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Advancing sustainable crab harvesting through intelligent technologies: a comprehensive review

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Crab fisheries are important components of coastal food systems, but their sustainable development depends on selective fishing gear, reliable field information, and reduced ecological disturbance. This review synthesizes 173 studies published from 2002 to 2025 and retrieved from Scopus, Web of Science, ScienceDirect, SpringerLink, and PubMed. The reviewed evidence covers crab pot and trap selectivity, underwater image acquisition, target detection, instance segmentation, sex and quality recognition, visual localization, sorting and handling automation, resource monitoring, catchability calibration, and derelict-gear impacts. The synthesis shows that intelligent crab harvesting should be evaluated as an integrated marine-engineering workflow rather than as isolated gear or algorithm performance. Machine vision can support individual identification, measurement, grading, behavioral observation, and resource assessment, but its management value depends on calibrated field deployment, traceable environmental metadata, robust edge inference, and explicit links between perception outputs and selective capture or handling decisions. Future research should prioritize standardized crab image datasets, lightweight and multimodal perception models, equipment-algorithm co-design, long-term field validation, catchability-aware monitoring, and life-cycle assessment of resource-conserving crab fishing systems.

KEYWORDS
crab fisheries, crab pots and traps, intelligent fishing gear, machine vision, resource conservation, selective harvesting

1 Introduction

Crab fisheries increasingly require a link between resource assessment, selective capture, visual perception, and operational decisions. Historical analyses of red king crab fisheries show that declines in commercial biomass and aggregation density can lead to periodic fishing closures, while new fishing grounds may overlap with areas important for population reproduction (Ivanov, 2025; Slizkin et al., 2025). Regional analyses of snow crab fisheries further indicate that catch is shaped not only by fishing effort, but also by stock abundance and environmental conditions such as sea ice (Tao et al., 2024). Crab harvesting therefore cannot be understood simply as a process of increasing catch. Gear parameters, fishing locations, operating periods, and conservation measures must be evaluated within a shared technical framework.

Throughout this review, the terms 'crab pot' and 'crab trap' are used interchangeably to describe passive, baited enclosures designed for trapping and retaining marine crabs. For consistency, the term 'crab pot' is adopted hereafter to encompass all structural variants of these trapping devices. Resource monitoring provides the foundation for management. Coleman et al. (2024) demonstrated that fishery-dependent and fishery-independent data can jointly support brown crab density monitoring, and that climate indices and temperatures during key developmental periods may affect population abundance. Willse et al. (2024) argued that management controls and biological reference points in data-limited crustacean fisheries should be set according to species-specific life-history traits. Studies of Chilean and Patagonian crab fisheries also show that spatial-temporal resource assessment, catch per unit effort, size composition, sex ratio, soak time, and escape-ring information are essential for identifying exploitation status and improving monitoring programs (Hamamé et al., 2024; avila-Thieme et al., 2025).

Crab pots and traps are the immediate interface through which resource status is converted into landings. They are relatively selective and generate less benthic disturbance than many active gears, but the unintended retention of undersized target individuals still limits their management value. Yu et al. showed in swimming crab pot fisheries that escape vents, mesh size, and mesh opening affect size selectivity and that laboratory prediction models can support offshore design screening (Yu et al., 2026). Gear optimization should therefore consider the whole sequence of approach, entry, retention, and escape rather than entry rate alone. Vertical lines between surface buoys and pots also create entanglement risk for marine animals; Matzen et al. proposed acoustic on-demand retrieval as one way to reduce persistent vertical-line exposure under specific operating conditions (Matzen et al., 2025).

As cameras, sensors, and embedded computing devices enter aquaculture and fishing sites, machine vision has become a data interface for individual identification, behavior recording, and resource monitoring. Gu et al. used deep-learning frameworks to connect detection, classification, carapace-width measurement, biomass estimation, and burrow recognition with spatial community analysis (Gu et al., 2026). However, Li et al. showed that underwater color attenuation, low contrast, visual noise, and scene-specific constraints can weaken carapace cues and reduce model transferability (Li X. et al., 2026). River crab feeding-platform monitoring and real-time underwater detection studies further show that image enhancement, lightweight inference, and environmental information must be evaluated as a complete sensing chain rather than as isolated model improvements (Ji et al., 2023; Sun Y. et al., 2026). This transition from visual perception to operational decision-making is supported by transferable evidence from AI-enabled agricultural equipment, object detection, and selective-harvesting vision systems (Jin et al., 2021; Gao et al., 2025; Khan et al., 2025; Wang W. et al., 2025; Zhu et al., 2025).

