AN INTEGRATED FMEA–QFD AND IMAGE PROCESSING APPROACH FOR OVARIAN MATURITY CLASSIFICATION IN CRAB PROCESSING SYSTEMS

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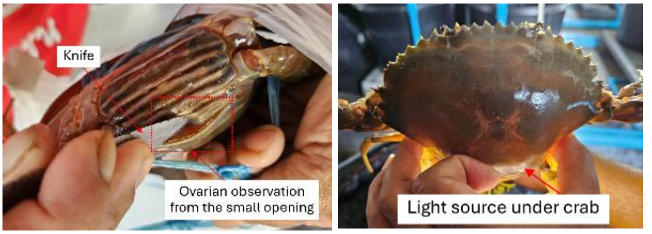
ABSTRACT: Mud crabs are high-value products in Thailand's seafood industry, though ovarian maturity significantly influences market price. In current production practice, ovarian maturity assessment relies on invasive and expert-dependent methods, resulting in variability, inaccuracy, and operational inefficiency. These constraints limit process standardization and industrial scalability. Therefore, this study aimed to develop a non-invasive crab ovarian maturity classification process to enhance assessment reliability, improve process consistency, and replace expert-dependent evaluation without causing harm to the crabs. The first step involved creating image acquisition equipment based on Failure Modes and Effects Analysis (FMEA) and Quality Function Deployment (QFD) principles. Subsequently, ovarian maturity stages were automatically classified using an image processing technique. The results of the integrated FMEA-QFD and image processing process demonstrated that ovarian maturity can be classified into four stages: developing, early maturing, late maturing, and fully maturing. The main categorization parameter was the ratio of the ovarian area to the carapace area, which increased with crab maturation. The ratio of full maturation was at least 60%, equivalent to premium market value. The approach attained an accuracy of 90% in comparison to expert evaluation. This innovative, non-invasive process for crab ovarian maturity classification can improve consistency and quality control, eliminate specialized workers, and ensure the crabs remain unharmed.

KEYWORDS: *Ovarian crabs; Non-invasive assessment; Failure modes and effects analysis; Quality function deployment; Image processing*

1.0 INTRODUCTION

Thailand's crab industry contributes significantly to the national economy, generating over USD 61 million in export revenue in 2021 [1]. Mud crabs (Scylla genus) are the most prevalent farmed species, accounting for over 95% of national production. In 2023, the production volume of mud crab farming reached 3,536.19 tons, marking a 22.60% increase from 2022, supported by the operation of 5,176 crab farms [2]. Female crabs with developed ovaries are highly preferred for consumption because of their superior flavor and high nutritional value. As a result, they consistently achieve premium market prices compared to male crabs, significantly influencing profitability and value grading within the industry [3]. In mud crabs, conventional assessments of ovarian maturity depend on invasive techniques, including ovary excision, carapace dissection, and subsequent histological or biochemical examinations [4,5]. These methods are difficult, time-consuming, and inappropriate for large-scale industrial applications [6]. In commercial practice, intrusive evaluation employing a pointed device that opens the carapace (Figure 1(a)) causes injuries and may result in false stage classification due to the limited observation area. These limitations highlight the need for a simple, non-invasive, and accurate evaluation system capable of delivering reliable, repeatable, and industrially scalable ovarian maturity classification while preserving product quality [6].



(a) (b)

Figure 1: Ovarian maturity assessment: (a) dissection with a pointed knife, (b) light transmission

Figure 1(b) illustrates a non-destructive visual inspection technique utilizing light transmission, which is significantly dependent on expert assessment. The absence of controlled imaging conditions limits visibility to the ovary region, leading to subjective interpretation and inconsistent classification results. Recent advances in computer vision (CV) provide a non-destructive approach for automated assessment and classification [7], enabling objective ovarian evaluation and maturity stage determination [6]. Candling, an optical light transmission technique, is widely used for internal quality evaluation of eggs to detect defects or monitor embryo development [8-9]. This technique has been integrated with image processing to improve inspection accuracy and speed. CV has also been combined with X-ray computed tomography for internal inspection, such as seeds, achieving high classification accuracy [10–12]. However, applications of CV in crab assessment remain limited, with most studies focusing on external evaluations, such as parasite detection, growth analysis [13], and molting stage prediction [14].

