Mitigating Training Bias in Cattle Breed Identification through Orientation-Aware Framework

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Abstract. This paper introduces a comprehensive strategy to mitigate training bias in cattle breed identification models, focusing on cow orientation in still frames. Leveraging YOLOv7 for face detection, our methodology incorporates a novel orientation-aware pre-processing step that categorizes images into right-oriented, left-oriented, original, and original with inverted orientations. The breed identification model, based on Convolutional Neural Networks (CNN), is trained on this augmented dataset. While the left-oriented approach achieves the highest accuracy, the original and inverted orientation strategy demonstrates superior validation accuracy, showcasing its effectiveness in addressing bias during real-world applications with varied cow orientations. These findings underscore the importance of orientation-aware training for robust cattle breed identification, providing a solution for an overlooked niche.

Keywords: Orientation labelling, Data augmentation, Convolutional Neural Networks (CNN), Cattle breed identification

1 Introduction

Cattle breed identification is pivotal for diverse applications in livestock management such as maintenance of pedigree and production records and its mandatory for the preservation of animal genetic resources **[1]**, comprehensive assessment of breeding history and breed purity **[2]**-**[3]**, strategic planning for breeding initiatives **[4]**, enhancement of supply chain integrity through product provenance inference **[5]**-**[7]**, and the conservation of locally specific species **[2, 8]**. Traditional methods such as ear tagging, ear notching, and electronic devices have been employed for individual identification **[9]-[11]**. However, these methods face challenges such as tag loss, electronic device malfunction, and reusability issues **[12]**. To address these shortcomings, there is a growing interest in leveraging advanced machine learning and computer vision technologies for precision livestock management **[13]**. Despite the commendable progress in cattle identification models, particularly those adopting a two-stage detection approach, there remains a critical gap in addressing real-world challenges, including training bias. Our proposed orientation-aware face detection approach directly tackles this issue, as farmers often capture images in preferred orientations, leading to datasets lacking the necessary diversity to ensure model robustness in handling varying cow orientations and breeds.

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2 Background

In the dynamic landscape of cattle breed identification, the integration of computer-vision technology has witnessed a surge in interest, particularly in harnessing visual features extracted from cattle images **[14],[15]**. This innovative approach involves the utilization of image processing and machine learning to discern unique patterns present in facial or body coat features, which serve as distinctive markers for individual cattle **[14]**, **[16]-[18]**. The versatility of these features is evident in their application across various classifiers, machine learning models, and deep learning models reflecting the diverse array of methodologies adopted in the field. Biometric features such as iris and retinal patterns, characterized by their stability over time, have been explored for cattle identification, albeit facing practical implementation challenges due to difficulties in image capturing **[19]-[21]**. An alternative biometric modality, namely muzzle prints or nose prints, distinguished by their unique grooves and patterns, has gained traction as a reliable identifier for individual cattle **[22]-[25]**. The strategic integration of machine learning models, including SVM, KNN, ANNs, decision trees, random forest, and logistic regression, since 2014 has significantly contributed to advancing the accuracy of cattle identification, with deep learning models such as CNN, ResNet, and Inception showcasing superior performance **[26]-[34]**.In the realm of cattle breed identification, addressing training bias is pivotal for robust model performance. Previous methodologies have leveraged neural networks with specific architectural features to optimize accuracy and efficiency in identification tasks. For instance, a lightweight neural network incorporating convolutional layers, Batch Normalization, and dropout layers, with global average pooling, has demonstrated efficacy in cattle face recognition. This network, trained on a dataset comprising over 10,000 cattle face images, achieved an impressive accuracy of 98.37%, highlighting its potential for real-world applications **[35]**. While the advancements demonstrate the strides in cattle breed identification, it is crucial to address the numerous inherent biases in visual data collection **[36]**. The uniform orientation of cattle images in datasets and the lack of variability in cow breeds may introduce bias, impacting the model's real-world performance, that are not identified or vetted in the studies above. As farmers often capture images in a preferred orientation, the training datasets should strive for diversity to ensure the model's robustness in handling varying cow orientations and breeds.

