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Automatic Counting of Shrimp Larvae using Artificial Intelligence

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ABSTRACT

The research is to revolutionize the shrimp farming industry by developing a computer vision and Artificial Intelligence (AI) system for accurate and efficient shrimp counting. Recently, the aquaculture industry plays important roles in the global demand for seafood. In particular, shrimp farming has become a significant contributor to the industry. However, the process of counting the shrimp larvae is a labour-intensive and time-consuming task that often requires manual effort, leading to inefficiencies, inaccuracies and increased operational costs. Thus, the project was conducted to challenge the shrimp larvae counting with robust and efficient method. The proposed system captures and analyses images of Macrobrachium Rosenbergii shrimp post larvae (PLs) of varying stages and quantities using a high-resolution webcam and a Convolutional Neural Network framework (CNN). The presence of molts, feed and debris in the imaging chamber is considered by the system. The goal is to have a low mean absolute error when counting large and small PLs. This technology's successful implementation will not only improve the accuracy and reliability of shrimp counting but will also clear the way for counting other small aquatic species in their larval stages, such as fish, crabs, oysters and eggs. The methodology of the project entails training the system with a large image dataset and testing its performance with the trained model. The development of a fast and precise shrimp counting AI system, which has the potential to revolutionize the industry and improve customer satisfaction, is one of the significant results and findings. Finally, this study proposes a different approach to automate counting shrimp larvae counting by combining computer vision and AI, providing a more accurate, efficient and reliable solution for the aquaculture industry.

1. Introduction

Intelligent and automated aquaculture is a promising solution for the sustainable growth of the shrimp farming industry [1-3]. It enhances resource utilization, production efficiency and

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environmental impact, promoting sustainability and resilience while meeting seafood demands [4]. In aquaculture sector especially in shrimp farming, the innovative solutions are revolutionizing its implementation such as for predictive analytics and precision aquaculture. Some of the approach used demonstrates the effectiveness of utilizing deep learning object detection models to automate image classification [5].

This project aims to introduce a more accurate and efficient method for counting shrimp larvae in aquaculture farms. Currently, farmers rely on outdated methods, such as weight-based calculations, to estimate the overall shrimp population in ponds [6]. The proposed solution utilizes Artificial Intelligence (AI) and image processing to automate the counting process and eliminate the need for manual counting. By training the AI system to recognize and process images of shrimp larvae, farmers can save time and reduce the stress associated with manual counting. This technology has the potential to increase productivity and shrimp production in the industry. The project leverages the benefits of modern intelligent technology, such as reduced labour costs, increased production and environmental friendliness [1-6]. By adopting machine learning techniques, the system can learn and recognize shrimp larvae attributes from the data it encounters, improving accuracy and efficiency. The success of this project can contribute to the overall growth and development of the shrimp aquaculture sector in Malaysia and potentially other regions.

Gathering and counting shrimp larvae has traditionally been a labour-intensive task in the shrimp industry, prone to human error as shown in Figure 1. However, a new system that uses Artificial Intelligence (AI) to automate the counting of shrimp larvae has been developed, resulting in a faster and more accurate counting process. The standard method for counting shrimp larvae entails collecting and measuring a representative sample of shrimp, calculating the total number of larvae in the pond and recording the information. Farmers' working conditions can be improved and their daily activities simplified by implementing this new framework. The AI system eliminates the need for manual counting in small containers, reducing labour requirements and errors. This advancement not only improves the shrimp industry's efficiency, but also ensures more precise data collection for better decision-making and overall productivity.

Fig. 1. Manual counting of post-larvae

Several previous studies have made significant contributions to automated aquatic larvae counting. Hu *et al.,* [7] used image processing and machine learning to create a shrimp larvae counting system with 98.72% accuracy. Deep learning with Convolutional Neural Networks (CNNs) was used by Bessa *et al.,* [8] to achieve a counting accuracy of 95.8% for fish larvae. Zhang *et al.,* [9] used the You Only Look Once (YOLO) network to count shrimp larvae with 93.16% accuracy. Chen *et al.,* [10] achieved 90.91% accuracy using Support Vector Machine (SVM). Yeh *et al.,* [11] used adaptive thresholding and contour detection to achieve a counting accuracy of 96.4% for white shrimp larvae. Hong *et al.,* [12] used image processing and CNNs to achieve a counting accuracy of 97.48% for fish larvae. These papers show how machine learning, deep learning and image processing techniques can improve the accuracy, time efficiency and labour-intensiveness of larvae counting systems for aquaculture management.

Several previous works in automated shrimp larvae counting have its limitations. Zhang *et al.,* [9] used the YOLO network, however, small larvae detection and localization may be difficult. Chen *et al.,* [10] encountered difficulties due to complex larval morphologies and imaging variations. Yeh *et al.,* [11] were highly sensitive to lighting and background noise. Hu *et al.,* [7] required a large amount of labelled data, whereas Chen *et al.,* [10] had generalizability limitations. These shortcomings highlight the need for further improvements in automated larvae counting systems' scalability, computational efficiency, robustness to different larvae characteristics and adaptability to varying environmental conditions as in [13-22].

