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

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Abstract:	Precision livestock farming (PLF) increasingly relies on advanced object localization techniques to monitor livestock health and optimize resource management. This study investigates the generalization capabilities of YOLOv8 and YOLOv9 models for cow detection in indoor free-stall barn settings, focusing on varying training data characteristics such as view angles and lighting, and model complexities. Leveraging the newly released public dataset, COws LOcalization (COLO) dataset, we explore three key hypotheses: (1) Model generalization is equally influenced by changes in lighting conditions and camera angles; (2) Higher model complexity guarantees better generalization performance; (3) Fine-tuning with custom initial weights trained on relevant tasks always brings advantages to detection tasks. Our findings reveal considerable challenges in detecting cows in images taken from side views and underscore the importance of including diverse camera angles in building a detection model. Furthermore, our results emphasize that higher model complexity does not necessarily lead to better performance. The optimal model configuration heavily depends on the specific task and dataset, highlighting the need for careful model selection tailored to the particular application. Lastly, while fine-tuning with custom initial weights trained on relevant tasks offers advantages to detection tasks, simpler models do not benefit similarly from this approach. It is more efficient to train a simple model with pre-trained weights without relying on prior relevant information, which can require intensive labor efforts. Future work should focus on adaptive methods and advanced data augmentation to improve generalization and robustness. This study provides practical guidelines for PLF researchers on deploying computer vision models from existing studies, highlights generalization issues, and contributes the COLO dataset containing 1254 images and 11818 cow instances for further research.
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Drs. Longsheng Fu, Manoj Karkee, Francesco Marinello, and Tomás Norton,
Editors-in-Chief, Computers and Electronics in Agriculture

Dear Drs. Longsheng Fu, Manoj Karkee, Francesco Marinello, and Tomás Norton,

I am writing to submit our manuscript titled "A Model Generalization Study in Localizing Indoor Cows with the COw LOcalization (COLO) Dataset." While AI-driven applications in agriculture have been extensively studied, there is a notable gap in evaluating the quality and generalizability of these applications in real-world scenarios. A persistent challenge for farm operators is determining how well existing models can adapt to their specific environments and the additional resources required for this adaptation.

Our study aims to address this challenge through a case study focused on cow localization within a free-stall barn setting. We investigate the generalization capabilities of existing models under varying conditions, including environmental lighting, model complexity, and camera view angles. Furthermore, we introduce a new dataset, the COw LOcalization (COLO) dataset, which serves as a benchmark for future research in this domain.

We believe that our findings will be of significant interest to the readers of *Computers and Electronics in Agriculture* and would be honored if you considered our manuscript for publication in your esteemed journal.

I appreciate your consideration.

Sincerely,

A handwritten signature in black ink, appearing to read 'Chun-Peng James Chen'.

Chun-Peng James Chen, Ph.D.
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Study Highlights

- This study provides guidelines for deploying an existing model in a new environment.
- Camera view angles impact the model performance more than variable lighting conditions.
- Higher model complexity does not necessarily yield better generalization performance.
- The advantage of fine-tuned weights from a relevant domain is not guaranteed.
- This study releases a benchmarking dataset with 1254 images and 11,818 cow instances.

A MODEL GENERALIZATION STUDY IN LOCALIZING INDOOR COWS WITH COW LOCALIZATION (COLO) DATASET

A PREPRINT

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ABSTRACT

1 Precision livestock farming (PLF) increasingly relies on advanced object localization techniques
2 to monitor livestock health and optimize resource management. This study investigates the gener-
3 alization capabilities of YOLOv8 and YOLOv9 models for cow detection in indoor free-stall barn
4 settings, focusing on varying training data characteristics such as view angles and lighting, and model
5 complexities. Leveraging the newly released public dataset, COws LOcalization (COLO) dataset,
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7 lighting conditions and camera angles; (2) Higher model complexity guarantees better generalization
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9 advantages to detection tasks. Our findings reveal considerable challenges in detecting cows in
10 images taken from side views and underscore the importance of including diverse camera angles
11 in building a detection model. Furthermore, our results emphasize that higher model complexity
12 does not necessarily lead to better performance. The optimal model configuration heavily depends
13 on the specific task and dataset, highlighting the need for careful model selection tailored to the
14 particular application. Lastly, while fine-tuning with custom initial weights trained on relevant tasks
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21 cow instances for further research.

22 **Keywords** Object detection · Cows · Model generalization · Model selection

23 **1 Introduction**

24 **Object Localization and Its Applications**

25 Localizing livestock individuals from images or videos has become an essential task in precision livestock farming
26 (PLF) [1]. Such techniques allow farm operators to manage animal well-being and health in real-time, optimizing their
27 resource management and improving sustainability [2, 3]. Technically speaking, in the field of computer vision (CV),
28 which is a subfield of artificial intelligence (AI) that focuses on translating visual information into actionable insights,
29 localization tasks can be further categorized into object detection, object segmentation, and pose estimation. Object
30 detection is the simplest form among these tasks, localizing objects of interest by enclosing them within a rectangular
31 bounding box defined by x and y coordinates, pixel width, and pixel height [4]. Successful instances in this category
32 include YOLO (You Only Look Once) [5], Faster R-CNN (Region Convolutional Neural Networks) [6], and SSD
33 (Single Shot MultiBox Detector) [7]. These models have been adopted and applied by animal scientists for detection
34 in precision livestock farming. For example, a study [8] leveraged the DRN-YOLO model [9] to predict the eating
35 behavior of dairy cows. This approach automates the assessment of feeding behavior, a critical indicator of cow health
36 and productivity, and has saved labor efforts in complex farm settings. Another notable work is presented in [10], where
37 the authors developed a posture detection system for pigs using deep learning models such as Faster R-CNN, SSD,
38 and R-FCN, coupled with 2D imaging. This system accurately identifies standing and lying postures of pigs under
39 commercial farm settings.

40 To achieve finer localization, object segmentation is employed to outline object contours pixel-wise, while pose
41 estimation is performed by orienting and marking the key points of the object [11]. Some popular object segmentation
42 models include Mask R-CNN [12], MS R-CNN [13], and U-Net [14]. This method of segmentation has also been
43 applied in the field of PLF. In the study [15], the authors developed a method using Mask R-CNN [12] to segment
44 and outline cattle in feedlots. Their technique enhances images and extracts key frames to accurately detect cattle,
45 achieving superior precision with a mean pixel accuracy of 0.92. This supports advanced, real-time monitoring of
46 cattle in PLF. Another study group [16] developed the PigMS R-CNN framework [13] to enhance the monitoring of
47 group-housed pigs. This framework employs a 101-layer residual network along with a feature pyramid network and
48 soft non-maximum suppression to effectively detect and segment pigs, thereby improving the accuracy of identifying
49 and locating individual pigs in complex environments.

50 **Model Generalization, Pre-Training, and Fine-Tuning**

51 Although implementing image-based systems in livestock production has become more common, current studies
52 primarily focus on accuracy in homogenous environments and rarely address the challenges of model generalization.
53 How a model can generalize to new environments is critical when farm operators deploy existing CV models in their
54 own settings. Good generalization performance ensures that the model can reproduce similar results as reported in the
55 original study, even in new environments with different conditions. Factors such as camera angles and the presence of

56 occlusions can impact generalization in the deployment environment. Deploying the same model in a new environment
57 does not necessarily guarantee the same performance as reported in the original study. Li et al. [17] also pointed out that
58 the lighting conditions on farms in real applications can be highly variable, leading to poor generalization performance.

59 One explanation for poor generalization is the discrepancy between the pre-training process and the specific use case.
60 Most CV models are released with pre-trained weights, obtained from training on a large-scale dataset. For example, the
61 COCO dataset [18] is a general-purpose dataset containing over 200,000 images and a wide range of object categories,
62 such as vehicles and household items. Directly deploying a model pre-trained on the COCO dataset to detect cows in a
63 farm setting may not ensure satisfactory performance, as the dataset does not contain enough cow instances in different
64 view angles or occlusions. To alleviate this discrepancy, fine-tuning is a common practice that modifies the prediction
65 head of the pre-trained model and updates the weights on a new dataset more relevant to the specific use case. Most
66 application studies have adopted this approach to improve model generalization on their specific tasks [19, 20, 21].

67 Nevertheless, fine-tuning is not guaranteed to be successful, as the outcome depends on both the quantity and quality of
68 the annotated dataset. For example, Zin et al. [22] deployed an object detection model to recognize cow ear tags in a
69 dairy farm. Although the model achieved a high accuracy of 92.5% in recognizing the digits on the ear tags, more than
70 10,000 images were required for fine-tuning. Assembling such a large dataset is labor-intensive and requires specific
71 training in annotating the images. The annotated dataset is rigorously organized in a specific format. For example, the
72 COCO annotation format [18] stores image information, object class, and annotations of the entire dataset in one nested
73 JSON format. In contrast, the YOLO format [23], another common format for object localization, stores information
74 of one image in one text file, with each line representing one object instance in the image. Additionally, unlike the
75 COCO format that stores bounding box coordinates in absolute pixel values, the YOLO format stores the coordinates in
76 relative values to the image size. These technical details are key to valid annotations, which are usually facilitated by
77 professional annotation tools such as Labelme [24], CVAT [25], or Roboflow [26].

78 Model Complexity and Performance

79 Another factor affecting model generalization is model complexity. Generally, model complexity is quantified by the
80 number of learnable parameters in a model [27]. A more complex model can often generalize better to unseen data with
81 high accuracy. However, this high complexity also comes at the cost of computational resources in the form of memory
82 or time [28]. The computational cost may further limit how models can be deployed in real-world applications, where
83 real-time processing or edge computing is desired for fast or compact systems. For instance, the VGG-16 model [29]
84 has 138 million parameters and requires a video memory of at least 8GB, while the ResNet-152 [30] has around 60
85 million parameters with a recommended video memory of 11GB. Recent models for object detection, such as YOLOv8
86 [31] and YOLOv9 [32], have been developed in different sizes, providing a flexible choice for researchers to balance
87 between generalization performance and computational cost. In YOLOv8, the spectrum of model complexity ranges
88 from the highly intricate YOLOv8x, containing 68.2 million parameters, to more streamlined variants like YOLOv8n
89 with only 3.2 million parameters. The memory demand for the model architecture alone, without considering the

90 intermediate results during training or inference, is larger by a factor of 21 for YOLOv8x (136.9 megabytes) compared
91 to YOLOv8n (6.5 megabytes). Therefore, the trade-off between model complexity and computational cost is a critical
92 factor to consider when deploying CV models in real-world scenarios.

93 YOLO Models

94 Before YOLO, object detection methods typically involved either using “sliding windows with classifier” or “region
95 proposals with classifier.” The sliding windows method required running the classifier hundreds or thousands of times
96 per image. On the other hand, advanced region proposal-based approaches divided the task into two steps: first,
97 identifying potential object regions (i.e., region proposals) and then applying a classifier to these regions. In contrast,
98 YOLO models are capable of performing object detection in a single pass through the network, which is why the
99 acronym YOLO stands for “You Only Look Once.”

100 YOLOv8 [31], building on the YOLOv5 [33] architecture, incorporates the C2F module (cross-stage partial bottleneck
101 with two convolutions), a refinement of the CSPLayer of YOLOv5 featuring two convolutional operations. It employs
102 SiLU activation over traditional ReLU and Sigmoid [34] for smoother gradient flow, enhancing CNN performance. The
103 module divides input from a convolutional layer, processes one half through bottleneck layers (offering two types: with
104 and without shortcuts similar to ResNet [35]), then merges it back for further convolution. This design, along with a
105 spatial pyramid pooling fast (SPPF) layer in its backbone, supports efficient feature pooling and multi-scale detection by
106 using three distinct heads, thereby optimizing object detection across varying sizes. Furthermore, YOLOv8 innovates
107 with an anchor-free approach, directly predicting bounding boxes and confidence scores, thus simplifying the network
108 and reducing computational overhead [36, 37, 38].