3 Proposed Model

Figure 1 depicts the proposed model for bias mitigated cattle breed identification. Each component will be explained in detail, in this section.

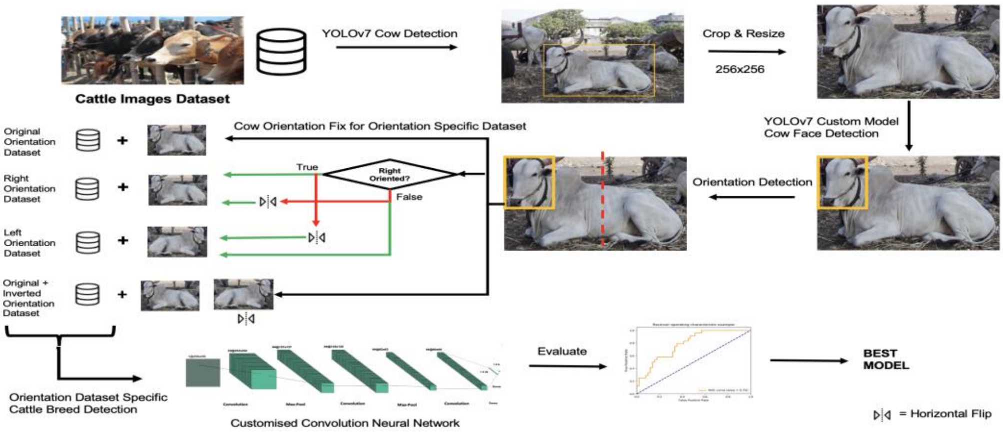


Fig. 1. Model Framework Architecture Diagram

3.2 YOLOv7 for Individual Cow Detection

YOLOv7 outperforms all existing state-of-the-art object detection systems in terms of both speed and accuracy, spanning a frame rate range of 5 to 160 frames per second (FPS) **[37]**. By employing pre-trained COCO weights, the algorithm adeptly recognizes cows in the provided images. The YOLOv7 algorithm yields bounding box coordinates, class labels, and a confidence value (p) for detected objects, with a specified confidence level of 0.25 in this study. After pinpointing cows within the images, identified as class 19 in the COCO dataset of 80 classes, the subsequent step involves cropping the images to concentrate exclusively on the cow's body. This entails utilizing the bounding box coordinates derived from the YOLOv7 algorithm to precisely crop the image.

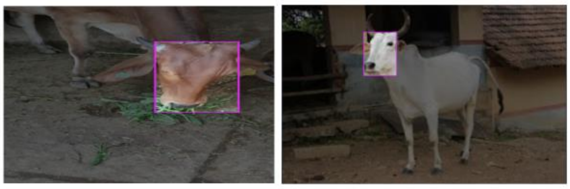
(a) YOLOv7 Body Identification **(b)** Cropped and Resized Image

Fig. 2. Cow Identification Process

This cropping procedure streamlines the data by eliminating extraneous information, directing focus exclusively to the region of interest—the cow's body. The selection of the cow with the highest confidence (p value) among multiple identified cows is determined for cropping. **Figure 2** illustrates this process, where, in a frame containing multiple cows, the cow with the highest confidence level is selected and cropped. The image is resized to 256X256 post cropping.

