Comparison of Biocode Based Machine learning and Segmentation Model for Automated Prawn Size Prediction for Real Prawn Farm

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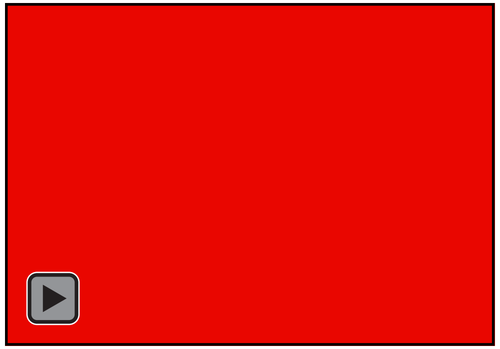
Problem Statement

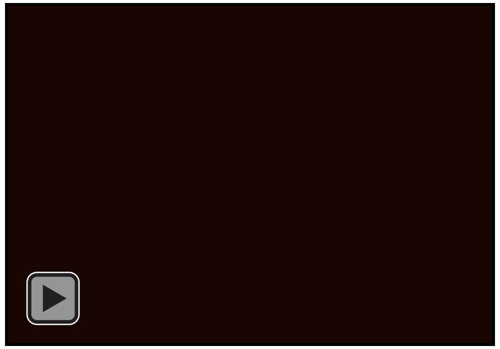
- Traditional prawn size measurement methods in aquaculture are:
  - Time-consuming
  - Laborious
  - Stressful for prawns (netting, handling)
  - Limited data collected (length only)
- Challenges of traditional methods:
  - Baited traps:
    - Reliant on prawn behaviour/preference
    - May miss smaller individuals
  - Hand netting:
    - Difficult to capture entire population
    - Incomplete capture, smaller prawns often hide from larger prawns

Project Objectives

- Utilise deep learning algorithm with ArUco as reference point to predict prawn length and width accurately.
  - Improve measurement efficiency
  - Reduce stress on prawns
  - Automate the prawn sampling process (no physical handling)
  - Cost-effective and portable solution (monocular vision)
- Evaluate the effectiveness of the proposed system with YOLOv8 Segmentation and YOLOv8 Object Detection combined with Segment Anything Model (SAM)

Deep Learning Techniques for Size Prediction





YOLOv8 (You Only Look Once)

- Released in January 2023 by Ultralytics
- Outperforms previous versions in speed and accuracy
- Key improvements:
    - Anchor-free architecture (simpler training)
    - Dynamic head network for multi-scale prediction (better object size detection)
    - Enhanced backbone network (improved object detection in difficult conditions)
- Five versions, from YOLOv8x (largest) to YOLOv8n (smallest)
- YOLOv8x version used in this project for prawn detection and segmentation

Segment Anything Model (SAM

- Released in April 2023 by Meta AI for image segmentation
- Trained on over 1 billion segmentation masks
- Capabilities:
    - Zero-shot segmentation (segmenting unseen objects)
    - Flexible prompting (points, bounding boxes, text descriptions)
    - Real-time mask generation
    - Handling object overlap in images
- Generates masks for objects in real-time, suitable for applications like autonomous driving and robotics
- Fine-tuning possible for specific use cases
- This project utilizes SAM with bounding box prompts from YOLOv8 for prawn segmentation

ArUco

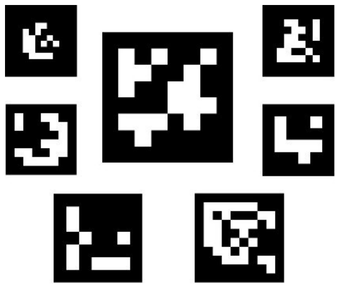
Synthetic square marker with black border for fast detection and binary matrix for identification

Compared to using a separate reference object detected through edge detection or a separate model, ArUco markers offer a more efficient approach, reducing detection inference time and increasing reliability