109 Deep learning models, including the YOLO family, encounter an information bottleneck issue [39, 40], where the
110 retention of input information diminishes as data is compressed into features. This loss is exacerbated in deeper network
111 layers, often leading to reduced model efficacy. One approach to mitigate this involves expanding the model’s width,
112 i.e., increasing the number of parameters, which allows for broader feature mapping and potentially recaptures lost
113 information. However, simply increasing model size can lead to unreliable data outputs and does not proportionally
114 enhance model performance.

115 YOLOv9 addresses these challenges through innovations like Programmable Gradient Information (PGI) and the
116 Generalized Efficient Layer Aggregation Network (GELAN) [32]. PGI optimizes gradient generation to minimize deep
117 layer information loss, featuring a main branch for inference and auxiliary branches for enhanced training. GELAN,
118 by integrating and pooling convolutional layers, ensures robust feature retention. This adaptive system notably boosts
119 inference speed by 20% [32] on the COCO dataset [18], while its multi-level auxiliary information facilitates the
120 detection of objects across varying sizes, making YOLOv9 particularly effective in identifying smaller objects compared
121 to its predecessors.

122 **Public Datasets**

123 A public dataset helps the community to develop methodology based on the same baseline. One famous example in
124 computer vision is the ImageNet dataset [41], which serves as a benchmark for image classification. AlexNet [42], the
125 winner of the ImageNet Large Scale Visual Recognition Challenge in 2012, demonstrated its outstanding capability to
126 classify images in the ImageNet dataset using Rectified Linear Units (ReLU) as the activation function, rather than
127 the traditional sigmoid function. The success of AlexNet accelerated the development of CV models in the following
128 years, such as VGG [43], GoogLeNet [44], ResNet [35], and DenseNet [45]. However, similar to the challenges that
129 pre-trained models face in specific use cases, a generic public dataset, such as ImageNet [41] and COCO [18], may not
130 be sufficient for PLF applications.

131 There have been efforts to create public datasets for livestock scenarios. For example, the CattleEyeView dataset was
132 collected to support applications like cattle pose estimation and behavior analysis, providing extensive annotations
133 across 30,703 frames from top-down video sequences of cows [46]. Another study [47] leverages a public dataset for
134 pigs comprising 3600 images from 12 videos of group-housed pigs. The dataset is particularly designed for applications
135 such as pig tracking. Additionally, the "OpenCows2020" dataset, developed by researchers from the University of
136 Bristol, is a public dataset specifically designed for advancing non-intrusive monitoring of cattle. It supports precision
137 farming applications such as automated productivity assessment, health and welfare monitoring, and veterinary research,
138 including behavioral analysis and disease outbreak tracing. The dataset consists of 11,779 images with 13,026 labeled
139 objects, mainly focusing on cattle [48].

140 **Study Objectives**

141 This study aims to use YOLO-family models to explore model generalization across varying environmental settings
142 and model complexities within the context of indoor cow localization. Object detection, being the simplest form
143 of localization, serves as an ideal baseline for extending to more complex tasks such as segmentation and posture
144 estimation. Starting with object detection allows for a clear and foundational understanding of model behavior and
145 performance, which can then inform and enhance the approach to more complex tasks. Consequently, this study
146 examines three hypotheses:

- 147 • **Model generalization is equally influenced by changes in lighting conditions and camera angles.** Should
148 camera angles prove more impactful than lighting conditions, it would be advisable to prioritize camera
149 placement when deploying CV models in new environments.
- 150 • **Higher model complexity guarantees better generalization performance.** If a highly complex model does
151 not ensure superior performance, future studies might consider adopting less computationally demanding
152 models that still enhance performance.
- 153 • **The advantages of using fine-tuned models as initial training weights are persistent over pre-trained
154 models.** If the advantages diminish as the training sample size increases in a similar cow localization task but

155 different environments, the fine-tuning efforts may be deemed unnecessary when the deployment environment
156 varies over multiple locations on a farm.

157 To facilitate these investigations, a public dataset named COws LOcalization (COLO) [49] will be developed and made
158 available to the community. The findings of this study are expected to provide practical guidelines for Precision Livestock
159 Farming (PLF) researchers on deploying CV models, considering available resources and anticipated performance.

160 **2 Materials and Methods**

161 **Cow Husbandry**

162 All procedures involving cow handling and image capturing were conducted in accordance with ethical guidelines and
163 approved by the Virginia Tech Institutional Animal Care and Use Committee (IACUC #22-146). The cows studied were
164 part of the dairy herd at the Virginia Tech Dairy Complex in Blacksburg, Virginia, USA, which comprises approximately
165 80% Holstein and 20% Jersey cows. For the 'External' setting, the study included 100% Holstein cows. The milking
166 cows were housed in pens within a free-stall barn, featuring two rows of sand-bedded stalls, headlocks at the feed bunk,
167 and two water troughs per pen. The stocking density was maintained at 100% (i.e., one cow per stall). Heat stress was
168 managed using automatic 48-inch diameter fans positioned over the stalls and feeding alleys. Cows were milked twice
169 daily at 1:00 am and 12:00 pm in a double-twelve parallel milking parlor. They were fed ad libitum (with less than
170 5% refusals) once daily at 8:00 am with a total mixed ration (TMR) consisting of approximately 42% corn silage, 8%
171 grass hay, and 50% concentrate on a dry matter basis. Manure from the stalls was removed at each milking session by
172 personnel driving the cows to milking. Manure from the walking alleys within the pen was cleared two or three times
173 daily using an automatic flushing system with recycled water. Fresh or recycled sand was added on a weekly basis.

174 **Image Dataset**

175 The images in this study were collected using the Amazon Ring camera model Spotlight Cam Battery Pro (Ring Inc.),
176 which offers a real-time video feed of dairy cows. Three cameras were installed in the barn: two at a height of 3.25
177 meters (10.66 feet) above the ground covering an area of 33.04 square meters (355.67 square feet). One camera provided
178 a top view while the other was angled approximately 40 degrees from the horizontal to offer a side view of the cows.
179 These are hereafter referred to as *the Top-View camera* and *the Side-View camera*, respectively. A third camera, termed
180 *the external camera*, was set at a lower height of 2.74 meters (9.00 feet) and covered a larger area of 77.63 square
181 meters (835.56 square feet). Positioned 10 degrees downward from the horizontal, it captured a challenging perspective
182 prone to occlusions among cows.

183 Images were captured using an Ring Application Programming Interface (API) [50], configured to record a ten-second
184 video clip every 30 minutes continuously for 14 days. Since the image quality relies on the camera's internet connection,
185 which was occasionally unstable, some images were found to be tearing or unrecognizable. Hence, the resulting dataset
186 was manually curated for consistent quality, comprising 504 images from *the Top-View camera*, 500 from *the Side-View*

187 *camera*, and 250 from *the external camera*. These images were further categorized based on the lighting conditions: for
 188 *the Top-View camera*, 296 images were captured during daylight, 118 in the evening under artificial lighting, and 90 as
 189 near-infrared images without artificial light. From *the Side-View camera*, 113 images were taken in the evening, and 97
 190 as near-infrared images. All images from *the external camera* were captured during the day. Image examples are shown
 191 in **Figure 1a**.

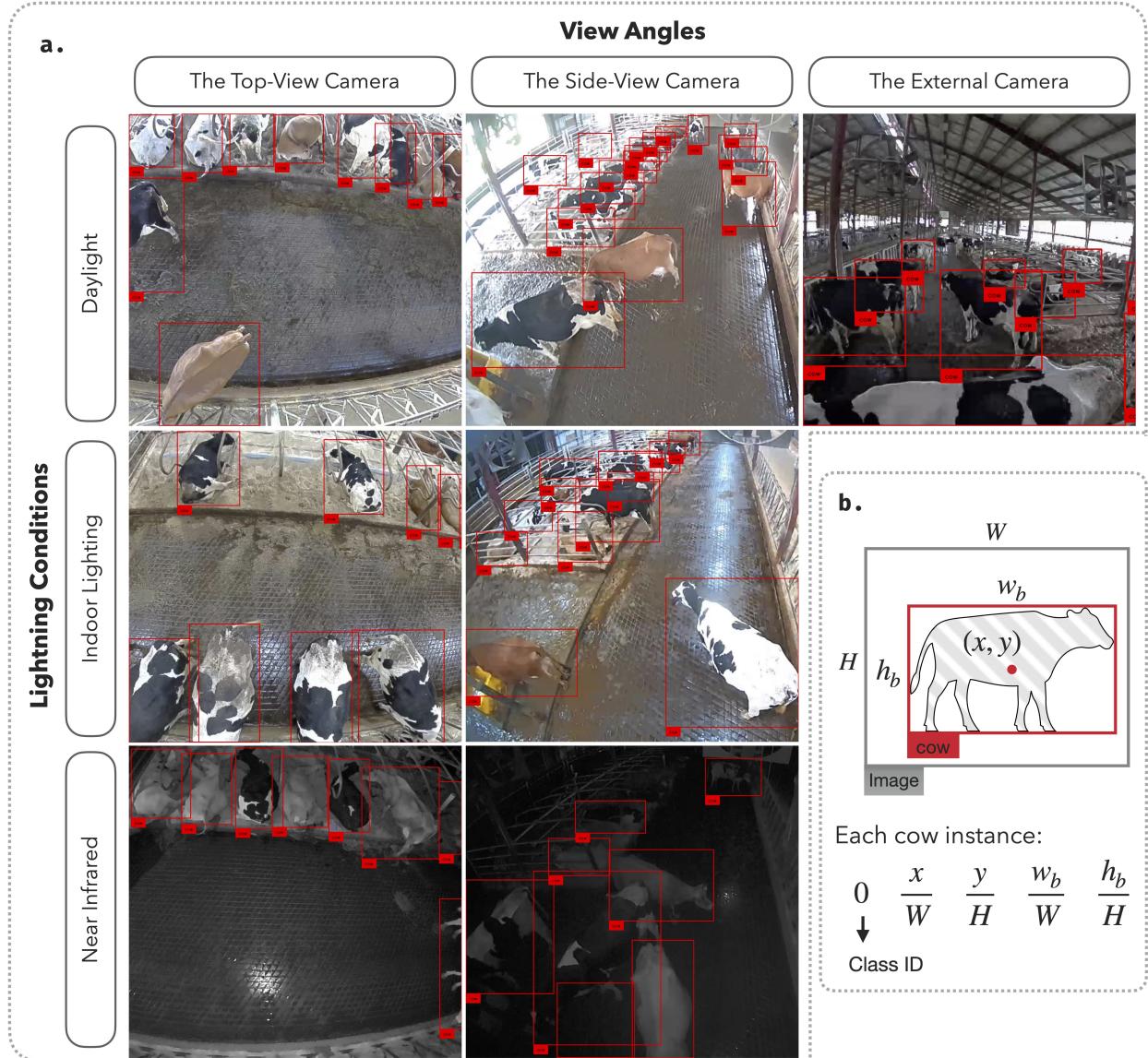


Figure 1: Overview of the COLO dataset. 1a. Seven instance images from the dataset with red bounding boxes labeling the location of cows. The columns show three different view angles: top-view, side-view, and external. The rows show three different lighting conditions: daylight, indoor, and near-infrared. 1b. An example of the annotated image in YOLO format. W , H , w_b , and h_b represent the width, height, width of the bounding box, and height of the bounding box, respectively. x and y represent the center coordinates of the bounding box.

192 The image annotations were conducted using an online platform, Roboflow [26], to define cow positions in the images.
193 The bounding boxes were manually drawn to enclose the cow contours, providing the coordinates of the top-left corners
194 and the width and height of the boxes. If cows were partially occluded, the invisible parts were inferred based on the
195 adjacent visible parts. If the cow position was too far from the camera, making important body features such as the head,
196 tail, and legs unrecognizable, the cow was excluded from the dataset. The final annotations were saved in the YOLO
197 format [23], where annotations were stored in a text file with one row per cow in the image, each row containing the
198 cow's class, center coordinates, width, and height of the bounding box. The graphical representation of the annotated
199 images is shown in **Figure 1b**.

