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IMAGE PROCESSING METHOD TO DETECT THE POSITION OF VANNAMEI SHRIMP IN MUDDY WATERS

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ABSTRACT

One way to help the feeding process vannamei shrimp in ponds that have cloudy surface using constructed with a size of 50 × 50 × 18 cm with a water height in the pond of 7 cm from bottom, where the data in the form of images was obtained from data collection 25 times using a camera is placed at a height of 52 cm above the water surface. The pond's entire surface was captured with one click of the camera. The number of vannamei shrimp used in this study was 7. The method used for data processing is thresholding, in which the threshold value is generated using a histogram-based technique from the image data. This method is employed to distinguish shrimp from non-shrimp regions in the image. From this study, a vannamei shrimp detection technique was developed, producing results in the form of a script that distinguishes vannamei shrimp objects from non-vannamei shrimp. The detection accuracy achieved using the thresholding method in this study is 94.28%. The positions of the shrimp were produced in the form of coordinates as a step to success according to the objectives of this study, which were able to detect positions, in order to help facilitate the process of feeding in ponds. This detection technique could be developed for application on full-scale ponds, utilizing cameras mounted on drones as a tool for detecting vannamei shrimp positions in cloudy pond water. This technology may be adapted to allow targeted feeding of shrimp in ponds, thus maximizing food consumption and minimizing food wastage.

KEYWORDS: Cloudy pond water; Miniature Pond; Image processing; Camera; Vannamei shrimp

INTRODUCTION

As a practical matter, feeding vannamei shrimp becomes difficult because the pond water is cloudy. The debris and wastewater spilled from the culture ponds, which resulted in pollutant loading, with respective values of per tonne production of 21.95 kg total Kjeldahl nitrogen and 1.12 kg total Kjeldahl nitrogen, 18.36 g Pb and 3.63 g Pb, and 31.30 g As and 1.94 (Na nakorn *et al*., 2017) As the results demonstrated that small-scale farms produced the highest pollution loading in wastewater and sediment for the same production. However, the average total suspended particles and ammonia nitrogen of harvesting effluent could not meet the Effluent Standard for Coastal Aquaculture for farms of any size (Na nakorn *et al*., 2017). Unexpected repercussions of shrimp aquaculture intensification include wastewater management issues and other issues arising from the effluent's environmental impact (Iber & Kasan, 2021). According to this study, some behaviors contributing to wastewater formation in shrimp aquaculture

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farming include excessive feed and fertilizer application, metabolite wastes, shrimp mortalities, oil spills from farm machinery, and drug and chemical abuse. It has been noted that the socioeconomic effects of shrimp effluent water discharge have both good and negative aspects (Iber & Kasan, 2021). Shrimp wastewater management expenses are unaffordable due to the high quantities of ammonia, nitrate, nitrite, and organic carbon in the wastewater produced by the new technology system (Mahari *et al*., 2024).

The previous studies have discovered the vision of computers, machine learning, and deep learning methods to estimate the length of the shrimp body (Hashisho *et al*., 2021; Lai *et al*., 2022), the length and shape of shrimp (Setiawan *et al*., 2022), weight of shrimp (Pan *et al*., 2009; Saleh *et al*., 2024; Xi *et al*., 2023), counting of shrimp (Awwaludin *et al*., 2019; Khai *et al*., 2022; Zhang *et al*., 2022: Liu *et al*., 2023; Zhou et al., 2024), and waste feeding (Chirdchoo & Cheunta, 2019; Zainuddin *et al*., 2022).

On the other hand, the murky pond water's condition causes feed to be thrown randomly, which is not accurate at the vannamei shrimp's position. (Xue *et al*., 2021; Liang *et al*., 2025). Throwing that is not right on target will result in the feed falling, causing new problems in the form of disturbed health of the cultivation water. Inaccurate feed throwing can cause the feed to fall outside the intended area, leading to water quality issues that may negatively affect the health of the culture environment

Targeted feeding at the correct position of the shrimp is an interesting potential that needs to be shared thought. With the condition of the cloudy surface, how can we determine the position of the shrimp distribution on the XY plane of the pond

To answer this challenge, we model the surface of the pond with a specific size, then with the help of camera technology capture the position of the shrimp on the surface of the pond in one click (Badgujar *et al*., 2024; Humayun et al., 2024; Ragab *et al*., 2024), covering the surface area of the pond, where the data from the capture of this camera technology is then extracted into information in the form of shrimp position coordinates against the pond bottom area. This extraction process is carried out using image data processing techniques (Yang & Chen, 2024; Awwaludin *et al*., 2020) the results of capturing the position of the shrimp in the form of digital image data, which is processed using data processing software to produce the position of the shrimp in distance units (coordinates) expressed in pixel coordinate units and then converted to centimeter distance units, which describe the position of the shrimp about the surface area of the pond. The important point in data processing here is creating a script (Ahmadi & Salari, 2017).

So that it can be used to extract image data to obtain the actual position against the reference surface of the shrimp pond. To enable the extraction of image data for determining the precise spatial position relative to the reference surface of the shrimp pond.

MATERIALS AND METHODS

Research design

The final objective of this study is to obtain a tool capable of reading the position of vannamei shrimp on the surface area of pond water expressed in position coordinates against the pond area. It begins with creating a brain based on data processing techniques using image processing. At this stage, the focus will be on processing data from input in the form of images obtained from the results of photography in the XY plane, such as the pond in Figure 1.