Quality Function Deployment (QFD), which transforms customer needs into engineering specifications, is a successful method for directing product and process design to enhance ovarian evaluation procedures in accordance with user expectations [15–16]. QFD has been incorporated with decision-making methodologies, including Failure Modes and Effects Analysis (FMEA) [17], Fuzzy Analytic Network Process (Fuzzy-ANP) [18], and Analytic Hierarchy Process (AHP) [19] to improve design resilience by merging systematic risk assessment with the capacity to represent intricate interdependencies among criteria. The integration of QFD and FMEA facilitates the systematic incorporation of technical, organizational, and human factors. QFD converts customer requirements into technical specifications, whereas FMEA systematically identifies and mitigates potential failure modes, resulting in enhanced reliability, reduced development time, and lower operational costs [18]. Based on the literature review, non-destructive internal assessment of crab ovarian development remains limited and uncertain. Therefore, this study proposes a non-invasive classification method for crab ovarian maturity that integrates FMEA and QFD with image processing techniques. FMEA and QFD were employed to guide the design of the image acquisition equipment. Image processing, an effective tool for feature extraction [20], was integrated using computer vision (CV) techniques to identify key variables for the automated classification of ovarian development stages, eliminating reliance on expert judgment. This non-invasive process enhances classification consistency, strengthens quality control, and enables scalable industrial implementation while preserving crabs and reducing dependence on specialized labor.

2.0 METHODOLOGY

The methodology to develop a non-invasive classification process for crab ovarian maturity, as illustrated in Figure 2, comprises three main steps: image acquisition, image processing, and ovarian maturity classification. The method starts with the design of ovarian imaging acquisition equipment based on FMEA and QFD techniques. FMEA was utilized to detect and evaluate potential design and implementation failures of previous assessment processes, whereas QFD was employed to convert user requirements into technical specifications. The acquired images were further analyzed to identify important features suggestive of ovarian development stages. These features were then investigated to generate classification criteria for identifying stages of ovarian maturity. A total of 90 crabs covering all ovarian maturity stages were imaged using the developed image acquisition equipment. The image data was divided into a training set (80 images) for feature extraction and the establishment of ovary to carapace ratio-based classification criteria. The remaining 10 images were used for validation with expert assessment regarding classification accuracy. The details of every step are explained in the subsequent subsections.