200 **Model Training**

201 The model training was implemented using the Python library Ultralytics [51]. The model hyperparameters were set to
202 the default values in the library. The training epochs were set to 100, and the batch size was set to 16. The implemented
203 data augmentation included randomly changing the image color hue, saturation, and exposure to improve the model's
204 generalization to different lighting conditions. Geometry augmentation was also applied by randomly flipping the
205 images horizontally, copying and pasting to mix up object instances across multiple images to increase data diversity,
206 and randomly scaling the images to simulate different distances between the camera and the cows. The details of the
207 hyperparameters are shown in **Table 3**. The training was conducted on an NVIDIA A100 GPU (NVIDIA, USA) with
208 80GB video memory provided by Advanced Research Computing at Virginia Tech.

209 **Model Evaluation**

210 The examined YOLO models are object detection models that return positions of detected objects (i.e., cows in this
211 study) for the evaluated images. The detections are represented by a list of bounding boxes. Regardless of specific
212 procedures among YOLO variants for computational efficiency, such as YOLOv8, which integrates objectness scores
213 and conditional class probabilities into a single confidence score, each detection generally consists of $4 + c$ elements:
214 the xy-coordinates, width, and height of the bounding box, and the c confidence scores indicating the probability of
215 the object belonging to each of the c classes. The class with the highest confidence score is considered the predicted
216 class of the object. To evaluate the model performance, two aspects are considered: the localization accuracy and
217 the classification accuracy. The localization accuracy is measured by the Intersection over Union (IoU) between the
218 predicted bounding box and the ground truth bounding box. On the other hand, the classification accuracy is measured
219 by the precision and recall given the confidence threshold. If the confidence score of a detection is higher than the
220 threshold, the detection is considered a positive detection. Otherwise, the detection is neglected. Combining the
221 localization and classification accuracy, the mean Average Precision (mAP) averages the area under the precision-recall
222 curve across all the classes. The curve is generated by varying the confidence threshold from 0 to 1 given an IoU
223 threshold. In this study, four metrics were used in the evaluation: the precision and recall at the confidence threshold of

224 0.25 and IoU threshold of 0.5, the mAP at the IoU threshold of 0.5 (noted as mAP@0.5), and the averaged mAP at
 225 varying IoU thresholds ranging from 0.5 to 0.95 (noted as mAP@0.5:0.95).

226 **Study 1: Benchmarking Model Generalization Across Different Environmental Conditions**

227 To compare the performance drop between different view angles and lighting conditions, we designed a cross-validation
 228 strategy where models were trained on one dataset configuration and tested on another. There are five training
 229 configurations in this study (**Figure 2**):

- 230 • **Baseline:** The model was trained and evaluated on the dataset characterized for all conditions, including
 231 top-view, side-view, daylight, evening, and near-infrared images. The images did not overlap between the
 232 training and evaluation sets.
- 233 • **Top2Side:** The model was trained on the top-view images and evaluated on the side-view images.
- 234 • **Side2Top:** The model was trained on the side-view images and evaluated on the top-view images.
- 235 • **Day2Night:** The model was trained on the daylight images and evaluated on the evening images, including
 236 both artificial lighting and near-infrared images.
- 237 • **External:** The model was trained on images collected by the Top-View and Side-View cameras and evaluated
 238 on the external camera images.

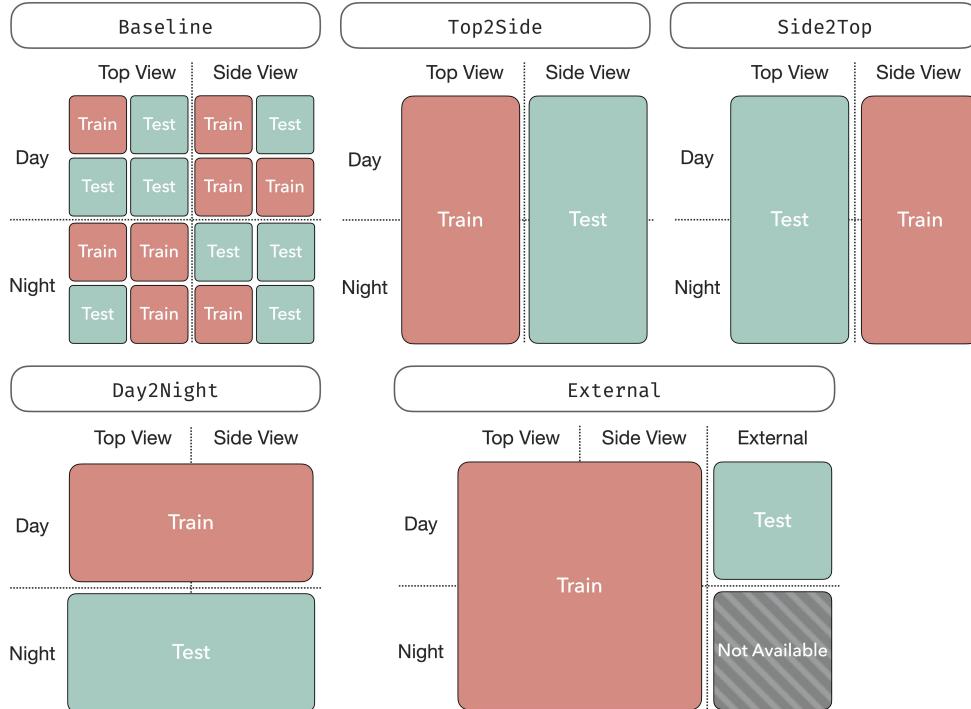


Figure 2: Cross-validation configurations. The training and testing sets were split into five different configurations: Baseline, Top2Side, Side2Top, Day2Night, and External.

239 To study how the training sample size affects model performance in each configuration, the testing set in the cross-
240 validation was fixed to the same 100 images. Then, the training set size was iteratively altered from 16 to 512 images,
241 with the sample size doubled at each step. Each training sample size was repeated 50 times with different random seeds
242 to ensure the robustness of the results. The YOLOv9e, which is the most capable model in the YOLO family to date
243 according to its performance on the COCO dataset, was used as the base model for this study.

244 **Study 2: The Correlation Between Model Complexity and Performance on the Tasks of Localizing Cows**

245 To investigate whether model performance increases with model complexity, five YOLO-family models were examined
246 in this study. Three of the models were selected from the YOLOv8 family: YOLOv8n, YOLOv8m, and YOLOv8x. All
247 YOLOv8 models share a similar architecture, differing in their depth multiplier, width multiplier, and ratio factor, which
248 collectively determine their parameter counts of 3.2 million (m), 25.9m, and 68.2m, respectively. The depth multiplier
249 determines how many convolutional layers are repeated in a C2F module, the novelty of YOLOv8. The width multiplier
250 and ratio factor collectively specify the channel numbers in the convolutional operations. Correspondingly, YOLOv8n,
251 YOLOv8m, and YOLOv8x are defined by depth multipliers of 0.33, 0.67, and 1.0, respectively. The width multipliers
252 are 0.25, 0.75, and 1.25, while the ratio factors are 2.0, 1.5, and 1.0 [52]. These variations enable the models to achieve
253 different balances between computational efficiency and accuracy.

254 The remaining two models were YOLOv9c and YOLOv9e, the latest models in the YOLO family, with parameter
255 counts of 25.6M and 58.2M, respectively. Unlike YOLOv8 models, these models have slightly different backbone
256 architectures. Although the majority of the components between YOLOv9c and YOLOv9e are the same, they primarily
257 differ in their layer counts, module complexities, and depth configurations. YOLOv9c has 618 layers and uses simpler
258 modules, resulting in a more efficient model with lower computational demands. Conversely, YOLOv9e has 1225
259 layers and employs more advanced modules [53].

260 All models were trained on 500 images in the five cross-validation configurations: Baseline, Top2Side, Side2Top,
261 Day2Night, and External (**Figure 2**). In addition to model performance, computing speed was also evaluated. The
262 training speed was recorded in seconds per 100 epochs on NVIDIA A100 GPUs (NVIDIA, USA), and the inference
263 time was recorded as frames per second (FPS) on both the CPU and GPU (Apple M1 Max chip, Apple Inc., USA).
264 The relationship between model complexity and time consumption was analyzed to provide insights into the trade-off
265 between model performance and computational cost.

266 **Study 3: Assessing the Advantages of Using Fine-Tuned Model Over the Pre-Trained Model as Initial Model
267 Weights**

268 Most models are released with pre-trained weights obtained from large datasets containing millions of object instances
269 (e.g., COCO [18] and ImageNet [41]). The pre-trained models have a general capability in recognizing common objects
270 such as vehicles, animals, and household items. When the model is required to recognize specific objects (i.e., cows
271 in this study), a model trained on a smaller but specific dataset is expected to have better performance. However,

such advantages may not necessarily persist as the training sample size increases. Having an equally large number of samples for both the pre-trained and fine-tuned models could diminish the performance gap between the two models. To investigate this hypothesis, this study evaluated the performance of fine-tuned models with two different initial weights. The first initial weight was the default weight from the pre-trained model on the COCO dataset, while the second initial weight was the weight from the fine-tuned model on the opposite view angle. The cross-validation settings are described in **Table 1**.

Table 1: Finetuning configurations with different initial weights

Finetuning and Prediction Task	Initial Weights
Top-View Camera	COCO (pre-trained) Side-View Camera (fine-tuned)
Side-View Camera	COCO (pre-trained) Top-View Camera (fine-tuned)
External Camera	COCO (pre-trained) Top-View and Side-View Cameras (fine-tuned)

The backbones of all models (i.e., YOLOv8n, YOLOv8m, YOLOv8x, YOLOv9c, and YOLOv9e) were fine-tuned across different training sample sizes: 16, 32, 64, 128, 256, and 500. The goal was to determine whether the advantage of using the fine-tuned weights persists under the interaction between model complexity and different fine-tuning samples. The performance of the models was evaluated using mAP@0.5:0.95.

3 Results and Discussion

Public Dataset: COLO

The COLO dataset contains 1254 images and 11818 cow instances captured from an indoor farm environment. The dataset is organized in YOLO and COCO formats and published on the online platforms GitHub (<https://github.com/Niche-Squad/COLO/>) and Huggingface (<https://huggingface.co/datasets/Niche-Squad/COLO>). The dataset consists of eight configurations (**Table 2**): *0_all*, *1_top*, *2_side*, *3_external*, *a1_t2s*, *a2_s2t*, *b_light*, and *c_external*. The *0_all* configuration serves as the baseline for this study, featuring non-overlapping training and testing images collected from both the Top-View Camera and Side-View Camera. The *1_top*, *2_side*, and *3_external* configurations contain images from their respective cameras. The *a1_t2s*, *a2_s2t*, and *b_light* configurations include training/testing splits for the Top2Side, Side2Top, and Day2Night scenarios, respectively. The *c_external* configuration features training images from the Top-View and Side-View Cameras, with testing images from the External Camera. The dataset hosted on GitHub is available as a compressed zip file for public access. In contrast, the dataset on Huggingface requires the Python package "datasets" [54] to download. The Huggingface version offers additional functionality to resize the images and annotations to specific resolutions, providing greater flexibility for various applications.

Table 2: Description of the COLO dataset configurations.

Configuration	Training Samples	Testing Samples
<i>0_all</i>	Top-View + Side-View	Top-View + Side-View
<i>1_top</i>	Top-View	Top-View
<i>2_side</i>	Side-View	Side-View
<i>3_external</i>	External	External
<i>a1_t2s</i>	Top-View	Side-View
<i>a2_s2t</i>	Side-View	Top-View
<i>b_light</i>	Day	Night
<i>c_external</i>	Top-View + Side-View	External

296 **Evaluation Metrics**

297 To assess the performance of the YOLO models, we used four key metrics: mAP@0.5:0.95, mAP@0.5, precision, and
 298 recall. These metrics provide a comprehensive understanding of how well the models detect and localize cows in the
 299 images from the COLO dataset. A pair-wise comparison of these metrics is presented in **Figure 3** to illustrate their
 300 interrelationships.

301 The mAP@0.5:0.95 metric is the most stringent, requiring the model to achieve both high positioning accuracy (i.e.,
 302 high IoU) and high precision across IoU thresholds from 0.5 to 0.95. Because it is less likely to be influenced by
 303 high-confidence predictions alone, it serves as a reliable indicator of overall model performance. Achieving an accuracy
 304 greater than 0.90 on this metric is generally unrealistic; typically, a value of 0.7 is considered good and is sufficient to
 305 yield precision and recall of around 0.9.

