Development of an Artificial Intelligence (AI)-Based Automated Crayfish Measurement System

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***Abstract*—This study presents the development of an automated crayfish measurement system using a deep learning approach based on the YOLOv8-pose architecture. The system aims to measure the length of crayfish from top-view images by detecting head and tail keypoints and converting the pixel distances into real-world measurements. A dataset of 1,787 annotated images was collected and enhanced through data augmentation. The model was trained and validated using GPU resources on the Kaggle platform, achieving a high mean Average Precision (mAP-50) of 0.98. The system integrates OpenCV-based calibration with a reference square to ensure consistent length estimation with real-world measurement. To verify the system, pre-recorded videos containing live crayfish with moderate movement were used. The experimental results show that the system can provide reliable and accurate measurements for both small and large crayfish samples, with a measurement error margin of less than 5%. This indicates that the proposed system offers an accurate solution for automated crayfish measurement.**

Keywords—Crayfish Measurement, Yolov8-Pose, OpenCV, Deep Learning, Aquaculture, Keypoint-Detection,

I. INTRODUCTION

Crayfish offer a range of health benefits when included in a balanced diet. These crustaceans, as shown in Figure 1, are typically found in freshwater habitats. They are rich in protein, low in saturated fat, and packed with essential nutrients like vitamins, minerals, and omega-3 fatty acids [1]. As more people focus on living healthier lives, the crayfish market is growing, offering delicious and nutritious options [2]. According to [3], the Global Crayfish Market is forecasted to grow, reaching an estimated USD 2.27 billion by 2027, with a compound annual growth rate (CAGR) of 6.48% from 2023.

Typically, a crayfish is graded based on its size, which is measured from its head to its tail. The traditional method for crayfish grading requires manual measurement by a human, which is time-consuming and can lead to human error. With the increasing demand for crayfish, it is necessary to develop a system that can grade crayfish quickly and efficiently.

To address this problem, this work aims to develop an automated crayfish measurement system by integrating a deep artificial intelligence (AI) model. While this approach provides a good opportunity for automation, the integration introduces significant challenges in maintaining the high accuracy of the system. This paper discusses our work in investigating this approach. The rest of the paper is organized as follows. Section II discusses the existing methods related to this work, while Section III highlights our methodology for conducting the experiments. The experimental results are discussed in Section IV. Finally, Section V concludes this paper.

Figure 1: Crayfish image

II. LITERATURE REVIEW

Over the past few years, a range of computer vision methods have been applied to automate measurement and grading tasks across industrial settings and aquaculture. For instance, authors in [4] discuss combining the Canny edge detector with NumPy and OpenCV, which enables systems to trace the outlines of simple items such as mobile phones or coins and draw bounding boxes around them. They then use a fixed scale to calculate their real-world dimensions on the fly.

In aquaculture, researchers have successfully merged traditional image-processing techniques with deep learning to streamline seafood grading. One example is the work in [5], which employs the Gray-Level Co-Occurrence Matrix (GLCM) to extract visual features such as color, shape, and size from lobster images. These features are then used to calculate the head-to-tail length measurements, which are stored in a grading database for later analysis.

Other authors have leveraged Mask-RCNN, a neural network designed for pixel-level segmentation. In [6], Mask-RCNN was used to isolate the carapace of lobsters and

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predict both their length and weight. This work achieved around 5% error in its prediction. Similar strategies have been tailored to fish measurement, as discussed in [7]. In this work, a Convolutional Neural Network (CNN) was trained to mark the head and tail key points of the fish. The pixel distance between those points was converted to the actual length using a calibrated colour plate. This method achieved over 98% accuracy and less than 5% error.

Authors in [8] paired YOLOv8 with a Bidirectional Feature Pyramid Network (BIFPN) to measure tuna. The method reduced the margin of length error to just 3.2% while also estimating weight consistently. For truly three-dimensional data, authors in [9] combined stereo-camera setups with Keypoint-RCNN. This approach enables species identification at over 94% accuracy and length measurements with less than 10% error. To lower costs, authors in [10] implemented single-camera systems that blend YOLO detection with MiDaS depth estimation. Using a pinhole-camera model, these systems predict fish length with roughly 12.4% average error.