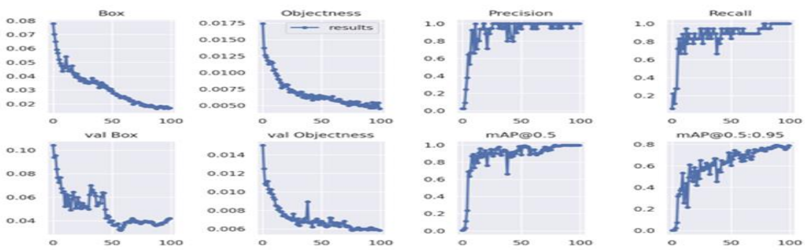
3.3 Custom Face Detection Model

Rectangular annotations were systematically applied to cow faces in various configurations, encompassing one, two, or multiple faces within a single image (**Figure 3a**). To mitigate biases introduced by crossbreeding, dehorning, or disbudding practices, the annotation process intentionally excluded horns. The YOLO V7 model was trained using a dataset comprising 442 images, employing Coco weights for initialization, a batch size of 32, and a confidence interval of 0.05. The training spanned 100 epochs, with subsequent testing and validation performed on 46 images. The training progress and predicted values, visualized in **Figure 3b**, illustrate the batchwise progression. Evaluation of the YOLO Face Detection Training was conducted based on macro-precision (mean average precision) and Recall. The model exhibited consistent improvement up to 15 epochs, followed by a gradual increase and eventual plateau at 1.0, as illustrated in **Figure 3c**.



a) Cow Face Annotation Samples

b) Batchwise Training



c) Model Training Evaluation

Fig. 3. YOLOv7 Custom Cow Face Detection Model

3.3 Face Positioning based Orientation Aware System

Cow Orientation Detection. This part of the process involves fixing the orientation. First, the cow orientation is detected, the decision-making process is straightforward yet effective, if the custom YOLO model detected cow face is positioned towards the horizontal left half (50%) side of the image, it is classified as left oriented. Conversely, if the face is on the horizontal right side (50%), the orientation is labelled as right oriented. This orientation-aware approach acknowledges the inherent spatial information within the images, ensuring that the model is trained on a diverse set of orientations commonly encountered in real-world scenarios. **Figure 4** visually illustrates these orientation labels, the yellow line indicates the horizontal midpoint, **Figure 4a** is a left oriented cow because the face is on the left side, similarly **Figure 4b is a** right facing cow because the face is to the right side of the image horizontal midpoint.

(a) Left Oriented **(b)** Right Oriented

Fig. 4. Orientation Detection System

Cow Orientation Specific Datasets. There are 4 processed datasets created post detecting the cow orientation. **Figure 5** illustrates the complete procedure, wherein an image from the dataset undergoes processing. The initial image is stored in the Original Orientation Dataset. Its original version, along with the horizontally flipped counterpart, is archived in the Original + Inverted Orientation Dataset. The identified orientation is examined and stored in the corresponding side (left/right), while its horizontally flipped representation is stored in the opposite orientation dataset.

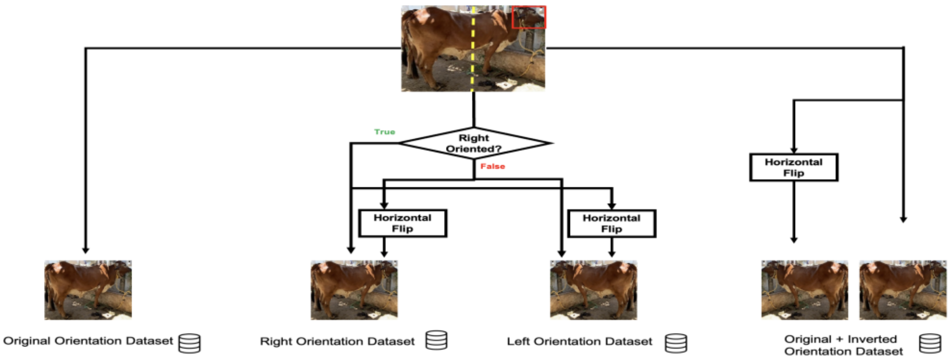


Fig. 5. Orientation Specific Dataset Segregation Pipeline

4 Model Training

4.1 Dataset

Through the Orientation Aware System's pre-processing, four datasets were generated: left-oriented (1572 images), right-oriented (1572 images), original (2255 images), and original + inverted (3144 images). Each dataset involves six cattle breeds, constituting a multi-class classification problem, namely Gir, Sindh, Rathi, Kangeyam, Kankrej, and Pulikulam. The images were collected from local farms in Tamil Nadu, India, with video clips and frames captured by dairy farmers under researcher supervision. The classes were balanced, with each cattle breed having 380 to 450 images in the original dataset. 80% of the data was allocated for training, and the remaining 20% for validation across all datasets.

