Cross Season Transfer Learning for Prawn Morphometric Estimation Using YOLOv11-Pose

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Abstract

Maintaining reliable computer vision models in dynamic aquaculture environments is challenging because real world imaging conditions change over time. Even in controlled indoor recirculating aquaculture systems (RAS), factors such as water turbidity, illumination, background reflections, and camera positioning vary across monitoring sessions and production seasons, introducing domain shifts that can degrade deep learning performance. This work addressed the challenge of reusing trained YOLOv11-Pose models for automated body length estimation of *Macrobrachium rosenbergii* under such changing environmental conditions. A dataset of 3,707 manually annotated underwater RGB images was collected during two consecutive production cycles (2024 and 2025) in three indoor RAS ponds. Each prawn was labelled with four anatomical keypoints to estimate carapace length (CL) and total length (TL) at millimetre scale. Cross season deployment caused asymmetric failure, with detection dropping below 60%. A staged transfer learning protocol with intermediate backbone freezing (Freeze 8) and only 50% of the target season labels (TL-Optim) restored detection to 97.2% (vs. 92.4% for the native baseline), with CL mean absolute error (MAE) of 2.37 mm and TL MAE of 5.96 mm. The framework supports season resilient deployment of vision based morphometric systems contributing toward scalable, data driven monitoring in precision aquaculture.

Keywords. Transfer learning, YOLOv11-Pose, Morphometrics, Aquaculture, Domain shift, Precision aquaculture.

Introduction

Body length is a key indicator used in aquaculture to monitor population structure, biomass, and growth performance in the giant freshwater prawn *Macrobrachium rosenbergii* (New 2002). However, manual measurement procedures are labour intensive, sparsely sampled and stressful for the animals (Levy et al. 2017), often resulting in biased biomass estimates and suboptimal feeding management. Automated morphometric monitoring therefore represents and important objective for modern aquaculture systems.

Recent advanced in deep learning and keypoint detection provide a promising pathway toward automated in-pond morphometric estimation (ADD REF). Nevertheless, underwater imaging conditions are highly variable, with changes in turbidity, illumination, background reflections and camera placement introducing domain shifts that can substantially degrade models trained under fixed acquisition conditions (Fabbri et al. 2018; Mohanty et al. 2016).

This study addressed the challenge of cross-season generalisation for keypoint-based morphometric estimation in a commercial RAS facility. First, the seasonal domain shift between the 2024 and 2025 production cycles was quantified. Next a structured transfer-learning protocol for YOLOv11-Pose was developed, combining partial backbone freezing with limited relabelling of target-season data.

Materials and Methods

Underwater video was acquired in three indoor grow out ponds (one rectangular, 2.5 m × 5 m; two circular, 3.6 m diameter) at the RAS facility of Ben-Gurion University of the Negev (Bergman Campus, Beer-Sheva, Israel). The 2024 frames were captured from two mobile platforms (detail them and add camera?); the 2025 frames were captured with an amphibious remote controlled vehicle and a GoPro Hero 11 camera (GoPro Inc., San Mateo, CA, USA). A total of 3,707 raw images were obtained after filtering (2024: 2,508; 2025: 1,199). Each prawn was annotated with four anatomical keypoints (rostrum tip, eye base, carapace start, telson). For each season the dataset was divided into a fixed test set (excluded from training and tuning) and a development set, which was further split 80:20 into training and validation. Offline augmentation (rotation, brightness jitter, mild Gaussian blur, random crop) was applied to the training split only, expanding it to 5,694 (2024) and 3,222 (2025) images, all resized to 640 × 360 pixels. Calibrated ImageJ (National Institutes of Health, Bethesda, MD, USA) measurements from laminated A3 checkerboard targets served as ground truth, with refraction aware fields of view (76.2°, 46.0°) and orientation aware anisotropic pixel to millimetre scaling. YOLOv11n-Pose (Ultralytics v8.3.170; Ultralytics Inc., Frederick, MD, USA) was trained at 640 × 640, batch size 8, with the AdamW optimiser (weight decay 5×10^{-4}), a cosine schedule, and a 3-epoch warm up.

Three transfer-learning strategies were evaluated: (I) full single season baselines, each trained on its own season and evaluated on both season test sets; (II) a fixed 2 stage transfer protocol (Stage 1, freeze = 10; Stage 2, freeze = 0) applied within and across seasons (S24 ↔ S25); and (III) a systematic grid (TL-Feat / TL-Tune) varying freeze depth (heads only, 4, 8, 10) and target data fraction (k = 25, 50, 100%), followed by a final TL-Optim model initialised from the 2024 checkpoint, fine tuned on the full 2024 training set plus 50% of the 2025 training set, and evaluated on the held out 2025 test set. Detection rate and per prawn mean absolute error (MAE) for CL and TL were computed both for each pond individually and aggregated across all ponds.

Results

Cross season generalisation was strongly asymmetric. The 2024 baseline transferred to 2025 with a detection rate of 95.2% and CL/TL MAE of 2.30 / 12.30 mm, whereas the 2025 baseline collapsed when applied to 2024, with detection dropping to 54.6% in Circular Pond 1 and 69.2% in the Square pond. A fixed two stage transfer protocol substantially recovered the harder direction (S25 → S24 detection 97–100% across ponds), but combined seasonal and pond shifts (Circular → Square across years) still degraded performance to 78.6% detection. In the systematic grid, intermediate backbone freezing (Freeze 8) reached 100% detection at k = 25% in Circular Pond 1 with TL MAE of 13.6 mm, while fully unfrozen backbones (Freeze 0) were unstable on the limited target data. Performance saturated between k = 25% and k = 50%. The final TL-Optim model (S24 → S25, Freeze 8, two stage fine tuning, k = 50%) outperformed the native Base-S25 baseline on detection reliability while matching its precision (Table 1). Using only half of the labelled target season data, TL-Optim achieved 97.2% detection versus 92.4% for native training, with a negligible increase in TL MAE (5.96 versus 5.59 mm).

Table 1. Operational validation on the 2025 test set.

Model (data used)	Detection rate (%)	CL MAE (mm)	TL MAE (mm)
Native Base-S25 (100%)	92.4	2.35	5.59
TL-Optim (this work, 50%)	97.2	2.37	5.96

Discussion and Conclusions

Cross season generalisation was strongly asymmetric: the visually challenging 2024 conditions acted as natural augmentation, producing more transferable features than the cleaner 2025 data, which explains why S25 → S24 collapsed while S24 → S25 transferred well. Intermediate backbone freezing (Freeze 8) emerged as a clear sweet spot between stability and plasticity: fully unfrozen backbones over fitted the limited target data, while heads only adaptation under fitted the new domain. Saturation between k = 25% and k = 50% indicates a practical data efficiency threshold for target season relabelling. TL-Optim translates these findings into an operational recipe, delivering higher detection reliability than full native retraining with only half of the annotation budget. This is a critical result for continuous multi season deployment. Cross season deployment of keypoint based morphometric models for *M. rosenbergii* is therefore feasible with careful adaptation, supporting season resilient, scalable vision based growth monitoring in precision aquaculture.

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