III. METHODOLOGY

This section details the methodology used to develop the automated crayfish measurement system, covering image collection, annotation, and model training using YOLOv8-Pose [11]. It also describes model validation and the combination of YOLOv8s-Pose and a black square model for length prediction. The rest of the section elaborates on these steps.

The image collection phase for the crayfish grading system began with the preparation of the crayfish dataset, consisting of a total of 1,787 images. Some of the images are shown in Figure 2(a). All images were captured using a Vivo iQOO Z5 smartphone, which can produce high-resolution output and has fast autofocus capabilities. The images were stored in JPEG format at a resolution of 4080 × 2296 pixels to allow detailed capture of fine features on the crayfish's head and tail.

To enhance the model's capability to work under diverse real-world conditions, the crayfish were captured against a variety of backgrounds. These included plain surfaces, patterned designs, natural textures, and rough or uneven backdrops. The dataset included crayfish of many different sizes, allowing the model to learn to handle a wide range of grading categories. Each crayfish was also positioned in various directions, such as facing left, right, up, down, and even at diagonal angles. During all this time, the position of the camera remained fixed to ensure that changes only came from the crayfish's movement.

Once the crayfish images have been captured, they are then prepared and annotated, with the focus placed on two keypoints as shown in Figure 2(b) to determine the length of the crayfish. These points are the tip of the pointed extension between the eyes at the front of the head, and the end of the central part of the tail fan.. The annotation process was carried out using the Roboflow platform [12]. To improve the adaptability of models and performance in different visual settings, several data augmentation techniques were applied. These included minor hue shifts within a range of −5° to +5°, slight brightness adjustments of ±5%, and the application of Gaussian blur with a maximum intensity of 1.1 pixels. In addition, all images were resized to 1280 x 1280 pixels to ensure consistent input dimensions during model training. As a result of the preprocessing steps, the dataset was expanded from 1787 to 3,039 images. The dataset was divided into three subsets: 70% for training, 20% for validation, and 10% for testing.

After annotating the images, a deep learning model was developed to determine crayfish length. Model training was conducted on Kaggle, utilizing an NVIDIA P100 GPU with 16 GB VRAM [13]. YOLOv8s-pose architecture was chosen in this work since it offers a balanced trade-off between processing speed and accuracy. To further optimise performance, key hyperparameters were adjusted before the training began. All images were resized to 1280 × 1280 pixels to match annotation dimensions and preserve crucial feature details. A batch size of 16 was chosen to enable smooth processing without overloading memory, and 200 training epochs were selected to ensure the model has ample opportunity to learn and refine its predictions. Once the model was trained, validation was carried out to determine the model's adaptability and accuracy when exposed to new data.

In the final phase of the study, a crayfish length measurement system was developed, as illustrated in Figure 3. The system comprises a Full-HD webcam, a laptop (Acer Nitro 5 equipped with an Intel i5-8300H processor, GTX 1050 GPU with 4GB VRAM, and 24GB RAM), background lighting, and a plastic container. The webcam is mounted 50 cm above the plastic container and connected to the laptop, which performs real-time inference for length estimation. Live crayfish are placed in the plastic container to ensure they remain within the camera's field of view during measurement. The measurement process consists of two main steps: (1) pixel-to-length calibration using OpenCV, and (2) crayfish length estimation using the YOLOv8s-pose model. This two-step approach ensures accurate and consistent real-world length measurements.

For the pixel-to-length calibration, a black square reference measuring 12.5 × 12.6 cm was placed within the camera's view. The system uses OpenCV edge detection and contour analysis to locate and outline this square. Its pixel dimensions were then recorded over five consecutive frames to establish a reliable pixel-to-inch conversion ratio. This minimize errors from slight camera or lighting shifts during measurement. Since the size of the black square is known, the pixel-to-length ratio is calculated, and the value is stored in the system. This scale is used in the next stage.

Once the pixel-to-length calibration is completed, the YOLOv8s-pose model identifies the two keypoints on each crayfish image. The Euclidean distance between these points was measured in pixels and converted to inches using the established pixel-to-length scale. To verify accuracy, these automated measurements were compared with caliper-based manual readings across various crayfish sizes.

