

International Journal of Statistics and Applied Mathematics

ISSN: 2456-1452
NAAS Rating (2025): 4.49
© 2026 Stats & Maths
Maths 2026; SP-11(7): 28-32
www.mathsjournal.com
Received: 18-04-2026
Accepted: 21-05-2026

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Deep learning-based detection and measurement of challenging linear traits in Sahiwal cows

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DOI: <https://www.doi.org/10.22271/math.2026.v11.i7Sa.2655>

Abstract

Accurate and objective assessment of dairy-cattle conformation is important for animal selection, breed evaluation, and the design of breeding programs. Linear type traits are traditionally assessed by visual appraisal or direct manual measurement; however, traits such as hoof angle and hump area are difficult to quantify consistently and are therefore vulnerable to observer-related variation. This study developed a deep learning-based framework using YOLOv8 to detect the hump and hoof regions of Sahiwal cows and to support automated estimation of hump area and hoof angle from digital images. The study reports the use of 600 annotated images, with image augmentation applied to increase the dataset to approximately 2,000 images. The model achieved a precision of 0.92, recall of 0.89, mAP@0.5 of 0.90, and IoU of 0.87 for hump detection. For hoof detection, the corresponding values were 0.90, 0.87, 0.88, and 0.85. Hump area was estimated from the detected contour, while hoof angle was calculated from vectors representing the detected hoof edges. The proposed approach demonstrates the potential of computer vision to reduce subjectivity in the assessment of difficult morphological traits and to support scalable livestock evaluation. Additional calibration and independent validation are required before the system can be used for precise physical measurement and routine field deployment.

Keywords: Hump area detection; hoof angle estimation; computer vision; YOLOv8; deep learning; image processing

1. Introduction

The dairy industry contributes substantially to the agricultural economy, and the identification of animals with desirable production and breeding characteristics is central to herd improvement. Linear type traits, defined as measurable morphological features of the animal, are frequently used to support breed classification and to infer functional or production-related potential. In routine practice, these traits are commonly assessed through visual inspection or manual measurement.

Although conventional assessment is accessible, it can be subjective, time-consuming, and sensitive to differences among observers. These limitations are especially important for traits that are difficult to measure directly. Hoof angle is relevant to hoof conformation, locomotion, weight bearing, and animal welfare, while the size and shape of the hump are recognized morphological features of Sahiwal cattle (Kaushik *et al.* 2020; Kumar *et al.* 2020; Niu *et al.* 2022) [8, 9, 13]. The source manuscript further treats hoof angle as relevant to weight bearing during mounting and hump morphology as an indicator used in breed-purity assessment.

Recent developments in artificial intelligence, deep learning, and computer vision have enabled automated analysis of animal images for detection, tracking, behavior recognition, and body-part localization. YOLO architectures are particularly suitable for such applications because they combine object localization with real-time inference (Redmon and Farhadi 2018; Zhao *et al.* 2019) [14, 17]. Recent YOLO-based livestock studies have also demonstrated the feasibility of real-time detection and behavior recognition (Chen *et al.* 2023) [5], while edge-AI approaches have been proposed for on-farm monitoring where cloud connectivity is limited (Liu *et al.* 2021) [11].

Despite this progress, difficult linear traits such as hump area and hoof angle are still generally described qualitatively or measured manually. Morphological descriptions of Sahiwal cattle emphasize a prominent hump, yet objective image-based quantification of this feature remains limited. Similarly, hoof-conformation studies have established the importance of hoof structure, but scalable image-based measurement remains challenging. This creates a gap between recognizing that these traits are important and measuring them consistently under field conditions.

The present study therefore developed a YOLOv8-based system for detecting the hump and hoof regions of Sahiwal cows. Image-processing procedures were then used to estimate hump area and hoof angle. The intended framework was designed as a non-intrusive and potentially scalable alternative to manual assessment, with possible future application in breed evaluation, posture monitoring, hoof-health screening, and precision livestock farming.

2. Materials and methods

2.1 Dataset collection and image acquisition

The source manuscript initially states that a dataset of 650 cow images was used for model training and subsequently reports that 600 images were acquired for the study. Images were obtained from the Sahiwal herd maintained at the Cattle

Yard of ICAR-NDRI, Karnal, from local dairy farmers, and from open datasets. Image selection focused on clear visibility of the hump and hoof regions under different body positions and lighting conditions.

