

a)
b)

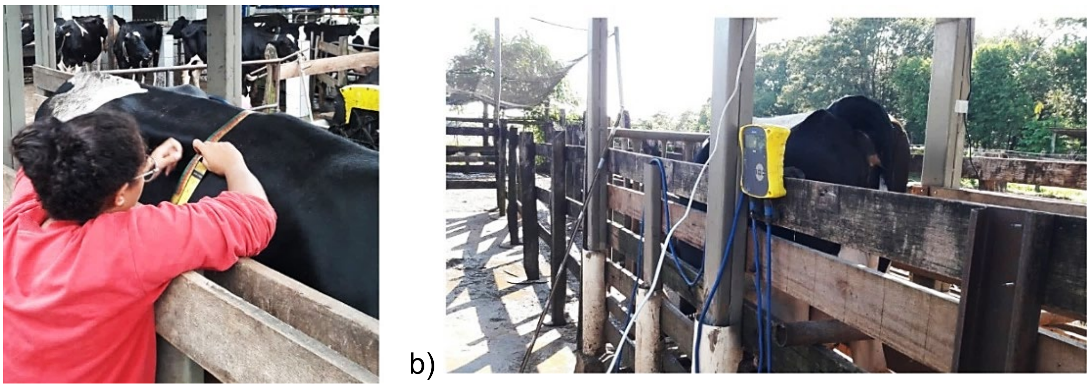

Figure 8. Measurements: a) CC measurement; b) BM measurement.

These BM and CC values were recorded as fundamental references for the validation and subsequent analyses performed on the captured images, ensuring greater accuracy and reliability in the results obtained from the computer vision approaches. Fig. 8 illustrates the methods of collecting CC measurements with the measuring tape and BM via the digital scale.

RESULTS AND DISCUSSION

The data presented in Table 1 include the minimum, mean, and maximum values of the body masses and perimeters analyzed. These values summarize the observed ranges of the studied variables, serving as a basis for sample characterization and subsequent analyses.

Table 1. Descriptive Statistics of BM and Measured CC in Dairy Cattle

Variable	Minimum	Mean	Maximum	Standard Deviation (%)
Body Mass (kg)	420	613.31	855	-
CC Physically measured[1] (cm)	184	209.23	241	4.44
CC measured in the images[2] (cm)	89.30	103.01	120.30	4.56
Adjusted CC[3] (cm)	178.60	206.03	240.60	4.56

[1] Chest Circumference measured in the field; [2] Chest Circumference measured in the images; [3] Chest Circumference adjusted by multiplication by 2.

The minimum and maximum ranges of the analyzed variables show a wide distribution, varying from 420 kg to 855 kg, reflecting the diversity of the morphological characteristics of the evaluated cows. The consistency observed between the adjusted CC values obtained from the images and the physically measured values suggests that the adopted adjustment technique (multiplication by 2) was effective in approximating the values to the actual measurements.

When comparing the physically measured CC with the adjusted CC obtained from 3D images, an average difference of only 3.2 cm is observed, indicating that the adjustment technique applied to the 3D images can be a viable alternative for estimating CC without the need for manual measurements. The standard deviation in percentage highlights the uniformity of the measurements relative to the calculated means, showing similar variations between the CC measurement methods. This stability is a positive indicator of data reliability for both physical measurements and image-based estimates.

Studies have demonstrated a strong correlation between CC and BM in cattle, reinforcing its use as a reliable predictor. Lukuyu et al. (2016), for example, identified a correlation of ($r = 0.84$) between CC and BM in crossbred cattle, working with a weight range of 102 to 433 kg. Later, Franco et al. (2017) confirmed the strong association between CC and BM when studying Holstein and crossbred heifers, finding an even higher correlation ($r = 0.94$) within a narrower weight range of 212 to 345 kg. More recently, Weber et al. (2020) analyzed Girolando cattle and reinforced these findings, reporting a correlation of ($r = 0.88$) for a weight range of 360 to 596 kg. These studies support the relevance of CC as a robust and widely applicable metric for weight estimation across different contexts and morphological conditions.

The results of this study reinforce the strong relationship between CC and BM in cattle. The Pearson correlation found between BM and the CC measured in the field ($r = 0.90$) falls into the 'very high' correlation category according to Mukaka (2012), indicating the strong accuracy of this traditional weight assessment method. On the other hand, the CC estimated from processed lateral images showed a slightly lower correlation ($r = 0.85$), classified as 'high' by the same reference. This difference may be attributed to the estimation method for the complete circumference, which involved doubling the value measured in the lateral image, as well as limitations associated with geodesic measurement in 3D meshes, such as possible segmentation inaccuracies or distortions in 3D capture. Nevertheless, the use of processed images proved to be a promising and non-invasive approach, capable of providing consistent results with potential for practical applications in BM prediction in cattle.