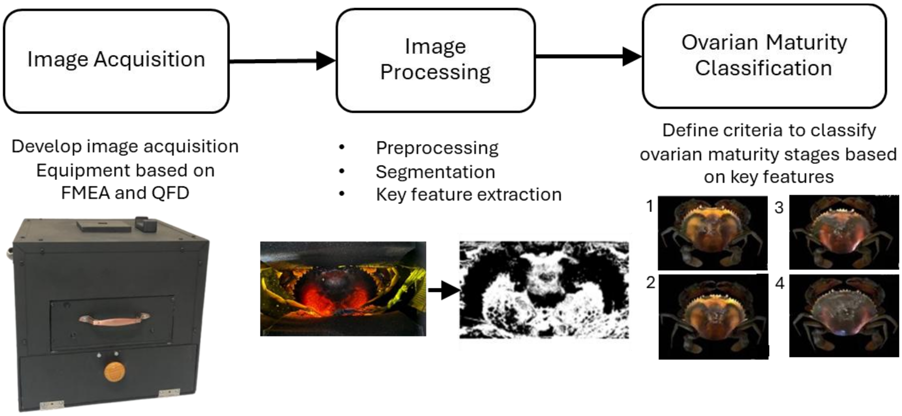


Figure 2: Methodology framework of a non-invasive ovarian classification process

2.1 Integration of FMEA and QFD for the Development of Image Acquisition Equipment

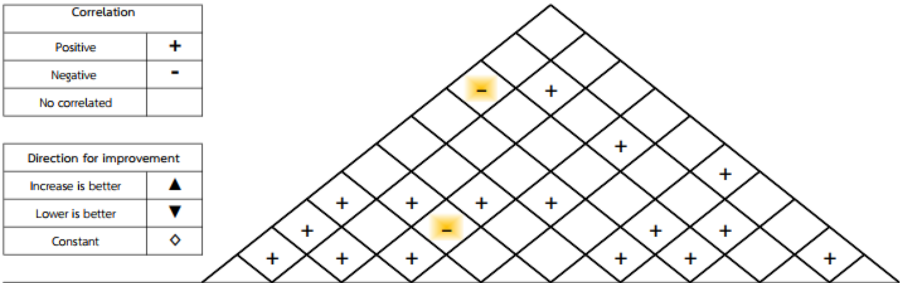
FMEA and QFD analyses were conducted to prioritize the key characteristics of the image acquisition equipment according to user requirements obtained from structured interviews with six crab researchers and four crab farmers. FMEA was applied to investigate usability issues and evaluate the risks associated with previous processes using the Risk Priority Number (*RPN*), calculated from three factors including severity (*S*), occurrence (*O*), and detection (*D*), as shown in Equation (1) [17]. Each factor was rated on a scale from 1 to 10, with higher values indicating greater impact, as detailed in Table 1. The analysis revealed that the electrical system posed the highest risk, with an RPN of 147, followed by the crab holding device and equipment size. Moderate-risk issues included the crab entry/exit channel, equipment materials, light source, and bulb position, as well as bulb color and power. An additional adaptable power supply system (e.g., AC/DC compatibility) was one of the design improvements suggested to reduce the risks.

$$RPN = S \; x \; O \; x \; D \tag{1}$$

The recommended actions from the FMEA analysis (Table 1) were subsequently correlated to the technical specifications of QFD analysis using the House of Quality (HOQ) matrix. The HOQ was employed to systematically convert user requirements into prioritized technical specifications for the design of the image acquisition equipment [21].

Table 1: FMEA for ovarian image-capturing equipment

Function	Failure Mode	Effect	Cause	S	O	D	RPN	Alternative Action
Light Source	Bulb position	Incorrect assessment of crab ovarian stages	Inability to clearly illuminate the crab ovary	6	6	2	72	Adjust the bulb position to be under the crab
	Bulb color and power	Incorrect assessment of crab ovarian stages	Inability to clearly illuminate the crab ovary	4	3	5	60	Adjust bulb color and power to provide more illumination
Equipment	Equipment material	Handle with care during use; cleaning is difficult.	Not durable and difficult to clean	6	5	3	90	Change material
	Equipment Size	Unable to fit the entire large crab	Size is insufficient for the large crabs	6	7	4	128	Change box size
	Crab holding device	Not suitable for large crabs	Restraint size is insufficient for large crabs	7	6	3	126	Change restraint size to fit all crab sizes
	Crab entry/exit channel	Inconvenient for users	Unable to stay open on its own	6	6	3	108	Change the opening mechanism
Power source	Electrical system	Inconvenient for users	Battery replacement is difficult	7	7	3	147	Offer various AC and DC power source options



	Technical Specification / Customer Requirement	Technical Specification (j)	Equipment weight	Equipment size	Equipement Material	Equipement shape	Equipement holder	Light source	Light placement	Power supply	Crab holding device	Camera mounting device
	Direction of Improvement		▼	▼	▲	◇	◇	▲	◇	◇	▲	◇
	Customer Requirement (i)	IMP										
Function	Clear imaging	5		1	3			9			9	9
	Stable crab positioning part	5			9	3					9	3
	Under-crab light positioning	5						9	9		9	3
	Crab ovarian light illumination	5						9	9	3	9	9
	Dual-mode power (AC/DC)	4						3	1	9		
Appearance	Suitable size	4	9	9	3	3	3				9	1
	Box shape	4	9	3	3	9	9		1		9	3
Characteristics	Usability	4		9		3		9	3		9	9
	Durability	2			9		3					
	Portability	2	9	9	9	3	9			1		
	Cleanability	3			9		3				9	3
	Maintainability	3			9				9	9	3	3
	Absolute Technical Requirement Importance		90	107	174	81	81	183	137	84	324	168
	Relative Technical Requirement Importance (%)		6.30	7.49	12.18	5.67	5.67	12.81	9.59	5.88	22.67	11.76

Figure 3. HOQ analysis for the crab ovarian capturing equipment

As shown in Figure 3, each cell in the matrix represents the intensity of the relationship between a user requirement and a technical specification, utilizing a nine-point scale. The absolute technical requirement importance (TRI_a) (Equation (2)) and the relative technical requirement importance TRI_r *(%)* (Equation (3)) were variables to identify significant critical design conditions. Equation (2) shows the importance rating, S_{ij}, where 1, 3, and 9 indicate equal, moderate, and extreme importance, respectively. This rating quantifies how changes in technical specifications impact user satisfaction. The TRI_a and TRI_r *(%)* of each technical requirement were derived by weighting the user requirements according to their importance and combining the weighted relationships across each column. These variables are calculated as:

$$TRI_{aj} = \sum_{i=1}^{m}\left(IMP_i \times S_{ij}\right) \quad (2)$$

$$TRI_r(\%) = \left(TRI_{aj}/\sum_{j=1}^{n}(TRI_{aj}) \times 100\right) \quad (3)$$

where *IMP* is the important weight ranked from 1 (low) to 5 (high), while i and j are the customer requirements and the technical specifications, respectively.