Vision technology is also expanding from close-range individual recognition toward multi-scale ecological monitoring. Multimodal classification tools for marine decapods, resident seafloor robots, UAV-based intertidal pipelines, and rapid bycatch assessment frameworks all demonstrate that images from different platforms vary in spatial scale, viewing angle, illumination, background, and target state (Chatzievangelou et al., 2022; Chen X. et al., 2025; Li et al., 2025; Zhou et al., 2025; Chen X. et al., 2026). Model accuracy is therefore meaningful only when interpreted together with task definition, dataset composition, and field conditions.

Existing studies have accumulated evidence on resource management, pot selectivity, visual recognition, and automated equipment. Yet the links among resource status, capture processes, visual outputs, and ecological impacts remain fragmented. This review synthesizes these links so that individual technical indicators can be translated into interpretable evidence for gear optimization and resource-friendly operations.

While the individual components of intelligent marine technologies have progressed rapidly, a critical gap remains in the secondary literature. Previous review papers have largely examined these domains in isolation. For instance, reviews on underwater machine vision and marine robotics (Reggiannini and Moroni, 2021; Liu et al., 2023; Li et al., 2024) predominantly focus on optical restoration and algorithmic performance metrics, lacking integration with physical capture mechanisms. Conversely, comprehensive reviews centered on sustainable fisheries and selective gear (Lucchetti et al., 2021; Petetta et al., 2021; Hilborn et al., 2026) typically evaluate structural modifications and bycatch reduction from a purely physical or ecological standpoint, without incorporating the potential of real-time artificial intelligence. Furthermore, literature synthesizing seafood processing automation is generally confined to post-harvest onshore factory settings, entirely decoupling the processing stage from the actual harvesting event.

The primary novelty of this review lies in dismantling these interdisciplinary silos. What this paper provides—which previous reviews on crab fisheries or automated harvesting have not—is the construction of an integrated, end-to-end "perception-to-action-to-impact" framework. By explicitly mapping the data and physical workflows from underwater resource observation and target perception, through dynamic gear response and shipboard handling, to macro-level ecological assessment, this review serves as the first comprehensive roadmap for transitioning fragmented intelligent technologies into a unified, resource-conserving crab harvesting system.

Within the specific context of this review, 'sustainability' is not treated as an abstract concept, but is explicitly defined as the capacity of a harvesting system to maximize target yield while verifiably minimizing unintended ecological impacts. This translates into concrete resource-conserving objectives: precise exclusion of non-target and undersized species, zero-harm handling to ensure high post-release survival, and the generation of high-fidelity biomass data to support dynamic quota management.

2 Review methods

To systematically map the rapidly evolving technological landscape of intelligent crab harvesting, this study was designed as a scoping review. The methodology was developed in alignment with the PRISMA-ScR (Preferred Reporting Items for Systematic reviews

and Meta-Analyses extension for Scoping Reviews) guidelines to ensure transparent and reproducible reporting of the cross-disciplinary literature.

This review synthesizes recent engineering and technological developments in intelligent crab harvesting equipment and visual recognition technologies, with emphasis on underwater imaging, crab target detection, sex and quality recognition, pot selectivity, automated processing, and resource-friendly fishing operations. Relevant literature published between 2002 and 2025 was searched in Scopus, Web of Science, ScienceDirect, SpringerLink, and PubMed; after duplicate removal, title-and-abstract screening, and full-text eligibility assessment, 173 studies were included.