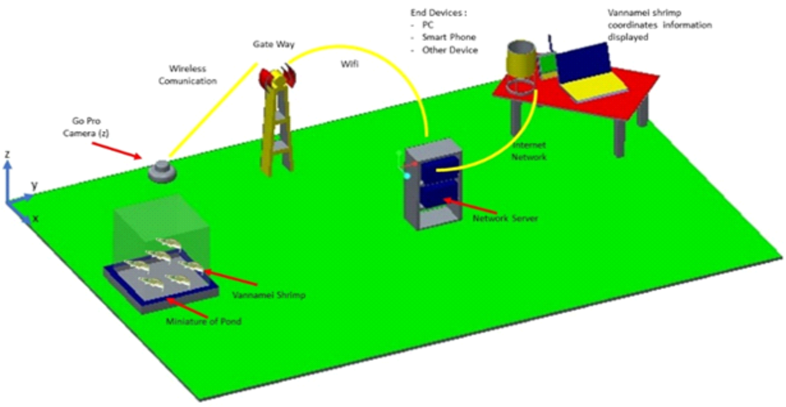

Figure 1. Pattern of design research in research on increasing the efficiency of the feeding process in vannamei shrimp cultivation.

Materials

Basic supporting system

Shrimp, cultured water, miniature pond with water surface size 50 cm x 50 cm, camera, camera support toll.

Basic knowledge system

In this category, the ability to use image data processing software is used so that it can be extracted into vannamei shrimp position information.

The sample used was shrimp at 40 days post-larvae, with 7 shrimp. Data taken as much as 25 data.

Instrument

For image processing data processing using image processing software, the software is used as an instrument in processing input data obtained from the camera. In addition to data processing software, the OPPO A31 camera was used in this study to collect data. The specifications of the OPPO A31 camera include recording at 30 frames per second with a resolution of 1080 pixels. Lighting was optimized to ensure crisp and detailed imagery under indoor environmental conditions.

The camera was placed at a height of 52 cm from the water surface, with a water depth to the bottom of the pond of 7 cm. At the time of data collection, the water was visible up to the bottom of the pond. and the camera positions is perpendicular to the water surface, to take the position of the shrimp on the XY plane. The camera captured the entire water surface in one click.

Methods

Data were collected using an OPPO A31 camera, resulting in a total of 25 images. Each image was captured at 5-minute intervals. This process was conducted as part of the data collection procedure.

1. Data pre-processing technique

Before proceeding with detection and classification tasks, several pre-processing steps were applied to enhance image quality and standardize the data:

a. Image Resizing: All images were resized to a fixed resolution to ensure uniformity for all input data image. All images were resized to a standardized resolution in order to maintain consistency across the entire dataset, ensuring that each input image adheres to the same dimensional requirements for optimal processing and analysis;

b. Color Correction and Normalization: Adjustments to brightness, contrast, for all input data image. To improve the overall quality and consistency of the dataset, brightness and contrast adjustments were systematically applied to each input image prior to further processing;

c. Color Conversion: RGB images were converted to grayscale to simplify processing for all input data image. All RGB images were converted to grayscale to reduce computational complexity and simplify the image processing tasks, ensuring uniformity and efficiency in handling all input data;

d. Thresholding: with input value of thresholding 175 was used to separate the shrimp from the background for all input data image. A thresholding value of 175 was applied uniformly across all input images to effectively separate the shrimp objects from the background, enhancing object visibility and facilitating accurate segmentation during the preprocessing stage. To obtain the thresholding value, a histogram of the grayscale image was generated. As shown in the graph, the histogram T value corresponds to the peak of the histogram, with a value of 175. This is illustrated in Figure 2.

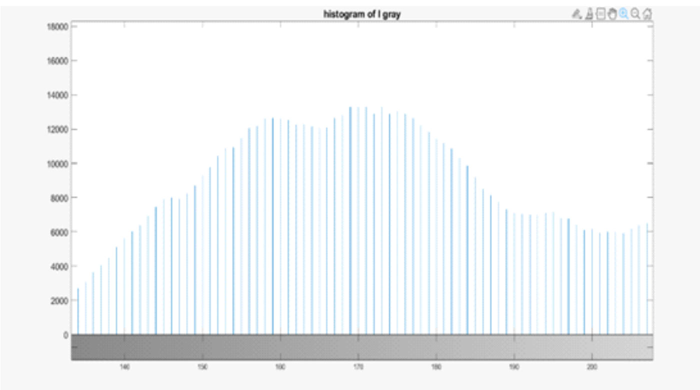

Figure 2. The histogram of the grayscale image, from which the thresholding value was obtained, shows a peak at a value of 175.

2. Feature extraction

Feature extraction was performed to identify unique visual cues of the vannamei shrimp that distinguish them from the pond background. This step is critical for improving model performance and includes:

a. Edge Detection: Using algorithms like Canny to highlight shrimp outlines. The Canny edge detection algorithm was utilized to enhance the visibility of shrimp contours by highlighting their edges, thereby facilitating more precise segmentation and feature extraction in the image processing workflow;

b. Color and Texture Analysis: Histogram-based color extraction technique are used to extract shrimp-specific texture features. To effectively extract texture features unique to the shrimp, histogram-based color extraction methods were applied, facilitating detailed characterization of color distribution patterns critical for precise image classification and recognition;

c. Centroid & Orientation: Used to detect positioning and alignment. The technique was utilized to detect and assess the spatial positioning and alignment of elements, which is critical for maintaining consistency and accuracy in subsequent processing steps;

d. Use command: stats = regionprops (binary Image, 'Area', 'Centroid', 'BoundingBox' to define the vannamei shrimp. Using the regionprops function on the binary image, key features including 'Area', 'Centroid', and 'BoundingBox' were extracted to accurately identify and delineate the Vannamei shrimp in the image.