The HOQ analysis revealed that precise imaging, stable crab positioning, and efficient light illumination are strongly correlated with particular technical characteristics. This is consistent with a previous study, suggesting that a suitable light source is essential for acquiring transmitted objects [8]. Figure 3 shows that the crab holding device has the highest importance (22.67%), emphasizing its crucial function in ensuring stable posture when capturing images. The light source (12.81%) and equipment material (12.18%) were also highly prioritized to improve image clarity. The crab holding device, equipment shape, equipment size, and light placement showed positive relationships, indicating opportunities for design integration to increase system efficiency. These findings highlight reliable mechanical stabilization, flexible lighting, and a compact design. The FMEA and QFD results determined the final equipment design, discussed in Section 3.1, which was then validated through performance testing.

2.2 Image Processing for Crab Ovaries

The captured images of ovarian crabs were analyzed through the image processing workflow, as shown in Figure 4. The image processing was compiled in Python using *NumPy* for numerical computing, *Matplotlib* for visualization, and *OpenCV* for image processing functions [22].

The implementation of the image processing technique was compiled using Python, leveraging libraries including *NumPy* for numerical computing, *Matplotlib* for visualization, and *OpenCV* for image processing functions [22]. From Figure 4, the workflow started with importing RGB images and then converting them to grayscale. The carapace region was then masked from the background using grayscale intensity analysis. The *BoundingRect* function was used to construct a mask to isolate and extract the carapace for further processing [22]. The *equalizeHist* function was applied to enhance contrast by redistributing pixel intensities across the grayscale range from 0 to 255 [22]. Ovarian segmentation was performed using a thresholding technique that converted the gray-scale image into a binary image (0 = ovary, 1 = carapace). This process effectively extracted vital features from the background [7,11]. The ovarian and carapace regions were quantified by pixel numbers, and their ratio was determined to classify the ovarian maturity stage with the specified criteria.

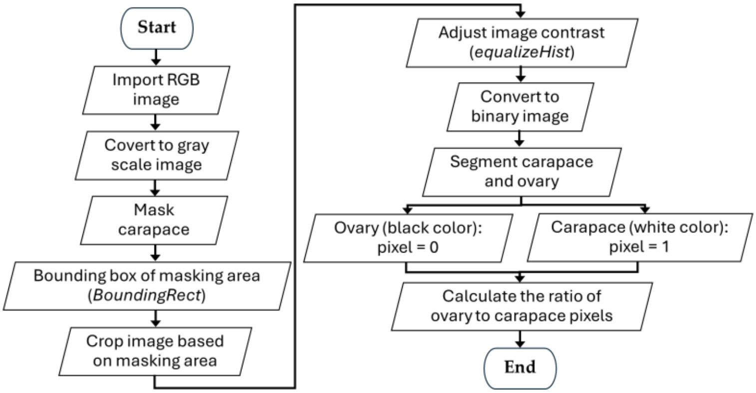


Figure 4: Image processing steps

2.3 Classification of Crab Ovarian Maturity Stages

Conventional assessment of crab ovarian maturity stage relies on invasive internal examinations of ovary color and thickness, resulting in the death of the crab [23-25]. The criteria for ovarian maturity stages were defined based on expert evaluation, establishing four stages, as shown in Figure 5 and explained in Table 2 [24].