Based on the above discussion, there is still room for improvement in having an effective and efficient counting system. In this research, a counting system is proposed to offer an acceptable percentage of accuracy in counting the larvae and able to minimize the percentage of error. Thus, the project's objective is to design a system for automatically counting shrimp larvae using Artificial Intelligent based on image processing for shrimp farming in aquaculture. The prototype for Artificial Intelligence system that can automatically count shrimp larvae will be developed and the performance of the system will be validated.

2. Methodology

2.1 Specification Design Methodology

Figure 2 shows a graphical representation of the system used in the development of the project Automatic Counting Shrimp Larvae Using Artificial Intelligence. The proposed method counts larvae using image detection techniques and includes two feature extraction methods: Local Binary Patterns (LBP) and red, green, blue (RGB). These methods extract important characteristics from input images. To accurately classify and count the shrimp larvae, the extracted features are put into a random forest (RF) algorithm, which acts as a collective tree classification method. The connections between the blocks represent the system's data flow and processing steps.

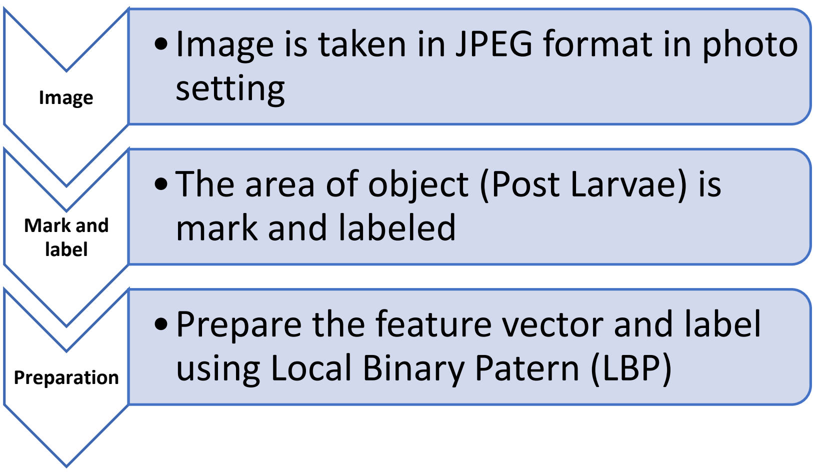

Fig. 2. Block diagram for automatic counting shrimp larvae using artificial intelligence

Figure 3 shows the development of an automatic shrimp counting software using a counting block diagram. This software is intended for use in both agriculture and marine sciences. The main contribution of this study is the use of artificial intelligence (AI) and image recognition algorithms to improve the counting system and its efficiency. To create an efficient and accurate shrimp larva counting system, the software uses the image block diagram's components, integrating image detection techniques, feature extraction methods and the random forest algorithm.

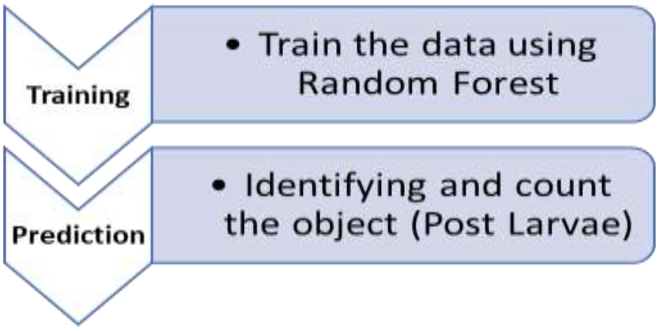

Fig. 3. Counting block diagram for automatic counting shrimp larvae using artificial intelligence

The flowchart starts with turning on the detection and counting software as shown in Figure 4 below. The system consists of two states, the first state is when the system receives a video feed from a webcam and the second state is a counting system based on the video feed. When using a video webcam, the system loads each frame from the video feed. Then a pre-trained model for segmentation is used, which aids in the identification and separation of shrimp larvae from the background. If the larvae are successfully detected, the system counts them using the identified boundary boxes. If no shrimp larvae are found, the flowchart loops back to the "load frame" step, allowing the system to process subsequent frames continuously until larvae are found. The counting process restarts every time there are no larvae detected in a frame, ensuring that the system keeps counting as long as it is running. The flowchart continues this loop until the system is stopped.