Based on the strong correlation observed between CC and BM, BM was estimated using a simple linear regression model. For this purpose, the data were split into 80% for training and 20% for testing, ensuring that the data used in the testing phase were not included in the model training process. During training, 10-fold cross-validation was applied to assess the model's stability and generalization capacity. Additionally, a residual analysis was performed to evaluate the fit and identify potential error patterns. Fig. 9 shows the results of the trained models, and Fig. 10 presents the residuals.

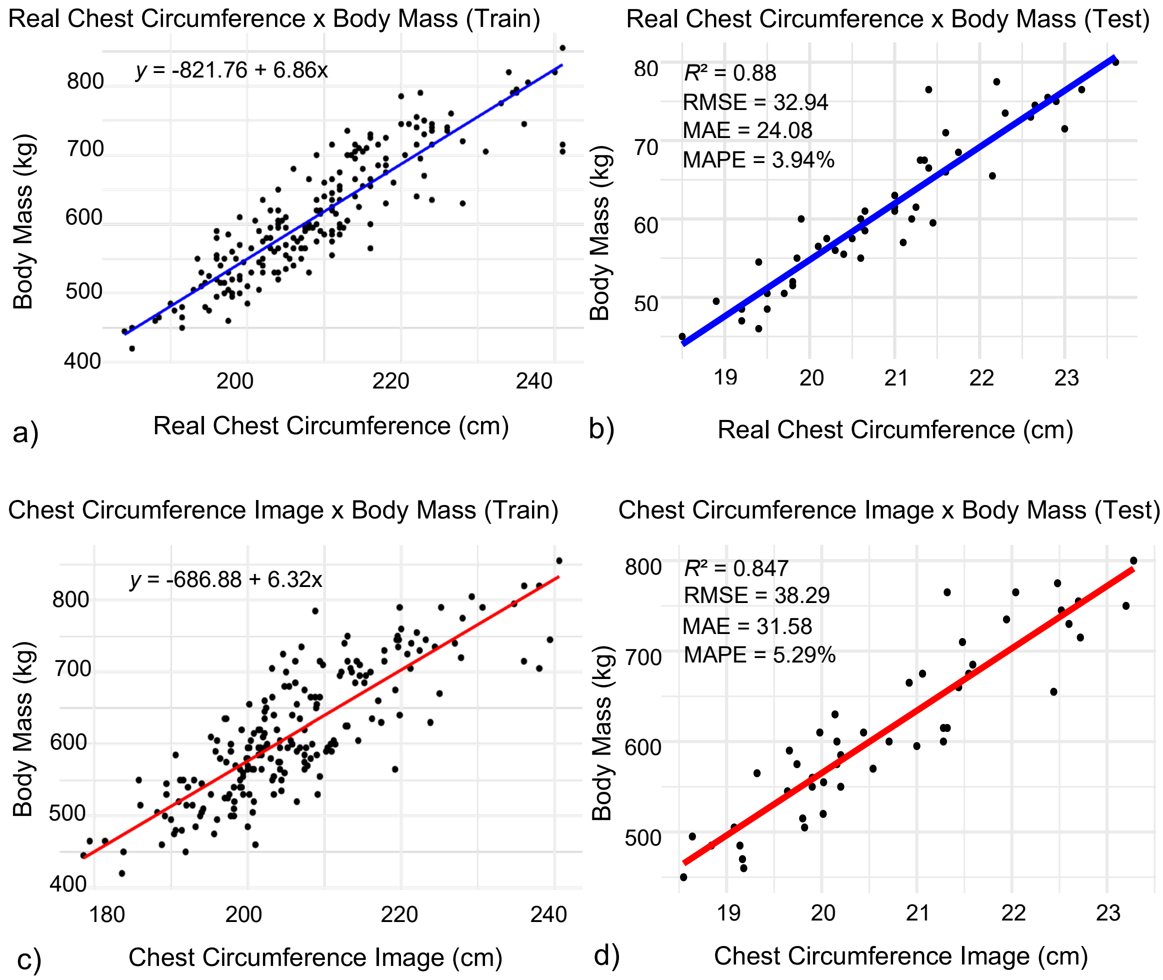

Figure 9. Regression plots: a) training data of chest circumference (CC) measured in the field and body mass (BM); b) test data of CC measured in the field and BM; c) training data of CC measured from images and BM; d) test data of CC measured from images and BM.