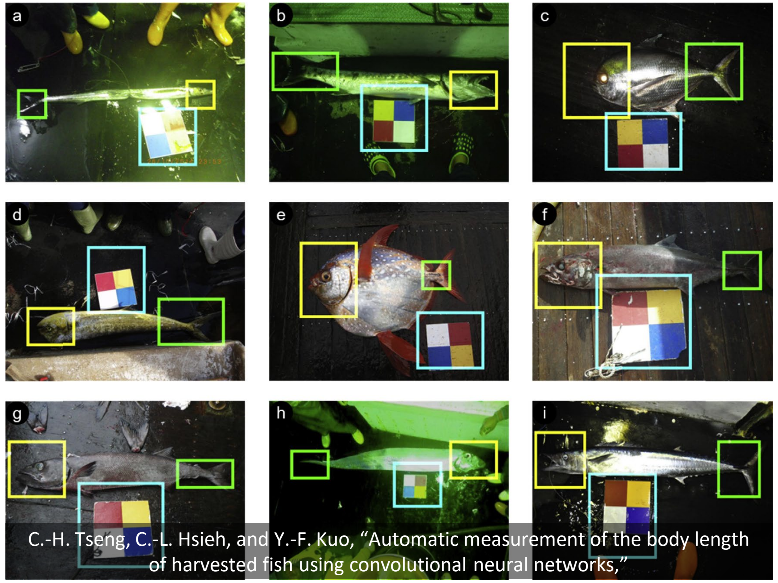
Seamless integration with OpenCV simplifies detection process without complex operations

In this study, a marker size of 4 cm per side addresses proximity-related issues between objects and cameras

By acting as a fixed reference point, ArUco markers eliminate distance-related issues in traditional vision-based measurements and accurate object size measurements can be obtained



G. G. Monkman, K. Hyder, M. J. Kaiser, and F. P. Vidal, "Using machine vision to estimate fish length from images using regional convolutional neural networks,"



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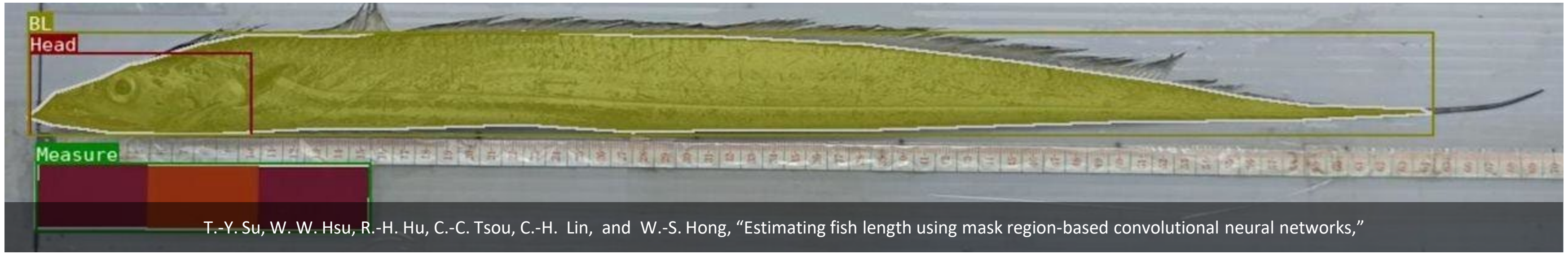

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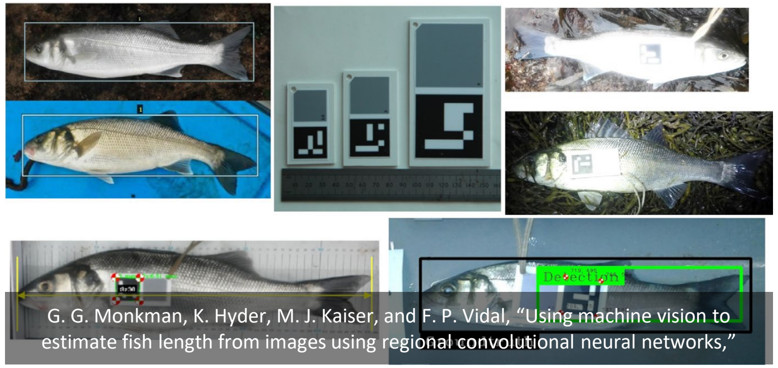

