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RESEARCH ARTICLE

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

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Abstract: Accurate selection of high-yielding dairy animals is essential for improving productivity and guiding future breeding programs. Linear type traits, which refer to specific anatomical features of cattle, have long been used to estimate milk production potential and assist in breed identification. However, certain traits such as hoof angle and hump area are particularly challenging to measure manually, often leading to subjective errors and inconsistencies across individuals. Literature suggests that while visual estimation of linear traits may suffice for breed prediction, actual measurement is crucial for assessing breed purity and production-related characteristics. In this study, we present a deep learning-based approach using the YOLOv8 object detection model to automatically detect and accurately measure the hoof angle and hump area of Sahiwal cattle from images. A dataset of 600 annotated Sahiwal cow images was used to train the model, achieving high precision in trait localization and quantification. Hoof angle, which influences reproductive performance, and hump area, a key indicator of breed purity in Sahiwal cattle, were specifically targeted due to their difficulty in manual measurement. This work offers a reliable and automated solution to overcome the limitations of manual assessment, contributing to improved livestock evaluation through advanced computer vision techniques.

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Introduction

The dairy industry plays a critical role in the global agricultural economy, with the selection of high-yielding animals being a key determinant of farm profitability and long-term genetic improvement. Among the various criteria used for animal selection, linear type traits, which are morphological features of an animal's body, are a significant contributor. The literature also reinforces the importance of linear traits or morphological traits of milching animals in estimating both production potential and breed classification. Therefore, farmers and field experts have relied on visual inspection and manual measurement of these traits to assess an animal's potential. However, this approach is often subjective, time-consuming, and prone to inter-observer variability, especially when evaluating traits that are difficult to measure precisely, such as hoof angle (Abdalla et al. 2024). Accurate measurement of these traits is essential: hoof angle is known to affect reproductive efficiency i.e. elaborate the weight bearing capability of animal during mounting process and hump area, the size and shape of the hump are critical in confirming the breed purity of Sahiwal (Khan et al. 2018) cow, one of the premier milch breed. Previous studies have also highlighted the genetic parameters of hoof disorders in dairy cows and genome-wide associations with hoof health traits (Abdalla et al. 2024).

The technological advancements in deep learning and computer vision accelerate across all sectors of agriculture also, and particularly livestock management. The integration of artificial intelligence (AI) and computer vision is revolutionizing cattle management for optimizing productivity, milk yield, and breeding strategies. These technologies can automate or remove the manual interference in the detection and accurate measurement of morphological features with high precision and consistency. Given the difficulty in trait assessment of animals and the progress made in integrating deep learning and computer vision, a transformative solution can be developed to measure the hoof angle and hump area of Sahiwal cows. The object detection models like YOLOv8 (Ultralytics 2023; Zhao et al. 2019) which has already shown exceptional performance in real-time image-based applications, will be a key solver of the current problem. The core of the system is YOLOv8 (Chen et al. 2023), it is a state-of-the-art real-time object detection model, and in parallel, image processing algorithms are also used to calculate angular relationships and real world area approximations of hump and hoof. The hardware, like NVIDIA Jetson Nano, will ensure on-site processing with minimal latency, which will give real-time insights.

In this study, these two traits were deliberately chosen due to the inherent difficulty in measuring them manually with an aim of addressing the challenges of manual livestock evaluation by developing an AI-driven system. This AI-enabled system provides a robust, non-intrusive, and scalable solution for breed assessment and cattle reproductive and health evaluation. The importance of morphological traits in cattle breeding programs has also been well documented (Khan et. Al. 2018).

A dataset of 600 annotated images of Sahiwal cows, divided into 540 training, 30 validation, and 30 testing images of Sahiwal cows was used to train the model. The developed system demonstrates its potential as a robust and scalable alternative to manual assessment, contributing to more objective selection, accurate breed monitoring, and efficient herd management. By offering a more accurate, efficient, and scalable solution, this framework represents a significant step forward in modernizing livestock assessment using cutting-edge AI technologies. It will empower the farmers with instant access to features like instant breed verification, posture monitoring, and milking-related trait evaluation by digitizing the visual examination process. To reduce the dependency on manual labor and increase efficiency by detecting diseases early, like lameness related to hoof angle too, taking forward the vision of Precision Livestock Farming.

Over the last decade, artificial intelligence has dramatically reshaped the landscape of precision livestock (Fuentes et al. 2022) farming. With real-time computer vision systems now capable of capturing and analyzing complex animal traits, the possibilities for improving livestock management have expanded enormously. Precision dairy farming technologies are rapidly advancing and provide critical applications for herd monitoring (Patricio and Rieder 2018).