Table 2: Criteria for ovarian maturity stages [24]

Maturity stage	Ovary color	Ovary thickness (mm)	Ovary-to-carapace ratio
Developing Mature	Yellow to golden-orange	2-3 mm	~10 %
Early Mature	Yellow to golden-orange	3-7 mm	~20 %
Late Mature	Deeper golden/yellow-orange	7-12 mm	~40-50 %
Fully Mature	orange to reddish-orange	10-20 mm	$\geq$ ~ 75%

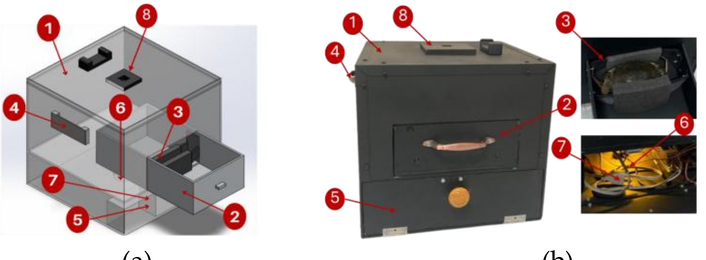
Figure 5: Ovarian maturity development stages (from Songkhla coastal aquaculture research and development center)

This study presents a noninvasive process for assessing ovarian maturity stages through the quantification of the ovary-to-carapace area ratio by image processing, thus eliminating the need for destructive carapace removal. The developed ratio-based criteria were subsequently compared with the results from prior studies and experts to confirm the reliability and practical application of the proposed process for evaluating ovarian maturity stages in mud crabs.

3.0 RESULTS AND DISCUSSION

3.1 Development of Image Acquisition Equipment

According to the integrated FMEA–QFD analysis (Section 2.1), image clarity was identified as the most critical requirement for accurate ovarian maturity classification, as ovarian area and size indicate maturity stage [23-24]. Usability, portability, and maintainability were also essential for field deployment. Therefore, these specifications informed the development of image acquisition equipment. Figure 6 shows the eight essential components, as detailed in Table 3.



(a) (b)

Figure 6: Image acquisition equipment showing (a) design and (b) prototype

Figure 7: Example of a captured crab ovary image

The equipment was constructed from black Plastwood to minimize image noise and improve focused light to the ovary. A 3,000-lumen LED provided regulated illumination, while flexible rubber and sponge holders secured crabs of various sizes. The light source significantly affects image quality based on illumination techniques, as reported in previous studies [8-9]. A total of 90 crabs were captured by the equipment, with 80 images allocated for the creation of the classification and 10 images reserved for validation with expert evaluation. The developed equipment effectively reduced noise and enhanced illumination in the ovarian region, resulting in a quality image, as illustrated in Figure 7.

Table 3: Components of the crab ovarian image acquisition equipment

Components	**Specifications**	**Components**	**Specifications**
1. Equipment shape 	- Square box with the size of 32 x 32 x 32 cm made by Plastwood	5. Maintenance channel 	Downward-opening maintenance and cleaning panel
2. Carb placement part 	- Drawer-style input-output compartment for crab insertion. - Size of 17×32×10 cm made by Plastwood	6. Light source 	Warm LED light bulb (3,000 lumens, 20 watts) aligned with crab placement point
3. Carb holding part 	Flexible crab-holding device made of sponge and rubber, supporting the largest crabs	7. Light power  	Dual-current electrical system compatible with AC and DC
4. Equipment handles 	User-friendly handles for easy movement	8. Image capturing part 	Crab photography and observation device with a camera/ phone

3.2 Crab Ovary Image Processing Results

Image processing was used to create ratio-based criteria for ovarian developmental stages on the 80 acquired images. According to the procedures shown in Figure 4, the image processing was implemented to extract crab features for stage estimation of ovarian maturity, with the results shown in Table 4. The RGB image was transformed to grayscale to improve edge detection and enable accurate cropping. Histogram analysis indicated a peak intensity of about 120 with a standard deviation of 14. Hence, the threshold ≥ 120 was selected to yield a binary image (0 = black, 1 = white) [22]. The overall count of black pixels indicated the ovarian region, while white pixels represented the carapace region. The ovary-to-carapace area ratio was calculated and employed to classify maturity stages based on [24]. Table 5 presents the mean ovary-to-carapace area ratios, exhibiting an increase with maturation: 24.31% (developing maturing), 37.77% (early maturing), 53.80% (late maturing), and 59.57% (fully maturing), accompanied by the standard deviation within 10%. The ratios for the late maturing and fully maturing stages are similar, possibly caused by difficulties in distinguishing the ovarian region from the surrounding carapace, particularly in the fully mature stage (Phase 4, Figure 5). This constraint results from a shortage in boundary gap and limited light penetration [24], causing decreased contrast and reduced segmentation ability.

