An Model Generalization Study in Localizing Indoor Cows with COw LOcalization (COLO) dataset

A Preprint

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Abstract

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Keywords Object detection · Model selection · Model generalization

1 Introduction

Object Localization in Animal Science

Define object localization

Object localication, also known as object detection in the computer vision community, is a task that identifies the location of objects within an image or a video frame. The location is typically defined by a rectangular bounding box that encloses the object of interest.

Economic values in animal and dairy science

Model generalization and public dataset

Define model generalization and fine-tuning

Importance of public dataset

Study objectives

Use YOLO models as studied models

Considering object deteciton is relatively simple task compared to segmen

- YOLO structure - YOLOv8 - YOLOv9

How environment affects the model generalization

How the model complexity impact the model performance

Comparing the fine-tuned and pre-trained model on new tasks

Release the COLO dataset to the public

The precise enumeration of cattle within pastoral environments is imperative for enhancing farm operational efficiency, exerting a significant influence on both the economic and ecological aspects of livestock management. Accurate cattle detection is a linchpin in the execution of strategic farm management, impacting resource allocation, health surveillance, and breeding practices. The advent of Computer Vision (CV) and Artificial Intelligence (AI) technologies in cattle detection systems has been revolutionary for agricultural methodologies. These innovations facilitate the automated monitoring of cattle, providing real-time, high-precision counts, while mitigating manual labor and its inherent inaccuracies. CV-driven AI algorithms are adept at identifying individual cattle amidst the complexity of farm settings, adjusting for variations in illumination, visual obstructions, and animal movement.

A salient application of such technology is evident in the optimization of alley flushing mechanisms within modern dairy operations. Preserving alley cleanliness is essential for averting diseases like mastitis, which can substantially affect both dairy output and bovine well-being. Traditional manual flushing, typically performed bi-daily, suffers from inefficiencies and a lack of responsiveness to the alley's dynamic conditions. The predetermined flushing schedules may not align with the actual sanitary requirements, potentially compromising cleanliness or wasting water. An AI system, empowered by computer vision, can refine this process by determining the optimal flushing moments. For instance, by detecting the number of cows present and initiating the flush when animal counts drop below a specific threshold—ideally when no cows are present—the system ensures a timely and efficient cleaning without human intervention. This not only conserves resources but also upholds a consistently hygienic environment conducive to animal health and productivity.

Application of animal science and agriculture

Animal scientists are increasingly leveraging AI-based object detection algorithms, such as those employed in recognizing cows, pigs, and sheep, for a plethora of purposes. Such as, classifying pig postures segmenting cattle instances, monitoring cow feeding behavior etc. Predominantly, research has focused on deploying various deep learning models to address different challenges within the domain. The utility of YOLO (You Only Look Once) models, in particular, transcends traditional object detection boundaries. These models have been adeptly applied in the agricultural sector for purposes such as identifying and classifying different crop types tian2019apple,lippi2021yolo, as well as detecting pests and plant diseases wu2020using, significantly contributing to the progress of precision agriculture and fostering the movement towards automated farming operations. Similarly, in the realm of biometrics and security, the flexibility of YOLO frameworks has been exploited for facial detection tasks, thus becoming a cornerstone for the enhancement of facial recognition technologies yang2018real,chen2021yolo. This multifaceted applicability of YOLO models underscores their versatility and potency in propelling forward a wide array of intelligent systems across diverse sectors.

A recent study introduced a method to accurately classify the posture of pigs based on images. They used YOLOv5, which achieved a pig detection accuracy of 0.994 with an APIoU=0.5. Then they utilized EfficientNet to classify the detected pigs into 'lying' and 'notLying' postures achieving a precision rate of 0.93. This innovative approach demonstrated the advantages of using models, for classifying pig posture resulting in improvements, in accuracy. These studies have addressed the issue that researchers aimed to solve witte2022introducing. Another recent advancement in precision livestock farming offers a cost-effective way to identify and monitor beef cattle using everyday surveillance cameras. This method can pinpoint cattle ear tags and even track their drinking behaviors, with the capability to read cow IDs with an impressive 89% accuracy. Such innovations not only streamline cattle management but also have the potential to significantly reduce monitoring costs for farmers prettonovel.