Yet, even as AI marches forward, one question persists: Why do many of our most critical breed selection decisions still depend on subjective, time-consuming visual assessments? Deep learning detectors have also been effectively applied in plant phenotyping tasks, demonstrating robustness across agricultural domains.

Traditional methods based on conformation, body structure, and expert judgment remain the norm for identifying breed purity and predicting productivity. These approaches are often inconsistent and inefficient. As a result, research has increasingly turned toward deep learning (Menezes et. Al. 2025) models, especially those capable of object detection and segmentation, to bring automation, accuracy, and speed into this space. Earlier foundational works on deep learning for object detection (Zhao et al. 2019) provide the basis for recent YOLO advancements.

But here's the curious gap: Some of the most breed-defining features such as the size and shape of the hump in Sahiwal cattle are described in rich morphological detail in manuals and studies, yet rarely quantified with precision. For example, a breed manual from Pakistan explicitly contrasts "erect" versus "drooping" hump, classifying the former as ideal for breed purity. Another study from Assam Agricultural University highlights the "massive hump (Kaushik et al. 2020)" as a signature feature of purebred Sahiwal (Kumar et al. 2020) cows. Yet in both cases, these observations stop short of one crucial thing: objective measurement of the hump area and its direct correlation to genetic purity.

A similar pattern emerges in hoof-related traits. Scientific studies point to how dorsal hoof angle, heel heights and hind feet positioning influence lameness, welfare, and even milk production. Still, there remains a disconnect can we actually quantify how hoof conformation metrics (like a 45° pastern angle or HFPS >17°) affect productivity and health at scale?

The literature reveals a clear paradox: we know which traits matter, but we don't yet have the tools to consistently measure them with the rigor they deserve. The YOLO (You-Only-Look-Once) architecture, which is prominent for its real time performance, has been the main front of animal detection research. Multiple research works have taken YOLO variants to detect cows, track their movements, and for segmentation of specific body parts. The classification of breeds has also witnessed significant progress using convolutional neural networks (CNN). This study enhances the YOLOv5 (Zhang et al. 2020) model by integrating a Filter Attention mechanism and Soft Pooling to improve the detection of cattle body parts such as the head, legs, and tail in complex farm environments. The improvements led to a mean Average Precision (mAP) of 90.74%, demonstrating the model's effectiveness in precision livestock farming. This paper presents an automated system utilizing an improved YOLOv8 (Chen et al. 2023; Ultralytics 2023) model to assess the hump area and hoof angle of Sahiwal cow. This paper applies YOLOv8 for detecting and segmenting cattle in grazing environments.In addition to this, the surge of edge computing has made it extremely easy to deploy AI models in remote farm environments, where cloud processing may not be feasible. Research studies has shown that YOLO v5 and YOLO v8 has better performance on low-power edge devices, therefore providing latency free. Which makes the task real-time feasible.

In light of the above studies and identified research gaps, YOLOv8 emerges as a promising tool to bridge this divide. By leveraging custom-labeled datasets and fine-tuned object detection models, it lays a robust foundation for practical, intelligent, and scalable livestock assessment.

Material and methods

Dataset collection and annotations

A dataset of 650 images of cows has been used to train the model. Images were collected from dairy farmers including on-field as well as open datasets. Our main goal during selection of the images was to get the hump and the hoof regions clearly in different positions and lighting conditions. Different types of commonly available user-friendly handheld mobile devices were used for image capturing for robustness of the model. To ensure diversity within the dataset, images were clicked in an open area as well as inside the milking area while maintaining a consistent distance between the camera and the cow. Additionally, height of the cameras was adjusted proportionally to the animal's height. A total of 600 images were acquired for this study. The images were collected from the herd of Sahiwal cows maintained at Cattle Yard of ICAR-NDRI, Karnal and local dairy farmers door step.

After collecting all the dataset images were augmented and approximately 2000 images were generated and annotated the dataset using bounding boxes. We labeled two specific regions on the image:

1. Hump Area: which is located over the shoulder and top-back portion of the cow.

Table 1. Performance metrics for Hump Area Detection

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

2. Hoof region**:** which focuses on the lower limbs and the hooves.

As we annotated the images, we did as precise annotations as it could be so that the dataset was clean, and the model could be trained perfectly. Then we formatted all these images for YOLOv8 using Roboflow in order to make the management of the dataset easier.

Choosing YOLOv8 for Detection. In order to keep our model fast and reliable with the limited dataset, we used YOLOv8. As our dataset was limited and we needed fast and efficient object detection, we used the model which was perfect fit for our project. We used ultralytics implementation of the YOLOv8 which is easy to setup and gives smoother training process as well as easy to code with numerous python libraries.