3. Object detection and classification

Object detection models were used to locate and identify shrimp within the images. All input image passed to detection model such as Figure 3. The flowchart below use to detection the vannamei shrimp with the background. The output from the flowchart are Centroid and coordinate of The vannamei shrimps.

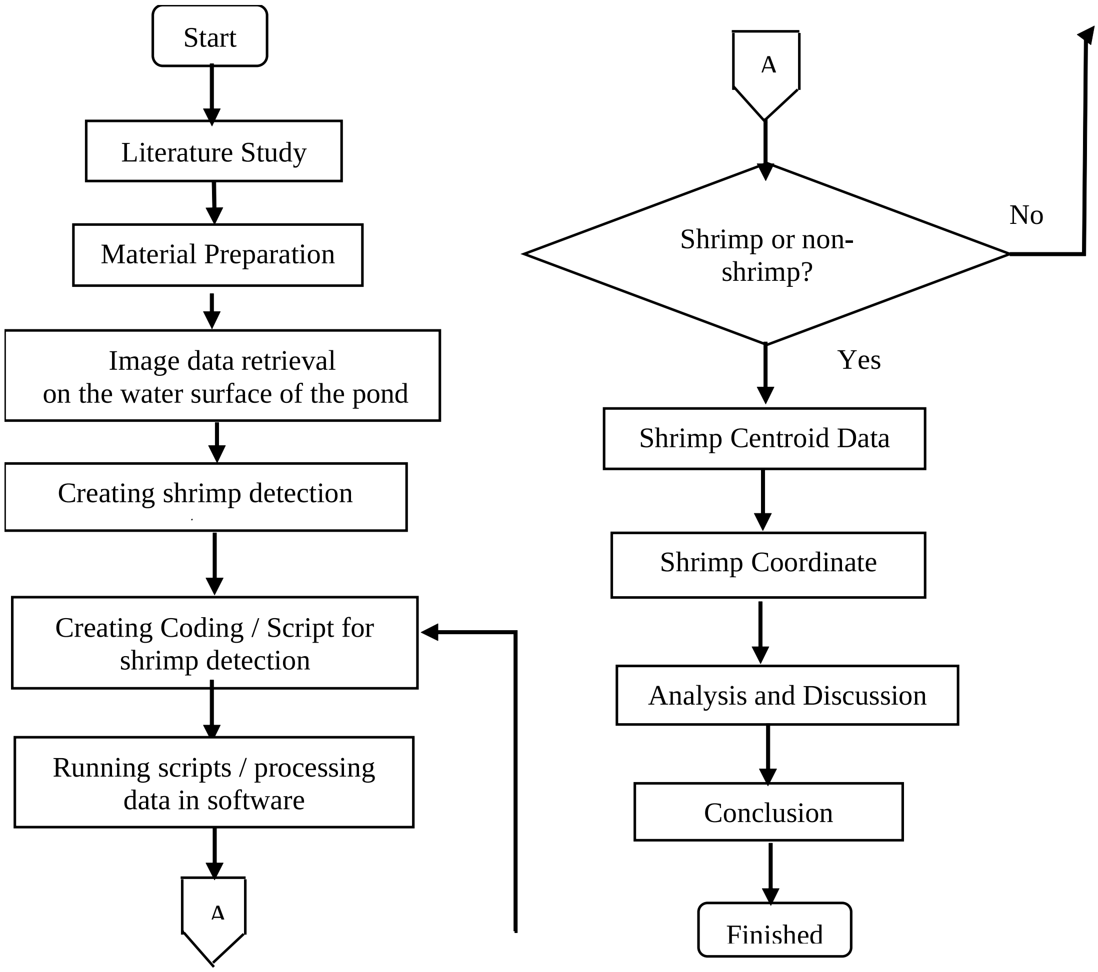

Figure 3. Flowchart of research on determining vannamei shrimp coordinates using image processing.

4. Validation and accuracy assessment

In this study, the concept of Ground Truth Comparison is utilized to evaluate the accuracy of the detection result. Manual counting of vannamei shrimp in each image for validation (7 per image expected). Each image was manually examined to count the number of vannamei shrimp present, with an expected count of approximately seven vannamei shrimp per image, to validate the accuracy of the detection process. Detection accuracy was calculated using the formula1:

accuracy = (correct Detections / total Shrimp) * 100% ……..(1)

where ‘correct Detections’ represents the number of vannamei shrimp accurately identified by the model, and ‘total Vannamei Shrimp’ denotes the total number of vannamei shrimp present in the ground truth annotations.

5. Tools and library

In the image processing stage, MATLAB software was used, specifically utilizing the Image Processing Toolbox. Several functions were applied, including *imread*, *rgb2gray*, *imbinarize*, *regionprops*, *bwlabel*, and *imshow*. The complete process can be seen in the script (Table 1) used for the Vannamei shrimp detection model, as presented below

To get the coordinate position of vannamei shrimp in the miniature pond model above with 25 data, the following script is used, see Table 1, where the central concept of this script is to be able to distinguish between vannamei shrimp objects and non-vannamei shrimp objects. The thresholding value method of 175 is used as a differentiator between vannamei shrimp and non-vannamei shrimp, then complement operations and morphological operations are carried out as segmentation steps. Labeling vannamei shrimp, extracting the centroid value of each object detected as a vannamei shrimp object, then from the centroid value, it is converted into a cm unit value by multiplying the pixel value of the centroid by the unit of the object whose measurement value is already known in cm units, which have also been photographed in the 25th image data, the last is the coordinate extraction result in cm units from each object detected as vannamei shrimp.

