Intelligent Systems with Applications 24 (2024) 200434

Contents lists available at ScienceDirect

Intelligent Systems with Applications

journal homepage: www.journals.elsevier.com/intelligent-systems-with-applications

A deep learning model for estimating body weight of live pacific white shrimp in a clay pond shrimp aquaculture

Nitthita Chirdchoo [a], Suvimol Mukviboonchai [b,*], Weerasak Cheunta [c]

[a] Department of Electrical Engineering, Nakhon Pathom Rajabhat University, 73000, Nakhon Pathom, Thailand
[b] Department of Data Science, Nakhon Pathom Rajabhat University, 73000, Nakhon Pathom, Thailand
[c] Department of Industrial Computer Technology, Nakhon Pathom Rajabhat University, 73000, Nakhon Pathom, Thailand

ARTICLE INFO

Keywords:
Image processing
Feature selection
Precision aquaculture
Precision feeding
Shrimp detection

ABSTRACT

This paper presents a novel approach to address the essential challenge of accurately determining the total weight of shrimp within aquaculture ponds. Precise weight estimation is crucial in mitigating issues of overfeeding and underfeeding, thus enhancing efficiency and productivity in shrimp farming. The proposed system leverages image processing techniques to detect individual live shrimp and extract pertinent features for weight estimation within a clay pond environment. Specifically, an automated feed tray captures images of live shrimp, which are then processed using a combination of Detectron2, PyTorch, and CUDA (Compute Unified Device Architecture) for individual shrimp detection. Essential features such as area, perimeter, width, length, and posture are extracted through image analysis, enabling accurate estimation of shrimp weight. An Artificial Neural Network (ANN) model, utilizing these features, accurately predicts shrimp weight with a coefficient of determination (R^2) of 94.50% when incorporating all extracted features. Furthermore, our system integrates a user-friendly web application that empowers farmers to monitor shrimp weight trends, facilitating precision feeding strategies and effective farm management. This study contributes a low-cost solution using a deep learning model to estimate the weight of live Pacific white shrimp in clay ponds, enabling daily weight calculations, helping farmers optimize feed quantities, providing shrimp size distribution insights, and reducing the Feed Conversion Ratio (FCR) for greater profitability. The procedure for shrimp feature extraction is also provided, including the calculation of shrimp length and width, as well as shrimp posture classification.

1. Introduction

In shrimp farming, feed constitutes a significant portion of operational costs, thereby emphasizing the crucial role of efficient feed management in ensuring successful crop outcomes. Efficient feeding practices are essential in attaining optimal shrimp size at harvest while minimizing operational expenses. The key to achieving efficient feeding lies in accurately determining the appropriate feed quantity for the shrimp population, thus averting the pitfalls of overfeeding and underfeeding. Overfeeding, characterized by the dispensation of excessive feed quantities beyond shrimp requirements (Bossier & Ekasari, 2017), results in residual feed accumulation and deterioration of water quality, thereby compromising shrimp health, growth, and farm sustainability (Emerenciano et al., 2022). Conversely, underfeeding entails inadequate provision of feed, leading to suboptimal growth rates and diminished overall productivity. This emphasizes the significance of precise feed management strategies in shrimp farming to optimize growth, mitigate environmental impacts, and ensure long-term profitability and sustainability (Boyd, 2018; Tacon & Metian, 2013).

Previous research indicates that determining the appropriate feed amount for shrimp cultivation often relies on assessing the total shrimp biomass within the pond (Tacon et al., 2002, 2013; Tacon & Metian, 2013). Estimating this biomass necessitates knowledge of the average weight of the shrimp population, a task that poses considerable challenges. Primarily, this process typically involves labor-intensive methods, leading to increased operational costs and the potential for contamination from human contact with the shrimp. Traditionally, farmers have employed specialized rulers to measure shrimp length as a proxy for weight estimation. However, this approach is fraught with limitations, including the need for physical contact with the shrimp during measurement and inaccuracies inherent in length-to-weight conversion algorithms embedded in these rulers. These challenges underscore the critical need for alternative methodologies in

* Corresponding author.
E-mail addresses: nitthita@webmail.npru.ac.th (N. Chirdchoo), suvimol@webmail.npru.ac.th (S. Mukviboonchai), weerasak@npru.ac.th (W. Cheunta).

https://doi.org/10.1016/j.iswa.2024.200434
Received 26 April 2024; Received in revised form 4 July 2024; Accepted 29 August 2024
Available online 1 September 2024
2667-3053/© 2024 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

accurately assessing shrimp biomass for an effective feed management strategy.

Prior studies have explored computer vision, machine learning, and deep learning approaches for estimating shrimp body length (Hashisho et al., 2021; Lai et al., 2022), shrimp length and shape (Setiawan et al., 2022), shrimp weight (Pan et al., 2009; Saleh et al., 2024; Xi et al., 2023), shrimp counting (Khai et al., 2022; Zhang et al., 2022), and waste feeding (Chirdchoo & Cheunta, 2019; Zainuddin et al., 2022). Lai et al. (2022) uses captured images from an underwater video system at the bottom of aquaculture ponds to detect shrimps and estimate shrimp body lengths. Hashisho et al. (2021) proposed a pipeline for shrimp monitoring using length estimation, assessment of the shrimp's digestive tract, and counting. Setiawan et al. (2022) proposed smart glasses, depth cameras, computer vision, and machine learning to detect shrimp distribution and growth from feed trays. Prawn size, length, and shape are estimated based on images to detect the growth trends of prawns. Saleh et al. (2024) utilizes deep learning to detect landmarks from shrimp images to derive five important shrimp traits and identify landmark-derived distances to predict shrimp weight. Xi et al. (2023) measures the body weight of shrimp using morphometric features based on underwater image analysis. Pan et al. (2009) proposed a weight prediction method from shrimp image processing and feature extracting. Khai et al. (2022) developed a deep learning model for underwater shrimp counting. Shrimp image data are captured by a robotic eye camera. The image data are classified into low density, medium density, and high density. Zhang et al. (2022) proposed a shrimp counting method using an image processing technique to construct a counting dataset. Zainuddin et al. (2022) proposed a feed waste detection system by collecting images of shrimp feed left in the water. Binary classification divided objects into shrimp feed and non-shrimp feed. Chirdchoo and Cheunta (2019) proposed a simple and low-cost shrimp food pallet detection algorithm utilizing a two dimension (2D) histogram and color space analysis to detect the amount of unconsumed feed left on the feeding tray.

The majority of shrimp production comes from Asia (Renub Research, 2023), with shrimp practically raised in natural clay ponds characterized by high turbidity, muddy water, and limited visibility, contrasting to the studies with controlled experimental setups in transparent ponds (Hashisho et al., 2021; Khai et al., 2022). This variance challenges the direct application to the context of clay pond shrimp farming in Thailand. Additionally, prior methods have relied on manpower (Setiawan et al., 2022), direct contact with the shrimp (Xi et al., 2023), and high maintenance of waterproof cameras (Lai et al., 2022; Xi et al., 2023), or centered on deceased shrimp (Pan et al., 2009), prompting the need to address these limitations.