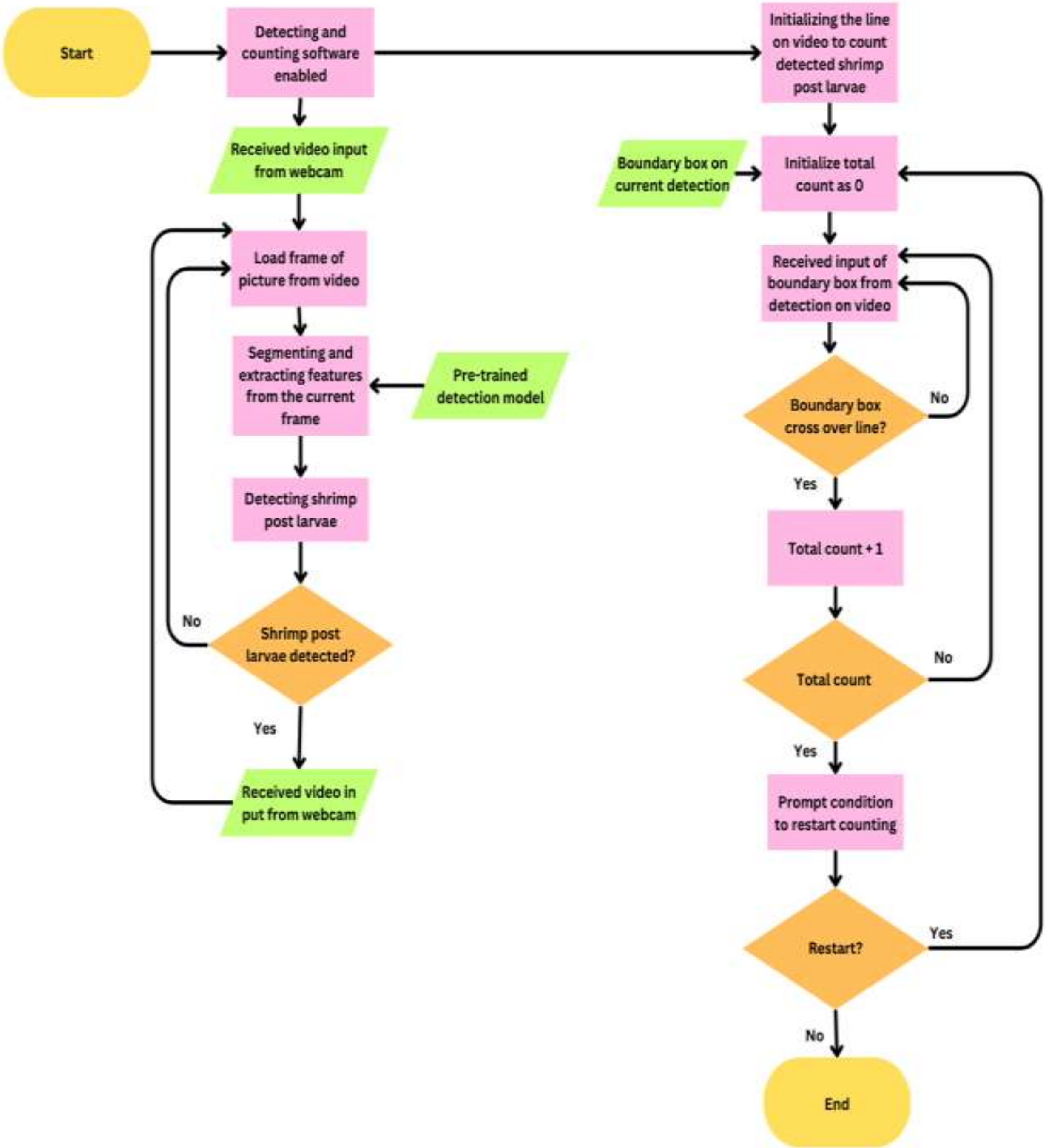

Fig. 4. Project flow chart for automatic counting of shrimp larvae using artificial intelligence

The developed prototype design for counting shrimp larvae includes key components such as a Latte Panda, a GPU, a power supply, an LCD and a webcam as illustrated in Figure 5. The Latte Panda is the central processing unit (CPU) in charge of efficiently managing the data processing tasks required for shrimp larvae counting. The GPU improves system performance significantly by accelerating complex calculations and image processing, resulting in faster and more precise counting results. A dependable power supply ensures that all components receive consistent and stable power. The LCD provides a user-friendly visual interface for convenient counting result monitoring and display. The provided webcam captures high-resolution images of the shrimp larvae, allowing for further analysis and accurate counting.