4.2 CNN (Convolution Neural Network) for breed identification

Within deep neural networks, Convolutional Neural Networks (CNNs) excel in image classification tasks. Our employed architecture, as depicted in **Figure 6**, follows a standard CNN structure renowned for its effectiveness. It consists of convolutional layers, each followed by max-pooling layers for feature extraction. The model starts with a convolutional layer having 32 filters (3x3 kernel, ReLU activation), followed by max-pooling layers. Subsequent convolutional layers with 64 filters capture intricate features. The final convolutional layer is flattened, creating a feature vector fed into densely connected layers. The output layer, utilizing SoftMax activation, has six nodes representing the cattle breeds. The model is trained for 10 epochs using the CNN structure.

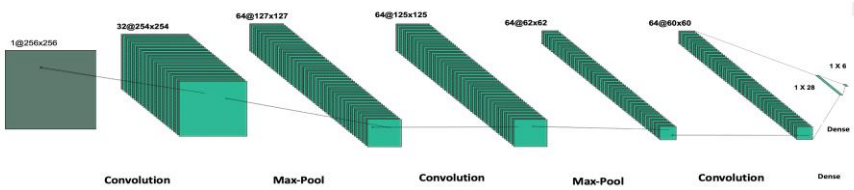
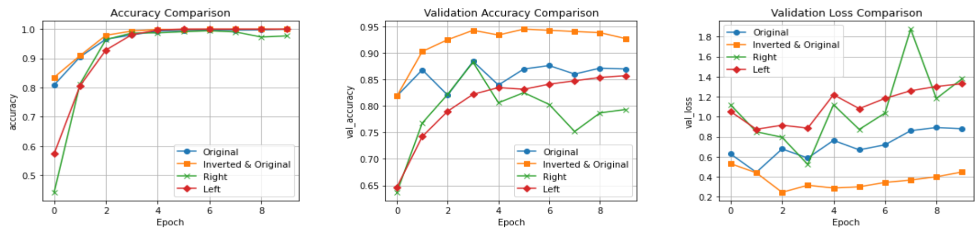


Fig. 6. Cattle Breed Identification CNN Model

5 Model Evaluation



a) Accuracy b) Validation Accuracy **c)** Validation Loss

Fig. 7. Model Evaluation: Accuracy & Loss vs Epochs Plots

After 10 epochs, the model exhibits distinct performance based on orientation. The Original Orientation dataset shows exceptional training accuracy (99.96%) and commendable validation accuracy (86.94%). The Inverted and Original Orientation dataset outperforms all other models with a validation accuracy of 92.68%. However, orientation-specific datasets, Right Orientation Only and Left Orientation Only, present challenges with potential bias issues, with extremely high validation loss. The model's versatility in handling varied orientations is evident, showcasing its robustness in real-world scenarios.

Table 1. Post 10 Epochs Model Evaluation Metrics

Dataset	Accuracy	Validation Accuracy	Loss	Validation Loss
Original	0.9996	0.8694	0.0017	0.8802
Inverted + Original	0.9994	0.9268	0.0009	0.4484
Right Orientation	0.9769	0.7930	0.0799	1.3792
Left Orientation	1.0000	0.8567	0.0001	1.3298

6 Conclusion

Our methodology for mitigating training bias in cattle breed identification, integrating YOLOv7 for face detection and CNN for breed identification, has shown significant advantages. The left-oriented approach achieves the highest accuracy, while the original and inverted orientation strategy exhibits superior validation accuracy, addressing bias in real-world scenarios. Despite robust performance, there are limitations, especially with orientation-specific datasets, indicating potential bias issues. Future work may involve expanding the dataset, refining orientation detection, and exploring advanced neural network architectures for enhanced performance in precision livestock farming.