(a) (b)

Figure 2: (a) Example of crayfish dataset collection (b) crayfish labelling

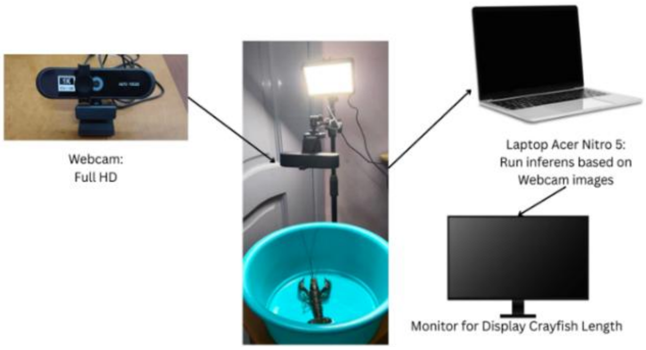


Figure 3: Crayfish measuring system overview

IV. RESULT AND DISCUSSION

During training, the model's learning progress was assessed by comparing training and validation loss curves, as illustrated in Figure 4(a). Tracking these curves revealed whether the model was improving over time. Various constants of the loss function were examined to evaluate different aspects of performance, such as box loss, pose loss, objectness loss, classification loss, and distribution focal loss (DFL). From the figure, the training and validation losses closely align, which indicates consistent learning and a well-fitted model to the training data. In addition, the pose loss shows a continuous decline. This reflects improved capability in detecting the crayfish's head and tail keypoints, which is crucial for accurate length measurement. Concurrently, reductions in box loss and objectness loss signalled enhanced precision in drawing bounding boxes around crayfish, even in complex backgrounds.

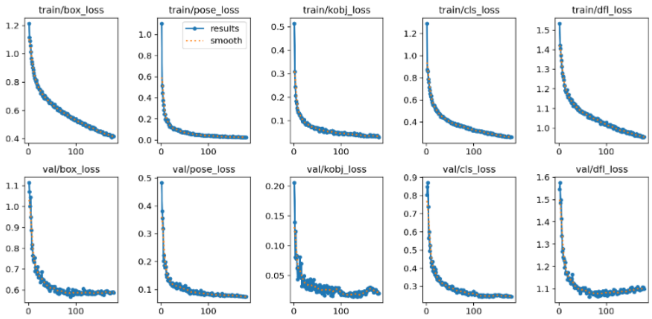
The model's accuracy was evaluated using standard metrics. As shown in Figure 4(b), both precision and recall were above 0.98 for bounding-box detection and keypoint estimation. This indicates very few incorrect detections and consistently accurate identifications. The mean Average Precision (mAP) results confirmed these findings. At the standard IoU threshold, mAP@0.5 reached 0.98, showing high accuracy. Under stricter conditions, mAP@0.5:0.95 reached up to 0.98 for keypoints and about 0.85 for bounding boxes. These results show that the model was well-trained, avoiding both underfitting and overfitting, and performed well on new data. Its consistent performance across various metrics confirms that it is suitable for automated crayfish length grading applications.

Figure 5 shows the output from OpenCV in detecting the black square as discussed in Section III. From the figure, the system is capable of detecting the black square edges accurately. The detected contour (coloured in bright green) aligns closely and precisely with the actual boundaries of the square. This fit ensures that the diagonal measurement obtained from the image is highly reliable. As a result, the conversion from pixels to real-world length units (inches) becomes accurate.

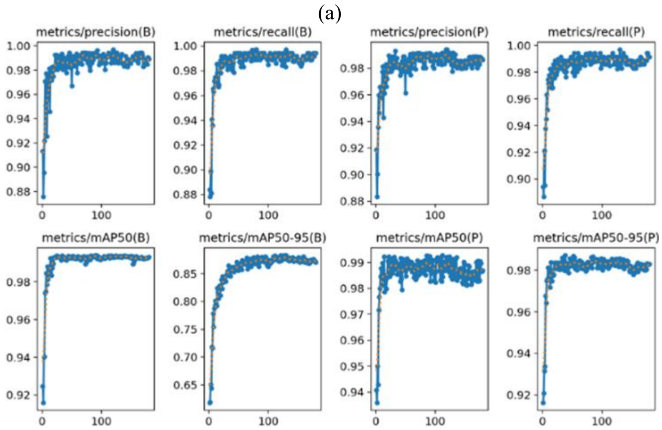
Following the calibration using the black square reference, the crayfish grading system was evaluated using two crayfish samples of different sizes. First, the result of estimating a small-sized crayfish was analysed. Then the result of estimating a large crayfish was obtained.