This paper endeavors to overcome these constraints by employing deep learning and image processing techniques to daily monitor live shrimp growth in a clay pond, enabling automated and precise shrimp weight estimation. We aim to accurately estimate the average weight of the shrimp in the pond from 2D images captured from feeding tray. With this available weight information, it is possible to determine the precise feed amount for shrimp culture, consequently alleviating the inefficiencies arising from the problems of overfeeding and underfeeding. Our study contributes a low-cost approach tailored for practical deployment in real-life scenarios by utilizing a deep learning model to estimate the weight of live Pacific white shrimp in clay ponds, enabling daily weight calculations, helping farmers optimize feed quantities, providing shrimp size distribution insights, and reducing the Feed Conversion Ratio (FCR) for greater profitability. The procedure for shrimp feature extraction is also described, covering the calculation of shrimp length and width, as well as shrimp posture classification.

This paper is organized as follows: Section 2 presents the materials and methods used in this study, Section 3 explains the experimental setup, Section 4 focuses on the corresponding results, Section 5 clarifies and interprets the main findings, and Section 6 presents the conclusions.

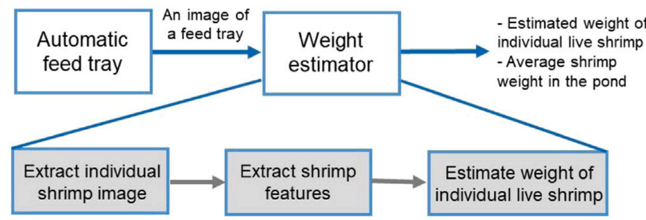


Fig. 1. The conceptual design of the proposed system.

2. Material and methods

2.1. The proposed system

The design of the proposed system for weight estimation of live shrimp in a clay pond in a real-time, low-cost, and non-abrasive approach, is illustrated in Fig. 1. The system comprises two main components: an automatic feed tray and a weight estimator. The automatic feed tray is designed to periodically capture images within a clay pond. The weight estimator, powered by a trained deep learning model, estimates the weight of each live shrimp visible in the captured feed tray image. This facilitates the acquisition of the average shrimp weight in the pond.

The design and development of the proposed system are described in detail as follows.

2.1.1. Automatic feed tray

The system repurposes the conventional feed tray as a tool for capturing live shrimp images in natural clay ponds characterized by high turbidity, muddy water, and limited visibility. This adaptation involves lifting the tray periodically to capture images of the live shrimp on the tray. The proposed automatic feed tray, designed and modified from the previous work (Chirdchoo & Cheunta, 2019), is outlined in Fig. 2, installed approximately 3–5 meters from the feeding control system. Constructed with a stainless-steel frame, it features an image-capturing shelter and an actual feed tray. The image-capturing shelter (Fig. 2(a)) is covered with opaque UV-resistant plastic sheets on all sides, except the bottom, allowing the feed tray to move freely in upward and downward directions during image capture. This shelter protects the tray and the camera from adverse weather conditions, ensuring high-quality images and reducing maintenance requirements. In addition, a white-light LED strip is installed inside the shelter to enhance illumination during image capture. Internally (Fig. 2(b)), the tray consists of a stainless-steel frame covered by blue netting on four sides, with the top remaining open and the bottom covered with a square-shaped blue plastic sheet. Positioned approximately 45 cm above the tray is a low-cost 2M pixel IP camera (OKER model 177). The controller utilized is a Raspberry Pi 4 Model B with 8 GB RAM.

The automatic feed tray is usually submerged approximately 30 cm above the pond's bottom, collecting leftover feed and shrimp during feeding. To facilitate image capture, a motor and chain mechanism elevates the tray to the water surface before descending for the next cycle. Software control, developed using Python V.3, manages all hardware components. The aerator control system is installed including three sets of paddle-wheel aerators, each equipped with 10–12 paddlewheels. The system features 3-phase motors with a reduction gear speed of 80–100 rpm to facilitate water circulation. Additionally, a feeding control system, including one feed centrifuge, is installed.

2.1.2. Weight estimator

Upon transmission and storage of images from the automatic feed tray to the server's database, image processing commences to estimate individual shrimp weight and the average weight of the shrimp population in the pond. The weight estimator is responsible for extracting

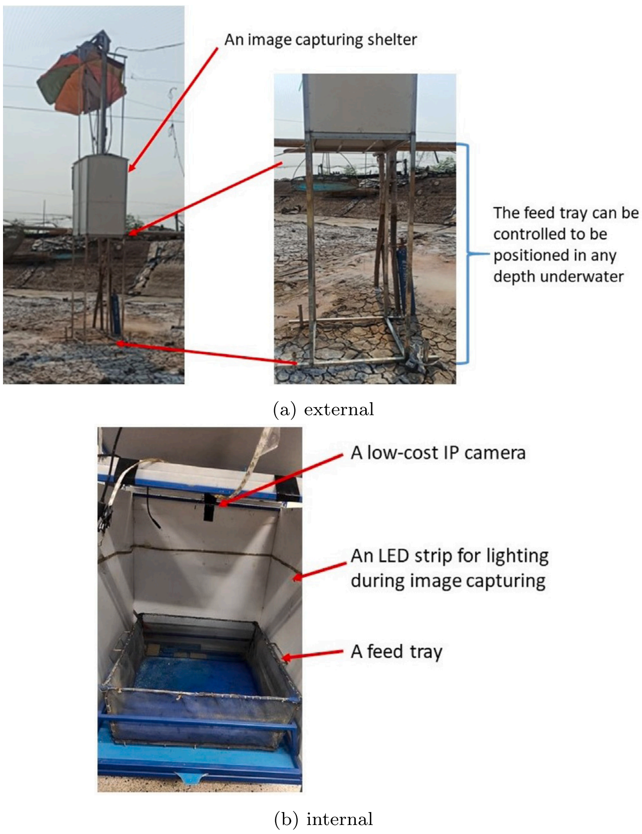


Fig. 2. Automatic feed tray architecture (a) external (b) internal.

individual shrimp images from the captured tray images. Each shrimp image undergoes feature extraction, encompassing area, width, length, perimeter, and body posture, crucial for accurate weight estimation. By employing a deep learning model, the extracted features are utilized to determine the weight of each shrimp. The process is detailed as follows.

Individual shrimp detection. In the captured feed tray image, multiple shrimps, leftover feed, and debris are included. The initial stage involves detecting and isolating individual shrimp images within this capture. This is achieved through the use of deep learning techniques for image segmentation. Specifically, we employ the object instance segmentation platform Detectron2 (Abhishek & Kotni, 2022; Cao et al., 2023), developed by Facebook AI Research (FAIR), in conjunction with PyTorch and CUDA (Compute Unified Device Architecture). Accurate segmentation requires training the model on a custom dataset of shrimp images.

