

Monitoring Piglet Growth via Instance Segmentation with YOLOv8[†]

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Abstract

In this paper, we present a method for monitoring piglet growth over time using instance segmentation with the YOLOv8 model. Our goal is to estimate the average weight gain of piglets by measuring changes in their visible body area in images. We fine-tuned the yolov8x-seg.pt model on a custom dataset of 471 annotated images, using polygonal masks created in Roboflow. The dataset captures piglets from multiple angles and developmental stages. After training, the model achieved accurate segmentation results, effectively distinguishing individual piglets in varied conditions. By computing the mean segmented area across images over time, we derive a reliable proxy for monitoring weight gain, offering a non-invasive, camera-based alternative to manual weighing. Our findings demonstrate that YOLOv8 instance segmentation can be a valuable tool for automated livestock monitoring and precision farming.

Keywords: piglet growth monitoring; YOLOv8 instance segmentation; precision livestock farming; non-invasive weight estimation; computer vision in agriculture

1. Introduction

Precision livestock farming (PLF) integrates advanced technologies to enhance animal welfare and optimize production efficiency. Traditional methods for monitoring piglet growth, such as manual weighing, are labor-intensive and can induce stress in animals [1]. Non-invasive techniques, particularly those utilizing computer vision, offer promising alternatives for continuous and stress-free monitoring [2].

Recent advancements in deep learning have facilitated the development of robust object detection and segmentation models. YOLOv8, the latest iteration in the YOLO series, combines real-time processing capabilities with high accuracy, making it suitable for applications in dynamic farm environments [3]. By employing instance segmentation, YOLOv8 can delineate individual piglets within images, enabling precise area measurements that correlate with growth metrics.



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2. Related Work

2.1. Instance Segmentation in Livestock Monitoring

Instance segmentation has been increasingly applied in livestock monitoring to identify and analyze individual animals. For example, reference [4] introduces the Center Clustering Network (CCLUSnet-Inseg) for occlusion-resistant piglet segmentation in farrowing pens, achieving a mean average precision (mAP) of 84.1%. Similarly, studies have demonstrated the efficacy of YOLOv8 in segmenting objects within complex agricultural environments, outperforming models like Mask R-CNN in both accuracy and inference speed [5].

2.2. Non-Invasive Weight Estimation Techniques

Traditional weight estimation methods often require physical contact, which can be stressful for animals. Recent approaches have explored the use of RGB-D cameras and deep learning models to estimate weight based on visual data. For instance, the study in [6] developed a dual-stream fusion network combining RGB and depth images to estimate pig weight, achieving a root-mean-square error (RMSE) of 4.082 kg and a mean absolute percentage error (MAPE) of 2.383%.

2.3. YOLOv8 in Agricultural Applications

YOLOv8 has been applied in various agricultural contexts due to its real-time processing and high accuracy. In dairy farming, the study referenced in [7] utilized YOLOv8 to predict calf body weight from depth images, achieving an intersection over union (IoU) score of 0.98. Additionally, YOLOv8 has been employed in orchard environments for object segmentation tasks, demonstrating superior performance compared to traditional models [5].

3. Materials and Methods

3.1. Dataset Collection and Annotation

We curated a diverse dataset comprising 471 images of piglets captured in a farm setting, encompassing various angles, lighting conditions, and developmental stages to ensure robust model training and evaluation. Six representative annotated images from this dataset are presented in Figure 1, illustrating the variability and complexity of the scenes.



Figure 1. Annotated samples from the dataset.

Annotations were performed using Roboflow, where polygonal masks delineated individual piglets. Initially, simplified polygons were employed (Figure 2); however, subsequent analyses indicated that more detailed annotations could enhance measurement accuracy (Figure 3).