Training the Model

Data augmentation techniques like flip, rotate, scale, and brightness changes were applied to the original 600 collected images to generate a final dataset of 2,000 images. These images were split into 90% training, 5% validation and 5% testing. These images were used to train YoloV8 model for speed in which we did 50 epoches with image size of 640x640 pixels and batch size of 8. We trained our model using Visual Code Studio on Mac, which gave us efficiency in training in short span of time.

Detecting the Hump and Measuring the Area

One of the major objective of this study was to accurately detect the of the cow as it is often a reference point for the breed-specific characteristics. After training the model, it was able to accurately detect the hump area with high confidence in side-view images and the bounding box were centered at the exact point where they were needed to be. To calculate the area of the hump region from the image, the following formula was used:

(a) (b)

Fig. 1. Images from the data set prepared for measuring the hump area and hoof angle (a) Hump Area (b) Hoof region

Step 1: Calculate the number of pixels in the detected bounding box area

$$A_{pixels} = \sum_{i=1}^{n} ContourArea(mask_i)$$

Where:

- Apixels = Area in pixels² of the hump contour
- Maski = Each detected contour point forming the hump
- shape using YOLOv8 bounding box prediction
- ContourArea is computed using OpenCV's cv2.contourArea() function.

Step 2: Area was kept in pixel units to ensure consistency, as no physical calibration object was available:

$$A_{cm^2} = A_{pixels} \times \left(\frac{H_{real}}{H_{pixels}}\right)^2$$

Where:

- = Hump area in square centimeters
- H_{real} = Pixel height of the cow (in cm)
- H_{pixels} = Pixel height of the same cow in the image
- $\left(\frac{H_{real}}{H_{pixels}}\right)$ = Pixel scaling factor (relative)

Detecting of hoof and measuring the Hoof Angle

The other major objective was to find the hoof region using the training data. The Predicted bounding box was used to extract that image part to estimated the hoof angle which was the inclination of the hoof with the contact surface. To estimate the hoof angle from the hoof bounding box edges, the angle between the two vectors formed by the detected hoof edges was calculated using dot product formula:

$$\theta = cos^{-1}\left(\frac{v_1 . v_2}{\|v_1\| . \|v_2\|}\right)$$

Where:

- $v_1 . v_2$ = Dot product of vectors
- $\|v_1\| . \|v_2\|$ = Magnitude of vectors

Convert Radians to Degrees:

$$\theta_{degress} = \theta \times \left(\frac{180}{\pi}\right)$$

This gives use the hoof angle expressed in degress which is then overlaid on the original cow image using OpenCV.

Results and Discussion

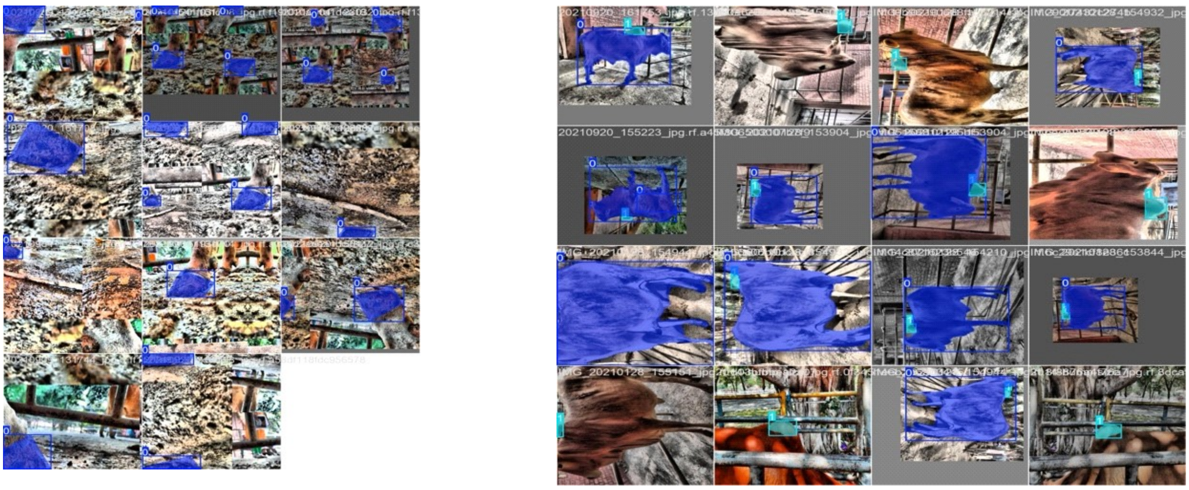
Performance Evaluation

To evaluate how well the model is performing, we used:

- Precision, Recall, and mAP for both Hump area and Hoof detection.
- IoU to measure how accurately the bounding boxes are matched over the annotated ground truth.