Feature extraction for weight estimation. After acquiring individual shrimp images, five features relevant to shrimp weight are extracted: area, perimeter, width, length, and the dimensions of the minimum bounding box. Examples of these extracted features are presented in Table 1, obtained through computer-vision-based techniques applied to the 2D binary shrimp images. OpenCV, a widely used computer vision library, is employed for feature extraction. Specifically, the area, perimeter, and minimum bounding box of the shrimp are determined using appropriate methods available in OpenCV for edge detection and contour extraction. Specifically, the 'contourArea' and 'minAreaRect' methods are used to derive the area and minimum bounding box, while the 'findContours' and 'arcLength' methods are used to extract the perimeter.

The process for determining shrimp length, involves skeletonization, branch detection, length construction, and total length calculation, together with the results obtained from each step as illustrated in Fig. 3. Skeletonization, achieved through morphological thinning in OpenCV, reduces thickness while maintaining connectivity and structural details. Since resultant skeletons as shown in Fig. 4, may contain branches, particularly in the area of shrimp tail. Hence, branch detection, pruning, and length construction are crucial processes for accurate total length estimation. Detecting branch origin (point A) and calculating d, the length between the origin point and line BC defined in Eq. (1) enhances accuracy. In the total length calculation, the lengths of all remaining contours are summed to determine the shrimp length ($l + d$).

$$d = \mathrm{AD} = \sqrt{x^2 - y^2} \tag{1}$$

Whereas:

d	=	the length between the origin point to the base BC
x	=	the length of any sides of the triangle (excluding the base side)
y	=	the length of a perpendicular line dropped from one of the endpoints of the base, such as point B or C, depending on the selected value of x, as illustrated in Fig. 4

The posture feature can be classified based on shrimp orientation into three forms: curve, semi-curve, and straight. This classification is determined by the value of *bb_ratio*, which represents the ratio between the length and width of the minimum bounding box. The length and the width of the minimum bounding box are denoted by max(*blbrX*, *blbrY*) and min(*blbrX*, *blbrY*), respectively, where "*blbrX*" and "*blbrY*" indicate the bounding box's width and length in Eq. (2). Table 2 outlines the conditions utilizing the *bb_ratio* value to determine shrimp posture. Table 3 illustrates how shrimp posture can be retrieved from the given dimensions of the bounding box.

$$bb\_ratio = \frac{\max(blbrX, blbrY)}{\min(blbrX, blbrY)} \tag{2}$$

To extract the width feature, the widest part of the shrimp must be identified, which is the longest line that is perpendicular to the shrimp's main skeleton. This can be achieved by utilizing the iterative algorithm. In each iteration i, the interesting shrimp area is divided into N sections along its skeleton, using N-1 lines (see Fig. 5). The length of each line specifies the width of the shrimp at each particular section and is denoted as $a_{i,n}$, where $1 \le n \le N-1$. Eqs. (3) and (4) determine the maximum width and the line number that holds the maximum width at iteration i, as a_i, and j_i, respectively.

$$a_i = \max_{n\in\{1,2,\ldots,N-1\}} a_{i,n} \tag{3}$$

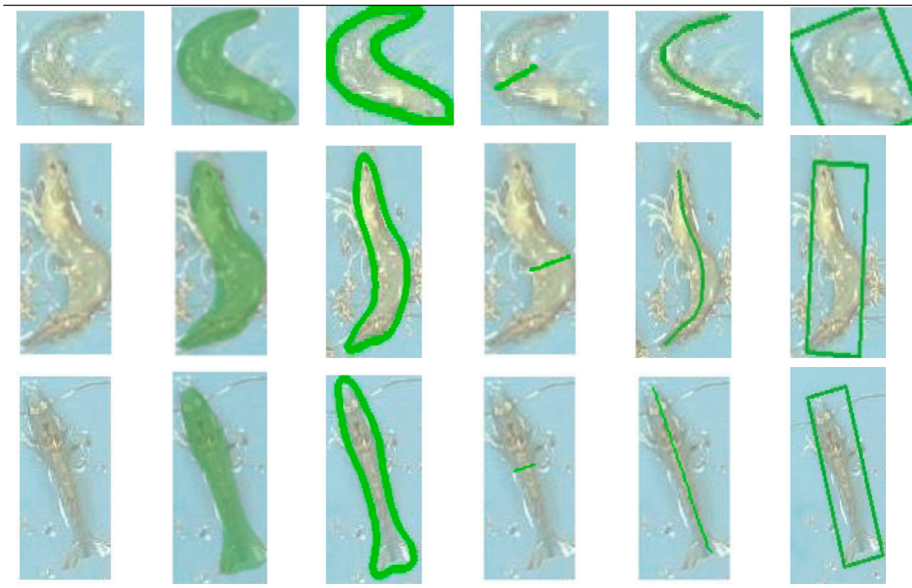
$$j_i = \arg\max_{n\in\{1,2,\ldots,N-1\}} a_{i,n} \tag{4}$$

After obtaining values a_i and j_i, the subsequent iteration $i+1$ focuses on the area between the line number $j_{i\text{-}1}$ and j_{i+1}. Repeating the process yield values a_{i+1} and j_{i+1}. This iterative process continues until a predefined value $\in$ is reached, where $|a_i - a_{i-1}| \le \in$. The shrimp width is then derived as a_l, where l denotes the last iteration.

Artificial neural network model construction to estimate shrimp weight. After obtaining the extracted features – area, perimeter, width, length, and posture – they are utilized as inputs for training and constructing an artificial neural network (ANN) deep learning model aimed at predicting shrimp weight. The model comprises 5 input nodes with two hidden layers of 64 and 128 neurons and one final output node. Rectified Linear Unit (ReLU) activation functions are applied in all layers except the output layer.

Table 1
Extracted features (area, perimeter, width, length, dimension of the minimum bounding box) from shrimp two dimension images.

Original image	Features extracted from shrimp binary images				
	Area	Perimeter	Width	Length	Dimension of min bounding box



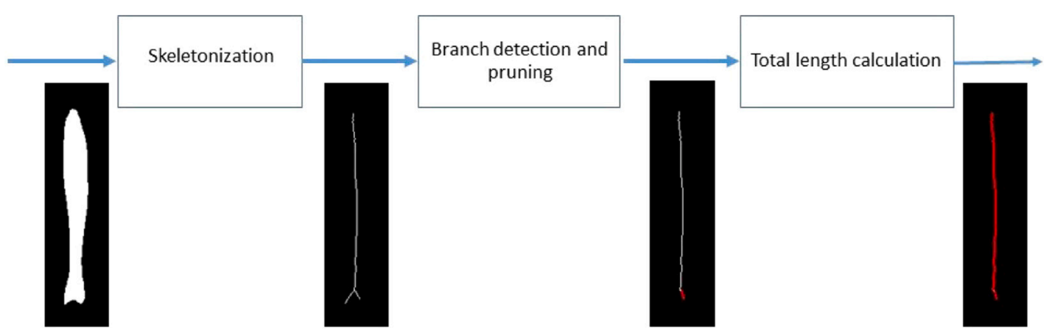


Fig. 3. Procedures to extract shrimp length from its binary image.