306 In contrast, mAP@0.5 is more lenient, requiring high confidence but only moderate IoU. It measures the average
 307 precision at an IoU threshold of 0.5. For applications where counting cows is more important than precise positioning,
 308 an mAP@0.5 value of 0.9 is sufficient. For example, our results showed that the YOLOv8n model, trained on 32
 309 samples, achieved an mAP@0.5 of 0.9, making it suitable for such applications.

310 Precision and recall metrics focus on the accuracy and completeness of the detections. Precision is the ratio of true
 311 positive detections to the total number of positive detections (true positives + false positives), measuring how accurate
 312 the positive predictions are. Recall is the ratio of true positive detections to the total number of actual positives (true
 313 positives + false negatives), measuring the model's ability to detect all relevant objects. Generally, higher precision is
 314 associated with higher recall. However, in some configurations, such as Side2Top and External with smaller sample
 315 sizes, models exhibited high recall but low precision. This indicates a tendency to misclassify non-cow objects as cows
 316 more frequently than missing actual cows, suggesting a tendency to overestimate rather than underestimate the number
 317 of cows in the images.

318 Our observations emphasize that for applications where counting cows is more critical than precise positioning,
 319 achieving a high mAP@0.5 is adequate, while the stringent mAP@0.5:0.95 metric serves as a comprehensive indicator

320 of overall model performance. These metrics provide insights into both the localization and classification capabilities of
 321 the models, helping to identify strengths and weaknesses under different environmental conditions and camera angles.

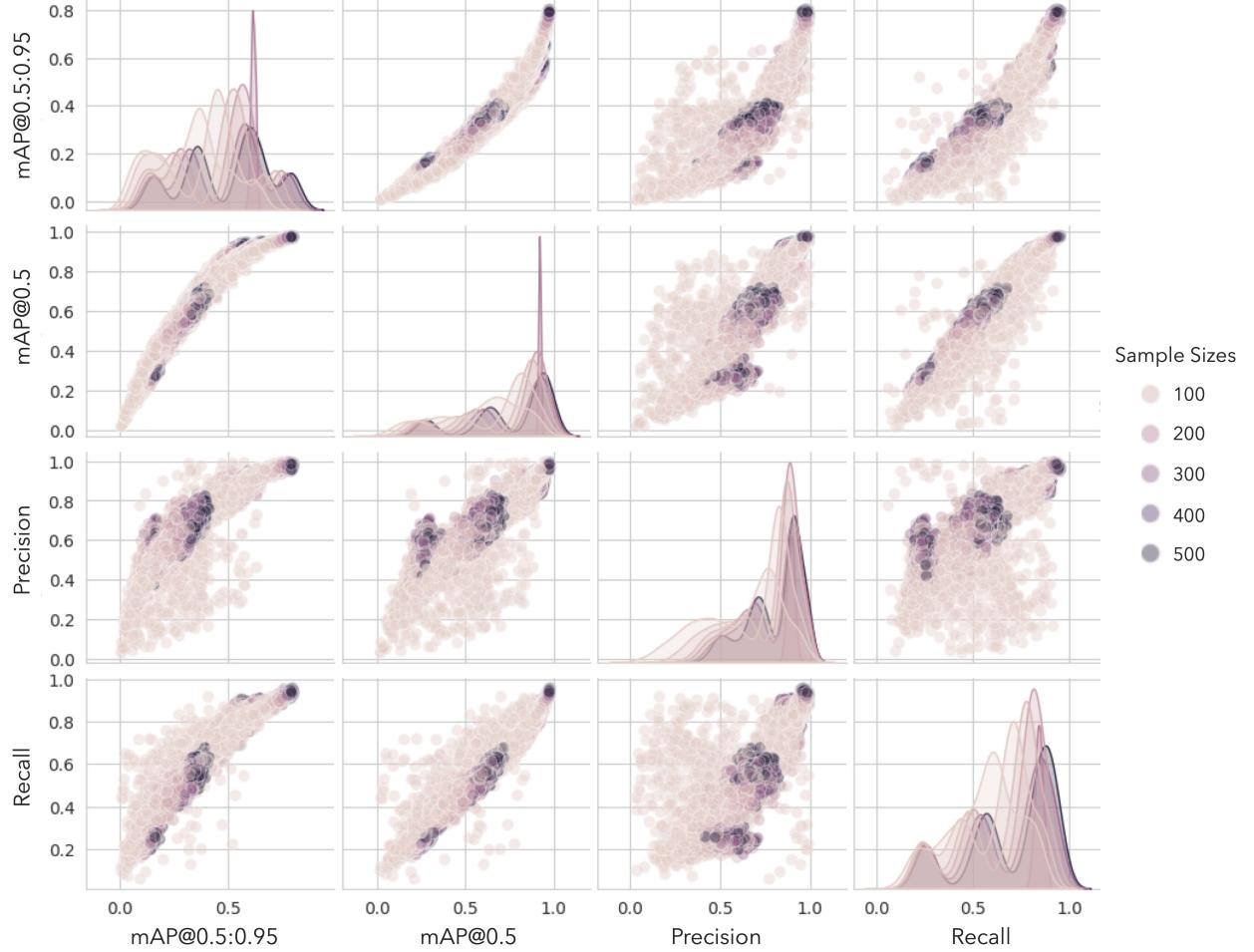


Figure 3: Pairwise scatter plots of the evaluation metrics: mAP@0.5:0.95, mAP@0.5, precision, and recall. Each point represents a different model configuration, with the color indicating the training sample size.

322 **Study 1: The Changes in Camera View Angles Dramatically Affect Model Performance**

323 The baseline training configuration showed good generalization capability, with over 90% of the predictions correctly
 324 positioning cows at the 50% IoU criterion (mAP@0.5). The generalization performance can be dissected into changes
 325 in view angles (i.e., Top2Side and Side2Top) and lighting conditions (i.e., Day2Night). Changes in lighting conditions
 326 did not dramatically affect model performance across all four metrics. However, changing camera views resulted
 327 in a performance drop of approximately 30% and 60% in mAP@0.5 for the Side2Top and Top2Side configurations,
 328 respectively. Across all metrics and training sample sizes, the Top2Side configuration consistently showed the worst
 329 performance.

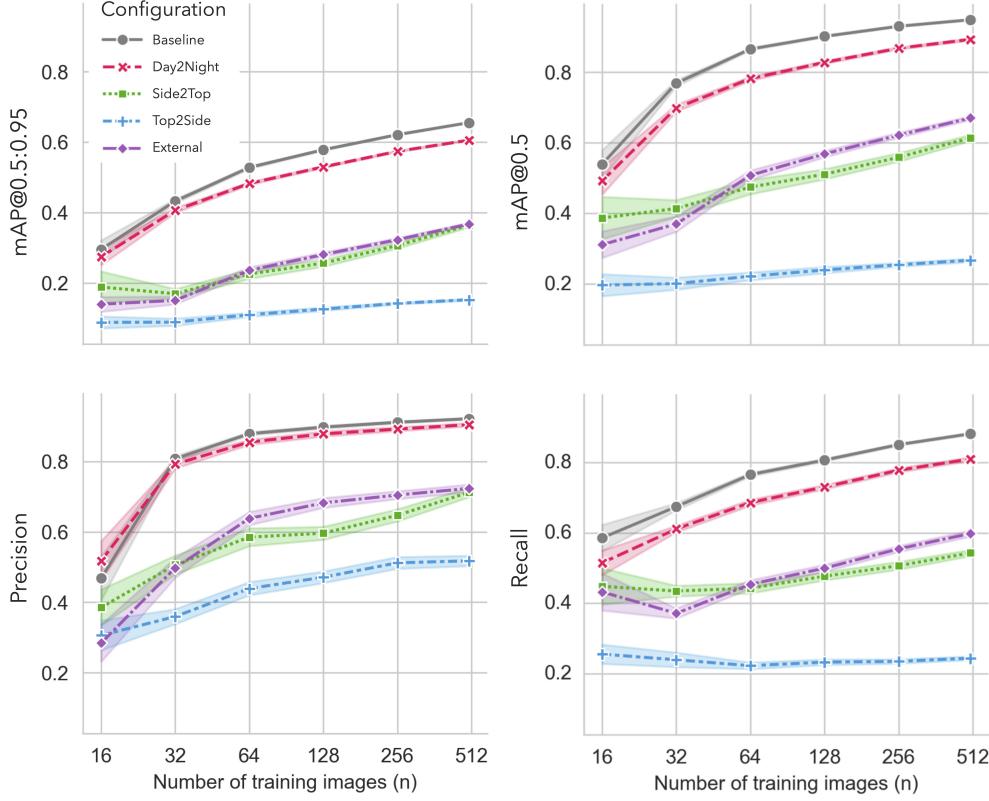


Figure 4: The generalization performance of YOLOv9e across various data configurations and training sample sizes. Sample sizes are depicted on the horizontal axis using a logarithmic scale with a base of 2, and the data configurations are represented by different colors and marker shapes. The upper left and right plots display the metrics mAP@0.5:0.95 and mAP@0.5, respectively, for different training samples across diverse data configurations. The lower left and right plots depict precision and recall values, also for varying training samples and configurations.

- 330 From the perspective of precision and recall, changing the camera view from Top2Side resulted in the model missing
 331 more than 7 out of every 10 cows, with only 50% of the detections being correct. For the 'External' configuration,
 332 our model identified 6 out of every 10 cows, which is not ideal but also not the worst performance observed. Notably,
 333 performance in the Day2Night configuration was close to the baseline in terms of precision, which only considers
 334 predictions with high confidence compared to mAP@0.5. Hence, by excluding low-confidence predictions, changes in
 335 lighting conditions did not affect model performance. Regardless of the configuration and evaluation metrics, model
 336 performance always increased as the training sample sizes increased.
- 337 This study provides a comparative analysis of the behavior of the model in various data configurations. It is clear
 338 that the 'Day2Night' configuration shows much better performance relative to the heterogeneous viewpoint-oriented
 339 configurations 'Top2Side' and 'Side2Top'.
- 340 Despite the various challenges in adapting models from day to night conditions, the 'Day2Night' configuration
 341 consistently maintains high precision, closely mirroring the 'Baseline' configuration across all training sample sizes.
 342 This suggests that changes in lighting have less impact on the model's ability to detect objects compared to changes in
 343 viewpoint. This robustness to lighting could be attributed to the inclusion of diverse lighting conditions in the training

344 phase. Specifically, model performance benefited from pixel-wise augmentation techniques such as adjustments to hue,
345 saturation, and value (HSV). These augmentations introduced a variety of color variations to the images, enhancing the
346 model’s ability to generalize across different visual conditions. Moreover, these YOLO models benefit from pre-training
347 on the COCO dataset, which is characterized by a wide array of images with varied lighting, aiding their adaptability to
348 shifts in light.

349 On the other hand, the models perform suboptimally in scenarios involving changes in viewpoint. Each new viewpoint
350 introduces fundamentally different object features that are not replicated through standard data augmentation methods
351 such as lighting or affine transformations. For example, when the camera is placed at a lower angle, cows are more
352 frequently occluded by stalls and fences. These additional objects introduce variations that cannot be mitigated by
353 augmentations in HSV space or image translation. Consequently, ‘Top2Side’ performs the worst, as it is particularly
354 challenging to identify cows from the side. Even for the ‘External’ configuration, the model struggles to generalize well
355 despite being trained on the ‘Baseline’ configuration because the camera angle is changed again in the ‘External’ setup.
356 In summary, camera view angle is crucial for model generalization, with side views being the most challenging.

