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Article

A Mobile App for Counting Shrimp Larvae Based on the YOLO V5 Method

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Abstract: Manual counting of shrimp larvae in aquaculture is labour-intensive and time-consuming. This study aims to develop a mobile application to automate the counting process using an object detection algorithm. The application features dual functionality for real-time camera capture and image upload. Model performance was evaluated using several metrics, including Mean Average Precision, precision, and recall. The object detection model achieved a Mean Average Precision (mAP) of 93.93%, precision of 91%, and recall of 89.3%. Trials of the application demonstrated an average accuracy rate of 91.03% in detecting shrimp larvae. Despite challenges in detecting transparent larvae and distinguishing them from debris, the results indicate that the application holds promise for enhancing efficiency in shrimp farming operations. Future improvements may be directed towards enhancing application performance by refining the dataset and tuning model parameters to increase recall without compromising precision. This study represents a significant step towards integrating AI-driven technologies into aquaculture, potentially transforming the shrimp larvae counting and management process in the industry.

Keywords: Counting Larva, Object Detection, Shrimp Larvae

1. Introduction

Brackish-water cultivation is widely used in Indonesia. Shrimp aquaculture is one of these. Indonesia's shrimp farming contributes to its foreign exchange, and it is the fourth largest exporter after India, Ecuador, and Argentina [1]. There are two main activities in shrimp farming: seeding and rearing [2]. The effectiveness of shrimp production relies not only on environmental elements and pond management but also on the precision of calculating the quantity and quality of stocked shrimp seeds. Accurate counting of shrimp fry is crucial for aquaculture operations, as it directly impacts the potential value of the product and overall farm management. Traditional manual counting methods are time-consuming and can potentially harm fry, leading to the development of more efficient and accurate techniques [3].

Digital image processing techniques are increasingly being applied in aquaculture to count and detect larvae, offering significant advantages over traditional manual methods. These techniques utilize computer vision and deep learning algorithms to automate the process, thereby improving the efficiency and accuracy of fish farming operations [5] [6]. Deep learning-based object detection techniques have shown promising results for simultaneously classifying and localizing fish of interest in images and videos [5]. For instance, in [8], a combination of canny edge detection techniques and clump analysis was used to count shrimp larvae. The results indicated that the proposed method achieved a Root Mean Square Error (RMSE) value of less than 6%, outperforming manual counting methods. Shrimpseed on [5], a modified CSRNet convolutional neural network, achieved higher accuracy in shrimp seed counting. The results showed that after only 50 iterations, the average absolute error of the algorithm was reduced to 17.28, with an accuracy rate of 95.53%. Other research [10] applied image segmentation, edge detection, and unsupervised machine learning methods to the Raspberry Pi Zero W. This system exhibits satisfactory speed to complete the calculation in one second and a high accuracy of 96%. Armavilia et al. [2] used YOLOv3 to automatically count shrimp larvae. The results of the YOLOv3 final model show a good performance with a mean Average Precision (mAP) value of 96.83% and an average accuracy value of 76.48%. Light-YOLOv4 exhibited better comprehensive performance in terms of counting accuracy, model size, and detection speed.

We used YOLOv5 to count the number of shrimp larvae in this study. A study by Wibowo et al. (2023) demonstrated the application of YOLOv5 for detecting fresh and spoiled fruit. In this experiment, YOLOv5 was used to automatically classify fruit as either fresh or spoiled, achieving excellent performance in terms of both speed and accuracy. YOLOv5 was able to classify fruit with high accuracy, which could significantly enhance the efficiency of fruit selection processes in the agricultural industry [11]. The success of YOLOv5 in detecting fresh and spoiled fruit further reinforces its suitability for other object detection tasks, such as shrimp larvae detection or agricultural pest identification. In this study, we counted the larvae using two methods: real-time using a camera accessed through an Android application installed on a smartphone or by uploading an image to the application.

2. Materials and Methods

The study described focuses on developing a mobile application for detecting and counting shrimp larvae using the YOLOv5 algorithm. This innovative approach combines advanced computer vision techniques with mobile technology to create a practical tool for aquaculture professionals. The system framework, as illustrated in Figure 1, outlines the key components and processes involved in the application's functionality.