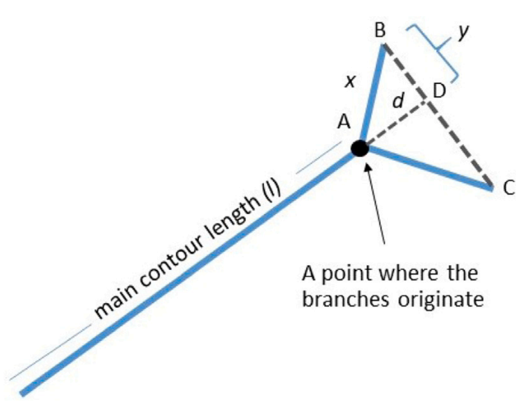


Fig. 4. Length construction from the two detected branches.

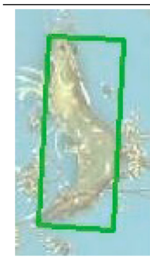
Table 2
Shrimp posture classification from the ratio of the dimension of the bounding box (*bb_ratio*).

bb_ratio	Shrimp posture
$0 < bb\_ratio < 2$	Curve
$2 \leq bb\_ratio < 4$	Semi-curve
$bb\_ratio \geq 4$	Straight

3. Experiment setup

The system was trialed at Mr. Nattapong Manakannan's shrimp farm in Bang Len District, Nakhon Pathom Province, Thailand. Data collection spanned 30 days from May to June 2022 for shrimp detection and 60 days from October to December 2022 for feature extraction, conducted within a 0.593 acre (1.5 Rai) rectangular clay pond lined with plastic sheets, measuring 50 meters on each side. Each cycle involved stocking approximately 100,000 Pacific white shrimps. Due to the vulnerability of small shrimp in the early farming stages, manual data collection is avoided to prevent potential disease contamination in

Table 3
Extracting shrimp posture from the dimension of the bounding box (*bb_ratio*).

Bounding box	max(*blbrX*, *blbrY*)	min(*blbrX*, *blbrY*)	*bb_ratio*	Shrimp posture
	8.8	7.04	1.25	Curve
	16.72	6.63	2.52	Semi-curve
	19.34	4.78	4.05	Straight

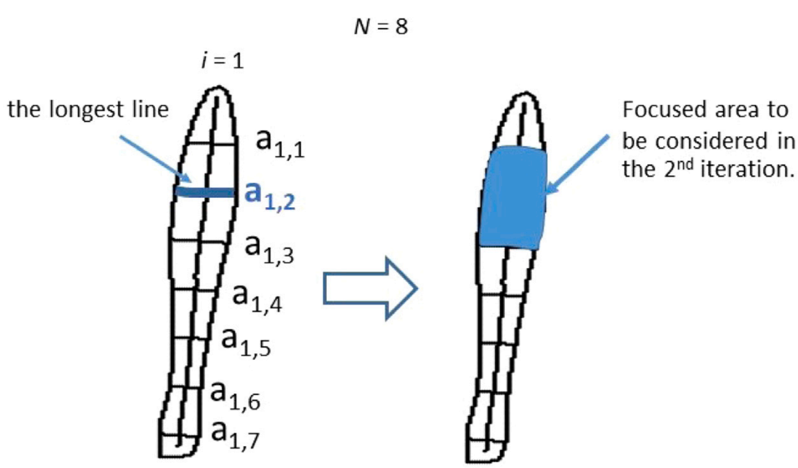


Fig. 5. An example of the first iteration of a width extraction when assuming the shrimp area is divided into eight section ($N = 8$).

the pond. Data collection starts when shrimp reach approximately 10 grams, extending until they reach 50–60 grams each.

3.1. System setup

The system initiates its operation as the automatic feed tray, positioned within the shrimp pond, emerges from underwater to capture images above the water's surface. The tray is configured to capture images repeated at a predefined interval throughout the day, for instance, every 15 min of hourly between 8 am and 6 pm. These captured images, encompassing multiple live shrimps, leftover feed, and debris, are wirelessly transmitted to the farm station's processing unit for analysis. The weight estimator in the processing unit extracts individual shrimp images from the feed tray images, employing deep learning techniques for weight estimation. Features such as width, length, perimeter, area, and posture are extracted and utilized by a trained deep learning model to estimate shrimp weight. The resulting individual live shrimp weight data is stored in the server database. At the end of each day, the system utilizes the collected shrimp weight data to compute the daily average shrimp weight.

3.2. Dataset preparation

To prepare the custom dataset from shrimp detection, images were captured by the automatic feed tray in the Pacific white shrimp farming pond. Ten images were captured daily from 8 am to 6 pm, one per hour,