Images were captured with commonly available handheld mobile devices to improve robustness to practical field conditions. Data collection was undertaken in open areas and milking areas. The camera-to-animal distance was kept consistent as far as possible, and camera height was adjusted in relation to the height of the animal.

2.2 Image annotation and data augmentation

Two target regions were annotated: (i) the hump area over the shoulder and upper back and (ii) the hoof region covering the lower limb and hoof. The images were annotated using bounding boxes and formatted for YOLOv8 through Roboflow. The annotations were prepared as precisely as possible to provide clean training labels for the model.

Flip, rotation, scaling, and brightness transformations were applied to the original 600 images, producing an augmented dataset of approximately 2,000 images. The Methods section reports that the augmented dataset was divided into 90% training, 5% validation, and 5% testing subsets. Elsewhere, the manuscript reports a split of 540 training, 30 validation, and 30 testing images for the original 600-image dataset.

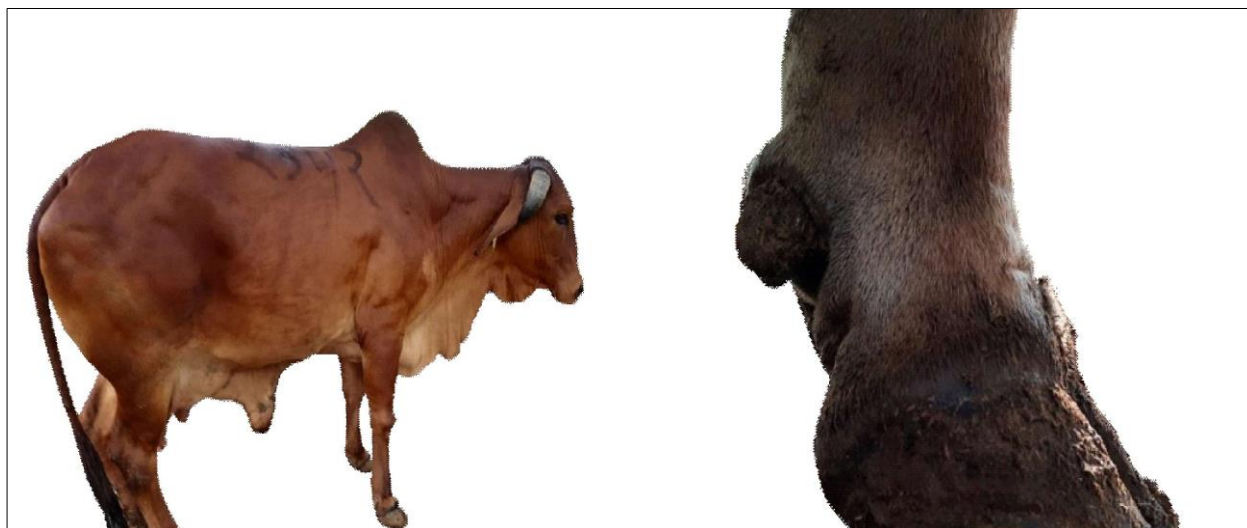


Fig 1: Representative source images used for trait assessment: (a) hump region and (b) hoof region.

2.3 Model selection and training

YOLOv8 was selected because the study required a fast object-detection model that could be trained with a relatively limited dataset. The Ultralytics implementation of YOLOv8 was used. Training was conducted for 50 epochs with an input image size of 640×640 pixels and a batch size of 8. The model was trained through Visual Studio Code on a Mac computer.

2.4 Hump detection and area estimation

After training, the model was used to localize the hump in side-view images. The detected region was represented by the predicted bounding box and associated contour or mask. The number of pixels enclosed by the detected hump contour was calculated with the OpenCV `cv2.contourArea()` function:

$$A_{\text{pixels}} = \sum_{i=1}^n \text{ContourArea}(\text{mask}_i)$$

where A_{pixels} is the hump-contour area in pixels^2 , mask_i denotes a detected contour or mask component, and `ContourArea` is calculated using OpenCV.

$$A_{\text{cm}^2} = A_{\text{pixels}} \times (H_{\text{real}} / H_{\text{pixels}})^2$$

where H_{real} is the physical height of the cow, H_{pixels} is the height of the same cow in the image, and $(H_{\text{real}}/H_{\text{pixels}})$ is the relative pixel-scaling factor. The manuscript also states that area was retained in pixel units because no physical calibration object was available.