The data collection process utilizes a high-quality Yi Camera, capable of capturing images at 16 megapixels and recording video at 60 frames per second. This ensures that the input data is of sufficient quality for accurate detection and counting of shrimp larvae. The research methodology comprises three main stages: data image collection and annotation, data training, and system testing. The image collection and annotation phase likely involves gathering a diverse set of shrimp larvae images and manually labeling them to create a robust dataset. This annotated dataset is then used to train the YOLOv5 model, which is known for its efficiency in real-time object detection tasks. Finally, the system undergoes testing to evaluate its performance and accuracy in detecting and counting shrimp larvae under various conditions, potentially including different lighting, water clarity, and larval densities.

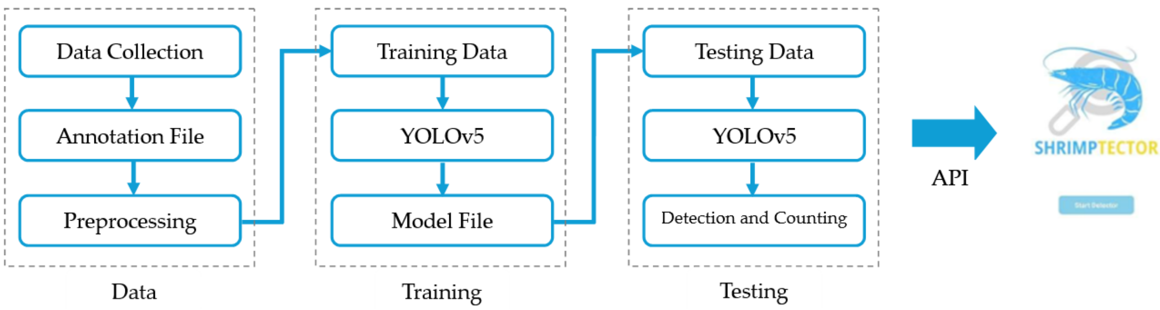

Figure 1. System Framework

2.1 Data Collection

Data collection for this research was conducted at the Banjar Kemuning Brackish Water Aquaculture Fisheries Center in Sidoarjo, East Java. The study focused on 5,000 shrimp larvae, specifically those in the PL 8 to PL 12 stages. A Yi camera was employed to capture images of these larvae, producing photographs in JPG format. The experimental setup involved placing the larvae in a white container with a water depth of 1.5 cm. The camera was positioned 20 cm above the container, and images were captured without any specific consideration for lighting conditions, as shown in Fig. 2.

The image acquisition process followed a systematic approach to create a comprehensive dataset. The larvae were divided into groups of increasing sizes, starting with ten larvae per container and progressively increasing to 20, 30, and so on, up to a maximum of 100 larvae per container. The larvae utilized were between 8 to 12 days old (PL8-PL12). Multiple photographs were taken for each group size. This methodical approach allowed for the creation of a diverse dataset that captured various densities of shrimp larvae, as illustrated in Fig. 3. The resulting dataset provides a valuable resource for analyzing shrimp larvae at different population densities, potentially aiding in the development of automated counting or monitoring systems for aquaculture applications.

Upon completion of the image acquisition process, the next step is to perform manual annotation. The annotation process is a crucial step in data processing for training object detection models such as YOLOv5. This process aims to label the shrimp larvae present in the images, enabling the model to effectively learn the patterns and positions of the larvae. The next step involves processing the annotated image results to ensure that the data is prepared for the model training phase. Detecting transparent larvae and distinguishing them from debris using YOLOv5 presents significant challenges, as the larvae possess transparent characteristics and shapes that closely resemble the background, while the debris can exhibit a wide range of colours and forms. To address the difficulty of differentiating transparent objects such as larvae from the background or other objects like debris, we incorporated several parameters into the preprocessing and augmentation stages. The images were resized to a "Fill (with centre crop)" in 640x640 pixels. For "Auto-Adjust Contrast", we opted for "Using Adaptive Equalization" and subsequently applied a grayscale transformation to enhance the image quality. In the augmentation stage, we incorporated a parameter for "90^o Rotate", allowing for both clockwise and counter-clockwise orientations. Additionally, we adjusted the saturation levels within a range of -14% to +14% and modified the brightness settings between -5% and +5%.