A predefined set of search keywords and Boolean operators was used across all databases. The primary search terms included combinations of: "crab fisheries," "crab harvesting," "crab pot," "trap selectivity," "escape vent," "soak time," "underwater video," "underwater crab detection," "machine vision," "computer vision," "YOLO," "crab segmentation," "sex recognition," "quality grading," "robotic processing," "ghost fishing," and "biodegradable escape device." The search strategy was adapted to each database using appropriate syntax and filtering tools. A reproducible example of the search logic is: ("crab" OR "crustacean") AND ("pot" OR "trap" OR "harvesting") AND ("machine vision" OR "computer vision" OR "YOLO" OR "segmentation").

The inclusion criteria comprised peer-reviewed journal articles, conference papers, and review studies focusing on crab harvesting technologies, visual recognition methods, intelligent fishing equipment, monitoring systems, gear selectivity, automated processing, and sustainable crab fishery operations. Studies were included if they provided quantitative or qualitative insights into equipment design, visual perception, behavioral response, capture performance, resource monitoring, or ecological impacts in crab-related applications.

The exclusion criteria eliminated non-English publications, studies unrelated to crabs or crustacean field applications, purely theoretical works without harvesting, monitoring, or equipment application, and duplicate records across databases. An initial screening of records was conducted based on titles and abstracts, followed by a full-text eligibility assessment. After removing duplicates and irrelevant studies, the final selection consisted of N = 173 studies included in the review. This language restriction may have excluded region-specific engineering studies and should be considered a limitation of the review.

To ensure methodological transparency, the study-selection procedure was systematically documented. The comprehensive literature search across the five selected databases was conducted between January 15, 2025, and February 28, 2025. The initial search yielded a total of 895 records. Using reference management software, 214 duplicate records were identified and removed, leaving 681 unique articles for the initial screening phase.

During the primary screening, two reviewers independently evaluated the titles and abstracts based on the predefined inclusion and exclusion criteria, resulting in the exclusion of 396 irrelevant studies. The remaining 285 articles were retrieved for comprehensive full-text assessment. Following the full-text review, an additional 112 articles were excluded for the following specific reasons: lack of direct relevance to intelligent crab harvesting technologies (n=45), insufficient technical depth or absence of empirical validation (n=52), and language restrictions or full-text unavailability (n=15).

Ultimately, 173 studies met all criteria and were included in the final review. To mitigate selection bias and ensure rigorous evaluation, both the title/abstract screening and the full-text assessment stages were conducted independently by two reviewers. Any disagreements regarding study eligibility between the primary reviewers were resolved through thorough discussion to reach a consensus, or when necessary, by consulting a third senior researcher for a final decision.

The included studies were organized into four evidence domains: visual perception, pot/trap selectivity, processing automation, and resource-conservation assessment.

To avoid treating visual recognition, pot design, processing automation, and conservation assessment as separate topics, this review organizes the evidence as a perception-to-action-to-impact chain. Resource status defines the management constraint; pot and trap structures determine the capture pathway; visual perception converts individuals, behavior, and operating conditions into measurable information; automation translates visual outputs into handling, sorting, or verification actions; and monitoring, catchability calibration, and ecological-impact assessment close the loop for resource-conserving crab fisheries.

Under this framework, the following sections move from information acquisition to capture control, then to operational execution and management feedback. Section 3 examines how crab images become reliable perception outputs. Section 4 links behavioral response and pot design with selective capture. Section 5 explains how visual outputs become actionable coordinates, trajectories, and sorting decisions. Section 6 returns these technical outputs to resource monitoring, catchability calibration, selective harvesting, and ecological-risk assessment.

To explicitly illustrate how these previously isolated technologies integrate into a unified workflow, Figure 1 presents the comprehensive system architecture of an intelligent crab harvesting operation. As illustrated, this framework bridges the gap between digital data flow and physical material flow through four distinct, interconnected layers:

1. Perception & Collection Layer: Raw multidimensional data-captured via underwater imaging, shipboard sensors, and UAVs-forms the foundational input stream, continuously logging environmental variables and target visual cues.
2. AI Analysis Layer: Acting as the computational core, this layer processes the incoming raw data through edge-computing architectures. It executes real-time tasks such as morphological preprocessing, species/sex/size attribute recognition, and DeepSORT-based counting and tracking, ultimately translating visual data into precise decision coordinates and anomaly alerts.
3. Operation & Execution Layer: The AI-derived decision outputs directly drive physical mechanical actions. In the water, this enables intelligent gear adjustments, catch selectivity optimization, and optimal soak-time control; on deck,