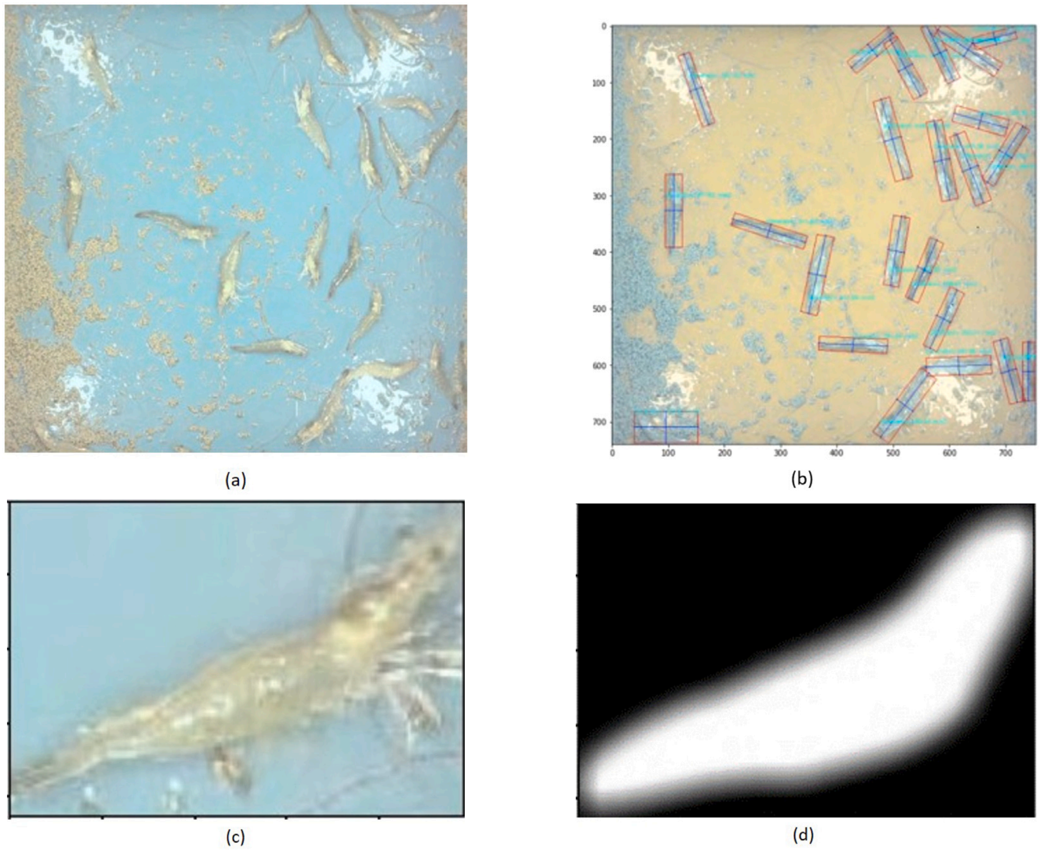


Fig. 6. Output images during the process of extracting individual shrimp (a) output from an automatic feed tray (b) shrimp detection (c) image of individual shrimp (d) greyscale image of individual shrimp.

totaling 650 images (blurry images were manually excluded). Each shrimp in the captured images was manually labeled using LabelImg software, resulting in 4982 labeled shrimp images. Image augmentation techniques, for example, rotation, color saturation, contrast variation, and brightness adjustment, were applied during model training. Fig. 6(a) and (b) illustrate the comparison between input and output images of the shrimp detection process, demonstrating the model's accuracy in isolating shrimps from feed particles on the tray. Fig. 6(c) and (d) depict the output of the shrimp instance segmentation process, showcasing individual shrimp images in their original and greyscale formats, respectively. The greyscale images will later be transformed into binary images for feature extraction.

To ensure the accuracy of the next weight estimation phase, it is crucial to filter out incomplete-body shrimp images. This can be achieved by considering the coordinates of the detected shrimps in the feed tray image. Any shrimps that touch any edges of the frame will be immediately removed. In Fig. 7, the shrimps highlighted with circles are filtered out based on this criterion. After the screening process, the original and greyscale shrimp images are stored in the daily shrimp image database to analyze and identify the features of shrimps for weight estimation.

The dataset is then created and divided into training (80%) and testing (20%) sets, as depicted in Table 4. A pre-trained model, "mask_rcnn_R_50_FPN_3x", is employed to train the custom shrimp dataset on Detectron2 with instance segmentation technique. The final fully connected layer is modified to one node to distinguish only shrimp objects.

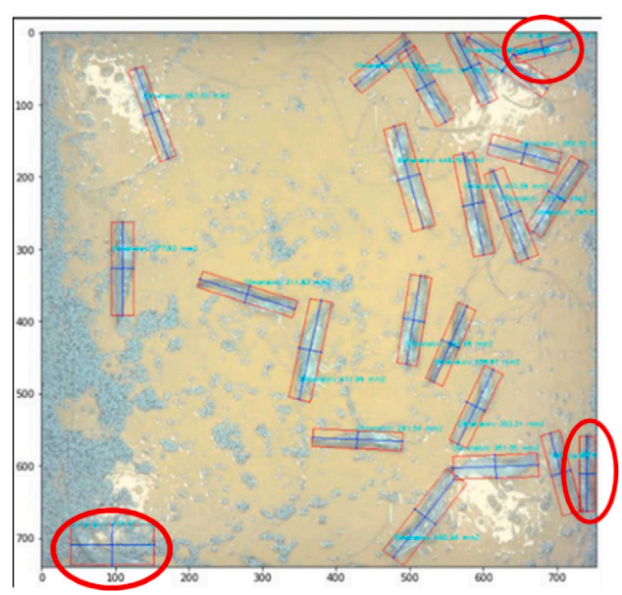


Fig. 7. Shrimps that touch the edges of the image are considered incomplete-body images.

Table 4
Individual shrimp images detected from captured images in dataset preparation.

	Captured image	Individual shrimp image
Training	520	3946
Testing	130	1036
Total	650	4982

Table 5
MAE and RMSE of the shrimp feature extraction.

Features	Mean	MAE	RMSE
Perimeter	29.48 cm	1.67 cm (5.66%)	2.11 cm (7.16%)
Area	25.34 cm^2	2.72 cm^2 (10.73%)	3.49 cm^2 (13.77%)
Width	1.81 cm	0.42 cm (23.20%)	0.55 cm (30.39%)
Length	14.41 cm	2.10 cm (14.57%)	2.80 cm (19.43%)

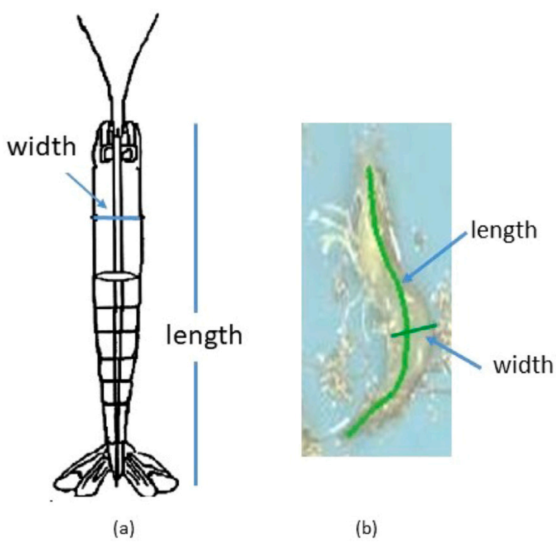


Fig. 8. Comparison of the actual and computer-vision based on length and width extractions: (a) actual (Mace & Rozas, 2015), (b) computer-vision based.

4. Results

4.1. Accuracy of feature extraction using image processing techniques

In this study, the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) are used as accuracy evaluation metrics to compare the actual values measured manually with the computer-vision extracted values, as the result represented in Table 5. Among the four features, the extracted perimeter shows the lowest MAE and RMSE, at 5.66% and 7.16%, respectively. The extracted area feature encounters higher MAE and RMSE at 10.73% and 13.77%. The MAE and RMSE of the length (14.57% and 19.43%) and width (23.20% and 30.39%) features are notably higher when compared with the extracted perimeter and area features.

The discrepancies in length and width extraction result from varying methodologies used to acquire these features. The actual area and perimeter extraction involves manually defining image contours followed by applying computer-vision-based techniques on the shrimp image to calculate the area and the perimeter. Conversely, the actual width and length are measured manually, assuming a straight shrimp posture depicted in Fig. 8. Since shrimp can exhibit various postures other than straight posture (e.g. curve, semi-curve), this leads to substantial errors in the real scenario.

4.2. Accuracy of shrimp weight estimation

The training dataset of the two hidden layer ANN shrimp weight estimation model contains 552 samples and undergoes preprocessing, including outlier detection via Interquartile Range (IQR) analysis on each feature. Outliers are identified beyond ±1.5*IQR and removed. Posture, a categorical variable, is encoded by one-hot encoding and scaled by standardization. After preprocessing, 548 samples remain. This dataset is split into a 75% training set (411 samples) and a 25% testing set (137 samples). Model accuracy was evaluated using a test set of 100 samples.