Figure 2. Acquisition Data

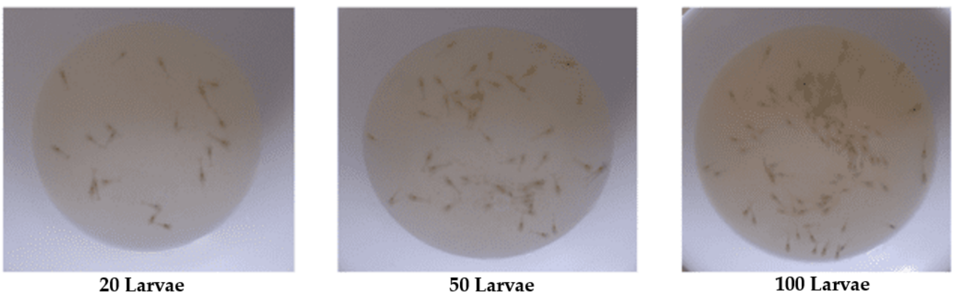

Figure 3. Group of Larvae Dataset

2.2 *Training Data*

The data training process is a fundamental step in the training of object detection models, wherein the model is trained using annotated data to recognize patterns and characteristics of the larvae.

This training process necessitates the availability of a well-prepared annotated dataset and the appropriate configuration of the algorithm employed for data training, which in this case is YOLOv5. YOLOv5 is a highly efficient object detection algorithm that processes input images and outputs bounding boxes containing the detected objects' locations, along with class probabilities [11][12]. One of the main advantages of YOLOv5 over earlier models is its ability to predict multiple bounding boxes and class probabilities simultaneously, all within a single neural network pass [14]. In a training experiment to detect shrimp larvae in stages PL 8 – PL 12, YOLOv5 was applied with 500 training iterations. The detection system relies on reusing classifiers or locators to perform detections, applying patterns at various positions and scales, with the best-performing areas considered as detection zones [13]. This method demonstrated high accuracy in detecting shrimp larvae, showing that YOLOv5 is particularly suited for real-time object detection tasks.

One major distinction between YOLOv5 and traditional CNNs is that YOLOv5 requires significantly fewer datasets for training. CNNs, by contrast, typically demand larger datasets and more training iterations to achieve comparable accuracy. YOLOv5 accelerates both the training process and the detection task, allowing faster and more efficient real-time processing of images [12]. This advantage makes YOLOv5 particularly well-suited for applications that require quick and accurate object detection, such as the identification of fresh and spoiled fruit or the detection of shrimp larvae.

YOLOv5 is a mature algorithm among target recognition algorithms which has the advantages of being lightweight and having a fast inference ability [16], as demonstrated in the study conducted by Babila et al. successfully implemented the YOLOv5 algorithm for detecting and inventory counting of stock, achieving an accuracy of up to 93% [17]. That study demonstrates a higher accuracy compared to previous research that utilized YOLOv3 and Light-YOLOv4. Another study by S. Gupta et al. utilized YOLOv5 for real-time object detection in surveillance videos, demonstrating its effectiveness and precision in identifying multiple object categories [18]. These studies highlight the successful implementation of YOLOv5 across various domains, including the detection of smaller objects within automotive contexts, where the YOLOv5 series has achieved commendable accuracy [19]. This indicates the algorithm's versatility and robust performance.