References

[1] Davies N, Villablanca FX, Roderick GK. Determining the source of individuals: multilocus genotyping in nonequilibrium population genetics. Trends Ecol Evol. 1999;14(1):17–21. [https://doi.org/10.1016/s0169-5347(98)01530-4]

[2] Maudet C, Luikart G, Taberlet P. Genetic diversity and assignment tests among seven French cattle breeds based on microsatellite DNA analysis. J Anim Sci. 2002;80(4):942–50. [https://doi.org/10.2527/2002.804942x]

[3] Paetkau D, Calvert W, Stirling I, Strobeck C. Microsatellite analysis of population structure in Canadian polar bears. Mol Ecol. 1995;4(3):347–54. [https://doi.org/10.1111/j.1365-294x.1995.tb00227.x]

[4] Rannala B, Mountain JL. Detecting immigration by using multilocus genotypes. Proc Natl Acad Sci U S A. 1997;94(17):9197–201. [https://doi.org/10.1073/pnas.94.17.9197]

[5] Luca F. Genetic authentication and traceability of food products of animal origin: new developments and perspectives. Ital J Anim Sci. 2009;8(2):9–18. [https://doi.org/10.4081/ijas.2009.s2.9]

[6] Lo YT, Shaw PC. DNA-based techniques for authentication of processed food and food supplements. Food Chem. 2018;240:767–74. [https://doi.org/10.1016/j.foodchem.2017.08.022]

[7] Bertolini F, Galimberti G, Calo DG, Schiavo G, Matassino D, Fontanesi L. Combined use of principal component analysis and random forests identify population-informative single nucleotide polymorphisms: application in cattle breeds. J Anim Breed Genet. 2015;132(5):346–56. [https://doi.org/10.1111/jbg.12155]

[8] Sun H, Olasege BS, Xu Z, Zhao Q, Ma P, Wang Q, et al. Genome-Wide and Trait-Specific markers: a perspective in designing conservation programs. Front Genet. 2018;9:389. [https://doi.org/10.3389/fgene.2018.00389]

[9] Awad AI. From classical methods to animal biometrics: A review on cattle identification and tracking. Computers and Electronics in Agriculture. 2016;123:423–435. https://doi.org/10.1016/j.compag.2016.03.019

[10] Neary M, Yager A. Methods of livestock identification (no. as556-w). West Lafayette: Purdue University; 2002.

[11] Ruiz-Garcia L, Lunadei L. The role of RFID in agriculture: Applications, limitations and challenges. Computers and Electronics in Agriculture. 2011;79(1):42–50. https://doi.org/10.1016/j.compag.2011.08.007

[12] Roberts CM. Radio frequency identification (RFID). Computers & Security. 2006;25(1):18–26. https://doi.org/10.1016/j.cose.2005.10.006

[13] Mahmud MS, Zahid A, Das AK, Muzammil M, Khan MU. A systematic literature review on deep learning applications for precision cattle farming. Computers and Electronics in Agriculture. 2021;187:106313. https://doi.org/10.1016/j.compag.2021.106313

[14] Andrew W, Hannuna S, Campbell N, Burghardt T. Automatic individual Holstein Friesian cattle identification via selective local coat pattern matching in RGB-D imagery. In: 2016 IEEE International Conference on Image Processing (ICIP). IEEE; 2016. p. 484–488.