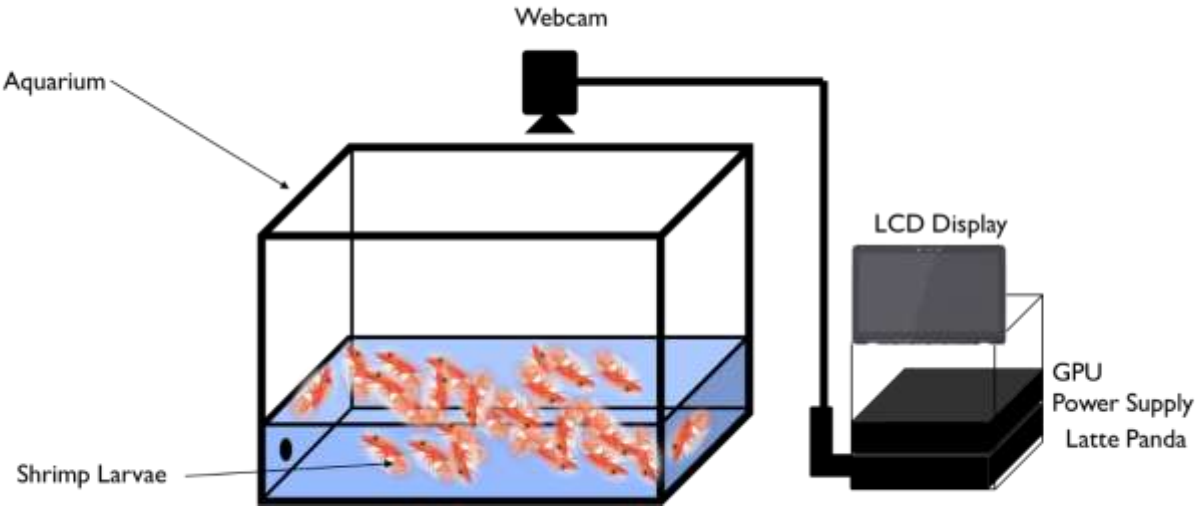

Fig. 5. The prototype design for automatic counting of shrimp larvae using artificial intelligence

3. Results
3.1 Results Observation by Experimental

This project was developed for an automatic counting of shrimp larvae using an Artificial Intelligence approach. YOLOv8 system is used as the basis for object detection of the PL and running it using Python software. A set of images was used, which included both self-captured samples taken with a camera and pre-existing samples. The self-captured samples included 88 images captured with a camera and a webcam under various lighting conditions. These images were then labelled using the Roboflow website, which is a platform designed specifically for image labelling tasks. The labelling process entailed annotating the images' objects of interest such as the eyes and tail. Following that, the Roboflow website generated a YAML file with the labelled images, allowing for further processing with the YOLOv8 machine-learning algorithm.

The images of shrimp larvae that have been carefully labelled and used as training data are shown in Figure 6. During the validation phase, the system will be trained using this trained dataset to produce the desired results. The system's ability to function effectively for the intended purpose illustrates the value of the training procedure and the potential for precise predictions in shrimp post-larvae calculation.

Fig. 6. Macro brachium Rosenbergii shrimp larvae sample

The comparison between shrimp larvae and the background is shown in a confusion matrix in the context of an AI prediction as shown in Figure 7. The purpose of this evaluation is to rate the system's performance in relation to the practiced data. The findings show that the system has a reliable post-larvae detection rate of 83%. According to this finding, the AI model has developed the ability to distinguish and identify shrimp larvae from the background with a high degree of accuracy. These positive results demonstrate the system's potential to support accurate and efficient shrimp quantification procedures.

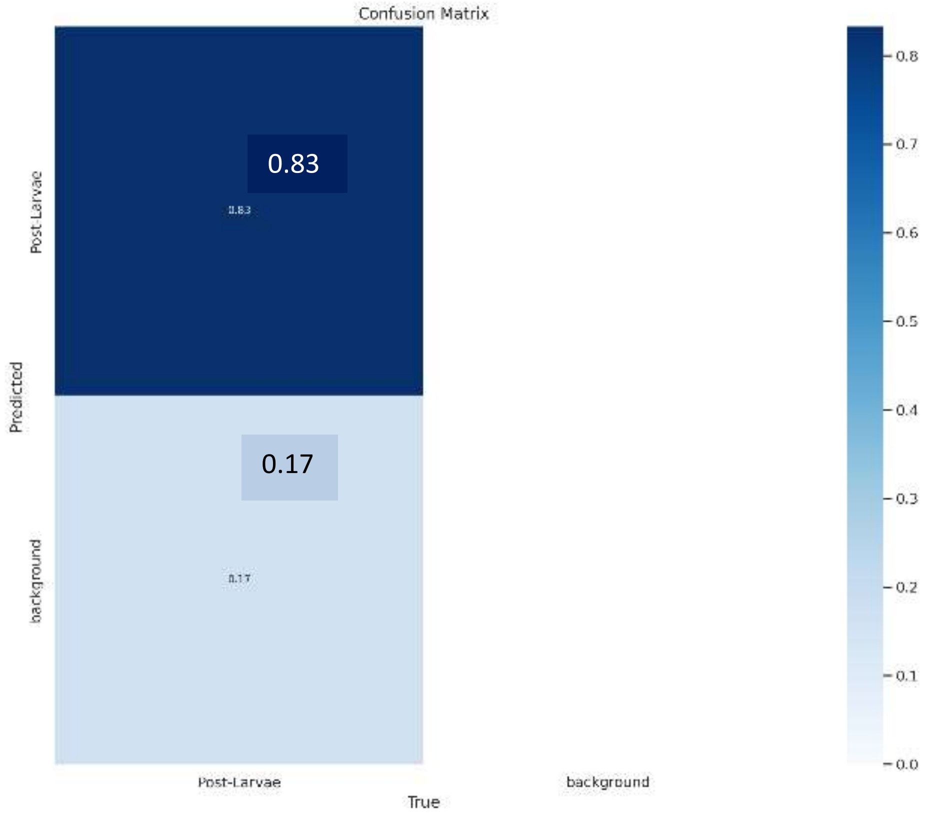

Fig. 7. Confusion matrix

The relationship between the precision of bounding box detection and the confidence evaluations given by the YOLOv8 model is visually represented by the Precision vs Confidence curve as shown in Figure 8.