Table 1. The script for image processing data processing uses Matlab with input in the form of a digital image to obtain the coordinates

```
[file]=uigetfile('*.jpg');
Img1 = imread(file);
Img2 = im2double(Img1);
Img3 =(Img2-
min(min(Img2)))./((max(max(Img2))-
min(min(Img2))));
Img4 = 255*Img3;
Img5 =uint8(Img4);
Img6=im2gray(Img5);
Img7=medfilt2(Img6);
[row, colum] = size(Img7);
T=175;
for im=1:row
   for j=1:colum
      if(Img7(im,j)<T)
         biner(im,j)=0;
      else
         biner(im,j)=1;
      end
   end
end
figure, imshow(imbinarize(biner));
L= imcomplement(imbinarize(biner));
figure, imshow(L);
M = imfill(L,'holes');
N = bwareaopen(M,23000);
[label,n]= bwlabel(N);
figure, imshow(label)
figure,imshow(Img5)
hold on
[c,~]= bwboundaries(label,'no holes’);
for k = 1: length (c)
   boundary = c{k};
   plot(boundary(:,2), boundary(:,1), 'r',
'LineWidth',3)
end
```

```
stats = regionprops(label, 'Area', 'Centroid',
'BoundingBox');
for k = 1:n
   luas_px=stats(k).Area;
   luas_cm2= round(((5/280)*(5/280))*(stats(k).Area));
   props=regionprops("table", label, "Centroid");
   centroid=stats(k).Centroid;
   koordinat=table2array(props);

koordinatdalamcm=round((1/280)*(5)*(stats(k).Centroid));
   bbox = cat(1,stats.BoundingBox);
   text(centroid(1),centroid(2)+40,num2str(k),'Color','y', ...
      'FontSize',10, 'font-weight', 'bold')
   text(centroid(1)+100,centroid(2)+50,num2str(luas_px),
...
      'Color', 'b', 'FontSize',8, 'FontWeight', 'bold')

text(centroid(1)+150,centroid(2)+100,num2str(luas_cm2),
...
      'Color', 'r',' FontSize',8, 'FontWeight', 'bold')
   text(centroid(1)-
100,centroid(2)+70,num2str(koordinatdalamcm), ...
      'Color', 'g', 'FontSize',10, 'FontWeight', 'bold')
   h = rectangle('Position', bbox(k,:),'LineWidth',1);
end
hold off
info=regionprops("table", label, "Area");
luas_px=table2array(info);
luas_cm2= (5/280)*(5/280)*(luas_px);
props=regionprops("table", label, "Centroid");
koordinat=table2array(props);
koordinatdalamcm=(1/280)*(5)*koordinat;
results.Img1     = Img1;
results.Img5     = Img5;
results.stats = stats;
result.props = props;
result. bbox = bbox;
```

The coordinates are obtained by extracting centroid data from 25 data, where each data contains 7 shrimp, extracting the centroid value into a distance coordinate value with formula 2:

Coordinate = (1/280)*(5cm)*(Centroid) …………(2)

To obtain the coordinate positions of shrimp on the water surface, a reference object with known dimensions was utilized. This object was placed within the pond area and captured simultaneously with the shrimp in a single image frame. The presence of this reference object enables the conversion of pixel-based measurements into real-world spatial coordinates. The dimensions of the reference object are shown in Figure 4.

RESULTS AND DISCUSSION

Data input at the image processing

Image data were acquired from a miniature model of a vannamei shrimp pond with dimensions of 50 cm × 50 cm. A camera was mounted vertically above the water surface (along the XY plane) to ensure complete coverage of the pond area within a single frame. The experimental setup was designed to capture the spatial positions of all seven vannamei shrimp present in the pond at each time point. A total of 25 images were captured at consistent time intervals, with each image fully encompassing the pond's surface. These images constitute the raw dataset for subsequent analysis using image processing techniques. Figure 5 illustrates the sequence of acquired image data.

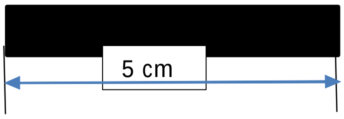

Figure 4. Dimensions of the object to use convert the coordinates vannamei shrimps.