Table 4: Image processing-based identification of key crab features for ovarian maturity assessment

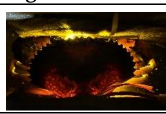
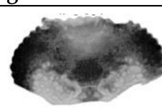
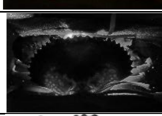
Image processing result		**Image processing result**	
1. Original RGB image		4. Enhance the contrast of the crab ovary	
2. Convert RGB to a gray-scale image		5. Segment ovarian feature	
3. Mask and crop the carapace from the image background		6. Collect the areas of the ovarian and carapace 	

Table 5: Average ratio of ovary to carapace area at each stage

Maturity stage	Ovary (pixel)	Carapace (pixel)	% Ratio (Std.)
Developing Mature	88,396.00	363,572.00	24.31 (7.67)
Early Mature	153,644.25	412,367.81	37.77 (8.31)
Late Mature	225,074.50	419,031.96	53.80 (10.67)
Fully Mature	247,245.17	418,590.05	59.57 (7.01)

3.3 Classification Results for Crab Ovarian Maturity Stages

The ratios from Table 4 were utilized to establish classification criteria for ovarian development stages based on the mean values and corresponding standard deviations. As mentioned previously, the late maturing stage showed ratio values that overlapped with those of the fully maturing stage. This is because of limited light penetration through the ovary [26]. In practice, classification boundaries can be defined within a range rather than as rigid criteria. A tolerance of 5% is typically considered insignificant in image analysis. Therefore, overlapping ratio intervals were established, allowing borderline cases to be classified within nearby categories (Table 6).

Table 6: Criteria for classifying the crab ovarian maturity stages

Maturity stage	Code	Ratio (%)	Overlapping ratio (%)	Ratio (%) from [24]
Developing Mature	1	< 30	28-32	10
Early Mature	2	30-45	28-32 and 43-47	20
Late Mature	3	45-60	43-47 and 58-62	40-50
Fully Mature	4	> 60	58-62	> 75

The ovary-to-carapace ratio revealed a similar increase compared to a previous evaluation [24] (Table 6). However, differences in ratio values were observed. The previous research performed carapace dissection to directly reveal the ovary, providing greater visualization [24]. Nevertheless, the proposed non-destructive process can identify all maturity stages without causing harm to the crabs [6]. Model accuracy was assessed using 10 samples, with the classification results verified by an expert, as shown in Table 7. The incorrect prediction was in the transition from stage 3 to stage 4, possibly due to an underestimation of the ovarian ratio resulting from limited light penetration [24].

Tables 7: Classification of ovarian maturity stages using area ratio estimation

Sample	Ratio	Criterion estimation	Expert estimation	Accuracy
1	25.68	1	1	TRUE
2	42.96	2,3	2	TRUE
3	31.63	2	2	TRUE
4	33.56	2	2	TRUE
5	50.14	3	3	TRUE
6	59.41	3,4	3	TRUE
7	60.00	3,4	3	TRUE
8	69.01	4	4	TRUE
9	59.54	4	4	TRUE
10	48.30	3	4	FALSE
				% Accuracy 90

The model achieved an overall accuracy of 90%, revealing an acceptable agreement between automated categorization and expert judgment for the various input images. This result is consistent with prior investigations that controlled image acquisition conditions and feature-based classification to enhance accuracy [11]. In addition, the average amount of time required for computing the classification was roughly 3 seconds, suggesting that this approach is robust for practical implementation. The non-invasive crab ovarian maturity classification system highlights the potential for integration within an Industry 4.0 framework by converting ovarian maturity into useful digital data for traceability, real-time monitoring, and data-driven decision-making [6]. Maturity-based classification can facilitate dynamic feeding and farming allocation strategies as well as supply segmentation from the perspective of farm or production management [25]. To improve automation, operational consistency, and labor efficiency, classification can also be implemented as a decision variable for robot picking or deep learning-based sorting systems. This integration improves product quality while facilitating scalable smart aquaculture production.