The residual analysis of the models, presented in Fig. 10, provides an initial assessment of how the predictions behave in relation to the actual body mass values. It can be observed that in both cases - the model using chest circumference measured in the field and the model using image-based estimates - the residuals are reasonably symmetrically distributed around the zero line, suggesting no evident systematic bias. However, some residual values with magnitudes close to or exceeding ± 50 stand out. These points may be considered outliers and warrant further investigation, as they could be related to specific morphological characteristics of the animals or to limitations in the predictor variable estimation. Still, they do not indicate a recurring pattern. Additionally, the distribution of residuals across the range of predicted values shows an approximately constant error variance - a feature known as homoscedasticity - which is a positive indicator for the validity of the applied simple linear regression models. This preliminary visualization of the residuals thus helps contextualize the results that will be presented next in terms of error metrics and predictive accuracy.

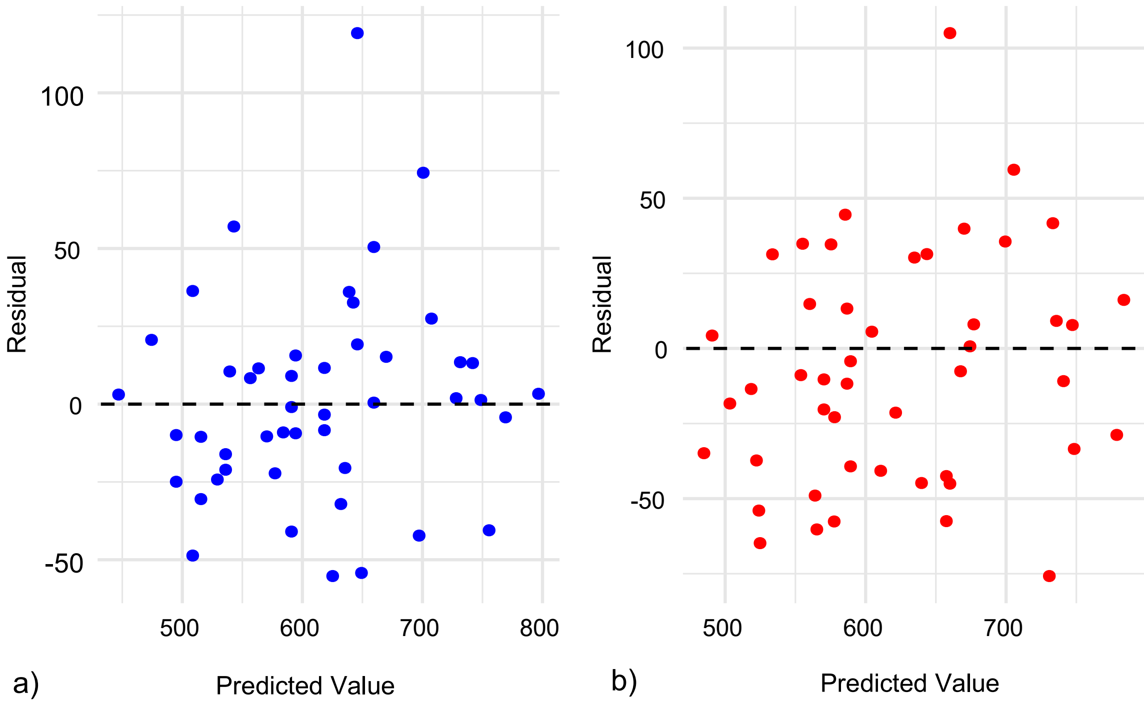

Figure 10. Distribution of residuals from simple linear regression models for predicting BM of cattle: a) residuals from the model using field-measured CC; b) residuals from the model using image-based CC.

Continuing the analysis, the results presented in Fig. 9 show that CC measured in the field exhibited a strong correlation with BM, serving as an efficient predictor, with a coefficient of determination (R^2) of 0.88 and a Mean Absolute Error (MAE) of 24.08 kg. This R^2 value indicates that the model explains 88% of the variation in the BM of the cattle, reflecting the reliability of CC as a predictor of BM. However, the MAE of 24.08 kg suggests that, despite the strong correlation, the estimate still has a considerable error, which may be deemed acceptable depending on the application context, such as in large herds where absolute precision may be of secondary importance.

Kashoma et al. (2011) investigated the relationship between CC and BM in Tanzania Shorthorn Zebu (TSHZ) cattle, with weights ranging from 170 to 390 kg. The study reported a coefficient of determination of $R^2 = 0.88$, demonstrating a strong linear relationship between these variables. Additionally, the authors highlighted that factors such as sex could influence this relationship, with males and females exhibiting differences in the association between CC and BM. Similarly, Franco et al. (2017) evaluated different equations based on CC to predict BM in cattle, with R^2 values ranging from 0.75 to 0.90, as presented in their models. This variation illustrates how different ap*proaches and adjustments can impact model accuracy, with the best performance* ($R^2 = 0.90$) achieved using a simple equation that considers only CC, with a coefficient of variation (CV) of 5.9%. These findings reinforce the robustness of CC as a predictive variable while also indicating that adjustments specific to herd characteristics and data collection methods can influence the results.