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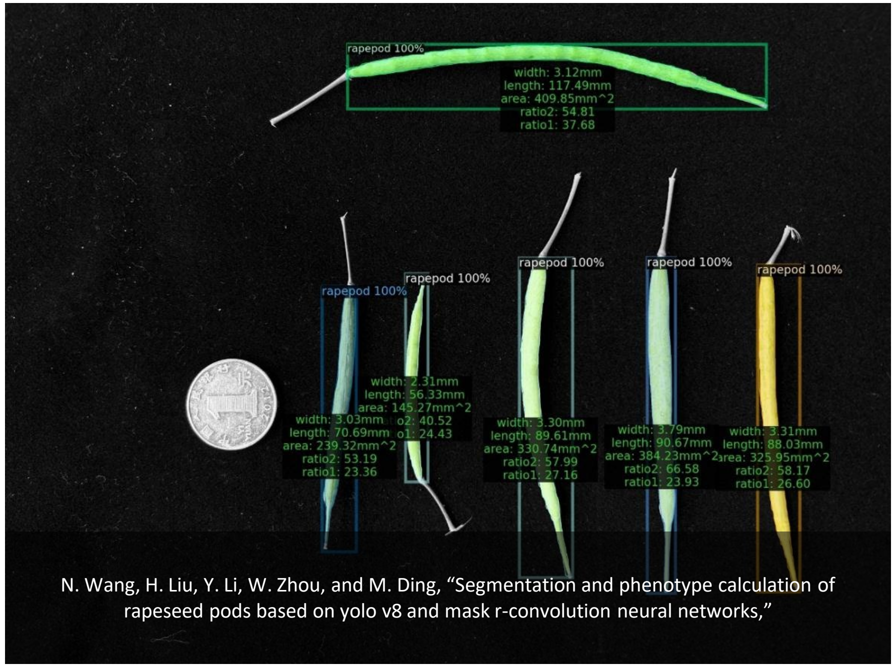


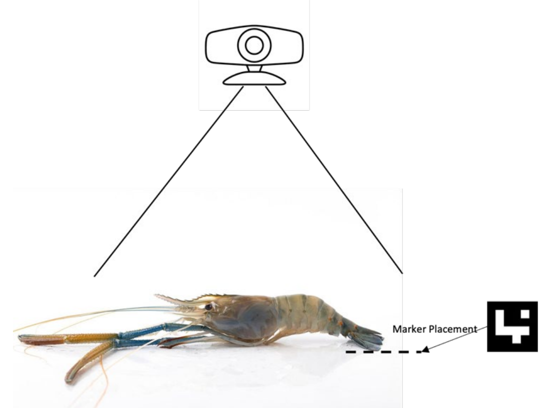
N. Wang, H. Liu, Y. Li, W. Zhou, and M. Ding, "Segmentation and phenotype calculation of rapeseed pods based on yolo v8 and mask r-convolution neural networks,"

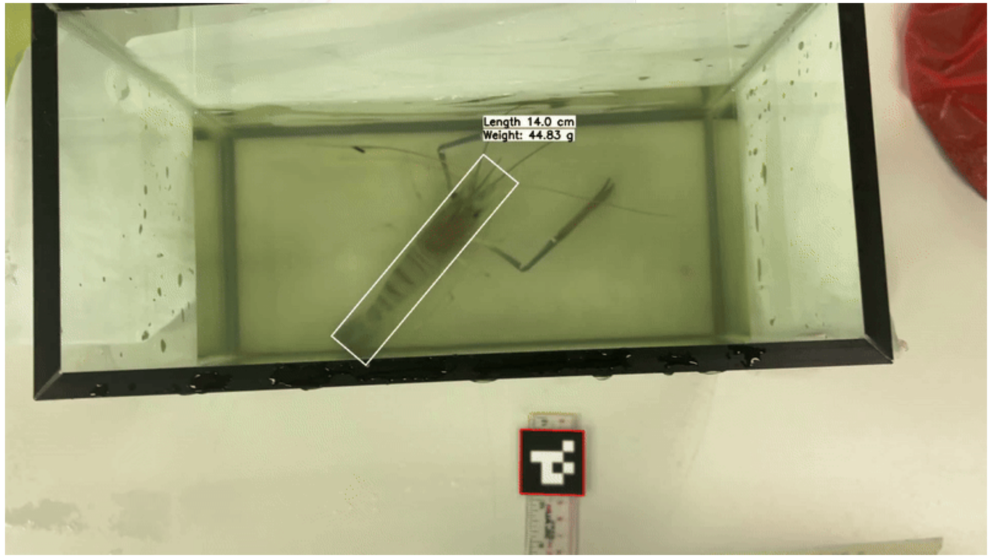
H. Kurnianto, W. Puspitasari, and R. H. Y. Perdana, "A computer vision- based for fish size measurement,"