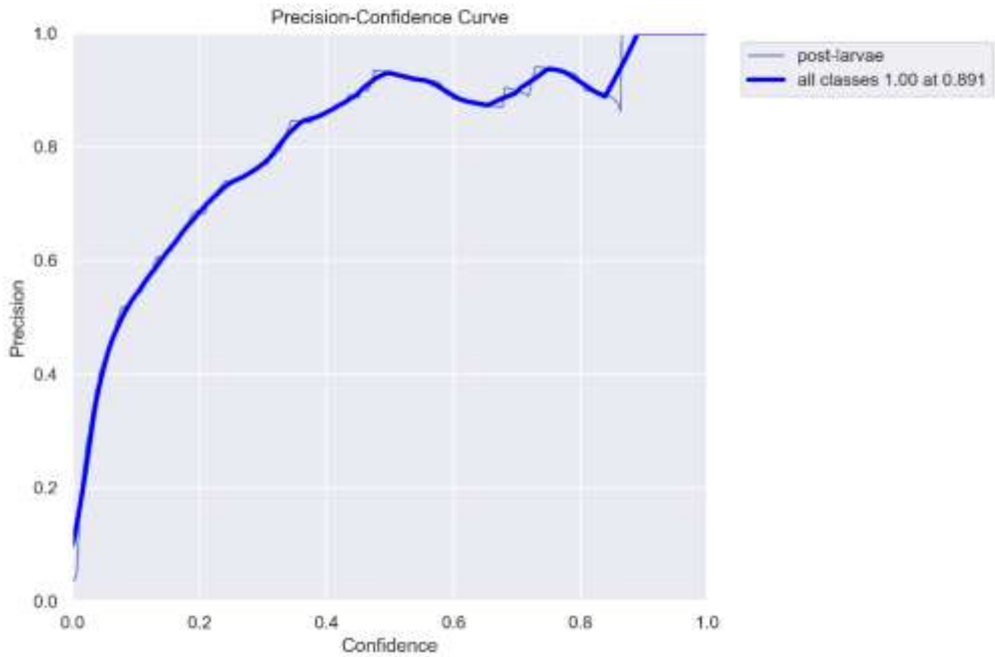

Fig. 8. Precision vs confidence curve

More accurate and precise detections are indicated by a higher precision score. The bounding box labels created by humans and those created by the YOLOv8 model after training are compared in Figure 9 and Figure 10 of the validation results.