Table 2. Performance metrics for Hoof Angle Detection

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



(a) (b)

Fig. 2 Intermediate images of YOLO v8 for the Hump Area and Hoof Angle Detection of Sahiwal Cows (a) Foot-Surface Dataset Annotations(b) Cow-Hump Dataset Annotations

Fig. 3 Graphs for Hump Detection

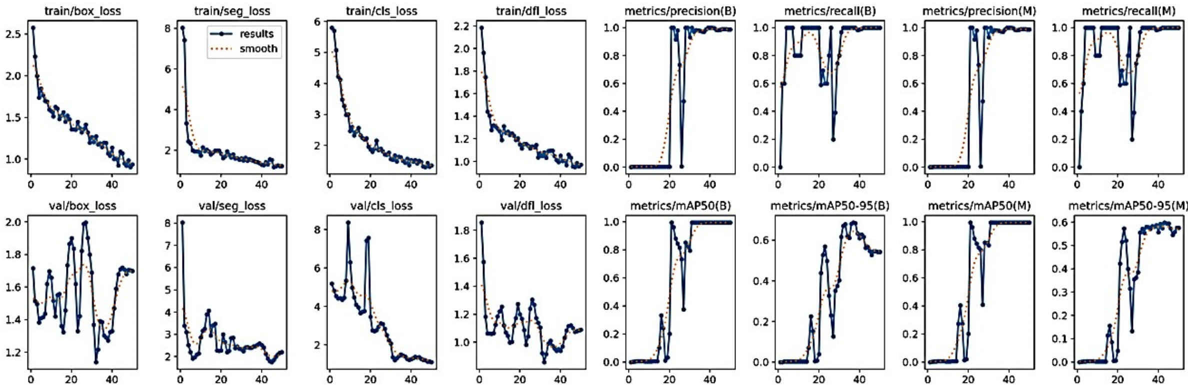
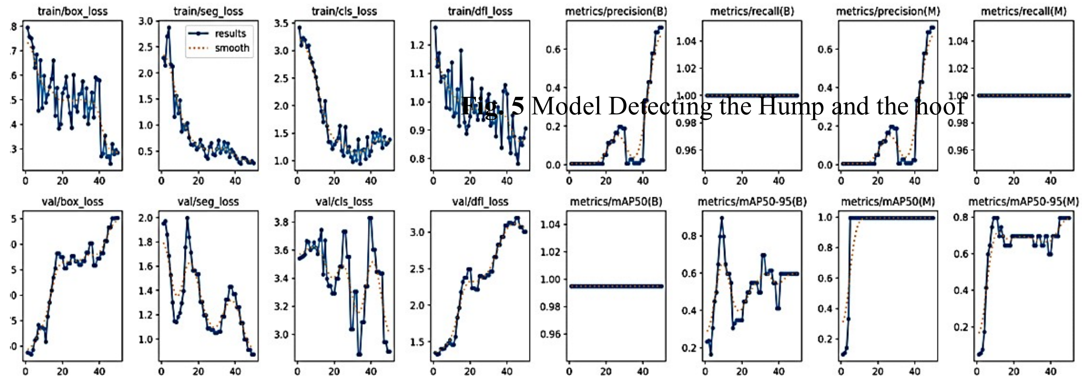


Fig. 4 Performance metrics for Hoof Detection



Even with all this small dataset, Yolov8 detected the hump and the hoof well with the precise measurements of hump area and hoof angle.

The proposed work showed efficient performance in detecting and analyzing the key physical features of cow, especially the hump area and the hoof angle from a dataset of under 600 annotated images. Performance metrics for the hump area detection model are shown in Table 1 and the Graphs for hump detection are shown in Figure 3.

Hoof Angle Detection

Performance metrics for the Hoof Angle Detection model are shown in Table 2 and the graphs for the Hoof angle selection are shown in Figure 4.

The sample of detection of the hump area as well as the hoof angle, is shown in the image of Sahiwal cow in Figure 5.

Fig. 5 Model Detecting the Hump and the hoof

Conclusion

In this study, an attempt has been made to develop a deep learning based model utilizing YOLOv8 for the segmentation of the hump region with the area estimation and geometric estimation of the hoof angle in the cows. The proposed model aims to support the automation of the two main physical parameters of cows which were often evaluated manually by veterinarians. The result of this proposed model demonstrates that it is capable of detection of hump and the hoof with the precise estimation of hump area and hoof angle. Deep learning detectors have also been effectively applied in plant phenotyping tasks, demonstrating robustness across agricultural domains.

In future, we aim to enhance the accuracy and generalization of the model through the expansion of the training dataset, including images from various angles, environmental conditions and cattle postures. Additionally, we will be integrating the live video stream processing which will allow real-time detection and tracking other morphological characteristics.

Conflict of interests

The authors declare that they have no conflict of interests.

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