Literature Review

Perspective Distortion and Limitations

- Perspective distortion causes objects farther away to appear smaller, even if they're the same size as closer objects, affecting accurate measurement.
- Ideally, the ArUco marker should be placed on top of the prawn for the most accurate measurement
- All images in this study have the marker placed on the surface beside the prawn, making it appear smaller and affecting scaling
- Simple calibration technique was applied by scaling down the result by a factor of 0.77 to reduce measurement error
- Factor was considered by using the average prawn height (3 cm for medium/large sizes) and the size difference of the marker if positioned 3 cm further away





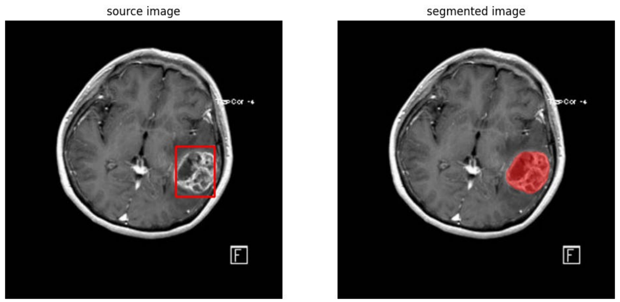
Experimental Setup

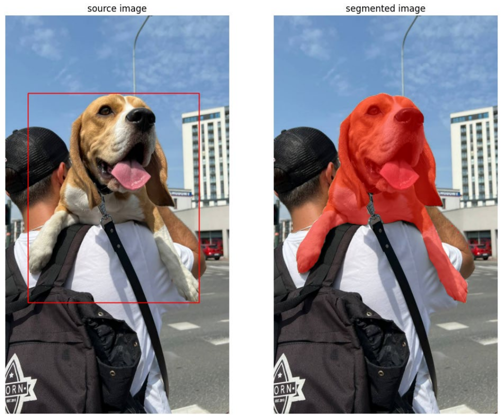
Two Approaches:

1. YOLOv8 Segmentation:
   - Directly segment prawns to obtain prawn shape information.
2. YOLOv8 Object Detection + SAM:
   - Use YOLOv8 to detect prawns and generate bounding boxes.
   - Utilize SAM with bounding boxes as prompts for prawn segmentation.

Measurement and Calculation:

- OpenCV calculates minimum area rectangle (oriented bounding box) for each prawn segmentation.
- ArUco marker perimeter is measured in pixels to establish a pixel-to-cm conversion ratio.
- Prawn length and width are calculated by: Multiplying the bounding box dimensions (longer side for length, shorter side for width) with the pixel-to-cm ratio.





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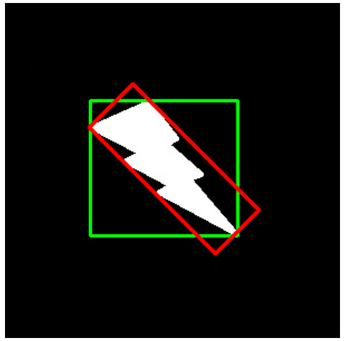


Source: OpenCV

Dataset:

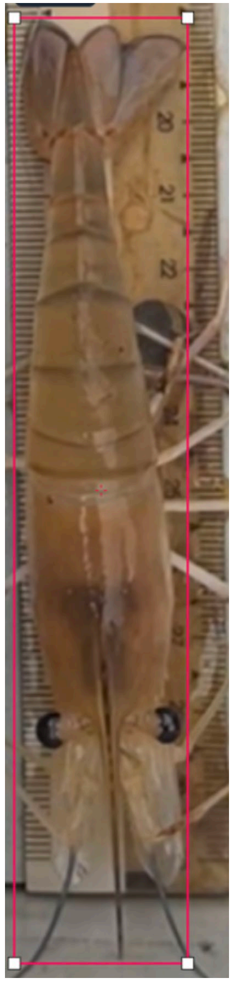
- 8,370 training images
- 711 validation images
- Images include freshwater prawns captured from a top view
- Annotations exclude prawn legs (chelipeds, pereiopods)