However, the costs, including labor, time, and computational resources, to implement the object detection were rarely addressed. For example, researchers conducted a study, on precision dairy farming, in Hokkaido, Japan. They successfully developed a system that could recognize cows ear tags using the object detector. To achieve this they needed a dataset of 20,000 training samples that were specifically focused on detecting cow heads zin2020cow. Preparing this amount of samples can be labor-intesntive, as formatting and labeling the positions of each object in an image requires professional training in programming language. For example, COCO annotation lin2014microsoft format is the most common format for object detection. It requires organizing the coordinates of the bounding box, the class of the object, and the image size in a JSON file. Without related expertise, there is a barrier to implement object detection in animal and dairy sciences. Another obstacle of the implementation is the computational resources. Not every computer can implement the modern object detection models, which have millions of parameters and requires up to 12 GB of video memory. For instance, the VGG-16 model simonyan2014very has 138 million parameters and recommends a VRAM of at least 8GB, while the ResNet-152 he2016deep has around 60 million parameters with a recommended VRAM of 11GB. Hence, knowing the computational cost is also an important factor for researchers to consider when implementing object detection. Lastly, the transfer-ability of the published studies is always missed to be discussed. This factor is important when one research want to reproduce the same published work in their own research, which may have different lighting or environment that affects the model performance. Transferring the model to a new environment usually requires providing additional training efforts, which is also a cost to consider.

Impressive results have been achieved using models such as YOLOv5 witte2022introducing Mask R CNN qiao2019cattle and DRN YOLO based on YOLOv4 zin2020cow. These approaches have proven successful in detecting postures performing segmentation and extracting useful features in complex farm environments. While these works have made contributions to precision livestock farming and laid the foundation for real time monitoring systems our research aims to push the boundaries by leveraging advanced models like YOLOv8, YOLONAS and DETR. Particularly noteworthy is DETR—a model that has gained recognition for its performance in object detection but has not yet been explored extensively in the field of animal science. Through harnessing these cutting edge models our goal is not to improve the accuracy and reliability of livestock recognition tasks but to spearhead the adoption of state of the art technologies, within the animal science sector.

Despite the promising advancements, the implementation of AI and CV technologies in animal science, particularly in precision livestock farming, faces significant challenges. High computational costs, the need for extensive training datasets, and the expertise required for data annotation are notable barriers that hinder the widespread adoption of these technologies. Additionally, the transferability of models across different environmental conditions remains a critical issue, as variations in lighting and camera settings can drastically affect model performance.

Addressing these challenges, our research introduces the "COWS ONLY LIVE ONCE (COLO)" dataset, an open-access resource designed to investigate the generalization capabilities of AI models in localizing indoor cows. By focusing on indoor environments, where conditions can be tightly controlled and monitored, this study aims to enhance the accuracy and reliability of livestock recognition tasks. Leveraging advanced AI models such as YOLOv8, YOLONAS, and YOLO V9, our work not only seeks to push the boundaries of what is currently achievable in livestock detection but also to facilitate the adoption of cutting-edge technologies in the animal sciences sector. Through the development of the COLO dataset, we address critical gaps in the field, such as the need for large, annotated datasets and the challenge of model transferability, paving the way for more efficient, responsive, and cost-effective livestock management solutions.

While notable advancements in object detection have been made within the domains of animal science and agriculture, our research endeavors to bridge certain gaps that remain unaddressed.

A critical concern is the determination of the necessary quantity of training samples to attain high accuracy, as measured by the Mean Average Precision (MAP). While it is common for researchers to gather data and fine-tune pre-trained models to secure MAP values exceeding 95%, the ideal dataset size for achieving such accuracy without incurring unnecessary computational costs remains undetermined. Excessive data may lead to computational redundancy, while insufficient data could result in diminished accuracy.