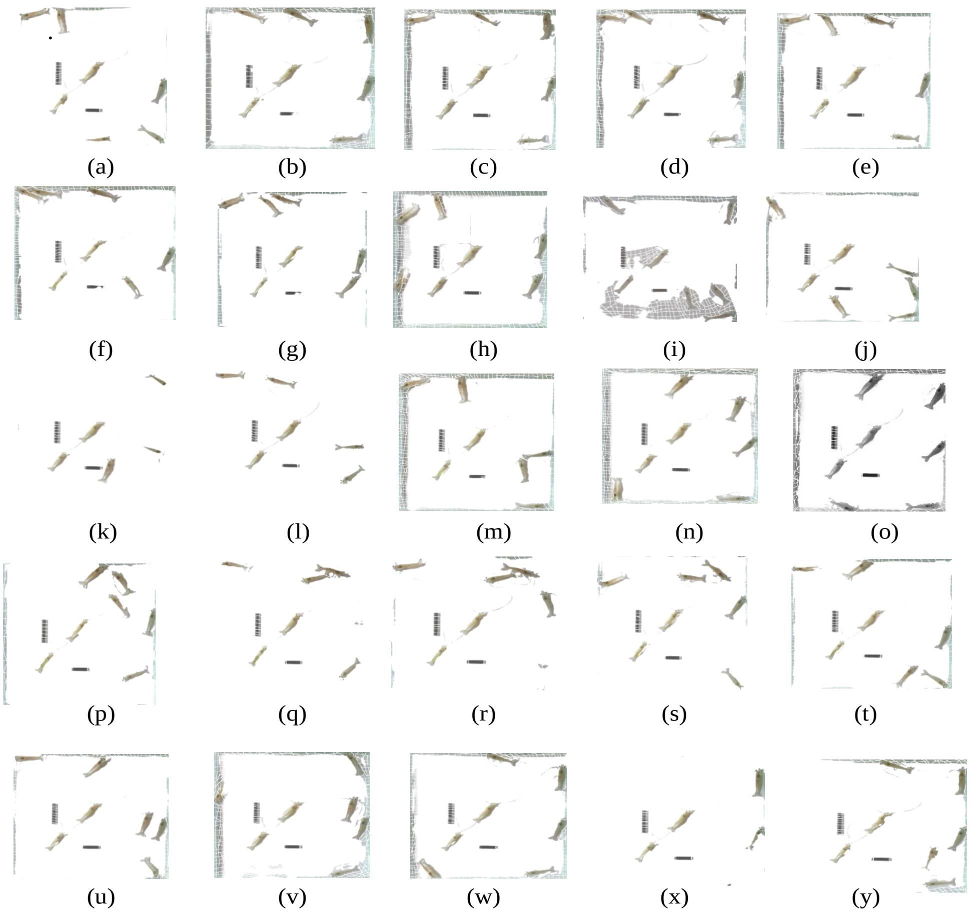

Figure 5. Raw data used as input for image processing, taken from a miniature shrimp pond measuring 50 cm x 50 cm, containing 7 vannamei shrimp. The images were captured at 5-minute intervals between each frame: (a) data 1; (b) data 2; (c) data 3; (d) data 4; (e) data 5; (f) data 6; (g) data 7; (h) data 8; (i) data 9; (j) data 10; (k) data 11; (l) data 12; (m) data 13; (n) data 14; (o) data 15; (p) data 16; (q) data 17; (r) data 18; (s) data 19; (t) data 20; (u) data 21; (v) data 22; (w) data 23; (x) data 24; (y) data 25.

Results of processing using images

The visual results of the data processing, executed using a predefined script, yielded 25 processed images corresponding to the original dataset. In each image, objects identified as vannamei shrimp were successfully detected and are highlighted using bounding boxes. For each detected object, the centroid coordinates were extracted and mapped within the spatial reference of the pond area (50 cm × 50 cm). This positional information enables precise localization of the shrimp within the pond surface. The complete set of visual outputs, including bounding boxes and centroid coordinate annotations, is presented in Figure 7.

Figure 6. Differentiation of the results of the thresholding process T = 175 in distinguishing between objects that are vannamei shrimp and non-vannamei shrimp objects.

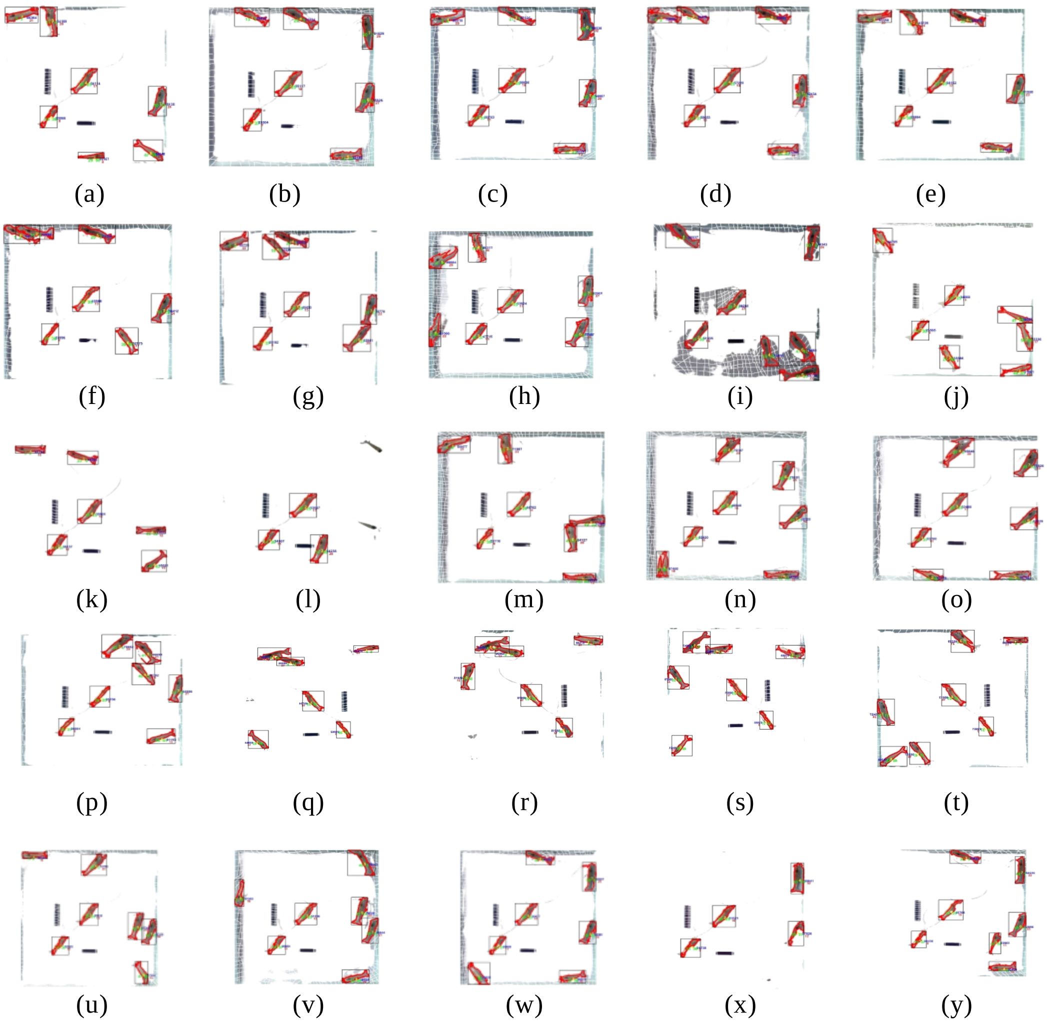

Figure 7. Visual results of data processing for all images: (a) data 1; (b) data 2; (c) data 3; (d) data 4; (e) data 5; (f) data 6; (g) data 7; (h) data 8; (i) data 9; (j) data 10; (k) data 11; (l) data 12; (m) data 13; (n) data 14; (o) data 15; (p) data 16; (q) data 17; (r) data 18; (s) data 19; (t) data 20; (u) data 21; (v) data 22; (w) data 23; (x) data 24; (y) data 25.