4.0 CONCLUSION

The innovative non-invasive crab ovarian maturity classification process was developed using the integration of FMEA, QFD, and image processing technology. The image acquisition equipment was created corresponding to user requirements using FMEA and QFD to minimize potential failure options, optimize imaging consistency, and enhance ergonomic usability and portability. Image processing was implemented to extract key features from the 90 acquired crab images for classifying ovarian maturity stages. Based on the analysis, a quantitative classification criterion defined by the ovary-to-carapace area ratio was established to objectively differentiate between the four stages of ovarian development. The results indicated that this ratio increased steadily as the crabs matured, with the fully mature stage having an ovary ratio of at least 60%. In addition, an overlapping range of 5% between neighboring classification levels was determined to accommodate natural variation and practical applicability under actual sorting conditions. The proposed classification process achieved an overall classification accuracy of 90% when validated with expert assessments, providing the feasibility of integrating structured engineering design principles with image-based maturity analysis. Therefore, this study contributes a novel concept for integrating quality engineering design and natural image processing analysis, resulting in an improved technique for evaluating ovarian maturity in crabs and other products requiring internal investigation. To further increase classification performance and scalability for industry, future research should emphasize classification robustness and accuracy by incorporating additional morphological features and implementing advanced machine learning techniques.

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AUTHOR CONTRIBUTIONS

K. Thongkaew: Conceptualization, Methodology, Data Curation, Equipment, Writing- Original Draft Preparation; R. Duangsoithong: Software, Validation, Writing-Reviewing and Editing; S. Chaiprapat: Methodology, Writing-Reviewing and Editing; S. Gonsrang: Equipment, Validation; N. Nuntapong: Validation; P. Chuaduangpui: Supervision;

CONFLICTS OF INTEREST

The manuscript has not been published elsewhere and is not under consideration by other journals. All authors have approved the review, agree with its submission and declare no conflict of interest on the manuscript.

REFERENCES

[1] Office of commodity trade, "Crab and products", Department of International Trade Negotiations, Nonthaburi, Thailand, 2022. [Online]. Available from: https://www.dtn.go.th/th/file/get/file/1.20220901c152d4fb3a9ec97d5db9e669a74eddd6170541.pdf. [Accessed: Dec. 20, 2023].

[2] Department of Fisheries Ministry of Agriculture and Cooperatives, *Statistics of sea crabs culture survey 2023*, Fisheries Development Policy and Planning Division. 6. 2024. [Online]. Available from: https://www4.fisheries.go.th/local/file_document/20250610095619_new.pdf [Accessed: July. 15, 2024].

[3] C. Shelley, A. Lovatelli, "Mud crab aquaculture – A practical manual", *FAO Fisheries and Aquaculture Technical Paper*, vol. 567, 2011.

[4] B. Chen, J. Zheng, C. Chen, K. Wu, F. Lin, L. Ning, H. Rong, C. Chen, F. Xiao, H. Zhang, X. Wen, "Differences in lipid accumulation and mobilization in the hepatopancreas and ovary of female mud crab (Scylla paramamosain, Estampador, 1949) during ovarian development", *Aquaculture*, vol. 546, no 739046, pp. 1-12, 2023.

[5] T. Zhu, Y. He, H. Cao, W. Zhan, Q. Zhou, W. Zhao, Y. Shen, P. Sun, M. Jin, "Insights into lipid function for ovarian development in the swimming crab (Portunus trituberculatus): A comparison of lipid mobilization and deposition in hepatopancreas and ovary", *Aquaculture Reports*, vol. 38, no 102326, pp. 1-11, 2024.

[6] G. Huang, K. Thongkaew, S. Chaiprapat, "A Review of Non-Destructive Technologies for Quality Assessment in Aquaculture", *Aquaculture Journal*, vol. 6, no 3, pp. 1-31, 2026.

[7] N. Thammachot, K. Waiyakarn, S. Chaiprapat and S. Jirasatitsin, "Computer vision for splendid squid size and species classification", *Journal of Advanced Manufacturing Technology*, vol. 13, no. 1, pp. 45-60, 2019.

[8] S.Y. Tsai, C.H. Li, C.C. Jeng, C.W. Cheng, "Quality assessment during incubation using image processing", *Sensors*, vol. 20, no 5951, pp. 1-10, 2020.

[9] W. Lumchanao, N. Potprarinya, "Development of Egg Incubator for Detecting Embryos in Chicken Eggs Using Digital Image Processing

Techniques", *Srinakharinwirot University Engineering Journal*. Vol. 13, no 1, pp. 151-165, 2018.

[10] A. Bhargava, A. Bansal, "Fruits and Vegetables Quality Evaluation Using Computer Vision: A review" *Journal of King Saud University - Computer and Information Sciences,* vol. 33, no 3, pp. 243-257, 2021.