Moreover, the problem of optimal model selection poses another significant challenge. The spectrum of model complexity ranges from the highly intricate, such as YOLOv8x, which consists 68.2 million parameters map-param, to more streamlined variants like YOLOv8n with its 3.2 million parameters. As indicated in Table table:model-map-param, YOLOv8x outperforms YOLOv8n with a notable higher MAP value of 53.9 compared to 37.3, respectively. This disparity might incline researchers toward selecting the more complex YOLOv8x due to its superior MAP. Nevertheless, this decision comes with trade-offs: models with a greater number of parameters, while more accurate, demand extensive computational resources, including higher memory usage. Conversely, models with fewer parameters are typically quicker to train, are more memory-efficient, but offer less precision. The pivotal question we seek to answer is whether the efficacy of a complex model over a simpler one persists when the scope of classes is narrower, such as in datasets unlike COCO, and what the implications are when fine-tuning models for these scenarios.

2 Materials and Methods

Our study starts with the systematic acquisition of image data, focusing on targeted cattle populations within Kentland Farm at Virginia Tech. All animal handling and media recordings were conducted following the guidelines and approval of the Virginia Tech Institutional Animal Care and Use Committee. This initial phase is succeeded by meticulous data processing steps which include the annotation and formatting of the dataset for machine learning applications. Subsequently, we proceed to fine-tune our dataset utilizing a variety of deep learning architectures. For each model, we meticulously calculate a suite of performance metrics.

Building upon the results obtained from these diverse models, we construct a "summary plot." This plot is designed to elucidate the findings related to the second and third questions delineated in Section contribution of our paper. It will visually guide the selection of an optimal model by delineating the relationship between dataset size and achieved accuracy, as well as the computational cost versus the precision of the models. Through this analytical representation, we aim to furnish a comprehensive tool that aids researchers in making informed decisions when it comes to choosing the most suitable object detection model for their specific requirements in livestock production studies.

Data Preparation

Recognizing the crucial role of lighting conditions on data integrity, we meticulously orchestrated our data gathering operations at assorted intervals throughout the day, specifically: dawn, midday, dusk, and late evening. This methodical approach was paramount in guaranteeing the inclusion of an extensive spectrum of lighting conditions within our dataset, thereby augmenting its diversity and resilience to various environmental challenges.

Moreover, cognizant of the effect camera angles and perspectives have on capturing the full gamut of cattle postures, we varied our image capture process accordingly. This variation not only accounted for the different positions and movements of the cattle but also for the heterogeneous nature of the environment in which they were situated. In addition, we aimed to ensure a broad representation of breeds by including both Jersey and Holstein cows in our dataset, recognizing that breed-specific characteristics could significantly influence the model's performance.

Animal Husbandry

The farm, hosting a diverse bovine community of over 200 individuals from the Jersey and Holstein breeds, served as an exemplary setting for our endeavor. It offered a plethora of varied scenarios and animal interactions, encapsulating the essence of a vibrant and dynamic agricultural environment. This multifaceted setting was critical in establishing a robust and comprehensive dataset reflective of the real-world complexity and variability one would expect in a livestock farming operation.

Camera Setup

The cornerstone of our data acquisition process was the deployment of Amazon Ring Cameras, as illustrated in Figure **??**. These cameras, primarily acclaimed for their real-time video surveillance capabilities, were judiciously selected for their advanced functionalities that are particularly conducive to farm monitoring applications. The Amazon Ring cameras are engineered to deliver 1080HD video quality, equipped with infrared night vision for after-dark monitoring, and Live View features for real-time observation.

Our rationale behind this choice stems from the device's capacity to provide high-definition 1080p video quality, ensuring that the clarity of the footage is not compromised, which is crucial for the accuracy of object detection algorithms. The integrated infrared night vision capability ensures continuous operation, day and night, which is imperative for creating a dataset that reflects all possible environmental conditions encountered in a farm setting.