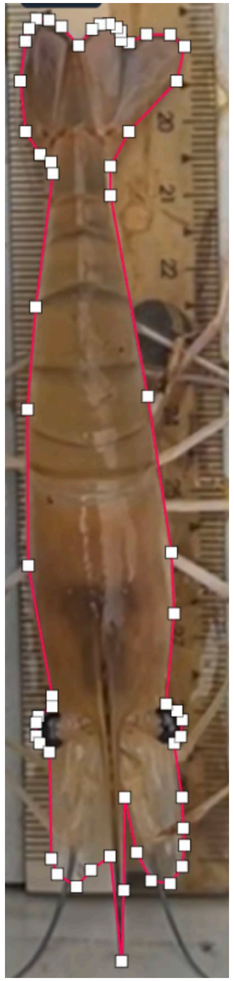
Training Process:

- Both YOLOv8 segmentation (YOLOv8x-seg) and object detection (YOLOv8x) models were trained
- 500 epochs with best epoch saved around epoch 110
- Image size set to 800 pixels

Evaluation:

- 59 prawn samples were tested
- Predicted length and width values are displayed on the images
- Results will be compared with actual measurements after scaling





Results & Discussion

Initial Findings:

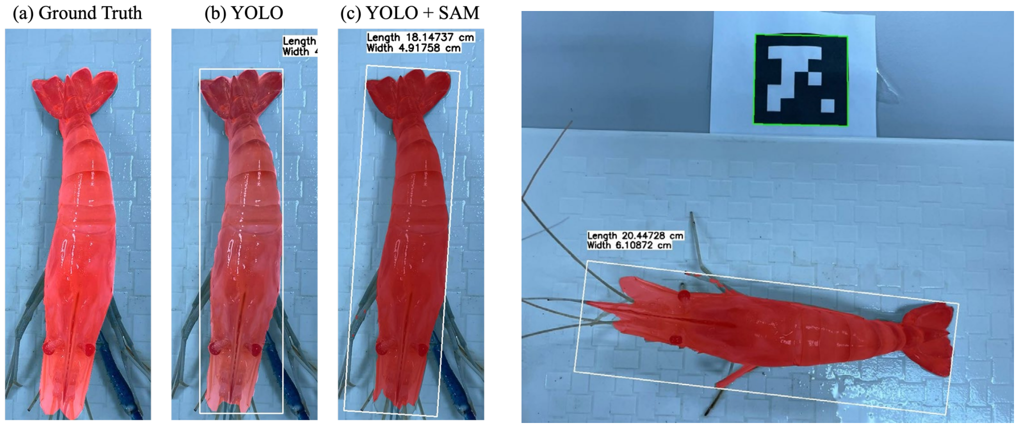
- Both YOLOv8 segmentation and YOLOv8 with SAM showed similar results with a significant overestimation of prawn length (predicted vs. actual: 20.5 cm vs. 15.7 cm and 20.8 cm vs. 15.7 cm, respectively)

Fine-Tuning:

- Fine-tuning significantly improved the accuracy of predicted prawn length for both models:
  - YOLOv8 segmentation: 15.8 cm (mean absolute error: 0.93 cm)
  - YOLOv8 with SAM: 16.0 cm (mean absolute error: 1.10 cm)
- YOLOv8 segmentation outperformed YOLOv8 + SAM in width prediction due to:
  - More accurate exclusion of prawn legs during training
  - SAM lacking a method to exclude legs in width estimation

Overall Performance:

- Length prediction achieved high accuracy with mean absolute errors below 1.2 cm
- Width prediction showed significant differences due to leg inclusion, or tail being wider than body in some cases