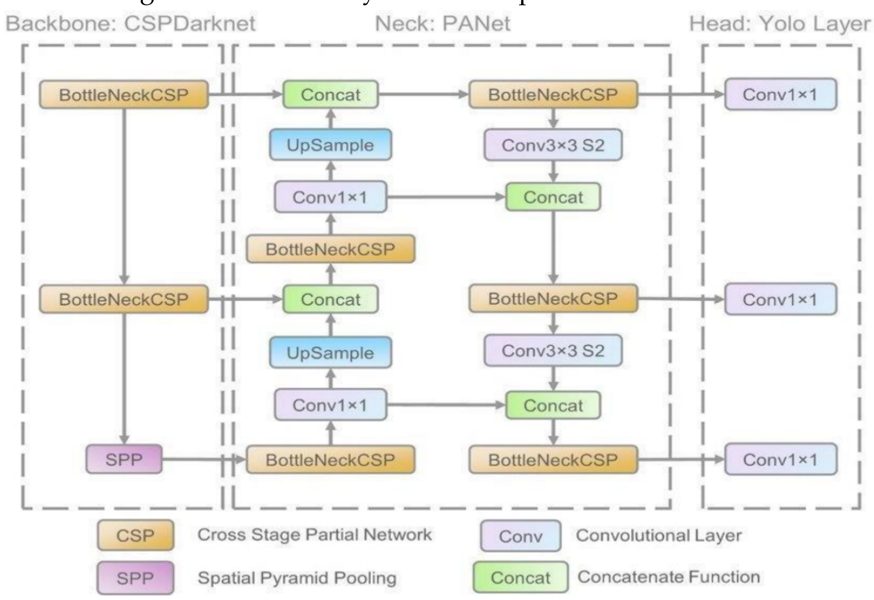

Figure 3. Network Architecture YOLOv5 [1]

2.3 *Testing*

The model evaluation is the next step or stage, which is conducted to see the accuracy value of the training process results on the dataset. This stage is important in detecting objects because stable object detection has a high accuracy value. For this reason, the accuracy value in object detection needs to be evaluated so that object detection has a more stable accuracy value on each image or video [2].

The detection result is the output of the entire process that has been carried out, where the results that have been detected for an object will be accompanied by an accuracy value. This stage will not occur if one of them is not run in the test framework stage. To determine the accuracy value in this study, the author uses an equation like the equation below:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100\%, \tag{1}$$

2.4 *Mobile Application*

The "Shrimp Tector" application represents a significant advancement in aquaculture technology, offering shrimp farmers a practical and efficient tool for larvae counting. By leveraging a React-based framework, the application ensures cross-platform compatibility and a smooth user experience. The dual-frame design, featuring an initial interface and a dedicated counting process frame, streamlines the workflow for farmers. This intuitive layout allows users to quickly navigate between different functionalities, enhancing overall usability.

The application's flexibility in image capture methods is particularly noteworthy, as it addresses the diverse needs of farmers operating in various environments. The option to either take a photo directly or select an image from the device's gallery caters to different preferences and situations. Moreover, the inclusion of an offline data collection feature demonstrates a thoughtful approach to real-world challenges, such as unreliable internet connectivity in remote farming locations. This feature allows farmers to capture images when convenient and process them later, ensuring that the application remains useful even in areas with limited network access. The server-side processing of images, coupled with the application's ability to interpret and display results, showcases the seamless integration of advanced object detection technology with a user-friendly interface, making complex larvae counting tasks accessible to farmers without specialized technical knowledge.

The application has been implemented in IBAP Banjarkemuning through community service conducted by Oktarina et al. According to the results of the questionnaire survey, staff and employees responded with "strongly agree" and "agree" to all questions posed. The percentage of "strongly agree" responses ranged from a maximum of 100% to a minimum of 80%. Conversely, the "agree" response rate was highest at 20% and lowest at 10% [20].

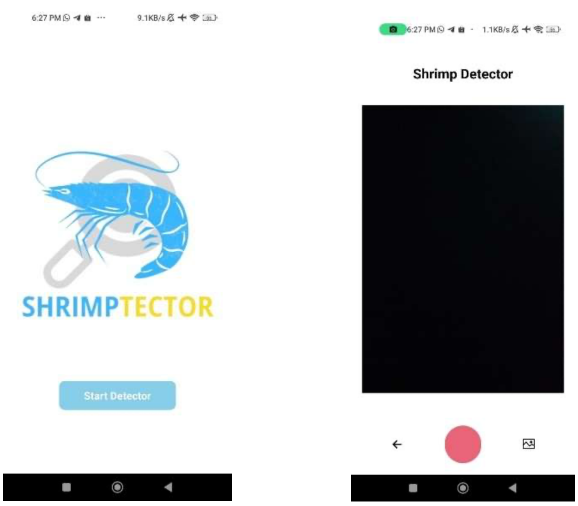

Figure 4. Shrimptector Mobile Application

3. Results

The dataset for training the YOLO model consisted of 811 images for training (70%), 232 for validation (20%), and 116 for testing (10%). The training process utilized 500 iterations with a learning rate of 0.001 and was conducted using Google Colab. The annotation process, crucial for object detection, was performed using YOLO mark tools. To enhance YOLO's performance in recognizing shrimp larvae, each image was divided into four parts. This resulted in a total of 1159 annotations across the dataset, with image sizes ranging from 0.03 MP to 15.93 MP and a median resolution of 3120 x 3456.