The coordinates presented in Table 2 were obtained by converting the centroid positions of detected objects into spatial coordinates in centimeters. The table provides detailed information on the centroid positions extracted from the 25 processed images using image processing techniques. Each detected vannamei shrimp is represented by its corresponding centroid coordinates. The complete set of centroid data for all 25 images is comprehensively presented in Table 2

Table 2. Shrimp centroids extracted from image processing in 25 observation image data (pixels)

	Name of file	Udang 1		Udang 2		Udang 3		Udang 4		Udang 5		Udang 6		Udang 7	
		x	y	x	y	x	y	x	y	x	y	x	y	x	y
1	data 1	296,52	149,92	825,55	2043,35	842,43	217,94	1450,91	1388,32	1611,29	2814,46	2628,89	2717,22	2800,52	1780,25
2	data 2	741,16	142,15	774,34	2098,10	1420,64	1418,24	1596,72	165,63	2430,89	2760,71	2788,69	1685,82	2812,44	428,74
3	data 3	286,97	207,82	853,05	2084,29	1497,14	158,40	1474,81	1410,24	2477,00	2753,76	2762,09	352,75	2814,98	1673,13
4	data 4	227,80	181,02	807,08	142,41	859,76	2057,46	1467,65	1397,98	2245,83	156,66	2467,10	2731,77	2798,37	1609,29
5	data 5	298,45	159,62	856,67	2041,41	995,36	215,97	1486,26	1379,39	1939,81	166,81	2480,51	2682,25	2838,59	1554,59
6	data 6	276,19	180,32	560,98	147,22	810,42	2128,37	1460,35	1425,09	1645,18	176,62	2189,13	2241,64	2830,45	1619,37
7	data 7	273,04	226,77	827,67	2094,31	1067,24	311,49	1357,21	168,58	1451,89	1421,08	2616,54	2056,52	2842,17	1500,67
8	data 8	216,89	583,51	96,22	2035,67	879,10	2097,10	882,64	283,38	1503,70	1422,36	2741,30	2059,68	2894,96	1214,49
9	data 9	510,22	207,06	776,25	2138,97	1416,68	1520,10	2032,70	2467,31	2631,76	2850,01	2629,04	2370,35	2815,28	343,68
10	data 10	172,36	307,46	871,62	2018,60	1377,71	2562,24	1497,66	1378,58	2637,71	1809,95	2661,93	2828,09	2798,85	2193,36
11	data 11	801,62	2031,18	1430,80	1377,33	1723,29	2226,41								
12	data 12	288,96	163,65	818,03	2057,09	1288,44	312,77	1444,59	1402,96	2591,43	1779,93	2631,98	2434,30		
13	data 13	245,39	245,97	836,74	2114,90	1225,47	294,32	1478,47	1450,44	2579,37	2888,21	2393,95	2094,20	2716,61	1767,84
14	data 14	314,17	2724,48	868,55	2094,58	1479,95	1447,44	1511,45	330,51	2531,85	2898,11	2560,53	878,92	2756,87	1724,55
15	data 15	852,58	2075,07	1026,98	2889,71	1473,56	1418,67	1521,06	269,22	2508,36	2881,21	2748,55	1711,78	2758,83	568,44
16	data 16	812,73	2058,68	1454,61	1397,88	1786,66	222,22	2255,05	856,86	2313,03	395,91	2568,89	2302,40	2870,17	1221,78
17	data 17	289,50	175,97	778,00	2103,86	1437,04	1427,82	1866,61	474,96	2223,73	326,57	2567,26	2364,71		
18	data 18	292,74	214,34	792,79	2113,82	1483,40	1404,78	1921,10	454,65	2283,45	319,59	2772,97	974,71		
19	data 19	245,78	562,47	836,02	2072,19	1480,03	1399,54	1907,99	477,69	2402,95	343,09	2706,44	2637,32	2804,96	1099,47
20	data 20	224,75	229,03	815,62	2078,43	1294,33	199,83	1468,24	1399,96	2137,37	2619,24	2665,78	2733,44	2829,95	1765,59
21	data21	259,86	108,83	842,02	2040,91	1476,81	1367,47	1597,05	298,09	2502,26	1636,97	2623,88	2670,50	2791,49	1776,19
22	data 22	102,81	1010,82	869,54	2053,87	1472,56	1394,76	2485,78	2788,34	2660,65	257,94	2604,10	1327,34	2817,69	1755,08
23	data23	377,98	2746,41	817,24	2066,44	1437,10	1396,41	1696,77	139,19	2418,95	2786,45	2777,98	1798,42	2817,01	575,55
24	data24	837,03	2021,20	1440,41	1383,01	2799,51	1713,54	2836,10	581,51						
25	data25	749,58	2086,49	1374,56	1414,63	1658,30	149,57	2413,96	2749,03	2265,69	2130,14	2741,60	1752,92	2771,09	491,34

Table 3 presents the coordinate data extracted from 25 processed images using image processing techniques. Each detected vannamei shrimp is represented by its corresponding spatial coordinates, which were obtained by converting centroid positions using Equation (1). This conversion transforms pixel-based centroid locations into real-world coordinates (in centimeters) within the pond area. The complete set of coordinate information for all 25 images is provided in Table 3. A graphical representation of the coordinate distribution from all 25 images is illustrated in Figure 8.