357 **Study 2: A Higher Model Complexity Does Not Always Lead to Better Performance**

358 The study found that the training configuration significantly affects the relationship between model complexity and
359 performance. Based on Study 1, predicting images from a side view using a model trained on Top-View camera images
360 is one of the most challenging tasks. In this configuration, increasing model complexity generally resulted in poorer
361 generalization, with simpler models often performing better. However, in other configurations that demonstrated better
362 generalization in Study 1, the peak performance was not always achieved by the most complex model. For example,
363 in the baseline configuration, the YOLOv9e model performed best in terms of mAP@0.5:0.95, mAP@0.5, and recall,
364 while the YOLOv8m model excelled in precision. Neither of these models had the highest parameter counts compared
365 to YOLOv8x. It is also worth noting that different model architectures showed different performance trends with varying
366 complexities. The YOLOv8-family models tended to perform best with mid-sized models (i.e., YOLOv8m), whereas
367 larger models in the YOLOv9 family usually performed better. Hence, the study concluded that model performance is
368 determined by both the training configuration and the model architecture.

369 The study results, as shown in **Figure 5**, indicate that although both YOLOv8 [31] and YOLOv9 [32] models exhibit an
370 increase in mAP@0.5 with more parameters when trained on the COCO dataset [18], this does not support a definitive
371 conclusion that more parameters consistently improve model performance. This may be because the prior work’s
372 findings were based on the COCO dataset, which includes 80 classes and mainly features standalone images. In contrast,
373 this study uses an indoor farm dataset focused exclusively on a single class: cows. Consequently, the model may not
374 need as many parameters to effectively detect cows. This suggests that researchers should not rely solely on public
375 dataset performance, as model generalization is specific to the task and dataset.

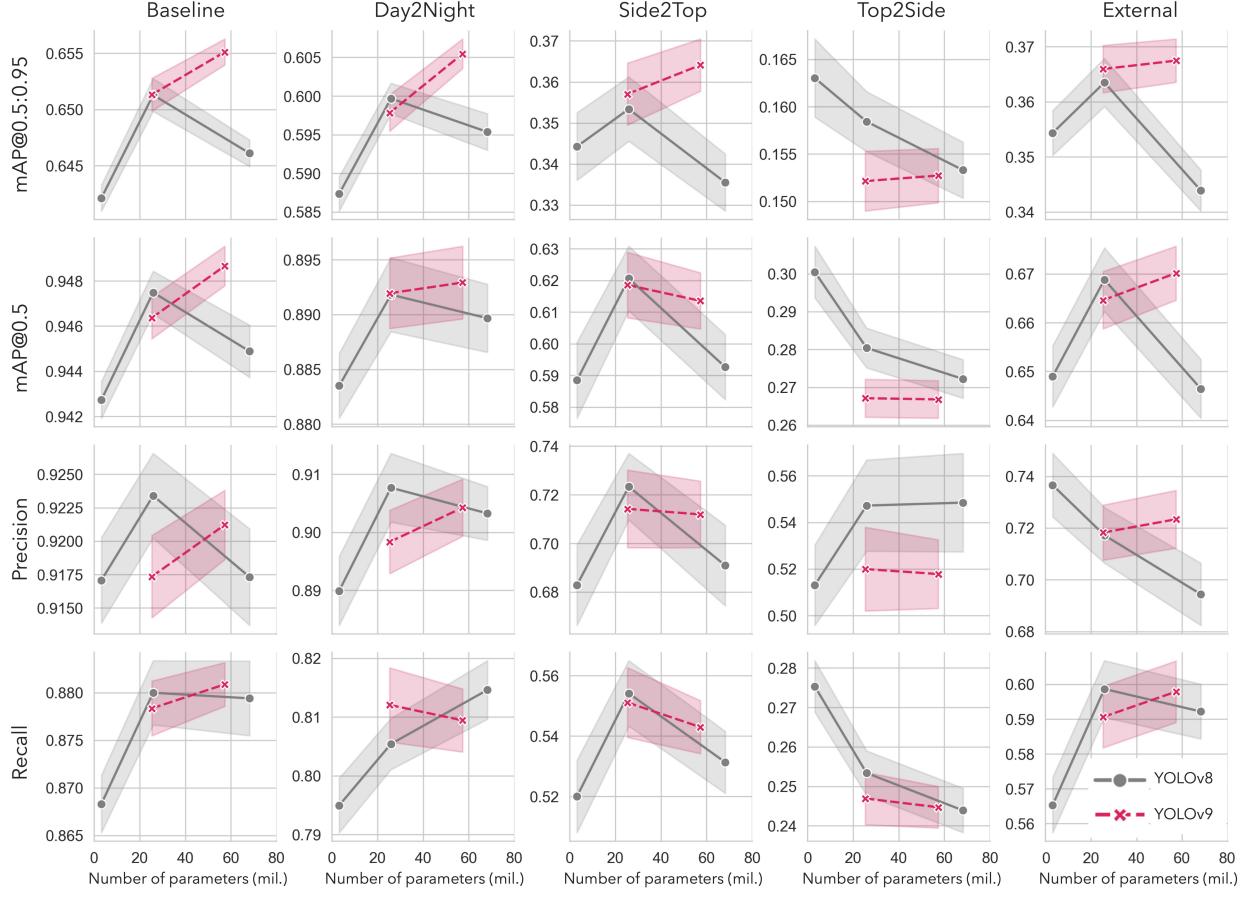


Figure 5: The performance of YOLOv8 and YOLOv9 models across various model parameters and data configurations, evaluated using four metrics: mAP@0.5:0.95, mAP@0.5, precision, and recall. Each column indicates a different data configuration, starting from top left to bottom right: ‘Baseline’, ‘Day2Night’, ‘Side2Top’, ‘Top2Side’, and ‘External’. The horizontal axis of all plots indicates the number of model parameters.

376 Additionally, this study found that a small model such as YOLOv8n, with only 3.2M parameters, can yield 90% accuracy
 377 with a relatively small size of training samples. This indicates that when one encounters a simple and homogenous task
 378 like positioning cows, deploying a small model is optimal in balancing computing time and prediction accuracy. This
 379 further underscores the importance of considering the specific characteristics of the task and dataset when choosing a
 380 model, rather than defaulting to more complex models under the assumption they will perform better.

381 Overall, our findings emphasize that higher model complexity does not necessarily lead to better performance. The
 382 optimal model configuration depends heavily on the specific task and dataset, highlighting the need for careful model
 383 selection tailored to the particular application at hand.

384 **Study 3: The Advantages of Custom Initial Weights are Limited When the Model is Simple**

385 The results presented in Figure 6 indicate that the benefit of using fine-tuned initial weights is minimal for simpler
 386 models. Specifically, when employing YOLOv8n, the performance difference between the default and fine-tuned

weights was insignificant when fine-tuning data from the Top-View Camera and Side-View Camera. However, as model complexity increased, a greater number of fine-tuning samples were required for the two different initial weights to achieve similar performance. For instance, in the case of YOLOv9e, the performance gap was eliminated when the number of fine-tuning samples reached 128 and 64 for the Top-View Camera and Side-View Camera data sources, respectively. A similar trend was observed with the External camera, where a significant performance gap of more than 25% in mAP@0.5:0.95 was observed for YOLOv9e when the sample size was 16. It is also noted that, although the performance gap was closed to zero for the Top-View Camera and Side-View Camera data sources, the gap was never closed for the External camera.

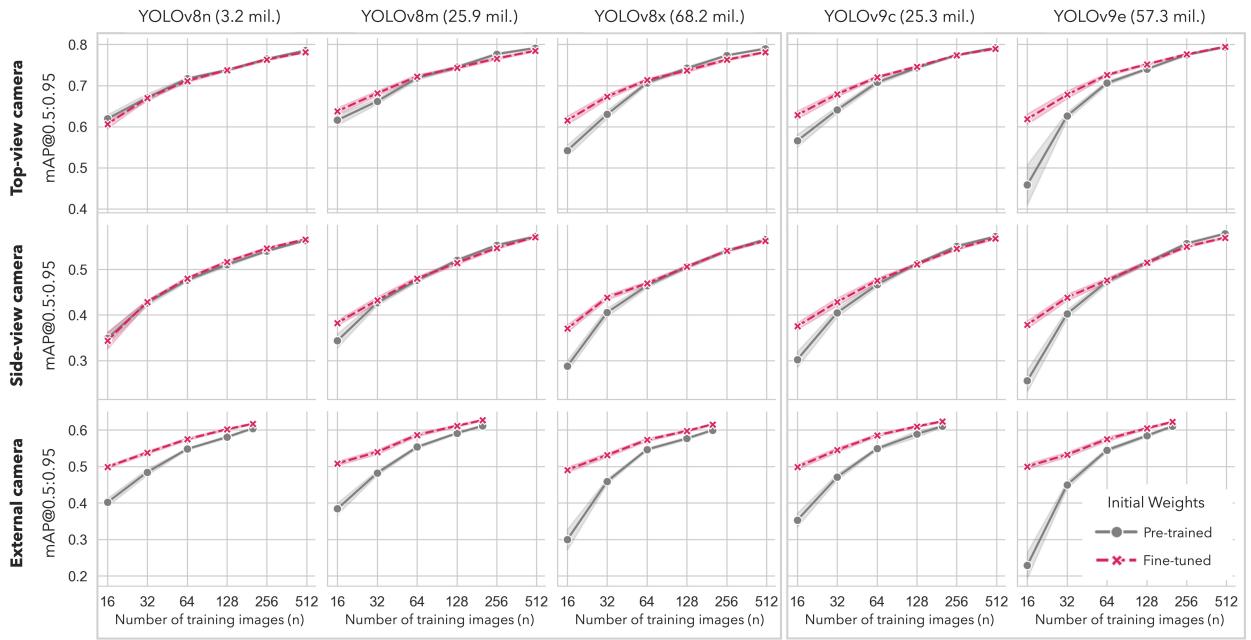


Figure 6: Varied generalization performance in mAP@0.5:0.95 with different initial weights. Red lines represent instances where weights were initialized with fine-tuned weights from other data configuration, while grey lines indicate scenarios employing pre-trained weights (i.e., trained with the COCO dataset). The horizontal axis indicates the number of training samples used for the fine-tuning procedure.

This study suggests that, for YOLO models with fewer parameters, such as YOLOv8n and YOLOv8m, the choice of weight initialization does not make a significant difference in fine-tuning performance. In contrast, larger models like YOLOv8x, YOLOv9c, and YOLOv9e exhibit improved performance when weights are initialized from a model that has been previously fine-tuned in a similar data configuration, as described in Table 1. Therefore, when fine-tuning larger models with a limited dataset, it is beneficial to utilize weights previously fine-tuned on various data configurations. This approach leverages the additional learned features and adaptability from the initial fine-tuning, resulting in better performance even with a small amount of new data. For example, our results showed that YOLOv9e achieved optimal performance with fewer fine-tuning samples when initialized with fine-tuned weights compared to default weights. Conversely, for smaller models, the weight initialization strategy does not significantly impact fine-tuning performance. This is likely due to the lower complexity and fewer parameters of these models, which makes them less dependent on

405 the initial weight configuration to achieve good performance. In practical terms, this means that for simpler models,
406 researchers can save time and computational resources by directly fine-tuning without the need for customized weight
407 initialization.

408 The analysis of Figure 6 also provides insight into performance across homogeneous viewpoint data configurations,
409 specifically ‘Top-View Camera’ and ‘Side-View Camera’. The data demonstrates that the ‘Top-View Camera’ configu-
410 ration consistently yields higher mAP values regardless of the training sample size and weight initialization conditions.
411 This implies that the ‘Side-View Camera’ configuration, where both training and test images are captured from the side
412 view, presents a more formidable challenge for cow detection compared to the ‘Top-View Camera’ configuration. The
413 side view poses difficulties due to occlusions by neighboring cows and additional distractions, such as obstacles in
414 aisles and fences. Furthermore, cows located further away in side-view images may not be as visible, complicating
415 feature extraction. In contrast, the ‘Top-View Camera’ configuration benefits from an unobstructed aerial perspective,
416 ensuring that the top view of all cow instances is clearly visible and free from such obstructions. This distinction in
417 visibility between the two configurations contributes to the ease of feature extraction and ultimately, the performance
418 disparity observed.

419 These findings align with the results from Study 1, which demonstrated that changes in camera view angles dramatically
420 affect model performance. In Study 1, we found that models trained on Top-View datasets struggled the most to detect
421 cows from side-view images, with performance dropping by approximately 60% in mAP@0.5. This significant drop in
422 performance is attributed to the same reasons identified in Study 3: the side view introduces occlusions and distractions
423 that are not present in the top view, making feature extraction more challenging.