Moreover, the Ring camera's battery-operated design introduces a level of convenience and adaptability that is ideally suited for the agricultural context. With a rechargeable battery that can last approximately one month per charge, the system provides a sustained, maintenance-low operation. This feature is particularly advantageous in farm environments where power sources may not be readily available at various points of interest.

Accessibility and manageability of the camera system are further enhanced through its compatibility with mobile and computer-based applications, allowing for remote access and control. Users receive prompt notifications on the status of the battery, thus ensuring that the camera's operation remains uninterrupted through proactive maintenance alerts for battery recharging or replacement. This negates the need for a permanent wired infrastructure and embodies a synergetic combination of high-resolution imaging capabilities with operational dexterity, making it an excellent tool for comprehensive monitoring and data collection in dynamic farm environments.

We used two Amazon Ring cameras for a dual-view approach. We positioned one camera to provide a top-down perspective, while the other was configured for lateral views. This bimodal configuration was designed to grasp the full geometric profile of the cattle, an approach that is conducive to enhancing the object detection algorithms' ability to discern the cows with greater precision.

The top view camera is critical in capturing the distinctive outlines and patterns of the cows' backs, which often include unique color markings and spine curvature, valuable features for individual identification and count. The side view camera, on the other hand, captures the profile shapes, including height, length, and body condition, offering a different set of attributes for the AI to analyze.

Together, these perspectives ensure that the AI algorithms have access to a richer array of visual information, improving their capacity to detect and differentiate between individual animals, even in a densely populated and dynamic environment such as a farm. This dual-view methodology also significantly widens the scope of detection, reducing blind spots and ensuring that the cows can be monitored effectively regardless of their orientation or position within the pen. The result is a robust dataset that simulates the multifaceted visual inputs required for a high-performing, real-world cattle monitoring system.

Data Annotation and Formation

- Talk about how the data was collected using pipes and Amazon Ring Cameras

- How the data is annotated on Roboflow The methodological rigor involved in data preparation is vital for the integrity of our machine learning model's training process. Here is a clear outline of the steps executed in preparing the dataset for cow detection in our investigation:

1. **Frame Extraction:** We utilized a customized Python script for the extraction of frames from the video streams, converting them into a series of static images. To guarantee uniformity across the dataset, we extracted frames at regular one-second intervals. This process yielded 'n' distinct images, which were then allocated to training, validation, and testing datasets for the subsequent stages of our machine learning endeavor.

2. **Annotation with Roboflow:** We uploaded the frames onto Roboflow, a versatile annotation platform. This tool enabled our team to annotate images by meticulously outlining cows with bounding boxes, ensuring that the AI model can learn to identify the target objects effectively. The annotated frames are exemplified in Figure **??**.

3. **Annotation Format Selection:** Roboflow's robust export options allowed us to obtain annotations in various formats suitable for different model architectures. We primarily opted for COCO and YOLOv5 formats, both widely recognized for their compatibility with state-of-the-art object detection algorithms.

4. **Data Storage and Maintenance:** Post-annotation, we stored the images in the universally accepted JPG format. Accompanying these images, the corresponding annotation files were meticulously cataloged, readying the dataset for the intricate process of model training and subsequent evaluation.

By adhering to these steps, we ensured the creation of a high-quality, standardized dataset poised for deployment in the development of an AI-powered cow detection system, geared towards enhancing the precision and efficiency of livestock management.

Simulation Design

Data Splits

We aim to thoroughly investigate model generalization across diverse conditions within livestock environments, specifically focusing on cattle localization. To achieve this, we meticulously designed and organized our dataset into five distinct configurations, each representing unique conditions under which the cattle were captured. These configurations are critical for evaluating the robustness and adaptability of object detection models, particularly in terms of their ability to generalize from one set of conditions to another. Below, we detail the dataset configurations and the rationale behind our data split strategy.