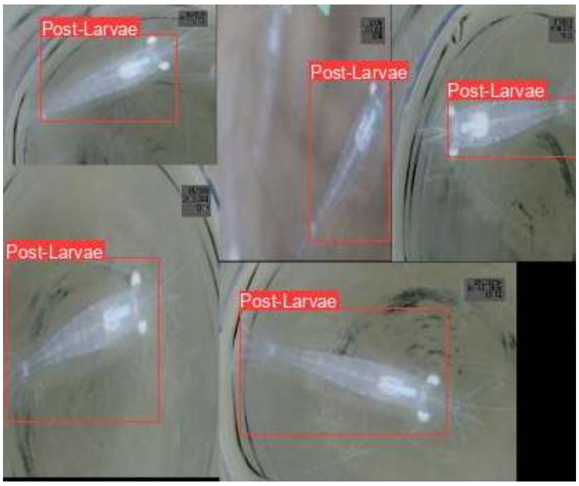

Fig. 9. Human generated bounding box

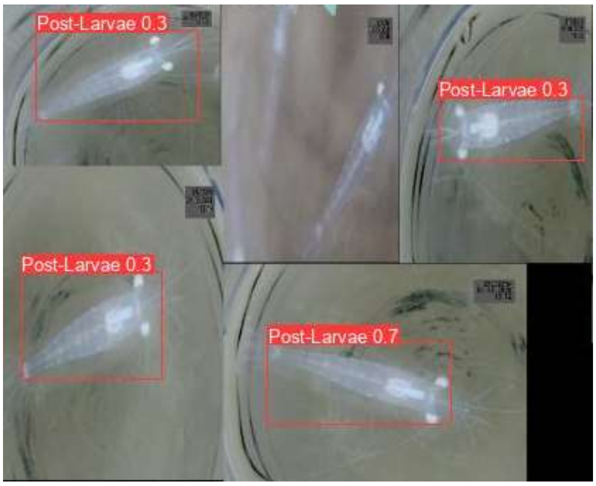

Fig. 10. YOLOv8 generated bounding box after training

Based on the manually created bounding boxes, these figures show that YOLOv8 was able to detect the majority of the images. The precision of the detections and the model's confidence scores were strongly correlated, as shown by how closely they were aligned. This suggests that the YOLOv8 model was successful in precisely locating post-larvae in the images and classifying them, leading to accurate predictions of bounding boxes. Insights into the model's performance and its ability to produce precise detections with high confidence scores can be gained from looking at the Precision vs. Confidence curve and the comparison between human and YOLOv8-generated bounding boxes.

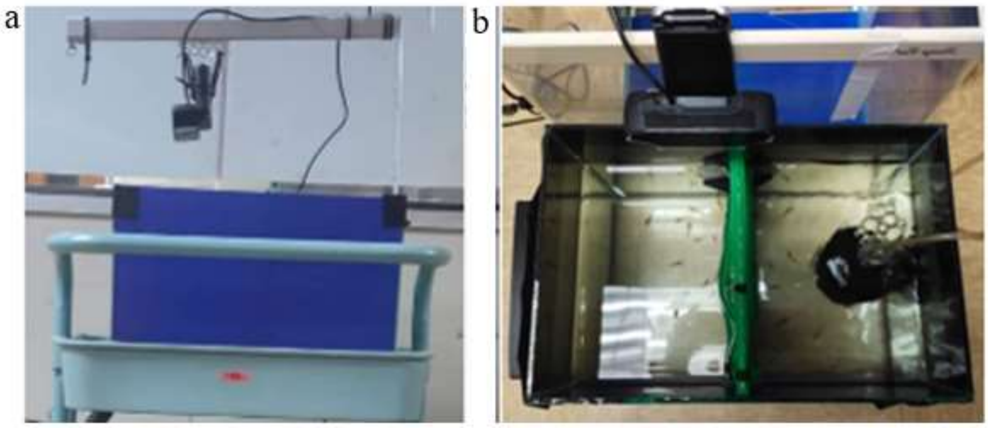

Fig. 11. Prototype for the system (a) front view (b) top view

The project has been successfully created and a prototype of an artificial intelligence system for counting shrimp larvae automatically has been developed. Modern technologies and algorithms are incorporated into the design in order to accurately and effectively calculate shrimp larvae. A fully operational system that can automatically count shrimp larvae with high precision and reliability was developed from the prototype's rigorous development and testing phases. The system demonstrates the ability to process large volumes of shrimp larvae images and generate accurate counts in a small fraction of the time compared to manual counting methods thanks to the integration of advanced computer vision techniques and deep learning models. The successful construction and operational implementation of the prototype highlights the AI system's potential to revolutionize shrimp larvae counting processes in a variety of industries, including aquaculture and fisheries.

Figure 12 shows the comparison of manual counting and YOLOv8 prediction for calculating shrimp post larvae revealed that the YOLOv8 model consistently attained an accuracy range of 90% and above. This demonstrates the capability of YOLOv8 to calculate the precise quantity of shrimps present. While manual counting has benefits like visual evaluation and customization possibilities, it is prone to human error and time constraints. On the other hand, YOLOv8 prediction offers consistent accuracy, quick processing and automation potential, though it necessitates a carefully selected training dataset and may encounter difficulties when confronted with unusual shrimp orientations.