3.1. Annotation Image

The annotation task for detecting shrimp eyes and larval black dots was complicated by several factors inherent to the nature of the specimens and imaging conditions. The transparency of shrimp larvae posed a significant challenge, as it made distinguishing the organisms from their surroundings difficult. This was further exacerbated by the presence of debris in the samples, which could easily be misidentified as shrimp, leading to potential false positives. The dynamic nature of the larvae during image capture introduced another layer of complexity, as their movement often resulted in blurred images that obscured key identifying features. This blurring effect made it particularly challenging to accurately locate and annotate the eyes and black dots, potentially leading to missed detections or inaccurate placements.

The issue of stacked shrimp presented a unique challenge in the annotation process, as it led to inconsistencies in larval detection. In cases where multiple shrimp overlapped, the annotators faced difficulties in accurately identifying and marking individual larvae. This resulted in variable outcomes, where sometimes two larvae were detected, other times only one was identified, and in some instances, none were recognized at all. These inconsistencies highlight the complexity of the annotation task and the need for robust guidelines and possibly advanced imaging techniques to improve accuracy. The impact of these challenges on annotation accuracy is clearly demonstrated in Figure 5 (a) and (b), which provides a visual representation of the distribution of accuracy levels across the annotations. This distribution reflects the varying degrees of difficulty encountered in different images, with factors such as image quality, larval positioning, and the presence of confounding elements contributing to the observed range of accuracy levels. After enhancing the quality of the dataset through the addition of parameters during preprocessing and augmentation, the accuracy level has improved.

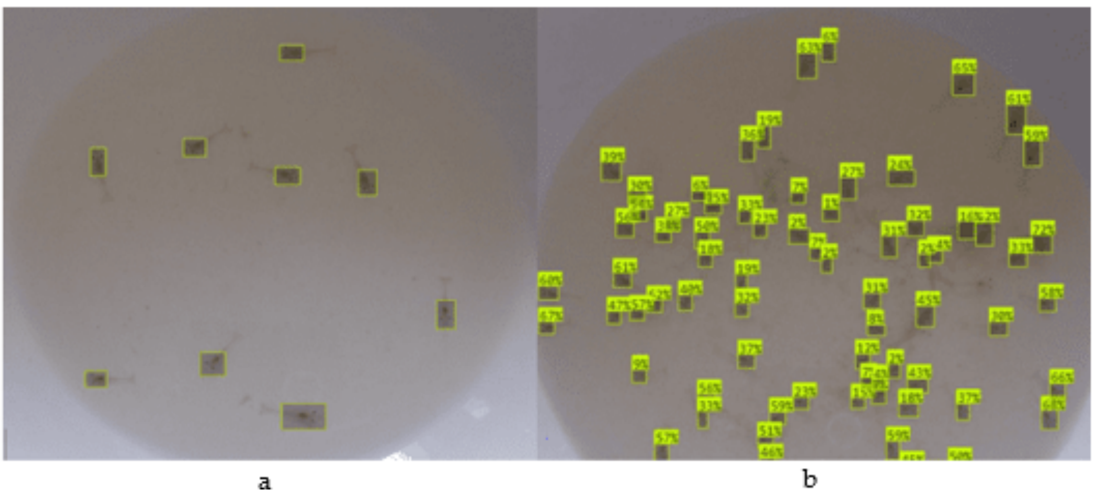

Figure 5. Annotation Process (a) small number and (b) large number

3.2 Training the Models

The data annotation is a crucial step in preparing the dataset for object detection model training. Once completed, the annotated dataset is imported into Roboflow, a platform that streamlines the machine learning workflow. Configuring the dataset in Roboflow using the prepared API key ensures seamless integration with the subsequent steps of the process. The choice of YOLOv5, for instance, segmentation [11], is significant, as it represents a state-of-the-art approach in object detection, offering a balance between speed and accuracy.

The training process for the object detection model involves fine-tuning various parameters to optimize performance. The author's decision to set the confidence threshold at 30% indicates a balance between detecting objects with reasonable certainty while minimizing false positives. Similarly, the overlap threshold of 30% helps manage instances where multiple bounding boxes may overlap for a single object. The training duration of 100 epochs suggests a comprehensive approach, allowing the model sufficient iterations to learn from the dataset and improve its accuracy. These carefully chosen parameters and the structured training process aim to produce a robust object detection model capable of accurately identifying and segmenting instances within images.