In contrast to the field measurements, which showed high accuracy, the CC estimated from lateral images exhibited slightly lower performance, with an R^2 of 0.847 and a MAE of 31.58 kg. Despite the slight reduction in precision, the correlation obtained is still considered strong, indicating that the image-based approach is capable of consistently capturing the relationship between CC and BM. The observed difference in MAE may be related to factors such as the morphological variability of the animals, possible limitations in image capture, or the lack of control over environmental conditions at the time of acquisition. Nevertheless, the use of lateral images represents a practical, non-invasive alternative with good performance for estimating BM, especially useful in scenarios with limited animal access or in large-scale herds where conventional measurement methods are less feasible. The results reinforce the potential of computer vision applied to precision livestock farming, even when compared to traditional methods.

The regressions performed demonstrate that as the CC increases, there is a proportional increase in BM, as evidenced by various studies, including those by Gomes et al. (2016), Weber et al. (2020), and several others. This behavior occurs because the CC is a measure directly related to the animal's thoracic volume, which reflects not only the overall body size but also the capacity to store internal organs, fat, and muscle mass (Heinrichs et al., 1992). In larger animals, the increase in CC is associated with a more advanced development of the body structure and greater deposition of lean mass and/or fat, which are the main determinants of live weight (Bene et al., 2007). Therefore, CC serves as a practical and accessible indicator for estimating BM, showing a strong correlation with this variable in various studies.

Complementing the evaluation of the predictive performance of the models, the root mean square error (RMSE) was 32.94 kg for the model using field-measured CC, and 38.29 kg for the model based on image-derived estimates. The mean absolute percentage error (MAPE) values were 3.94% and 5.29%, respectively. These results indicate that both models demonstrated good accuracy, with slightly better performance for the model using physical measurements, although the image-based approach also showed relatively low error, considering its practical application context.

When compared to some studies, the MAPE values obtained in this work demonstrate competitive performance. Dang et al. (2022) used a set of ten manually collected body measurements to estimate the live weight of Hanwoo cattle using different machine learning algorithms. Among the models tested, LightGBM achieved the best performance, with an RMSE of 24.75 kg and a MAPE of 4.72%. Although this absolute error is lower than the RMSE obtained in the present study (32.94 kg and 38.29 kg), it is important to highlight that Dang et al.'s (2022) models used a multivariate set of predictors, whereas the present study used only CC as the independent variable.

Even so, the model using physical measurements achieved a lower MAPE (3.94%), demonstrating the strong predictive power of this single variable and its potential for use in simpler and more practical models for field application.

In a more recent study, Peng et al. (2024) explored the use of lateral depth images combined with pose estimation algorithms to estimate cows CC and subsequently predict BM. The model proposed by the authors achieved a mean percentage error of 4.43%, an intermediate value between those obtained in the present study by the models using real chest circumference (3.94%) and estimated 3D image-based circumference (5.29%). Although Peng et al.'s (2024) methodology represents an advance in terms of automation and reduction of direct measurements, the results presented here suggest that 3D image-based approaches with lateral segmentation are also capable of achieving similar performance, even with relatively simpler processing and fewer input variables.

Based on the reviewed research, it is possible to observe that including other variables in the models, such as age, sex, and specific characteristics of the cattle, or even using different techniques, can contribute to greater accuracy in predicting body mass. However, the method used in this study, which integrates direct measurements and advanced computer vision techniques, has proven to be efficient and innovative, allowing for precise and automated analysis, with potential for practical application in dairy herds of different configurations. This approach represents a significant advancement over traditional methods, proving to be a robust tool to assist in management and decision-making.

CONCLUSIONS

Based on the results obtained, it can be concluded that chest circumference is a reliable predictor of body mass in cattle, both through direct measurements and estimates from three-dimensional images. Although the estimation via images showed a slight reduction in accuracy compared to direct measurements, it presents itself as a viable and non-invasive alternative, especially for large or hard-to-reach herds. The imaging technique, despite being subject to limitations such as uncertainties in geodesic measurements and adjustments by multiplication, offers a practical solution for remote BM monitoring. With the advancement of technologies and the expansion of the database, the accuracy of the models is expected to improve, broadening the applications of these techniques in precision agriculture and efficient herd management.

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