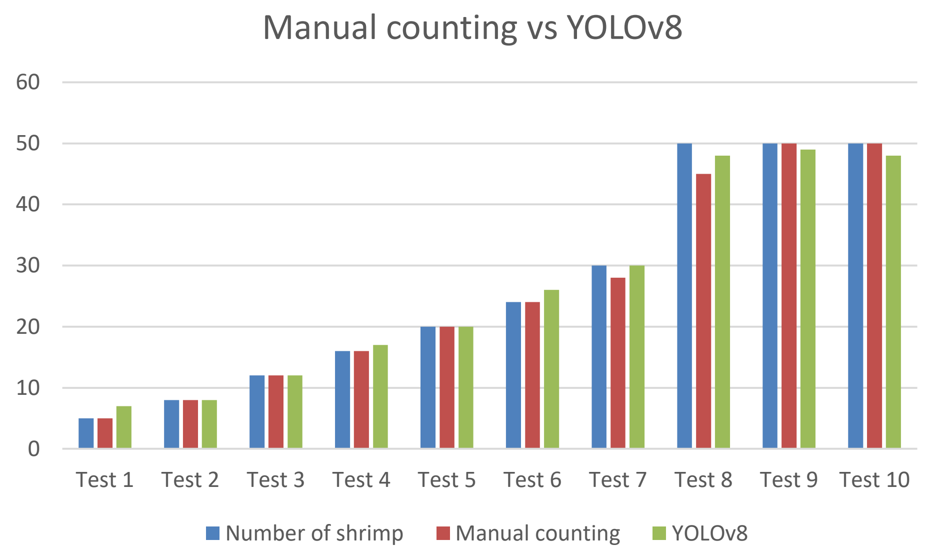

Fig. 12. Differences between manual and YOLOv8

Table 1 shows the results of a comprehensive evaluation conducted to compare the efficiency of manual counting and YOLOv8 to determine the number of shrimp post larvae. The testing procedure was repeated ten times to ensure the findings' reliability. The results of tests 7 and 8 showed that YOLOv8 had a slightly superior capability in counting shrimp post larvae when compared to manual counting. These findings highlight the potential of YOLOv8 as a promising tool for precise and efficient counting of shrimp post larvae that can outperforming the traditional manual counting method.

Table 1
Result table for counting difference between manual and YOLOv8

No. of testing	Number of shrimp post larvae	Manual counting	YOLOv8	Accuracy result
Test 1	5	5	7	71.43%
Test 2	8	8	8	100%
Test 3	12	12	12	100%
Test 4	16	16	17	94%
Test 5	20	20	20	100%
Test 6	24	24	26	92.3%
Test 7	30	28	30	93.33%
Test 8	50	45	48	96%
Test 9	50	50	49	98%
Test 10	50	50	48	96%

The real time result for the shrimp is shown in Figure 13.

Fig. 13. Real time result counting

4. Conclusions

The design of an automatic shrimp larva counting system based on image processing for shrimp farming in aquaculture, building a simulation of an artificial intelligence system for automatic shrimp larvae counting and verifying the performance of the Automatic Counting of Shrimp Larvae Using Artificial Intelligence, were met.

The system demonstrates successful image recognition and achieves more than 83% accuracy rate in calculating quantities based on the detected images.

Further testing is needed to improve the precision and confidence of the YOLOv8 model and ensure a more accurate outcome. More testing will help improve the model's performance by fine-tuning the precision and confidence thresholds, resulting in better detection and counting of shrimp larvae.

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References

[1] Chellapandi, Paulchamy. "Development of top-dressing automation technology for sustainable shrimp aquaculture in India." *Discover Sustainability* 2, no. 1 (2021): 26. https://doi.org/10.1007/s43621-021-00036-9

[2] Santhanam, P., N. Manickam and P. Perumal. "Biofloc-copefloc: A novel technology towards sustained aquaculture." *J. Indian Soc. Coast. Agric. Res* 38 (2020): 43-50.

[3] Barua, Dhrubo and Md Sazzad Hossain. "Environmental impacts of commercial shrimp farming in coastal zone of Bangladesh and approaches for sustainable management." *International Journal of Environmental Sciences & Natural Resources* 20, no. 3 (2019): 84-92. https://doi.org/10.19080/IJESNR.2019.20.556038

[4] Lee Tzu, Namira, Wan Ahdan Rahman Wan Ezzati Farha, Musa, Naimah, Mei Rifqi, Mursyidah, Hidayati, Sari, Pratiwi, Hesti, Mohd Aris, Nur Athirah, Musa, Nadirah, Rasid, Rasina, Abd Aziz, Mohd Fazrul Hisam, Musa, Najiah and Lani, Mohd Nizam. (2024). "Sensing Technologies and Automation: Revolutionizing Aquaculture Towards Sustainability and Resilience."*Semarak International Journal of Agriculture, Forestry and Fisheries, no. 1* (2024): 10-18. https://doi.org/10.37934/sijaff.1.1.1018

[5] Mohammad Yamin, Umair, Sazali, Norazlianie, Kettner, Maurice, Mohd Razman, Mohd Azraai and Wei, Robert. "Comparison of Different Deep Learning Object Detection Algorithms on Fruit Drying Characterization." *Journal of Advanced Research in Applied Sciences and Engineering Technology*, (2024):237-250. https://doi.org/10.37934/araset.60.1.173186

[6] Hung, Dinh, Nguyen Hong Nguyen, Raul W. Ponzoni, David A. Hurwood and Peter B. Mather. "Quantitative genetic parameter estimates for body and carcass traits in a cultured stock of giant freshwater prawn (Macrobrachium rosenbergii) selected for harvest weight in Vietnam." *Aquaculture* 404 (2013): 122-129. https://doi.org/10.1016/j.aquaculture.2013.04.027

[7] Hu, Wu-Chih, Liang-Bi Chen, Meng-Heng Hsieh and Yuan-Kai Ting. "A deep-learning-based fast counting methodology using density estimation for counting shrimp larvae." *IEEE Sensors Journal* 23, no. 1 (2022): 527-535. https://doi.org/10.1109/JSEN.2022.3223334