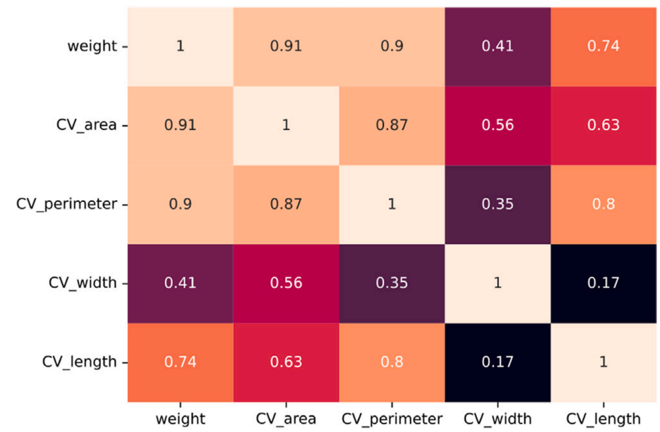


Fig. 9. Correlation matrix of shrimp weight and the extracted shrimp features obtained by computer-vision techniques.

Table 6
Accuracy in shrimp weight estimation using different sets of input features.

Model	Accuracy (%)
Area-Perimeter-Length-Width-Posture (ACLWP)	94.50
Area-Perimeter-Length-Width (ACLW)	92.72
Area-Length-Width (ALW)	92.31
Area (A)	81.05

From the extracted shrimp feature correlation illustrated on Fig. 9, it is evident that both area and perimeter are obviously related to shrimp weight, whereas length and width exhibit a weaker correlation with weight, particularly width with the lowest correlation. This distinction arises from area and perimeter serving as 2D representations capturing comprehensive size and shape information, while length and width offer limited one dimension (1D) insights into shrimp dimensions. Despite width showing the lowest correlation ($r_{weight,\ CV\_width} = 0.41$), it remains notably significant in demonstrating a relationship with shrimp weight.

In this study, we examine four sets of input features to perform shrimp weight prediction: A, ALW, ACLW, and ACLWP; where A, C, L, W, and P stand for area, perimeter, length, width, and posture obtained by using computer-vision techniques, respectively. Table 6 shows the accuracy in weight estimation of each set of input features. From the correlation matrix, the area exhibits the strongest correlation with shrimp weight, therefore, it is included as our performance baseline. Model A which includes only area achieves 81.05% accuracy. Incorporating area, length, and width in model ALW notably improves accuracy to 92.31%, indicating the value of length and width in weight prediction. However, model ACLW does not show a significant improvement. This is primarily due to the high correlation between area and perimeter, with a correlation coefficient $r_{CV\_area,\ CV\_perimeter} = 0.87$. Consequently, this strong correlation between area and perimeter results in only marginal enhancement in the model's performance. On combining all features in model ACLWP, a notable accuracy increases to 94.50% is observed, underscoring the substantial contribution of shrimp posture to enhancing weight prediction accuracy.

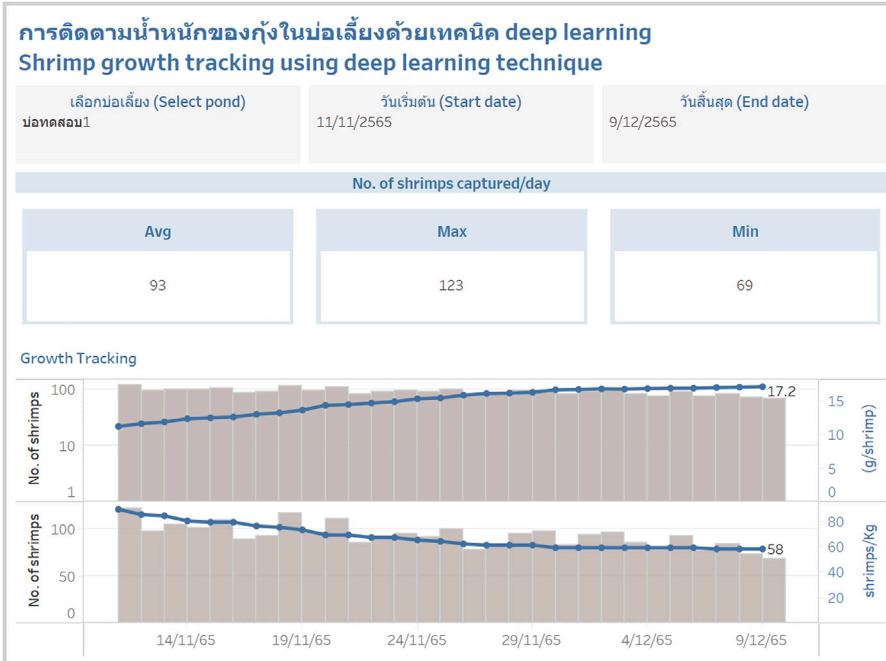


Fig. 10. Shrimp weight tracking web application.

4.3. Real-world implementation

The automated feed tray conducts hourly shrimp checks, capturing images ten times daily. These images, time-stamped upon capture, are wirelessly transmitted to the farm station server via WiFi. At the server, image processing extracts shrimp features. The system logs shrimp images, time-stamps, and weights, into a MySQL database. Through a web application in Fig. 10, farmers can conveniently monitor the average shrimp weight in the pond on a daily basis.

The web application offers real-time data updates, keeping farmers informed about shrimp growth. Farmers have the flexibility to filter data by pond and specific date range. The system provides filtered data, offering daily shrimp counts, along with corresponding average, maximum, and minimum weights. It also displays fluctuations in average shrimp weight and the number of shrimps per kilogram. This data empowers farmers to determine feeding decisions aligned with their feeding formula.

Based on the data showcased in Fig. 10, the system effectively tracks shrimp growth in the pond. Early-stage shrimps exhibit faster growth compared to the later stages. Additionally, as shrimp size increases, the daily capture count decreases, indicating a declining survival rate over time. Furthermore, the system facilitates farmers to lower shrimp density by selling shrimp upon reaching a density of 70 shrimps per kilogram, fostering a healthier environment for the remaining shrimp to thrive optimally.