Dataset Configurations:

1. **Top View:** Images captured from an overhead perspective, providing a comprehensive view of the livestock area.
2. **Side View:** Images taken at a 60-degree (approx.) angle to the ground, offering a profile perspective of the cattle.
3. **Daylight:** Images captured during daylight conditions from both the top and side views, ensuring natural lighting.
4. **Nighttime:** Images obtained during nighttime from both the top and side views, with lighting conditions significantly reduced.
5. **Breed Specific:** A subset of images exclusively featuring the Holstein breed, allowing for breed-specific model training.

Training and Testing Strategy To rigorously assess model generalization, we employed a cross-testing methodology where models were trained on one dataset configuration and tested on another. This approach enabled us to isolate and understand the impact of various factors—such as viewing angle, lighting conditions, and breed variation—on model performance. The specific training and testing scenarios were as follows:

1. **Viewing Angle Generalization:** Models were trained on the Top View dataset and tested on the Side View dataset, and vice versa. This setup assesses the model's ability to adapt to changes in perspective.
2. **Lighting Condition Generalization:** Models trained on Daylight data were tested on Nighttime data to evaluate performance under varying lighting conditions, and vice versa.
3. **Breed Variation Generalization:** Models trained on the Breed Specific (Holstein) dataset were tested on a mixed-breed dataset (Holstein and Jersey), assessing the impact of breed diversity on detection accuracy.
4. **Comprehensive Generalization:** Finally, models were trained on a combination of all dataset configurations to examine overall generalization capabilities across viewing angles, lighting conditions, and breed variations.

This structured approach to data split and testing is designed to provide insights into the extent to which object detection models, trained under specific conditions, can accurately generalize to different, untrained conditions. By systematically varying training and testing datasets, we aim to uncover potential limitations and strengths of current object detection technologies in the context of livestock monitoring, contributing valuable knowledge towards the development of more robust and adaptable solutions in precision agriculture.

Objective 1: How model performance is decomposed by different factors

To investigate the model generalization. Factors such as lightning..

Each data configuration

Objective 2: How a fine-tuned model performed on a new dataset

Model Training and Evaluation

Trianing hyperparameters

- how to cross validation is Design with different sample Size - Iteration - Evaluation metrics

Data Augmentation

Model evaluation and cross validation

3 Results

The organize dataset is published on the huggingface dataset repository. It's organized in two formats: YOLO and COCO

Model performance decomposition

Model size and architecture performance

Fine-tuned versus. Pre-trained model performance

- by data configuration - by sample Size - by model architecture

External evaluation on the new dataset

3.1 Dataset release

4 Discussion

4.1 Why the lighting condition has less impact on the performance drop?

4.2 Is complex model architecture always better?

4.3 How does the model generalization study help in real-world applications?

5 Conclusion

Your conclusion here

Acknowledgments

This was was supported in part by......

References

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6 Headings: first level

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6.1 Headings: second level

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7 Examples of citations, figures, tables, references

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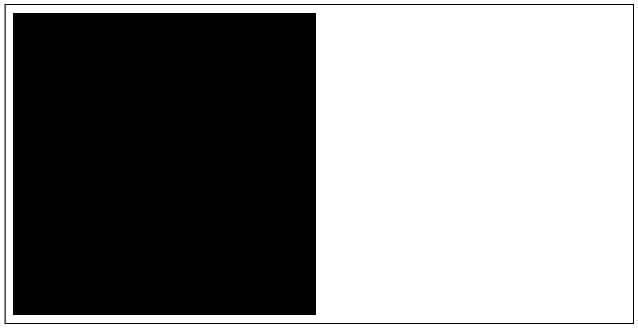

Figure 1: Sample figure caption.

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Of note is the command `\citet`, which produces citations appropriate for use in inline text. For example,

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> Hasselmo, et al. (1995) investigated...

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7.1 Figures

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[1] Sample of the first footnote.

Table 1: Sample table title

Part		
Name	Description	Size (μm)
Dendrite	Input terminal	$\sim$100
Axon	Output terminal	$\sim$10
Soma	Cell body	up to 10^6

7.2 Tables

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7.3 Lists

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