424 This study highlights that when working with external or unseen datasets, fine-tuning with custom initial weights trained
425 on relevant tasks brings advantages to the detection tasks. On the other hand, simpler models do not benefit much from
426 customized weights, suggesting that it is more efficient to train a simple model with pre-trained weights without relying
427 on prior relevant information, which sometimes requires intensive labor efforts.

428 Computational Resource Requirements

429 The evaluation of computational resource requirements is crucial for understanding the feasibility of deploying YOLO
430 models in real-world applications, especially in environments with limited computational resources. This section
431 compares training time (Figure 7a), inference time (Figure 7b), and model weight sizes (Figure 7c) for various YOLO
432 models.

433 The training time for each model was measured and expressed as a multiple of the baseline training time, which is
434 the time required to train the YOLOv8n model with 32 samples. The results indicated that using the largest model,
435 YOLOv8x, which has 20 times more parameters, increased training time by 4 to 6 times, depending on the training
436 sample size. Additionally, the YOLOv9 models generally required more training time and had slower inference frames

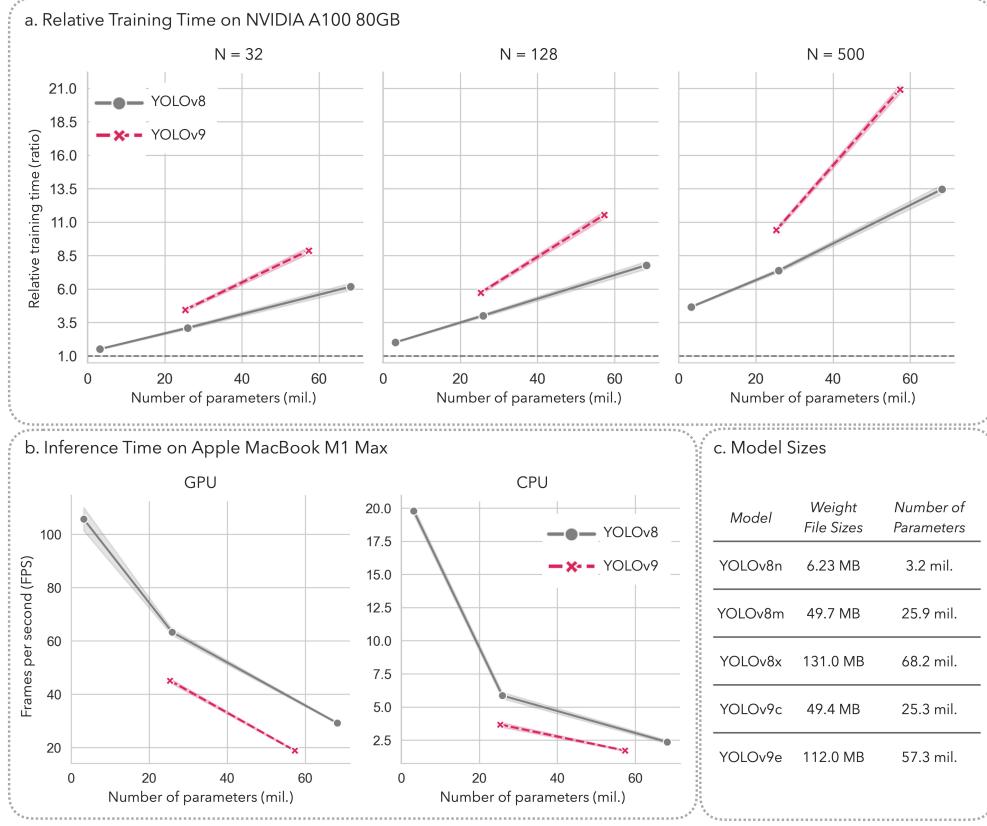


Figure 7: Comparative evaluation of computational resource requirements. (a) Training time (expressed as a multiple of baseline time) versus number of parameters for YOLOv8 and YOLOv9 models, presented for training sample sizes of 32 (left), 128 (middle), and 500 (right). (b) Inference frequency versus number of parameters for YOLOv8 and YOLOv9 models on GPU (left) and CPU (right). (c) A table displaying the weight sizes and parameter counts of various YOLOv8 and YOLOv9 models.

437 per second (FPS) compared to the YOLOv8 models. The gap in training time expanded as the number of training
438 samples increased.

439 Inference time was measured as the average FPS in a batch of 64 images. Running the models on a CPU with the
440 smallest model (YOLOv8n) was slower than running the largest model (YOLOv8x) on a GPU. For example, the FPS
441 for the small, YOLOv8n, on a CPU was 19.77, while the FPS for YOLOv8x on a GPU was 29.21. High FPS models
442 are essential for real-time inference, which usually requires a model with an FPS higher than 30. The results indicate
443 that implementing YOLO models on a CPU may not meet real-time requirements, especially for larger models.

444 Lastly, model weight sizes were also considered, impacting memory requirements and deployment feasibility, especially
445 in edge computing environments. The weight sizes and parameter counts of various YOLO models are displayed in
446 Figure 7c.

447 In conclusion, this evaluation highlights the trade-offs between model complexity and computational efficiency. The
448 larger YOLO models, while offering potentially better performance, require significantly more computational resources.

449 This analysis helps researchers and practitioners select the appropriate model based on the available computational
450 resources and the specific requirements of their application.

451 **4 Conclusion**

452 This study examined the impact of various training configurations and model complexities on the performance of
453 YOLOv8 and YOLOv9 models for cow detection in indoor farm environments. Our results indicate that model
454 performance is highly dependent on camera viewpoints, with side views presenting the greatest challenges. Additionally,
455 fine-tuning models with weights from similar datasets substantially enhances performance, particularly for complex
456 models in scenarios with limited data. We also introduce a public cow localization dataset, 'COLO', to support the
457 research community.

458 The findings indicate that while increasing model complexity can improve performance, this is not always the case,
459 especially in challenging configurations like 'Top2Side', which predict images from a side view using a model trained
460 on top-view images. Models trained on a single viewpoint exhibit limited generalization, underscoring the importance
461 of incorporating diverse and consistent camera angles in the training data.

462 Despite the promising results, this study has certain limitations. The models' performance was evaluated under specific
463 indoor farm conditions, which may not generalize to all livestock environments. Moreover, the reliance on pre-defined
464 configurations may limit the applicability of our findings to more dynamic settings.

465 Future work should explore adaptive methods for enhancing model generalization across varied viewpoints and
466 environmental conditions. Additionally, investigating the integration of advanced data augmentation techniques and
467 more diverse datasets could further improve detection accuracy and robustness.

468 In conclusion, this study offers practical insights into reproducing model performance in new environmental settings
469 and provides the public 'COLO' dataset to facilitate further research and advancements in the field.

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608 Appendix
609 Hyperparameters in Ultralytics library

610 The table below show the hyperparameters used in the Ultralytics library for training the models in this study.

Table 3: Hyperparameters for the training procedure

Hyperparameters	Description	Value
epochs	Number of training epochs	100
batch	Number of images in each batch	16
optimizer	Optimizer used for training	auto
hsv_h	Altering the hue value of the image	0.015
hsv_s	Altering the saturation of the image by a fraction	0.7
hsv_v	Altering the brightness of the image by a fraction	0.4
translate	Randomly translating the image by a fraction of the image size	0.1
scale	Randomly scaling the image by a fraction of the image size	0.5
fliplr	Randomly flipping the image horizontally with the given probability	0.5
mosaic	Combining four images into one mosaic image with the given probability	1.0
mixup	Randomly mixing up the object instances across multiple images with the given probability	0.15
copy_paste	Randomly copying and pasting the object instances across multiple images with the given probability	0.3



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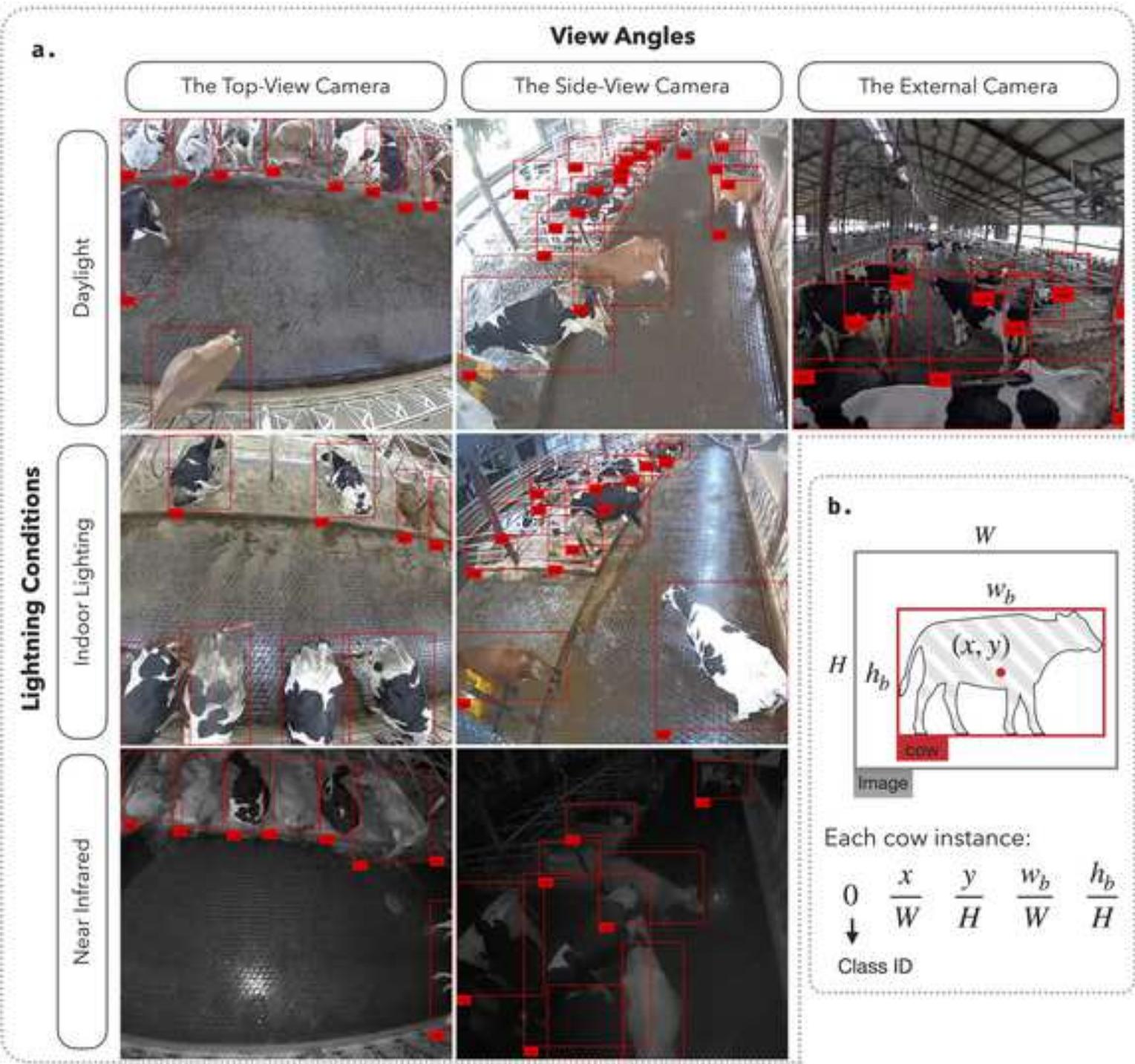
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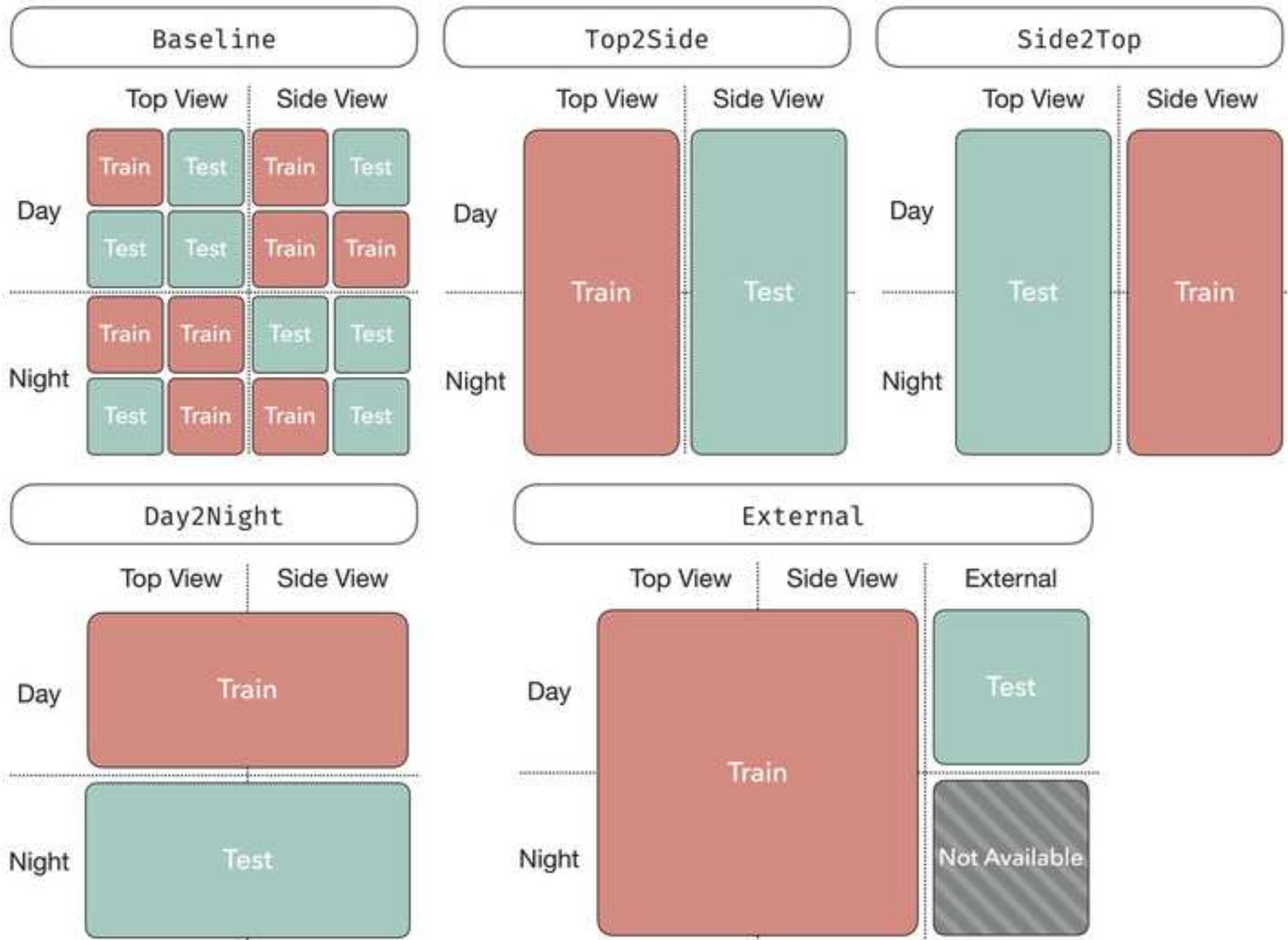