Table 3. Shrimp coordinates obtained from image processing in 25 observation image data (cm)

	Name of file	Udang 1		Udang 2		Udang 3		Udang 4		Udang 5		Udang 6		Udang 7	
		x	y	x	y	x	y	x	y	x	y	x	y	x	y
1	data1	5,30	2,68	14,74	36,49	15,04	3,89	25,91	24,79	28,77	50,26	46,94	48,52	50,01	31,79
2	data2	13,23	2,54	13,83	37,47	25,37	25,33	28,51	2,96	43,41	49,30	49,80	30,10	50,22	7,66
3	data3	5,12	3,71	15,23	37,22	26,73	2,83	26,34	25,18	44,23	49,17	49,32	6,30	50,27	29,88
4	data4	4,07	3,23	14,41	2,54	15,35	36,74	26,21	24,96	40,10	2,80	44,06	48,78	49,97	28,74
5	data5	5,33	2,85	15,30	36,45	17,77	3,86	26,54	24,63	34,64	2,98	44,29	47,90	50,69	27,76
6	data6	4,93	3,22	10,02	2,63	14,47	38,01	26,08	25,45	29,38	3,15	39,09	40,03	50,54	28,92
7	data7	4,88	4,05	14,78	37,40	19,06	5,56	24,24	3,01	25,93	25,38	46,72	36,72	50,75	26,80
8	data8	3,87	10,42	1,72	36,35	15,70	37,45	15,76	5,06	26,85	25,40	48,95	36,78	51,70	21,69
9	data9	9,11	3,70	13,86	38,20	25,30	27,14	36,30	44,06	47,00	50,89	46,95	42,33	50,27	6,14
10	data10	3,08	5,49	15,56	36,05	24,60	45,75	26,74	24,62	47,10	32,32	47,53	50,50	49,98	39,17
11	data11	14,31	36,27	25,55	24,60	30,77	39,76								
12	data12	5,16	2,92	14,61	36,73	23,01	5,59	25,80	25,05	46,28	31,78	47,00	43,47		
13	data13	4,38	4,39	14,94	37,77	21,88	5,26	26,40	25,90	46,06	51,58	42,75	37,40	48,51	31,57
14	data14	5,61	48,65	15,51	37,40	26,43	25,85	26,99	5,90	45,21	51,75	45,72	15,69	49,23	30,80
15	data15	15,22	37,05	18,34	51,60	26,31	25,33	27,16	4,81	44,79	51,45	49,08	30,57	49,26	10,15
16	data16	14,51	36,76	25,98	24,96	31,90	3,97	40,27	15,30	41,30	7,07	45,87	41,11	51,25	21,82
17	data17	5,17	3,14	13,89	37,57	25,66	25,50	33,33	8,48	39,71	5,83	45,84	42,23		
18	data18	5,23	3,83	14,16	37,75	26,49	25,09	34,31	8,12	40,78	5,71	49,52	17,41		
19	data19	4,39	10,04	14,93	37,00	26,43	24,99	34,07	8,53	42,91	6,13	48,33	47,10	50,09	19,63
20	data20	4,01	4,09	14,56	37,11	23,11	3,57	26,22	25,00	38,17	46,77	47,60	48,81	50,53	31,53
21	data21	4,64	1,94	15,04	36,44	26,37	24,42	28,52	5,32	44,68	29,23	46,85	47,69	49,85	31,72
22	data22	1,84	18,05	15,53	36,68	26,30	24,91	44,39	49,79	47,51	4,61	46,50	23,70	50,32	31,34
23	data23	6,75	49,04	14,59	36,90	25,66	24,94	30,30	2,49	43,20	49,76	49,61	32,11	50,30	10,28
24	data24	14,95	10,38	25,72	36,09	49,99	24,70	50,64	30,60						
25	data25	13,39	37,26	24,55	25,26	29,61	2,67	43,11	49,09	40,46	38,04	48,96	31,30	49,48	8,77

Then, after the model enters the input data from the data collection results, it is processed using image processing to obtain extraction in the form of coordinates in distance units, where these coordinates are against the pond area, XY.

The implemented script applies a thresholding value of 175 to differentiate vannamei shrimp objects from the background and non-shrimp elements within the image. This thresholding method was consistently applied to all 25 image datasets. An example of its application is illustrated in Figure 6. In the resulting binary image, pixels corresponding to detected vannamei shrimp appear in white, while non-shrimp areas are represented in black. Based on this process, seven distinct shrimp objects were successfully identified, which is consistent with the actual number of vannamei shrimp placed in the miniature pond model.