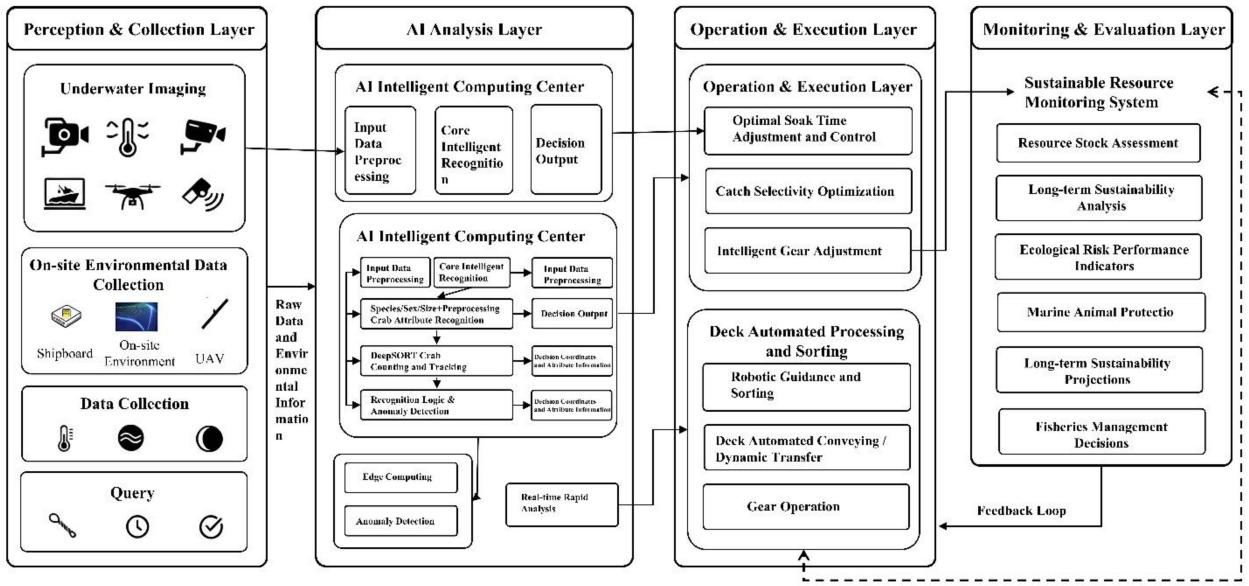


FIGURE 1
The comprehensive system architecture of an intelligent crab harvesting operation, illustrating the continuous data and physical workflow across the perception & collection, AI analysis, operation & execution, and monitoring & evaluation layers.

it provides the spatial coordinates required for robotic guidance, automated conveying, and dynamic sorting.

4. Monitoring & Evaluation Layer: The continuous, granular data generated during sorting operations feeds into macro-level sustainable resource monitoring systems. This supports long-term stock assessments, ecological risk performance indicators, and informed fisheries management decisions.

Crucially, a systemic feedback loop connects the macro-level sustainability projections back to the operational and perception layers, ensuring that the intelligent harvesting system continuously adapts to dynamic marine environments and resource conservation mandates.

2.1 Data extraction and evidence synthesis

Following the final study selection, data were systematically extracted using a predefined, standardized spreadsheet to ensure consistency across all reviewers. For each of the 173 included studies, the following key variables were systematically recorded: author(s) and publication year, target crab species, specific technological intervention, methodological approach, key performance metrics, and identified environmental or computational limitations.

The evidence synthesis was structured around four primary operational domains. These domains were generated through a hybrid deductive-inductive approach. Initially, the broad categories were predefined deductively, mirroring the sequential conceptual workflow of intelligent crab harvesting (i.e., perception, capture, processing, and management). Subsequently, during the full-text review process, these boundaries were inductively refined to precisely map the actual technological contributions found in the literature. Consequently, the extracted evidence was coded as follows: (1) studies focusing on underwater imaging and target recognition were assigned to the 'Visual Perception' domain; (2) research detailing escape-vent geometries and catch-retention mechanisms was mapped to 'Selective Catch Operations'; (3) papers addressing robotic handling and machine-vision-guided sorting were classified under 'Deck Processing Automation'; and (4) literature centered on population dynamics and ecological impact modeling was grouped into 'Macro-Level Resource Monitoring.' Studies bridging multiple domains were assigned to their primary area of technological innovation while cross-referenced in subsequent systemic discussions to illustrate the integrated data flow.