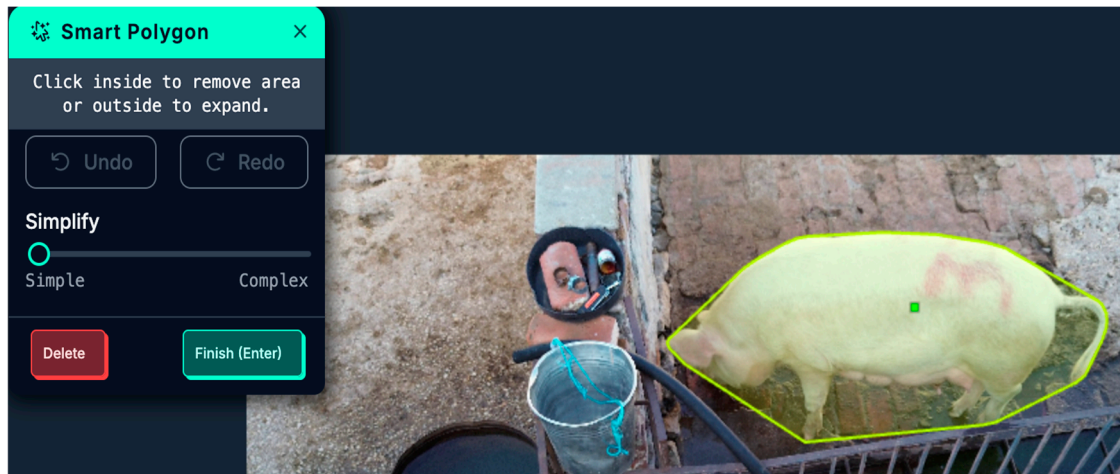


Figure 2. Simplified polygonal masks.

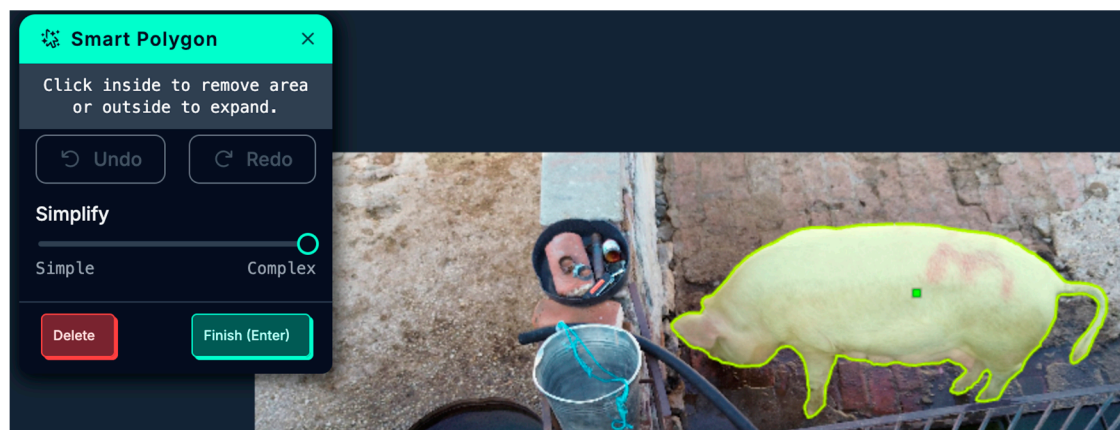


Figure 3. Detailed polygonal masks employed to improve measurement accuracy.

3.2. Model Architecture and Training

Initially, we experimented with the default pretrained yolov8x-seg.pt model, which had been trained on the COCO dataset. However, the results from this initial application were unsatisfactory, as illustrated by the first experimental image shown in Figure 4a.



Figure 4. (a) The same image processed by the default model; (b) the fine-tuned model.

To improve performance, we fine-tuned the model specifically for piglet instance segmentation. The fine-tuning process involved training the model for 100 epochs and applying data augmentation techniques including horizontal flipping, color jittering, and scaling to enhance robustness. The training process graph, shown in Figure 5, illustrates the changes in mAP@0.5 and mAP@0.5:0.95 across epochs. The improved results after fine-tuning are demonstrated in the corresponding image presented in Figure 4b.