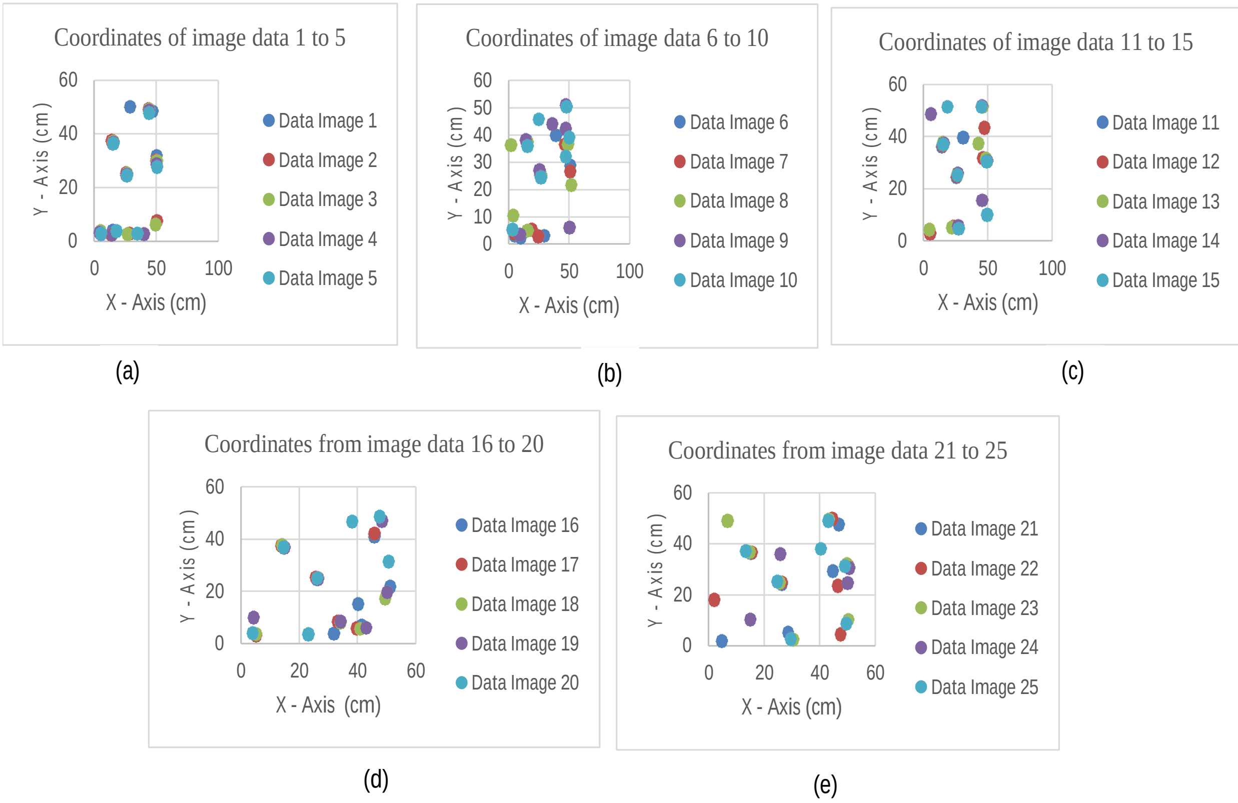

Figure 8. A graphical representation of the coordinate distribution from all 25 images: (a) Coordinates of image data 1 until 5; (b) Coordinates of image data 6 until 10; (c) Coordinates of image data 11 until 15; (d) Coordinates of image data 16 until 20; (e) Coordinates of image data 21 until 25.

Table 4. Information of validation about detection of shrimps vannamei at 25 data

Data input	Real number of shrimp	Detected amount	Validity (%)	Data input	Jumlah Real number of shrimp	Detected amount	Validitas (%)
Data 1	7	7	100	Data 14	7	7	100
Dara 2	7	7	100	Data 15	7	7	100
Data 3	7	7	100	Data 16	7	7	100
Data 4	7	7	100	Data 17	7	6	85,7
Data 5	7	7	100	Data 18	7	6	85,7
Data 6	7	7	100	Data 19	7	7	100
Data 7	7	7	100	Data 20	7	7	100
Data 8	7	7	100	Data 21	7	7	100
Data 9	7	7	100	Data 22	7	7	100
Data 10	7	7	100	Data 23	7	7	100
Data 11	7	3	42,8	Data 24	7	4	57,1
Data 12	7	6	85,7	Data 25	7	7	100
Data 13	7	7	100		Average		94,28

In this study, the concept of Ground Truth Comparison was employed to evaluate the accuracy of the detection results. To establish ground truth, each image was manually examined, and the number of vannamei shrimp present was counted, with an expected count of approximately seven shrimp per image. This manual counting served as a validation benchmark for the automated detection process. Detection accuracy was calculated using a predefined formula. Based on the 25 datasets presented in Table 4, the object detection process achieved a validity rate of 100% in 20 datasets, 85.7% in 3 datasets, 57.1% in 1 dataset, and 42.8% in another dataset. Overall, the implemented detection script attained an average validity of 94.28%.

Correlation analysis between the spatial distribution of shrimp, obtained through image processing techniques, and daily feeding patterns represents a critical approach for optimizing data-driven shrimp aquaculture management. By utilizing images captured periodically using cameras or surface drones, the positional coordinates of shrimp within a pond unit can be extracted and modeled to represent the spatial distribution of the shrimp population. This spatial data can then be correlated with feeding information—such as feed quantity, timing, frequency, and spatial application—to evaluate the efficiency of feed dispersion in relation to the actual distribution of shrimp within the pond. However, it should be noted that the correlation analysis itself is not explored in depth within the scope of this paper.

CONCLUSION

Based on the results obtained from 25 observations, the system achieved a validity rate of 94.28%. This level of accuracy demonstrates the system's potential for integration into a coordinate detection tool aimed at enhancing the efficiency of the feeding process, ensuring that feed is delivered precisely to the shrimp's location on the turbid pond surface. Considering these findings, the system developed in this study is recommended for application in locating shrimp positions within aquaculture ponds. The technique of determining the position of vannamei shrimp on the pond surface through image processing offers a practical foundation for developing a shrimp position detection tool on the pond's XY plane, which can further support the automation of feeding systems.

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