2.5 Hoof detection and angle estimation

The predicted hoof bounding box was used to extract the hoof region. Hoof angle was defined as the inclination of the hoof relative to the contact surface. Two vectors were constructed from the detected hoof edges, and the angle between them was calculated using the dot-product relationship:

$$\theta = \cos^{-1}[(v_1 \cdot v_2) / (||v_1|| ||v_2||)]$$

$$\theta_{\text{degrees}} = \theta \times (180 / \pi)$$

Here, $v_1 \cdot v_2$ is the dot product of the edge vectors and $||v_1||$ and $||v_2||$ are their magnitudes. The resulting angle in degrees was overlaid on the original image using OpenCV.

2.6 Performance evaluation

Model performance was evaluated using precision, recall, mean average precision at an intersection-over-union threshold of 0.5 (mAP@0.5), and intersection over union (IoU). Precision and recall summarized detection

performance, mAP@0.5 represented detection accuracy across predictions at the stated threshold, and IoU quantified the overlap between predicted regions and the annotated ground truth.

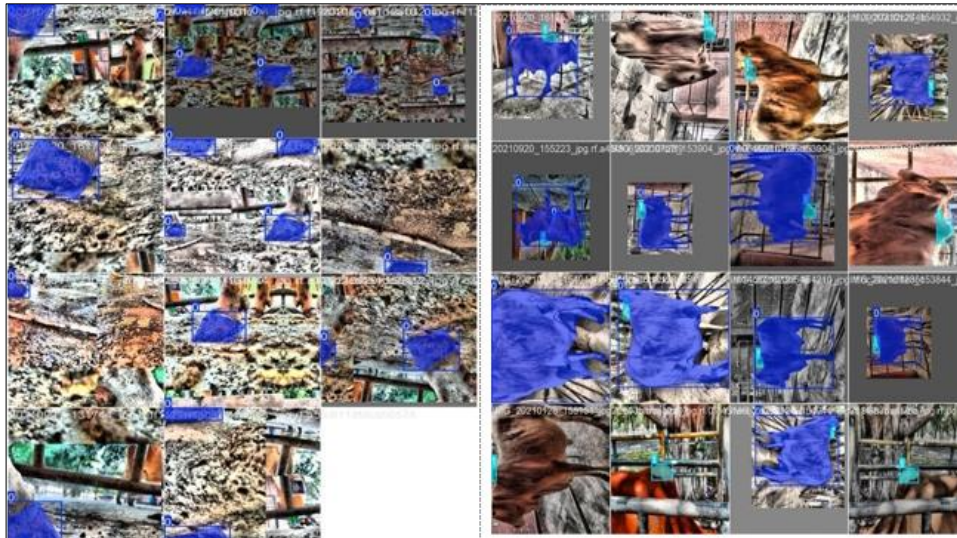


Fig 2: Intermediate YOLOv8 annotation outputs: (a) foot-surface dataset annotations and (b) cow-hump dataset annotations

3. Results

3.1 Hump-region detection

The YOLOv8 model localized the hump region in side-view images. As reported in Table 1, hump detection achieved a precision of 0.92, recall of 0.89, mAP@0.5 of 0.90, and IoU of 0.87. These values indicate strong agreement between the predicted hump regions and the annotated targets within the evaluated dataset. The training and validation curves for hump detection are shown in Figure 3. The training losses generally declined across the 50 epochs, whereas several validation curves fluctuated across epochs. The reported

performance values therefore summarize the final detection results, while the plotted curves provide additional information about optimization and validation behavior.

Table 1: Performance metrics for hump-area detection.