5. Discussion

5.1. Comparison to the traditional approach

The conventional method employed by farmers for estimating the weight of individual shrimp involves the utilization of a specialized ruler, which establishes a relationship between the shrimp's length and its weight. This method is currently prevalent within the shrimp farming community and is extensively employed for both feeding management and grading purposes. Previous research endeavors have also concentrated on the estimation of shrimp length (Hashisho et al., 2021; Lai et al., 2022; Setiawan et al., 2022) employing a diverse array of techniques, including image processing and AI methodologies. However, examination of the correlation between shrimp weight and actual length, as depicted in Fig. 11, indicates that it is comparatively less significant than that observed between weight and parameters such as perimeter and area. It is also found that the accuracy of weight estimation using actual length results is 41.84% which is the lowest compared to the accuracy of the models presented in Table 6. This suggests that the traditional approach of using shrimp length in a straight posture to estimate shrimp weight is not accurate and thus should be avoided, to prevent the underfeeding and overfeeding problems. This also can be explained that the length feature only represents one-dimensional information about the shrimp. Consequently, reliance solely on length measurements for shrimp weight estimation is prone to yield substantial errors. In light of these considerations, our proposal advocates for the incorporation of five distinct features in tandem to facilitate more accurate shrimp weight estimation. If limited to the utilization of a single feature for weight estimation, we recommend prioritizing the perimeter due to its ease of manual measurement and ability to provide accurate estimates of weight.

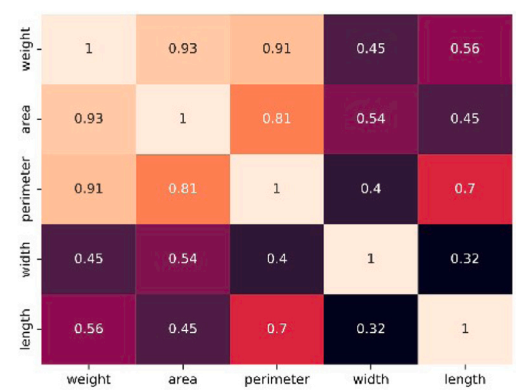


Fig. 11. Correlation matrix of shrimp weight and the actual values of shrimp features.

5.2. Comparison to previous studies

To benchmark with the previous study, employing a machine learning approach to estimate shrimp body weight using six morphometric features achieved 96% accuracy (Xi et al., 2023), which is similar to our 94.50% with five features, confirming our findings that multiple features are necessary for achieving high accuracy in weight estimation. This study differs from ours in that it implements an underwater camera, which requires high maintenance. However, our contribution in this paper is not only proposing a highly accurate system for estimating shrimp weight in high turbid water ponds but also providing a low-cost and low-maintenance system compared to Hashisho et al. (2021), Lai et al. (2022), Setiawan et al. (2022), Xi et al. (2023) and Khai et al. (2022). Our design of the automated feed tray requires low maintenance because no electronic devices are submerged and it can operate through one crop with little need of human intervention for maintenance. Moreover, from the result as shown in Table 6, it is possible to trade off the accuracy with a lower number of features (e.g. using the area feature alone can achieve up to 81% accuracy) to accommodate any hardware constraints in real implementation.

Previous studies in shrimp length feature extraction have commonly operated under the assumption of shrimp maintaining a straight posture, which is facilitated by high-resolution cameras positioned above transparent water ponds, where such posture is easily observable. However, this assumption is applicable primarily to plastic ponds with maintained water clarity. With the assumption of shrimp having a straight posture, the length of the shrimp is the length of the shrimp's bounding box. Unfortunately, in clay pond farming environments, characterized by increased turbidity, this assumption may not hold true. Our research presents a novel approach for length estimation in high turbidity water that employs an automatic feeding tray for shrimp sampling, facilitating image captures above the water level. This enables the utilization of cost-effective, low-resolution cameras. Moreover, as no electronic components are submerged underwater, lower maintenance costs for the system can be expected. It is also essential to note that employing the length of the bounding box as the length of the shrimp is valid only for shrimp exhibiting a straight posture. In cases of crooked posture, utilizing the length of the bounding box may lead to errors in length estimation. The length and width estimations proposed in this paper have been developed to accommodate not only straight postures but also a variety of other postures, making them suitable for diverse applications.

5.3. Further application

Shrimp farmers typically adhere to feeding regimens dictating feed quantity based on shrimp weight. Therefore, the proposed shrimp weight estimation system can be applied to predict precise shrimp feeding by calculating the daily feed quantity required for the shrimp population in the pond, from the average shrimp weight, the number of shrimps in the pond and recommended feed quantity (Limsuwan, 2010) as in Eq. (5). The proposed system provides the average shrimp weight throughout the day. The number of shrimps in the pond can be determined by various shrimp population estimation techniques such as random sampling Hutchins et al. (1980), deep learning Khai et al. (2022), Zhang et al. (2022), and survival rate estimation (Mace & Rozas, 2015). The recommended feed quantity can be determined based on the farmers' chosen feeding regimen which may fluctuate depending on specific farming factors as an example (TNAU Agritech Portal, 2022) in Table 7.

$$F = \frac{w_{\text{avg}} \times n \times f}{100} \tag{5}$$

Whereas:

F	=	feed quantity in kilograms
w_{avg}	=	average weight of shrimp in the pond
n	=	total number of shrimp in the pond
f	=	recommended feed quantity (% of shrimp weight)

Table 7
An example of a white shrimp feed regime (TNAU Agritech Portal, 2022).

Shrimp weight (g)	Recommended feed quantity (% of shrimp weight per day)
2–3	8.0-7.0
3–5	7.0-5.5
5–10	5.5-4.5
10–15	4.5-3.8
15–20	3.8-3.2
20–25	3.2-2.9
25–30	2.9-2.5
30–35	2.5-2.3
35–40	2.3-2.1

6. Conclusions

This study introduces a deep learning model to estimate live Pacific white shrimp weight in a clay pond while minimizing direct contact to prevent disease transmission. The proposed system consists of two main components — an automatic feed tray system and a weight estimator. The automatic feed tray system, applied from a traditional left-over feed tray, captures shrimp images in a clay pond at specified intervals. It is designed to be ideal for challenging natural clay pond conditions with high turbidity, muddy water, and poor visibility. The weight estimator then processes these captured images by extracting shrimp features including area, width, length, perimeter, and posture using image processing techniques.

The deep learning model achieves 94.50% accuracy when utilizing all feature combinations. This system enables daily average shrimp weight calculation, aiding farmers in precise feed quantity determinations, while also facilitating insights into shrimp size distribution and optimization of feed formulas to reduce Feed Conversion Ratio (FCR) for enhanced profitability.

The proposed system can be applied to feeding optimization to reduce overfeeding issues, production costs, and wastewater contamination, while maintaining traditional farming methodologies. Beyond weight estimation, the feature extraction methods proposed in this study hold potential for other aquatic animal applications. Ultimately, it promises efficiency improvements, precision feeding, and increased competitiveness in the shrimp aquaculture industry.

In our future research, researchers could potentially focus on estimating feeding quantity. Additionally, leftover food on the feeding tray can be incorporated to adjust the feeding quantity, encouraging precise feeding.

CRediT authorship contribution statement

Nitthita Chirdchoo: Conceptualization, Field study, Methodology, Laboratory, Software, Validation, Formal analysis, Writing – review & editing, Supervision, Visualization. **Suvimol Mukviboonchai:** Field study, Laboratory, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Weerasak Cheunta:** Funding acquisition, Field study, Investigation, Resources, Methodology, Laboratory, Hardware - design, Development, Deployment, Software, Validation, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

The study was financially supported by fundamental funds from the National Research Council of Thailand [grant number TSRI_65_5.1]; and Thailand Science Research and Innovation and National Telecom Public Company Limited [grant number RDG6250075].