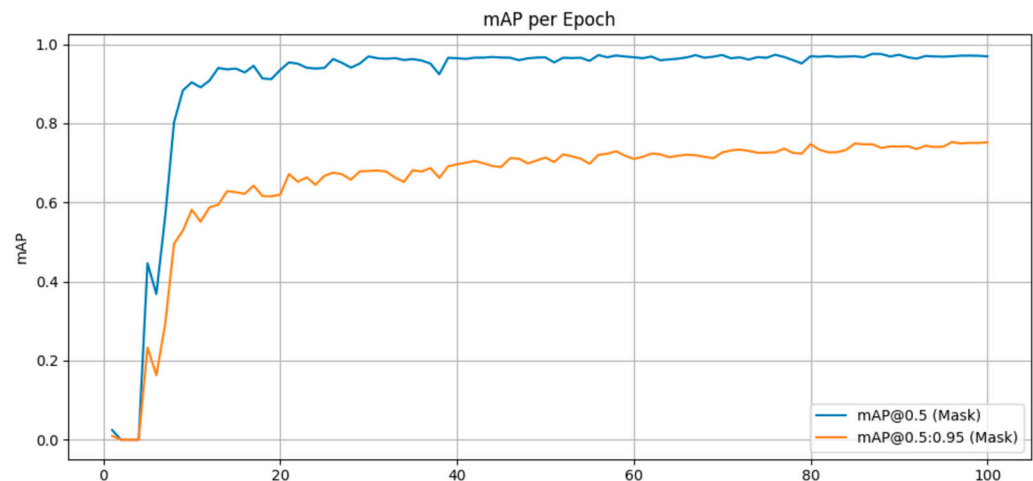


Figure 5. Results, obtained from the training result file, are illustrated in the training graph shown in this figure.

The results, obtained from the training result file, are illustrated in the training graph shown in Figure 5.

3.3. Evaluation Metrics

Model performance was assessed using the following metrics:

- Mean Average Precision (mAP) at IoU thresholds of 0.5;
- Mean Average Precision (mAP) at IoU thresholds of 0.5:0.95;
- Visual Assessment of segmentation quality.

3.4. Area Measurement and Growth Estimation

Segmented masks were utilized to calculate the visible body area of piglets in pixels. By tracking mean area values over weekly intervals, we estimated relative growth trends. While pixel area does not directly equate to body weight, it serves as a consistent proxy under controlled imaging conditions.

4. Results

The fine-tuned YOLOv8x-seg model effectively segmented piglets across diverse scenes, surpassing the baseline model without fine-tuning. Example segmentation results are shown in Figure 6, which presents a representative frame from the processed video. Similar segmentation quality was observed consistently across other frames throughout the video.

The model achieved a mean Average Precision (mAP) of 0.96931 at the 0.5 Intersection over Union (IoU) threshold, and an mAP of 0.75195 across the range of IoU thresholds from 0.5 to 0.95.



Figure 6. Segmentation result from the fine-tuned YOLOv8x-seg model.

5. Discussion

Our findings affirm that YOLOv8 instance segmentation provides a reliable, non-invasive method for monitoring piglet growth. The study emphasizes the significance of high-quality annotations; simplified polygons may limit measurement precision, whereas detailed annotations yield more accurate area estimations.

Future directions include:

- Expanding the dataset with more images and refined annotations;
- Implementing stationary cameras for continuous monitoring;
- Exploring 3D reconstruction methods for improved volume estimation.

6. Conclusions

This research demonstrates the potential of YOLOv8 instance segmentation in facilitating stress-free, accurate monitoring of piglet growth. By reducing reliance on manual weighing, the approach supports enhanced animal welfare and aligns with the objectives of precision livestock farming.

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