[8] Bessa, Willian RB, Vinicius N. Barbosa, Danielly G. Leite, Francisco M. M. Neto, Vinicius S. Santos, Tarcio G. Silva, Glacio S. Araujo, Mario WL Moreira and Oton C. Braga. "Image Filtering Model Based on Convolutional Neural Networks for Automatic Counting of Post-larvae in Aquaculture." In *Proceedings of the 11th Euro American Conference on Telematics and Information Systems*, pp. 1-7. 2022. https://doi.org/10.1145/3544538.3544642

[9] Zhang, Lu, Xinhui Zhou, Beibei Li, Hongxu Zhang and Qingling Duan. "Automatic shrimp counting method using local images and lightweight YOLOv4." *Biosystems Engineering* 220 (2022): 39-54. https://doi.org/10.1016/j.biosystemseng.2022.05.011

[10] Chen, Fudi, Ming Sun, Yishuai Du, Jianping Xu, Li Zhou, Tianlong Qiu and Jianming Sun. "Intelligent feeding technique based on predicting shrimp growth in recirculating aquaculture system." *Aquaculture Research* 53, no. 12 (2022): 4401-4413. https://doi.org/10.1111/are.15938

[11] Yeh, Chi-Tsai and Ming-Sheng Ling. "Portable Device for Ornamental Shrimp Counting Using Unsupervised Machine Learning." *Sensors & Materials* 33 (2021). https://doi.org/10.18494/SAM.2021.3240

[12] Hong Khai, Teh, Siti Norul Huda Sheikh Abdullah, Mohammad Kamrul Hasan and Ahmad Tarmizi. "Underwater fish detection and counting using mask regional convolutional neural network." *Water* 14, no. 2 (2022): 222. https://doi.org/10.3390/w14020222

[13] Boksuwan, Sungwan, Sumit Panaudomsup and Thepjit Cheypoca. "A prototype system to count nursery pacific white shrimp using image processing." In *2018 18th International Conference on Control, Automation and Systems (ICCAS)*, pp. 1187-1189. IEEE, 2018.

[14] Kaewchote, Jirabhorn, Sittichoke Janyong and Wasit Limprasert. "Image recognition method using Local Binary Pattern and the Random forest classifier to count post larvae shrimp." *Agriculture and Natural Resources* 52, no. 4 (2018): 371-376. https://doi.org/10.1016/j.anres.2018.10.007

[15] Solahudin, M., W. Slamet and A. S. Dwi. "Vaname (Litopenaeus vannamei) shrimp fry counting based on image processing method." In *IOP Conference Series: Earth and Environmental Science*, vol. 147, no. 1, p. 012014. IOP Publishing, 2018. https://doi.org/10.1088/1755-1315/147/1/012014

[16] Lainez, Sheryl May D. and Dennis B. Gonzales. "Automated fingerlings counting using convolutional neural network." In *2019 IEEE 4th International Conference on Computer and Communication Systems (ICCCS)*, pp. 67-72. Ieee, 2019. https://doi.org/10.1109/CCOMS.2019.8821746

[17] Zakiyabarsi, Furqan, Muhammad Niswar and Zahir Zainuddin. "Crab larvae counter using image processing." *EPI International Journal of Engineering* 2, no. 2 (2019): 127-131. https://doi.org/10.25042/epi-ije.082019.06

[18] Awalludin, Ezmahamrul Afreen, MY Mat Yaziz, NR Abdul Rahman, Wan Nural Jawahir Hj Wan Yussof, Muhammad Suzuri Hitam and TN T. Arsad. "Combination of canny edge detection and blob processing techniques for shrimp larvae counting." In *2019 IEEE International Conference on Signal and Image Processing Applications (ICSIPA)*, pp. 308-313. IEEE, 2019. https://doi.org/10.1109/ICSIPA45851.2019.8977746

[19] Armalivia, Siska, Zahir Zainuddin andani Achmad and Muh Arief Wicaksono. "Automatic counting shrimp larvae based you only look once (YOLO)." In *2021 international conference on artificial intelligence and mechatronics systems (AIMS)*, pp. 1-4. IEEE, 2021. https://doi.org/10.1109/AIMS52415.2021.9466058

[20] Nguyen, Khai-Thinh, Chanh-Nghiem Nguyen, Chien-Yao Wang and Jia-Ching Wang. "Two-phase instance segmentation for whiteleg shrimp larvae counting." In *2020 IEEE international conference on consumer electronics (ICCE)*, pp. 1-3. IEEE, 2020. https://doi.org/10.1109/ICCE46568.2020.9043075

[21] Hu, Wu-Chih, Liang-Bi Chen, Meng-Heng Hsieh and Yuan-Kai Ting. "A deep-learning-based fast counting methodology using density estimation for counting shrimp larvae." *IEEE Sensors Journal* 23, no. 1 (2022): 527-535. https://doi.org/10.1109/JSEN.2022.3223334

[22] Qian, Kun and Hong-chao Duan. "Optical counting platform of shrimp larvae using masked k-means and a side window filter." *Applied Optics* 63, no. 6 (2024): A7-A15. https://doi.org/10.1364/AO.502868