Metric	Value
Precision	0.92
Recall	0.89
mAP@0.5	0.90
IoU	0.87

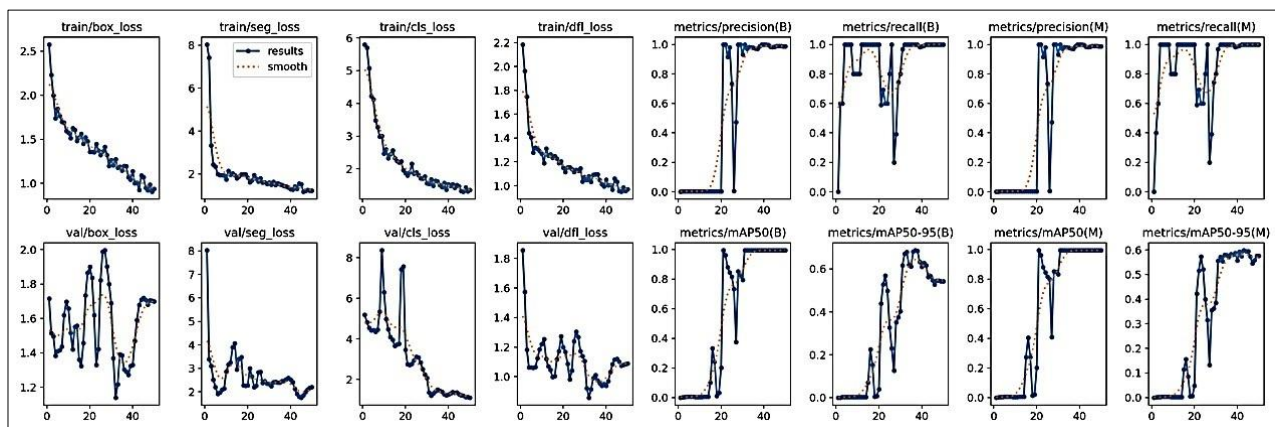


Fig 3: Training and validation curves for hump detection.

3.2 Hoof-region detection and angle estimation

The model also detected the hoof region and provided the image crop required for geometric angle estimation. Table 2 shows a precision of 0.90, recall of 0.87, mAP@0.5 of 0.88, and IoU of 0.85 for hoof detection. The reported values were slightly lower than those obtained for hump detection but still indicated effective localization within the test data. Figure 4 presents the training and validation curves for the hoof model. As with the hump model, the training losses changed across the 50 epochs, while the validation losses and performance curves showed substantial variation. Figure 5 provides an

example of the combined output. The displayed image reports a hump estimate of 0.0646 sqft and hoof-angle values of 55.6 degrees and 20.7 degrees.

Table 2: Performance metrics for hoof-angle detection.