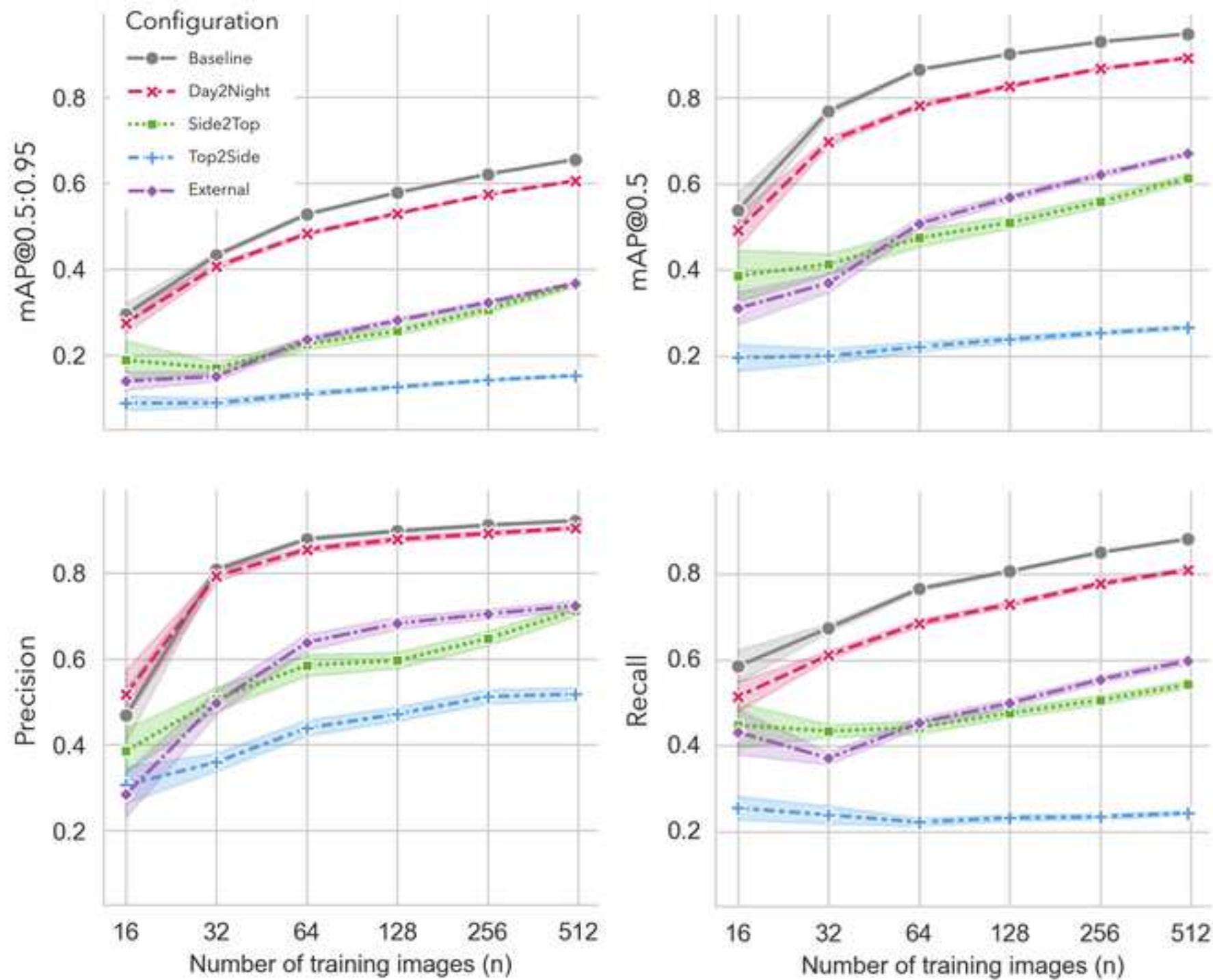
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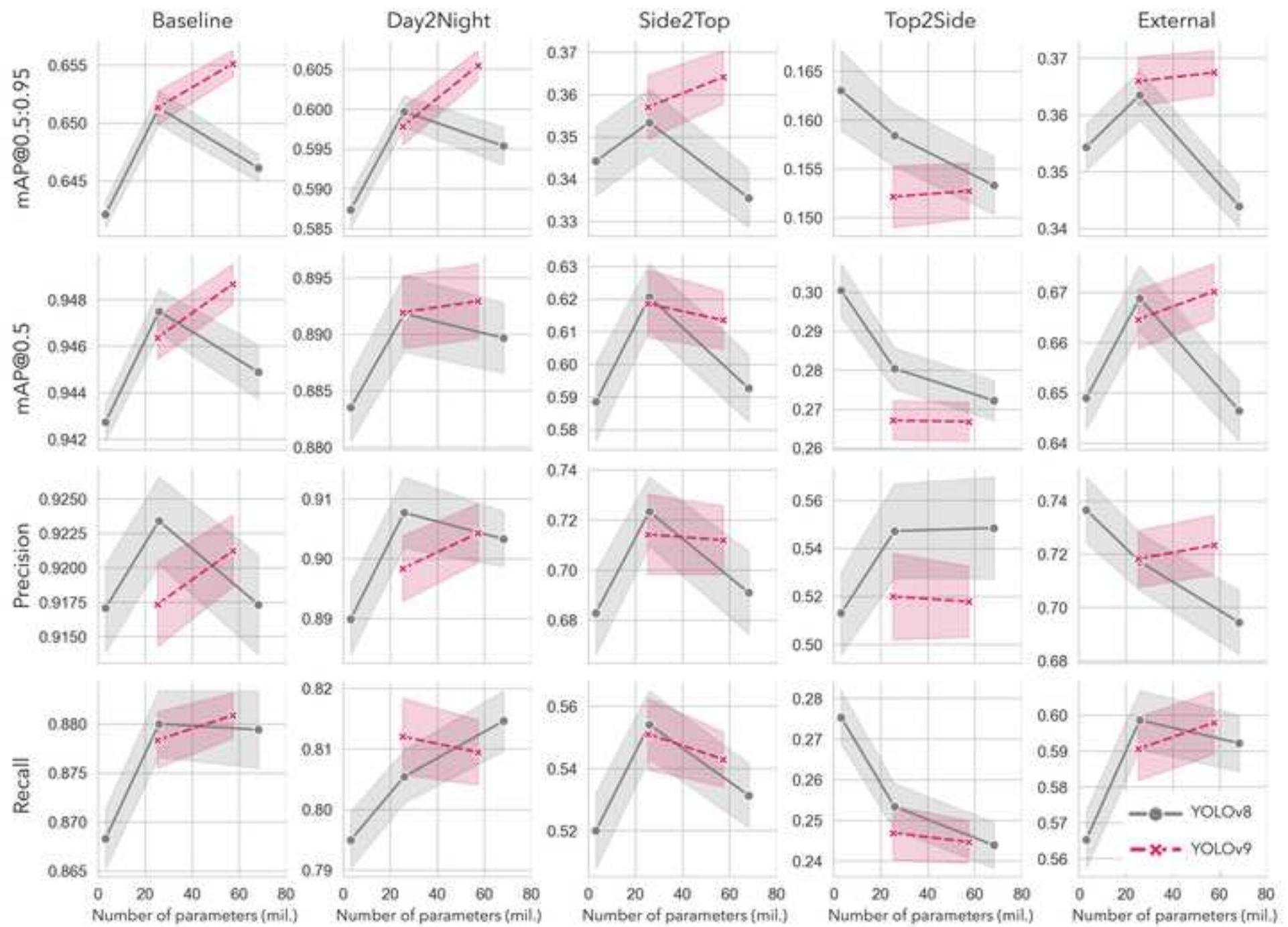