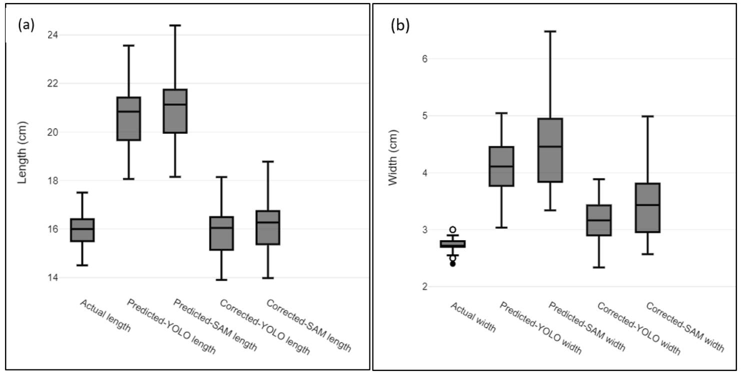
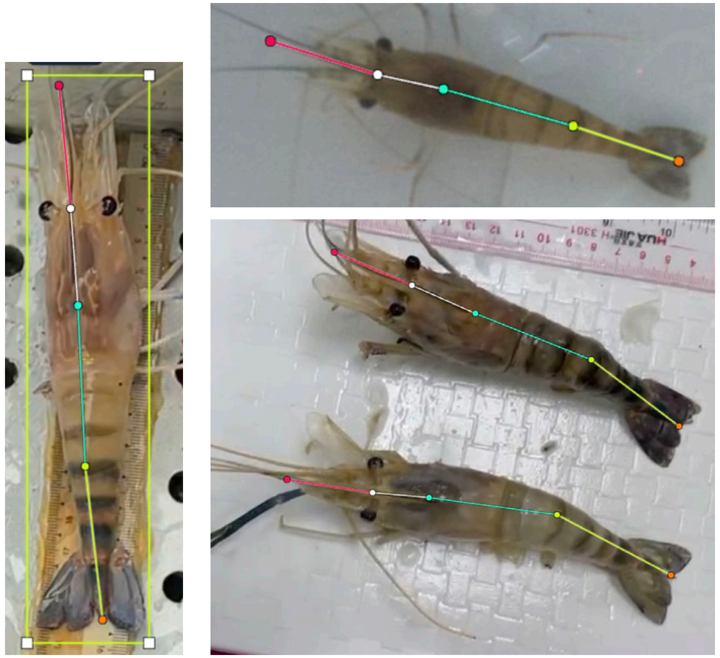


TABLE I

Mean and error values between actual, predicted and corrected values based on YOLO and SAM models of prawn measurements. *Asterisks indicate significant differences with the actual values at p ¡ 0.05 using t-test and KS-test.

	Actual values	Predicted-YOLO values	Corrected-YOLO values	Predicted-SAM values	Corrected-SAM values
Length measurement					
Mean length (cm)	15.7	20.5*	15.8	20.8*	16.0
Mean absolute error (cm)		4.72	0.93	5.00	1.10
Error percentage (%)		30.2	5.79	32.0	6.97
Width measurement					
Mean width (cm)	2.71	4.1*	3.16*	4.50*	3.47*
Mean absolute error (cm)		1.39	0.48	1.79	0.78
Error percentage (%)		51.6	17.7	66.4	28.8

Conclusion & Future Work



Overall Findings and Significance:

- This study demonstrates the potential of computer vision for automated prawn size measurement
- YOLOv8 segmentation achieved good accuracy in length and width prediction with proper training
- The proposed approach offers a non-invasive and efficient alternative to traditional manual methods

Benefits for Prawn Aquaculture:

- Improved efficiency in prawn sampling and size measurement
- Reduced stress on prawns by eliminating handling
- Potential for real-time size monitoring and data collection

Challenges and Limitations:

- Width Measurement Difficulties
- Perspective Distortion

Future Research Directions:

- **Keypoint/Landmark Detection**: Enhance accuracy by detecting specific body points for measurement (e.g. to identify specific prawn body parts for accurate length measurement)
- **Stereo Camera**: Utilize depth information for more precise size estimation without the need of a reference point
- **Weight Regression Model**: Develop a model to predict weight using length and width data
- **Improved SAM Training**: Train SAM models to better distinguish prawn bodies from legs

Thanks for listening