3.3 Testing

The evaluation of the trained model reveals promising results in terms of its performance metrics. The Mean Average Precision (mAP) value of 93.93% indicates a strong overall accuracy in detecting and classifying shrimp larvae across various scenarios. This metric takes into account both precision and recall, providing a comprehensive measure of the model's effectiveness. The precision value of 91% indicates a strong capability in minimizing false positive detections. Meanwhile, the recall value of 89.3% demonstrates that this model is proficient in identifying the majority of larvae present in the images. However, there remain a few undetected objects (false negatives), which could be attributed to factors such as overlapping larvae, poor lighting conditions, or the small size of the larvae. Based on the data presented in Table 1, it can be concluded that the model consistently demonstrates a high level of predictive accuracy. Among the 30 images tested, the prediction accuracy ranged from 84.00% to 96.00%. The highest accuracy of 96.00% was achieved for images 14 and 23, while the lowest accuracy was recorded for image 15 at 84.00%.

In general, a majority of the images exhibited an accuracy exceeding 90%. However, there were several outliers with lower accuracy, specifically for images 4, 15, and 20. This discrepancy may be attributed to factors such as uneven lighting, overlap among larvae, or variations in larvae size. Nevertheless, for images containing a larger number of larvae (≥60), the model maintained commendable performance with an accuracy above 85%, indicating its scalability concerning a greater number of objects. The average accuracy across all trials was 91.03%, suggesting that the YOLOv5 model is sufficiently reliable for use in automated larvae counting applications. It is advisable to retrain the model using a more diverse dataset and to implement preprocessing techniques aimed at improving image quality. Additionally, conducting trials with supplementary datasets under varying environmental conditions is recommended to assess the model's generalization capabilities. These testing results indicate that YOLOv5 holds significant potential for practical implementation in the aquaculture sector, thereby improving both efficiency and accuracy in larvae counting processes.

Table 1. Detail Accuracy of the Model

Image	Prediction	Manual	Accuracy
1	8	9	88,89%
2	8	9	88,89%
3	8	9	88,89%
4	17	20	85,00%
5	19	20	95,00%
6	19	20	95,00%
7	27	30	90,00%
8	28	30	93,33%
9	28	30	93,33%
10	36	40	90,00%
11	37	40	92,50%
12	38	40	95,00%
13	45	50	90,00%
14	48	50	96,00%
15	42	50	84,00%
16	56	60	93,33%
17	55	60	91,67%
18	54	60	90,00%
19	64	70	91,43%
20	60	70	85,71%
21	63	70	90,00%
22	74	80	92,50%
23	76	80	95,00%
24	72	80	90,00%
25	80	90	88,89%
26	81	90	90,00%
27	84	90	93,33%
28	83	90	92,22%
29	80	90	88,89%
30	83	90	92,22%

4. Conclusions

This research developed a mobile application called "Shrimp Tector" to count shrimp larvae using the YOLOv5 algorithm. The system offers two methods for image capture: real-time using a smartphone camera or uploading an image. The model achieved a Mean Average Precision (mAP) of 93.93%, a precision of 91%, and a recall of 89.3%. The application demonstrated an average accuracy of 91.03% from 30 trials, indicating its potential to facilitate and expedite the counting process for shrimp farmers. However, despite the relatively high values of precision and recall, there is a notable difference between precision and recall values (91% vs. 89.3%). This indicates that the model is slightly more focused on avoiding false positive detections rather than capturing all existing objects. To achieve a better balance, adjusting the detection threshold or retraining the model with a larger dataset that encompasses diverse environmental conditions could be considered.

Integrating this application into actual shrimp farming operations has the potential to enhance both efficiency and accuracy in the monitoring of shrimp larvae. However, it is essential to consider various challenges, including technical, operational, and user adoption aspects. It is crucial to implement technical adjustments such as improving dataset quality, utilizing superior hardware, optimizing models, and providing user training to ensure that the application functions efficiently and effectively in real-world conditions. Future work may focus on enhancing model performance through improvements in the dataset and tuning model parameters to increase recall without compromising precision while also expanding its capabilities to accommodate various developmental stages of shrimp larvae.

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