2.2 Evidence quality classification

Given the extreme heterogeneity of the included literature—which spans algorithmic machine-learning experiments, mechanical prototypes, field fishing trials, and macro-ecological monitoring—assuming equivalent methodological strength across all studies is invalid. Because formal quality-assessment instruments (such as clinical risk-of-bias tools) are inappropriate for such cross-disciplinary engineering literature, this review established a transparent evidence-quality classification framework.

Studies were evaluated and classified into one of three tiers based on their validation environment and methodological completeness:

1. Tier 1 (In-silico and Conceptual Validation): Studies confined to numerical simulations (e.g., finite element analysis) or deep-learning models trained and tested exclusively on offline, pre-recorded datasets without hardware deployment. The evidence reliability at this level is heavily contingent on dataset diversity and metric transparency, but it lacks physical validation.

2. Tier 2 (Controlled Laboratory/Tank Experiments): Studies featuring physical prototypes evaluated in highly controlled environments, such as flume tanks, soil bins, or laboratory processing lines with optimal lighting. These studies demonstrate high internal validity and proof-of-concept mechanical viability, but deliberately exclude real-world marine or shipboard interferences.
3. Tier 3 (*In-situ* and Commercial Field Trials): Studies deploying integrated systems on active fishing vessels, automated deck conveyors, or in actual marine habitats. This represents the highest tier of evidence quality for applied engineering, as the methodologies must account for real-world variables, including dynamic weather, severe occlusion, biological bycatch, and continuous operational stress.

Throughout the evidence synthesis (Sections 3 through 6), findings are contextualized within this framework to ensure that the technological maturity of laboratory-scale concepts is not conflated with field-ready commercial reliability.

2.3 Classification of evidence source proximity

To prevent overstating the technological maturity of intelligent crab harvesting and to maintain scientific objectivity, the evidence synthesized in this review is explicitly classified into three hierarchical levels based on source proximity:

1. Direct crab evidence: Studies explicitly developing or validating technologies for crab species (e.g., Eriocheir sinensis, Portunus trituberculatus, Snow crabs). This forms the primary empirical foundation of the review.
2. Other crustacean/marine evidence: Literature focusing on functionally similar marine organisms or environments (e.g., lobsters, benthic fish, general underwater robotics). This evidence is utilized to bridge gaps in underwater locomotion and marine sensor deployment.
3. Cross-domain transferable evidence: Terrestrial agricultural studies (e.g., robotic harvesting of apples, grapes, or tea shoots). These are explicitly invoked strictly as conceptual models to illustrate potential automation solutions (such as end-effector design or canopy-penetrating vision) that have not yet been empirically realized in crab fisheries.

3 Crab target perception, visual recognition, and field deployment

3.1 Underwater crab image acquisition and imaging interference

Underwater crab images are not a single homogeneous data type. They are evidence carriers shaped by observation scale, imaging medium, and task output. Close-range individual images preserve carapace appearance, contour, and local texture; continuous video provides temporal information under occlusion and blur; water-column observations and benthic traces correspond to spatial distribution and habitat structure. If scene, time, viewing distance, and environmental conditions are not stored with the image, later model errors cannot be separated into target differences, imaging degradation, or sampling bias.

Although these studies are not crab-specific, Comparable studies using spectral, microscopic, and food-quality imaging further indicate that imaging modality, illumination condition, and material state must be reported together before visual features can be interpreted reliably (Xu et al., 2018; Yao et al., 2022; Huang et al., 2023; Liang et al., 2023; Jiang et al., 2025; Xi et al., 2025; Yao et al., 2026).