[11] S. Chen, Y. Li, Y. Zhang, Y. Yang, X. Zhang, "Soft X-ray image recognition and classification of maize seed cracks based on image enhancement and optimized YOLOv8 model", *Computers and Electronics in Agriculture*, vol. 216, no 108475, pp. 1-11, 2024.

[12] T.V.D. Looverbosch, Md.H.R. Bhuiyan, P. Verboven, M. Dierick, D.V. Loo, J. D. Beenbouwer, J. Sijbers, B. Nicolai, "Nondestructive Internal Quality Inspection of Pear Fruit by X-ray CT using Machine Learning", *Food Control* vol. 113, no. 107170, pp. 1-13, 2020.

[13] R. Ali, M.M. Yusro, M.S. Hitam, M. Ikhwanuddin, "Machine Learning with Multistage Classifiers for Identification of Ectoparasite Infected Mud Crab Genus Scylla", *TELKOMNIKA Telecommunication, Computing, Electronics and Control*, vol.19, no 2, pp. 406-413, 2021.

[14] R. R. Baharuddin, M. Niswar, A.A. Ilham, S. Kashihara, "Crab Molting Identification using Machine Learning Classifiers", *International Seminar on Machine Learning, Optimization, and Data Science*. pp.295-300, 2021.

[15] L.K. Chan, M.L. Wu, "Quality Function Deployment: a Literature Review", *European Journal of Operational Research*, vol. 143, pp. 463-497, 2002.

[16] V. Bouchereau, H. Rowlands, "Methods and Techniques to Help Quality Function Deployment (QFD)", *Benchmarking: An International Journal*, vol. 7, no 1, pp. 8-20, 2000.

[17] B. Almannai, R. Greenough, J. Kay, "A decision Support Tool Based on QFD and FMEA for the Selection of Manufacturing Automation Technologies", *Robotics and Computer-Integrated Manufacturing*, vol. 24, no 4, pp. 501-507, 2008.

[18] M.Z. Mistarihi, R.A. Okour, A.A. Mumani, "An Integration of a QFD Model with Fuzzy-ANP Approach for Determining the Importance Weights for Engineering Characteristics of the Proposed Wheelchair Design", *Applied Soft Computing Journal*, vol. 90, no 106138, pp. 1-12, 2020.

[19] D. Buakum, · C, Daesa, · R. Sinthavalai, · K. Noppasri, "Designing temperature-controlled medicine bag using an integrated AHP-QFD methodology", *International Journal on Interactive Design and Manufacturing*, vol. 18, pp. 659-670, 2024.

[20] N. Awang, M.H.F.M. Fauadi, Z. Abdullah, S. Akmal, N.I. Anuar, A.Z.M. Noor, S.A. Idris, M.H. Nordin, "Classification of weld bead defects based on image segmentation method", *Journal of Advanced Manufacturing Technology* vol. 12, no. 1(4), pp. 51-60, 2018.

[21] D. Maritan, *Practical Manual of Quality Function Deployment*. Springer, 2015.

[22] R.R. Asaad, R.I. Ali, Z.A. Ali, A.A. Shaban, "Image Processing with Python Libraries", *Academic Journal of Nawroz University*, vol. 12, no. 2, pp. 410-416, 2023.

[23] E. T. Quinitio, J.D. Pedro, F.D. Parado-Estepa, "Ovarian maturation stages of the mud crab Scylla serrata", *Aquaculture Research*, vol. 38, pp. 1434-1441, 2007.

[24] M.S. Islam, K. Kadoma, H. Kurokura, "Ovarian Development of the Mud Crab Scylla Paramamosain in a Tropical Mangrove Swamps", *Thailand Journal of Science*, vol. 2, pp. 380-389, 2010.

[25] Q. Wua, K. Waiho, Z. Huang, S. Li, H. Zheng, Y. Zhang, M. Ikhwanuddin, F. Lin, H. Ma, "Growth performance and biochemical composition dynamics of ovary, hepatopancreas and muscle tissues at different ovarian maturation stages of female mud crab, Scylla paramamosain", *Aquaculture*, vol. 515, pp. 734560, 2020.

[26] HD. Vo, NT. Tran, M. Fukuzawa, "Spectrometric Feature Analysis of Mud Crab Portions for Automatic Internal Quality Grading", *SN Computer Science,* vol. 6, pp. 1-12, 2025.