References

Abhishek, A. V. S., & Kotni, S. (2022). Detectron2 object detection & manipulating images using cartoonization. *International Journal of Engineering Research & Technology*, *10*(8), 322–326. http://dx.doi.org/10.17577/IJERTV10IS080122.

Bossier, P., & Ekasari, J. (2017). Biofloc technology application in aquaculture to support sustainable development goals. *Microbial Biotechnology*, *10*(5), 1012–1016. http://dx.doi.org/10.1111/1751-7915.12836.

Boyd, C. E. (2018). Aquaculture pond fertilization. *CABI Reviews*, 1–12. http://dx.doi.org/10.1079/PAVSNNR201813002.

Cao, L., Li, Y., Zhang, X., Ouyang, X., Li, Z., Wang, Y., Guo, Q., Han, L., & Zhang, D. (2023). Comparison of two deep learning models YOLOF and Detectron2 for mesoscale eddies identification in the South China Sea. *International Journal of Remote Sensing*, http://dx.doi.org/10.1080/01431161.2023.2176726.

Chirdchoo, N., & Cheunta, W. (2019). Detection of shrimp feed with computer vision. *Interdisciplinary Research Review*, *14*(5), 13–17. http://dx.doi.org/10.14456/jtir.2019.43.

Emerenciano, M. G. C., Rombenso, A. N., Vieira, F. D. N., Martins, M. A., Coman, G. J., Truong, H. H., Noble, T. H., & Simon, C. J. (2022). Intensification of penaeid shrimp culture: An applied review of advances in production systems, nutrition and breeding. *Animals*, *12*(3), 236. http://dx.doi.org/10.3390/ani12030236.

Hashisho, Y., Dolereit, T., Segelken-voigt, A., Bochert, R., & Vahl, M. (2021). AI-assisted automated pipeline for length estimation, visual assessment of the digestive tract and counting of shrimp in aquaculture production. *Vol. 4*, In *Proceedings of the 16th international joint conference on computer vision, imaging and computer graphics theory and applications* (pp. 710–716).

Hutchins, D. L., Chamberlain, G. W., & Parker, J. C. (1980). Estimation of shrimp populations in ponds using mark-recapture and stratified random sampling methods. *Journal of World Aquaculture Society*, *11*(1–4), 142–150. http://dx.doi.org/10.1111/j.1749-7345.1980.tb00107.x.

Khai, T. H., Abdullah, S. N. H. S., Hasan, M. K., & Tarmizi, A. (2022). Underwater fish detection and counting using mask regional convolutional neural network. *Water*, *14*(2), 222. http://dx.doi.org/10.3390/w14020222.

Lai, P. C., Lin, H. Y., Lin, J. Y., Hsu, H. C., Chu, Y. N., Liao, C. H., & Kuo, Y. F. (2022). Automatic measuring shrimp body length using CNN and an underwater imaging system. *Biosystems Engineering*, *221*, 224–235. http://dx.doi.org/10.1016/j.biosystemseng.2022.07.006.

Limsuwan, C. (2010). How to prevent high feed conversion ratio in shrimp farming. *Journal of Fisheries and Environment*, *34*(1), 28–34.

Mace, M. M., & Rozas, L. P. (2015). Estimating natural mortality rates of juvenile white shrimp litopenaeus setiferus. *Estuaries and Coasts*, *38*(5), 1580–1592. http://dx.doi.org/10.1007/s12237-014-9901-7.

Pan, P. M., Li, J. P., Lv, G. L., Yang, H., Zhu, S. M., & Lou, J. Z. (2009). Prediction of shelled shrimp weight by machine vision. *Journal of Zhejiang University Science B*, *10*(8), 589–594. http://dx.doi.org/10.1631/jzus.B0820364, 2.

Renub Research (2023). *Global shrimp market, volume, size, forecast 2023-2028, industry trends, growth, share, outlook, impact of inflation, opportunity company analysis*: *Report*, (p. 280).

Saleh, A., Hasan, M. M., Raadsma, H. W., Khatkar, M. S., Jerry, D. R., & Azghadi, M. R. (2024). Prawn morphometrics and weight estimation from images using deep learning for landmark localization. *Aquacultural Engineering*, *106*, http://dx.doi.org/10.1016/j.aquaeng.2024.102391.

Setiawan, A., Hadiyanto, H., & Widodo, C. E. (2022). Shrimp body weight estimation in aquaculture ponds using morphometric features based on underwater image analysis and machine learning approach. *Revue d'Intelligence Artificielle*, *36*(6), 905–912. http://dx.doi.org/10.18280/ria.360611.

Tacon, A. G. J., Cody, J. J., Conquest, L. D., Divakaran, S., Forster, I. P., & Decamp, O. E. (2002). Effect of culture system on the nutrition and growth performance of Pacific white shrimp Litopenaeusvannamei (Boone) fed different diet. *Aquaculture Nutrition*, *8*(2), 121–137. http://dx.doi.org/10.1046/j.1365-2095.2002.00199.x.

Tacon, A. G. J., Jory, D., & Nunes, A. (2013). Shrimp feed management: issues and perspectives. In M. R. Hasan, & M. B. New (Eds.), *On-farm feeding and feed management in aquaculture*: *FAO Fisheries and Aquaculture Technical Paper No. 583*, (pp. 481–488). FAO.

Tacon, A. G. J., & Metian, M. (2013). Fish Matters: importance of aquatic foods in human nutrition and global food supply. *Reviews in Fisheries Science*, *21*(1), 22–38. http://dx.doi.org/10.1080/10641262.2012.753405.

TNAU Agritech Portal (2022). Shrimps culture. Retrieved from https://agritech.tnau.ac.in/fishery/fish_cul_brackish_shrimps_feed.html. (Accessed 6 May 2022).

Xi, M., Rahman, A., Nguyen, C., Arnold, S., & McColloch, J. (2023). Smart headset, computer vision and machine learning for efficient prawn farm management. *Aquacultural Engineering*, *102*, Article 102339. http://dx.doi.org/10.1016/j.aquaeng.2023.102339.

Zainuddin, Z., Tuluran, J., Achmad, A., Areni, I. S., & Tahir, Z. (2022). The waste detection system of shrimp feeding with a waterproof camera using Yolo algorithm. *Journal of Physics: Conference Series*, *2312*, Article 012083. http://dx.doi.org/10.1088/1742-6596/2312/1/012083.

Zhang, L., Zhou, X., Li, B., Zhang, H., & Duan, Q. (2022). Automatic shrimp counting method using local images and lightweight YOLOv4. *Biosystems Engineering*, *220*, 39–54. http://dx.doi.org/10.1016/j.biosystemseng.2022.05.011.