Studies on Chinese mitten crab gender detection and mud crab detection show that simple backgrounds, simulated backgrounds, aquaculture cages, continuous frames, occlusion, and blur correspond to different forms of image degradation (Yu et al., 2025; Li X. et al., 2026). Color attenuation, low contrast, noise, dynamic light, background structure, target movement, and occlusion alter the usable regions for detection. Multi-sensor water-column observations and three-dimensional burrow imaging further show that target location is constrained by water-mass structure, substrate, and habitat media (Grassian et al., 2023; Wang Y. et al., 2024; Wang Y. et al., 2025). Underwater flickering light may also alter the conditions under which animals use brightness cues (Venables et al., 2022). These input conditions determine which visual cues should be preserved in feature construction.

Fundamentally, underwater visual perception is constrained by physics-driven degradation: wavelength-dependent light absorption and forward/backward scattering intrinsically cause color distortion, low contrast, and severe blurring. Furthermore, constructing robust datasets under these conditions is plagued by extreme class imbalance and labor-intensive annotation. To overcome these bottlenecks, recent algorithmic adaptations increasingly employ marine-specific data augmentation, such as underwater Generative Adversarial Networks and synthetic data generation, to artificially expand training distributions and enhance model robustness without prohibitive field-sampling costs.

The interpretability of image data depends on binding images to environmental metadata. Camera position, light-source state, background type, target posture, and occlusion determine which cues are available in close-range images. Frame rate, target motion, and inter-frame background change determine whether video can compensate for single-frame loss. Platform trajectory, observation depth, and substrate information determine whether water-column or benthic surveys can be converted into spatial indicators. For cross-scene application, unenhanced images and processing parameters should be preserved as baselines for separating environmental variation from algorithmic effects.

3.2 Crab visual recognition models and field deployment

3.2.1 Conventional machine-vision feature construction and classification

Conventional machine vision uses color, texture, edge, shape, and geometric relationships as interpretable inputs. Tasks typically

proceed through candidate-region restriction, local feature extraction, and classification or measurement. In crab operations, local color and geometric templates can express body-part position and path reference, whereas whole-body appearance and weighing information can define quality variables. Both task types require the visible image cues to correspond to target regions, individual posture, and measurement objects, not merely to a recognizable image. Related machine-vision studies based on color, texture, block classification, and feature fusion provide useful methodological references for keeping handcrafted features physically interpretable (Liu et al., 2018; Peng et al., 2021; Zhu et al., 2023; Qiu et al., 2024; Guo et al., 2025; Memon et al., 2025).

Current applications of conventional machine vision in crab processing highlight a distinct evolution in feature utilization, driven by the specific demands of spatial localization versus quality discrimination. Early approaches successfully relied on 2D local color clustering and template matching to translate specific body parts into actionable cutting lines (Wang et al., 2018), or combined shell color with morphological traits for automated grading (Wang et al., 2023). While these 2D methods excel in environments with controlled lighting and isolated targets, they reveal significant limitations when faced with complex spatial overlaps. To address this, recent advancements have incorporated RGB-D segmentation and pose estimation (Ali et al., 2026), demonstrating that depth mapping and 3D keypoints are indispensable for resolving boundaries in piled or heavily occluded crab catches-a task where color or template methods alone consistently fail.

Synthesizing these studies reveals a critical trade-off in conventional machine vision: while handcrafted features offer highly interpretable variable paths (e.g., color directly maps to grade; local position maps to tool approach), their robustness is intrinsically fragile. The physical meaning of these variables is highly susceptible to shifts in illumination, target posture, or background noise. Therefore, determining the maturity of a conventional vision system requires evaluating not just its isolated accuracy, but its operational stability under dynamic imaging conditions.

3.2.2 Progress in convolutional neural-network object detection

Outputs of convolutional neural networks in crab vision have expanded from single bounding boxes to community counting, sex and species recognition, molting-state detection, carapace keypoint measurement, and quality-variable extraction. Inputs include underwater images, intertidal aerial images, close-range processing images, and multimodal observations, while outputs support occurrence records, individual-attribute recognition, morphological measurement, and operation-object screening. Model comparison should therefore be organized around target scale, background type, annotation object, and output form. Consequently, the rationale for architectural selection and hyperparameter tuning must be strictly driven by task-specific constraints-balancing the need for aggressive data augmentation to prevent overfitting on small marine datasets against the spatial precision required for automated handling.