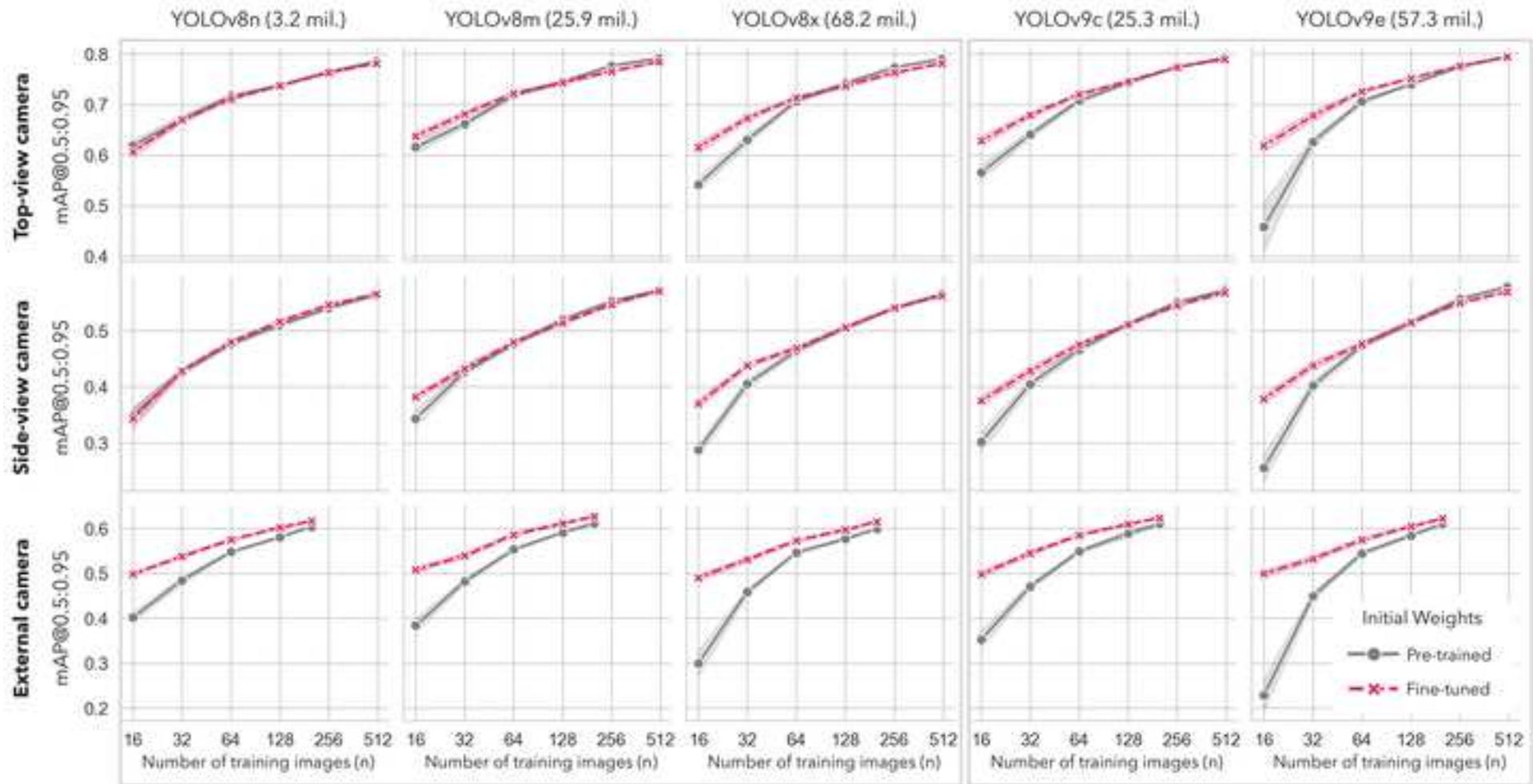
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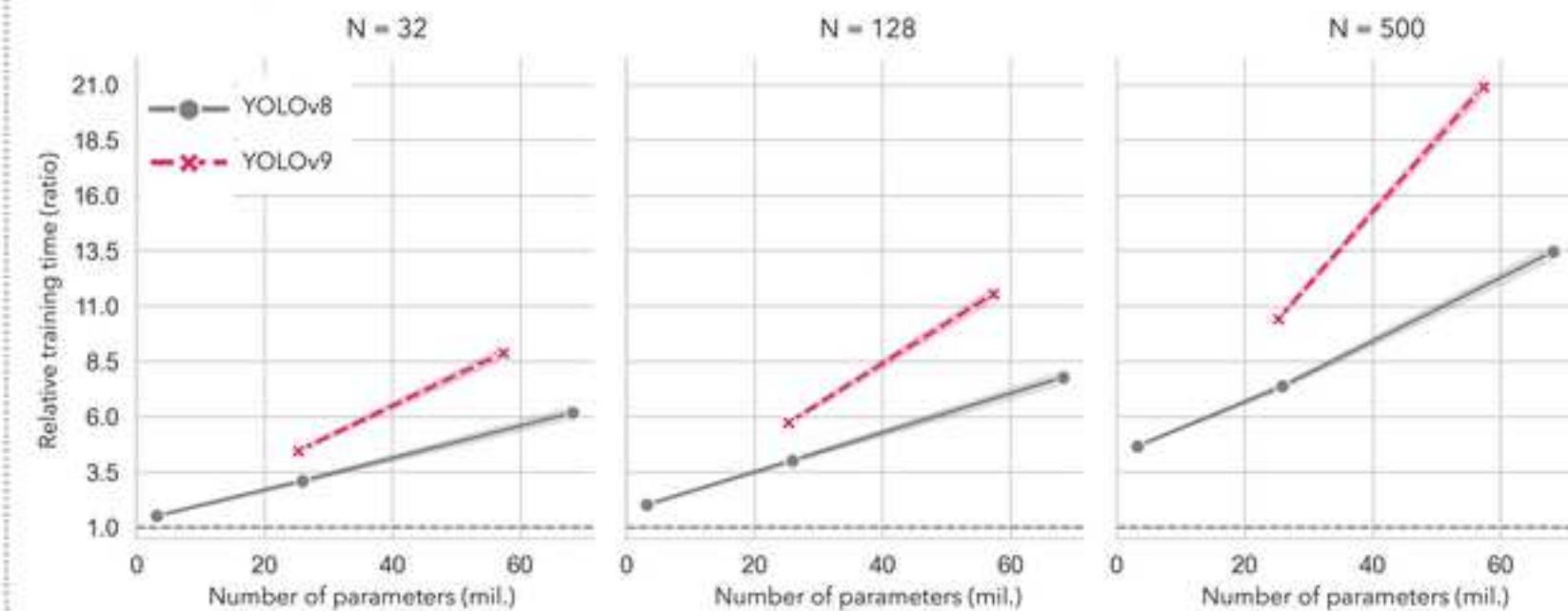




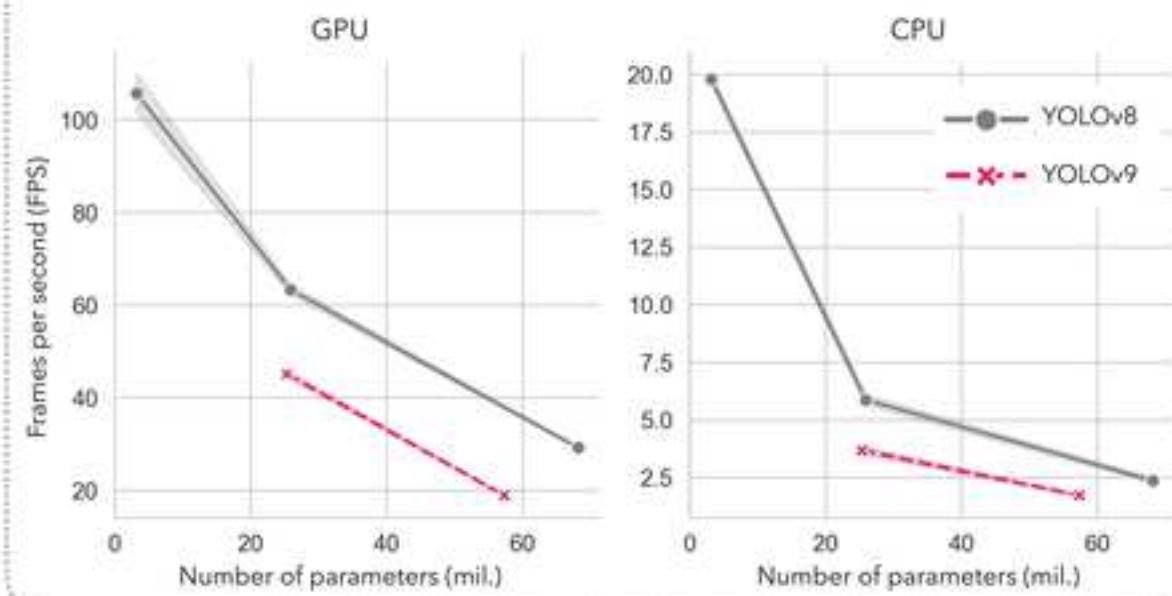




a. Relative Training Time on NVIDIA A100 80GB

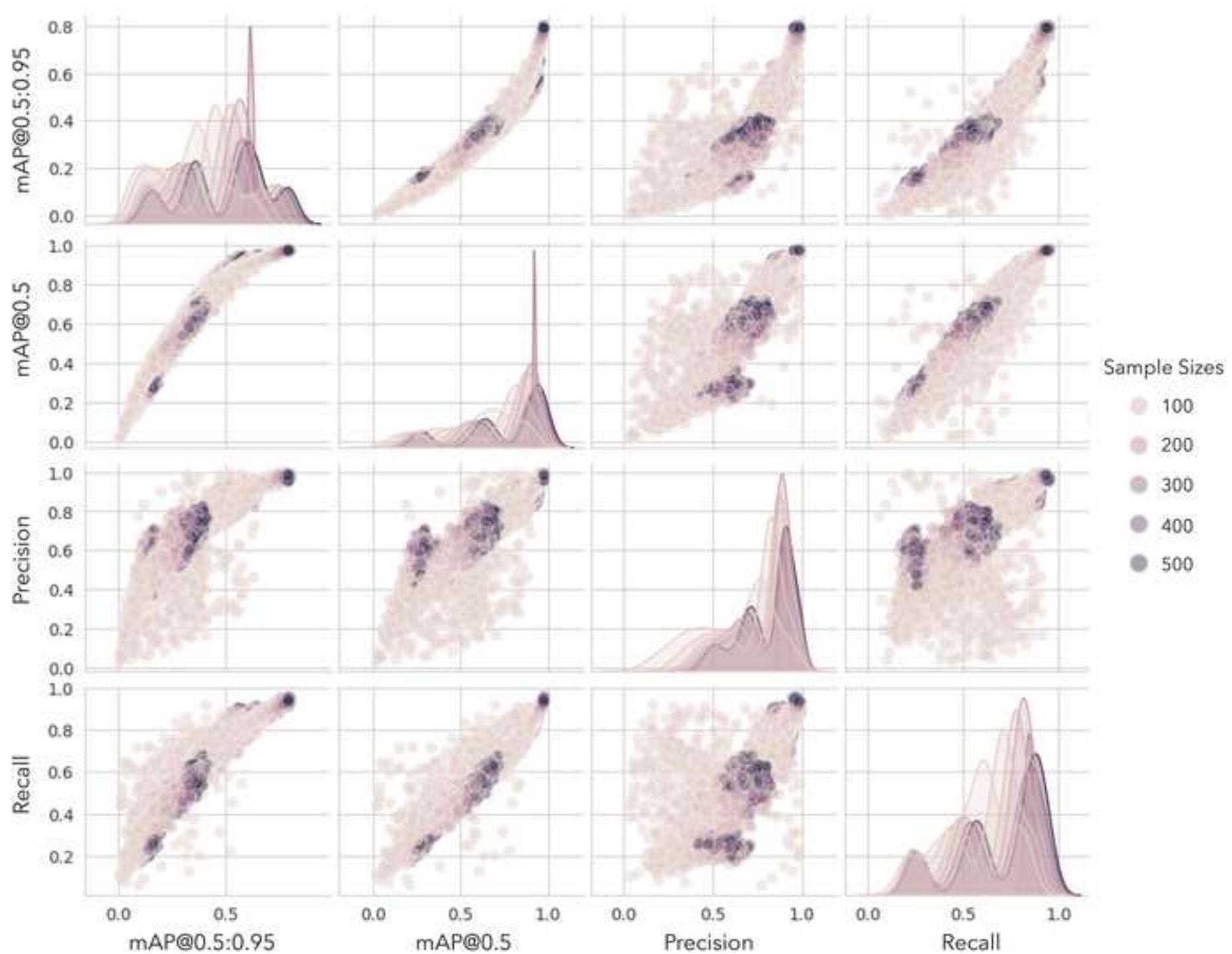


b. Inference Time on Apple MacBook M1 Max



c. Model Sizes

Model	Weight File Sizes	Number of Parameters
YOLOv8n	6.23 MB	3.2 mil.
YOLOv8m	49.7 MB	25.9 mil.
YOLOv8x	131.0 MB	68.2 mil.
YOLOv9c	49.4 MB	25.3 mil.
YOLOv9e	112.0 MB	57.3 mil.



Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

C. P. James Chen reports a relationship with National Institute of Food and Agriculture that includes: funding grants. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.