Metric	Value
Precision	0.90
Recall	0.87
mAP@0.5	0.88
IoU	0.85

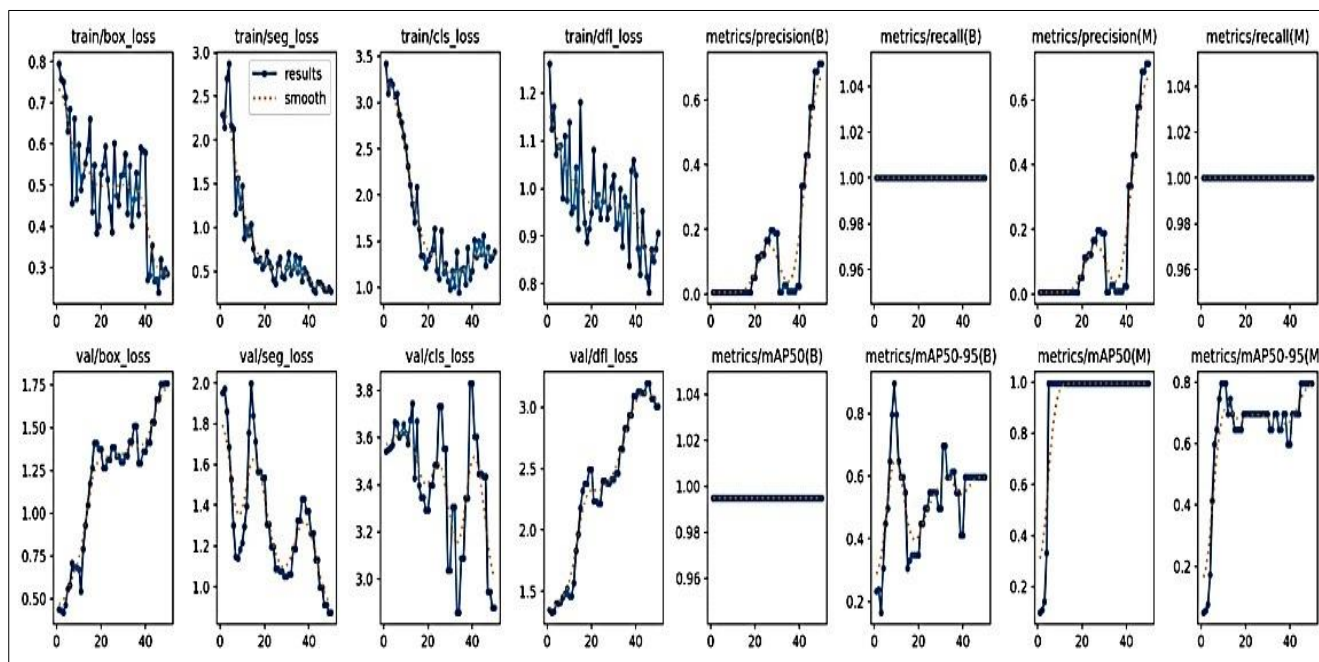


Fig 4: Training and validation curves for hoof detection.

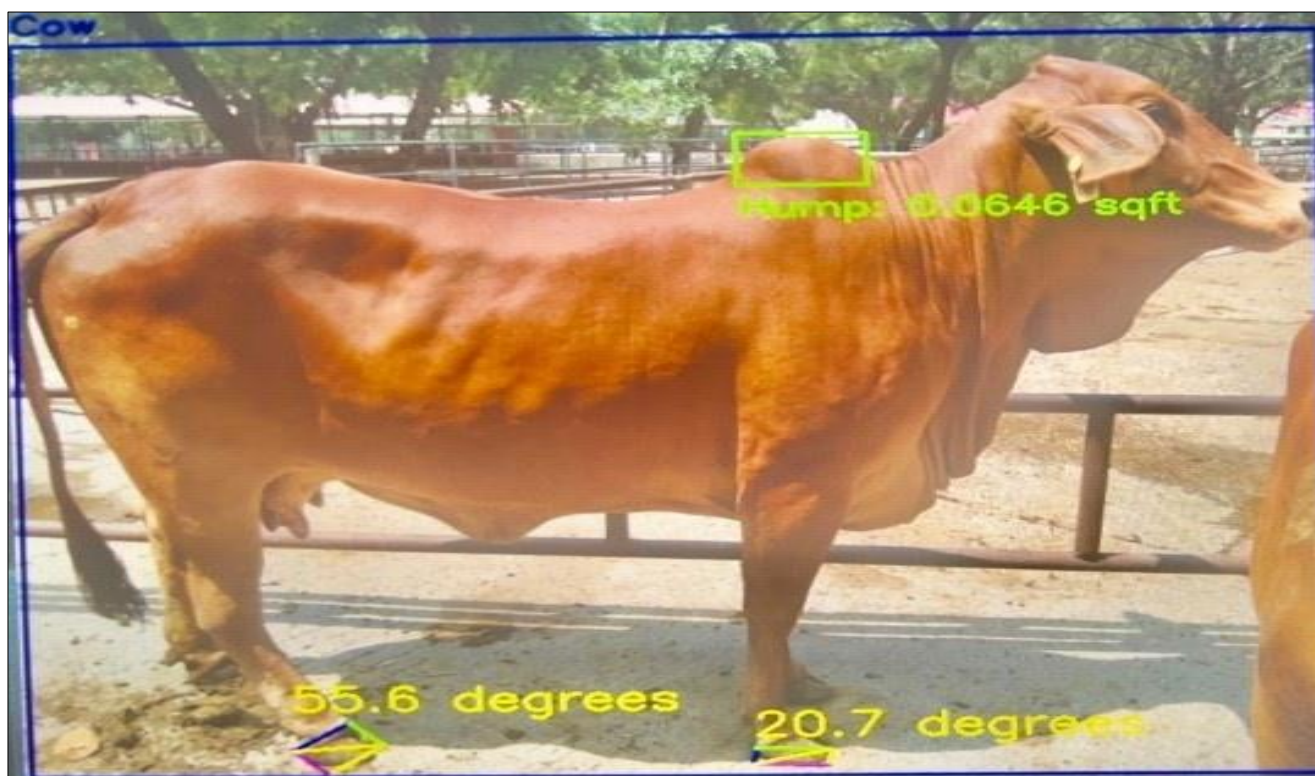


Fig 5: Example model output showing hump detection and hoof-angle estimates in a Sahiwal cow.