Figure 6(a) and (b) show a small-sized and a large crayfish measured manually with a recorded length of 3.30 inches and 5.30 inches, respectively. From Figure 7, the system estimates the crayfish length in a single frame. The system first identifies the head and tail of the crayfish. Using the number of pixels between these two key points, the system calculates the small and large crayfish's length as 3.33 inches and 5.24 inches, respectively. This correspondence validates the effectiveness of the pixel-to-inch conversion process following the initial calibration.

Figures 8 and 9 illustrate the live small and large crayfish length predictions performed using a pre-recorded video containing 100 consecutive frames. The crayfish were free to move in the container. Measurements were performed on each frame. Since the crayfish were actively moving, the measured length varied. For small crayfish, the distribution of measured lengths had a mean of 3.33 inches. This corresponds to a mean absolute error of 1.21%. For large crayfish, the system reported a mean length of 5.25 inches, which corresponds to a mean error of 0.94%.



(a)



(b)

Figure 4: Model training result graph (a) training and validation loss curve, (b) model accuracy

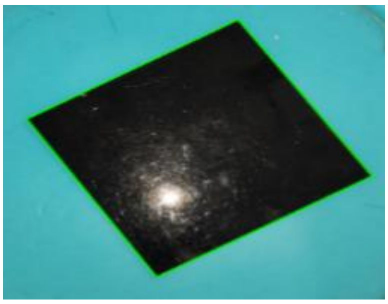


Figure 5: Result calibration with black square

(a) (b)

Figure 6: Real length manual measurement (a) small crayfish (3.30 inches). (b) large crayfish (5.30 inches).

(a) (b)

Figure 7: (a) Small crayfish automatic measurement (3.33 inch), (b) large crayfish automatic measurement (5.24 inch)

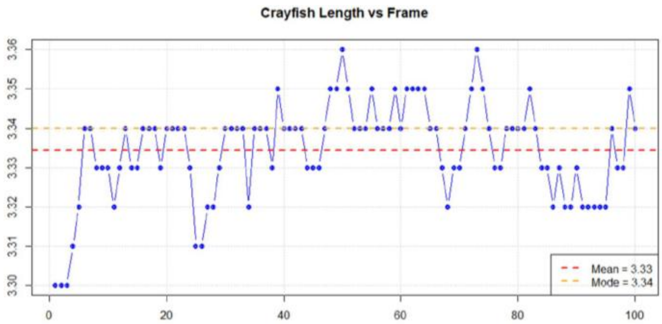


Figure 8: Small crayfish length measurement (in inches) vs. frame number.

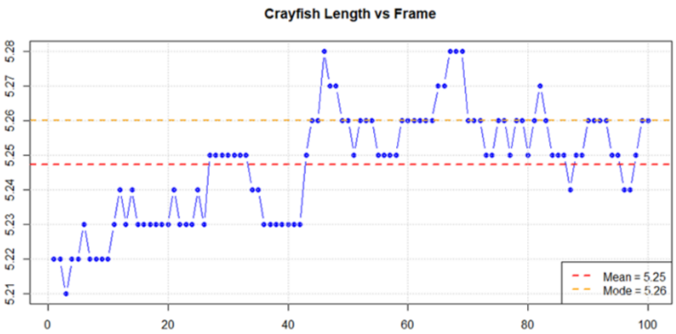


Figure 9: Large crayfish length measurement (in inches) vs. frame number.

V. CONCLUSION

This work has presented an automated crayfish measurement system that combines deep learning and computer vision to measure crayfish length. The YOLOv8s-pose model was trained to detect the head and tail keypoints in top-view images. In addition, an OpenCV-based calibration using a black square was used to convert pixel distances into real-world inches. The system was evaluated using two live crayfish of different sizes on pre-recorded videos. Based on the experimental results, the system provides high accuracy (precision, recall, and mAP above 0.98) and maintains errors under 5%.

In the future, several enhancements could further improve the system, such as deploying the model on FPGAs or other specialized hardware to boost inference speed and energy efficiency. Extending the system to predict other crayfish characteristics, such as weight or gender, via similar deep learning approaches would be useful. Finally, augmenting the training dataset with a wider array of backgrounds, lighting conditions, and crayfish species would strengthen the model's robustness in varied real-world environments. This approach could pave the way toward a comprehensive, scalable solution for automated crayfish grading in commercial and research settings.

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