[15] de Lima Weber F, de Moraes Weber VA, Menezes GV, Junior AdSO, Alves DA, de Oliveira MVM, et al. Recognition of Pantaneira cattle breed using computer vision and convolutional neural networks. Comput Electron Agric. 2020;175:105548.
[16] Noviyanto A, Arymurthy AM. Beef cattle identification based on muzzle pattern using a matching refinement technique in the SIFT method. Comput Electron Agric. 2013;99:77–84.
[17] Arslan AC, Akar M, Alagöz F. 3D cow identification in cattle farms. In: 2014 22nd Signal Processing and Communications Applications Conference (SIU). IEEE; 2014. p. 1347–1350.
[18] Andrew W, Greatwood C, Burghardt T. Visual localisation and individual identification of Holstein Friesian cattle via deep learning. In: Proceedings of the IEEE International Conference on Computer Vision Workshops; 2017. p. 2850–2859.
[19] Allen A, Golden B, Taylor M, Patterson D, Henriksen D, Skuce R. Evaluation of retinal imaging technology for the biometric identification of bovine animals in Northern Ireland. Livest Sci. 2008;116(1-3):42–52.
[20] Lu Y, He X, Wen Y, Wang PS. A new cow identification system based on iris analysis and recognition. Int J Biometrics. 2014;6(1):18–32.
[21] Andrew W, Gao J, Mullan S, Campbell N, Dowsey AW, Burghardt T. Visual identification of individual Holstein-Friesian cattle via deep metric learning. Comput Electron Agric. 2021;185:106133.
[22] Kusakunniran W, Chaiviroonjaroen T. Automatic cattle identification based on multi-channel LBP on muzzle images. In: 2018 International Conference on Sustainable Information Engineering and Technology (SIET). IEEE; 2018. p. 1–5.
[23] Awad AI, Hassaballah M. Bag-of-visual-words for cattle identification from muzzle print images. Appl Sci. 2019;9(22):4914.
[24] Kumar S, Singh SK, Singh AK. Muzzle point pattern based techniques for individual cattle identification. IET Image Process. 2017;11(10):805–814.
[25] Kumar S, Singh SK. Cattle recognition: A new frontier in visual animal biometrics research. Proc Natl Acad Sci India Sect A Phys Sci. 2020;90(4):689–708.
[26] Yang Z, Xiong H, Chen X, Liu H, Kuang Y, Gao Y. Dairy cow tiny face recognition based on convolutional neural networks. In: Chinese Conference on Biometric Recognition. Springer; 2019. p. 216–222.
[27] Joachims T. Making large-scale SVM learning practical. Technical report. 1998.
[28] Cover T, Hart P. Nearest neighbor pattern classification. IEEE Trans Inf Theory. 1967;13(1):21–27.
[29] McCulloch WS, Pitts W. A logical calculus of the ideas immanent in nervous activity. Bull Math Biophys. 1943;5(4):115–133.
[30] Rumelhart DE, Hinton GE, Williams RJ. Learning representations by back-propagating errors. Nature. 1986;323(6088):533–536.
[31] Kumar S, Pandey A, Satwik KSR, Kumar S, Singh SK, Singh AK, et al. Deep learning framework for recognition of cattle using muzzle point image pattern. Measurement. 2018;116:1–17.
[32] Alzubaidi L, Zhang J, Humaidi AJ, Al-Dujaili A, Duan Y, Al-Shamma O, et al. Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. J Big Data. 2021;8(1):1–74.
[33] He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2016. p. 770–778.
[34] Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556. 2014.
[35] Li, Z., Lei, X., & Liu, S. (2022). A lightweight deep learning model for cattle face recognition. Computers and Electronics in Agriculture, 195, 106848.
[36] Simone Fabbrizzi, Symeon Papadopoulos, Eirini Ntoutsi, Ioannis Kompatsiaris, "A survey on bias in visual datasets," Computer Vision and Image Understanding, vol. 223, 2022, article no. 103552, ISSN 1077-3142, https://doi.org/10.1016/j.cviu.2022.103552.
[37] Wang CY, Bochkovskiy A, Liao HY. YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors. InProceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition 2023.