3.3 Integrated model output

Representative source images and annotated intermediate outputs are shown in Figures 1 and 2. Together, the figures illustrate the sequence from image collection and annotation to automated region detection and trait estimation. The model was able to identify both target regions using a comparatively small image dataset and to generate numerical outputs for the selected morphological traits.

4. Discussion

The study demonstrates the feasibility of using YOLOv8 to localize two morphologically important but difficult-to-measure regions in Sahiwal cows. Hump detection produced precision, recall, mAP@0.5, and IoU values of 0.92, 0.89, 0.90, and 0.87, respectively, while hoof detection produced

corresponding values of 0.90, 0.87, 0.88, and 0.85. The similarity of these results indicates that the model detected both target regions with comparable performance, although the hump model was marginally stronger for each reported metric. The findings are consistent with the broader use of deep learning for agricultural and livestock image analysis. YOLO-based models are attractive in this context because they combine detection speed with spatial localization, and improved YOLOv8 approaches have been applied to livestock detection and behavior recognition (Chen *et al.* 2023) [5]. The proposed system extends this general approach from whole-animal detection toward the localization of specific linear-trait regions. This is relevant because hoof conformation is associated with lameness and productivity (Niu *et al.* 2022) [13], whereas hump morphology is a recognized phenotypic

characteristic of Sahiwal cattle (Kaushik *et al.* 2020; Kumar *et al.* 2020) [8, 9]. The reported detection metrics support the ability of the model to locate the hump and hoof regions; however, detection performance is not equivalent to validated measurement accuracy. The study does not report comparison of image-derived hump area or hoof angle against independent manual measurements, repeated measurements, or a physical ground-truth standard. Consequently, the numerical outputs in Figure 5 should be interpreted as illustrative model estimates rather than fully validated anatomical measurements.

A further limitation concerns physical calibration. The Methods section states that hump area was retained in pixel units because no calibration object was available, yet it also presents a conversion to square centimeters using the ratio between real and pixel height, and Figure 5 displays an estimate in square feet. A clearly defined calibration procedure is required to convert image area into physical units reliably, particularly when camera distance, viewing angle, and animal posture vary. The manuscript also provides inconsistent descriptions of dataset size and partitioning. It refers to 650 images, 600 acquired images, a 540/30/30 split, and an augmented set of approximately 2,000 images divided in a 90%/5%/5% ratio. The unit of partitioning is not specified at the individual-animal level. Future validation should ensure that images from the same cow do not appear in both training and evaluation subsets, because such overlap could inflate apparent generalization performance.

The variable validation curves in Figures 3 and 4, together with the limited description of hyperparameters and computational settings, indicate the need for additional model-development reporting. External testing across farms, cameras, backgrounds, seasons, postures, and viewing angles would provide a stronger assessment of generalizability. The manuscript proposes future edge deployment and real-time video processing, but these capabilities were not experimentally evaluated in the reported study. Future work should therefore expand and document the dataset, define animal-level train-validation-test splits, report the exact YOLOv8 variant and training configuration, and validate image-derived measurements against standard manual or instrument-based measurements. Incorporating a reference object, camera calibration, or depth information would improve physical area estimation. Real-time implementation on low-power edge hardware could then be evaluated for latency, reliability, and field usability, consistent with the goals of precision livestock farming (Liu *et al.* 2021) [11].

5. Conclusion

A YOLOv8-based framework was developed to detect the hump and hoof regions of Sahiwal cows and to support automated estimation of hump area and hoof angle. The reported detection results were strong for both regions, with precision values of 0.92 and 0.90 and mAP@0.5 values of 0.90 and 0.88 for hump and hoof detection, respectively. The approach offers a practical foundation for reducing subjectivity in the assessment of challenging linear traits. Nevertheless, the present evidence primarily establishes region-detection performance. Reliable physical measurement and field deployment will require consistent dataset documentation, independent measurement validation, physical calibration, animal-level external testing, and evaluation under real-time operating conditions. With these additions, the framework could contribute to objective breed assessment, hoof monitoring, and precision livestock management.

Acknowledgements

No acknowledgement statement was provided in the source manuscript.

Conflict of interests

The authors declare that they have no conflict of interests.

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