Recent YOLO-based recognition, segmentation, localization, and picking-point studies in selective harvesting also support evaluating model performance according to target scale, occlusion, localization output, and downstream action requirements (Ji et al., 2022; Wang et al., 2022; Hu T. et al., 2023; Xie et al., 2024; Liu D. et al., 2025; Peng et al., 2025b).

Deep learning has been used for automated crab community monitoring, underwater gender detection, cross-frame mud crab detection, incremental species recognition, phenotypic keypoint detection, soft-shell crab discrimination, juvenile sex identification, and fatness grading (Zhang Z. et al., 2024; Duan et al., 2025; Wu et al., 2025). Underwater tasks must handle color attenuation, occlusion, and background mixing, whereas processing and grading tasks emphasize body parts, posture, and paired variables from the same individual. After image-level classification shifts toward detection, instance segmentation, and keypoint prediction, annotation rules and acquisition conditions become part of the interpretation of model results (Yu et al., 2025; Gu et al., 2026; Li X. et al., 2026).

Training samples determine not only what a model can recognize but also how it interprets scene changes. If one class always co-occurs with a specific background, size range, or acquisition method, the network may use those co-occurring properties as discriminative cues. Crab detection datasets should therefore decouple species, sex, size, and operational state from background, illumination, and view as much as possible, while reporting the scene composition of training, validation, and test subsets.

Whether a detection result can enter an operational workflow depends on whether its output granularity matches control requirements. Bounding boxes are suitable for rapid individual discovery, instance masks express actionable boundaries, keypoints provide size or posture references, and class labels express attributes. Mixing these outputs can mismatch localization tasks and model tasks; selecting output forms by equipment stage reduces information loss during coordinate conversion and manual reinspection.

Object detection constitutes the core stage of vision-based perception in intelligent crab harvesting systems. Among existing deep-learning frameworks, two-stage detectors remain an important technical route because they explicitly separate region proposal generation from object classification and localization. The Faster R-CNN architecture integrates feature extraction, region proposal generation, region-of-interest pooling, object classification, and bounding-box regression into a unified detection framework, providing the fundamental workflow for many subsequent developments in crustacean visual recognition systems.

Table 1 shows that crab visual-recognition studies have moved beyond single bounding-box detection toward a multi-output perception chain that includes segmentation, keypoints, grading variables, molting states, and UAV-based monitoring. This evidence supports the theme of this review: visual outputs become useful for intelligent harvesting only when they are linked to downstream sorting, measurement, guidance, or monitoring requirements.

3.2.3 Robustness under complex illumination and occlusion

Complex illumination and occlusion simultaneously alter target color, local contrast, visible boundaries, and inter-frame continuity

TABLE 1 Summary of representative visual recognition models for intelligent crab harvesting.

Task & target species	Algorithm/ architecture	Input modality	Performance metrics (mAP/ accuracy)	Inference speed (FPS)/ latency	Environmental robustness & trade-offs	Reference
Sex detection (Chinese mitten crab)	BLC-YOLOv8n (Field deployment) + Image Enhancement	Underwater Carapace images	mAP@0.50: 93.05%; mAP@0.50:0.95: 74.92%	High (Optimized for edge deployment)	Robustness: Handles mild color attenuation. Trade-off: Highly dependent on unobstructed ventral/dorsal visibility; struggles with severe occlusion.	(Li X. et al., 2026)
Underwater detection (Mud crab)	TMAE-YOLO; TD-AFPN	Multi-frame underwater RGB	Improved accuracy in self-built dataset (specific metric not standardized)	Moderate (Latency introduced by enhancement modules)	Robustness: Specifically designed to compensate for high turbidity and cross-frame dynamic occlusion. Trade-off: Higher computational overhead.	(Yu et al., 2025)
Segmentation & pose (Piled blue crabs)	CrabFormer (Lab tank); RGB-D Swin-T	RGB-D images	Segmentation AP: 69.76; Keypoint AR: 85.48	Low (Computationally heavy 3D processing)	Robustness: Highly robust against severe spatial overlap and dense piling by utilizing depth data. Trade-off: Slower inference, unsuitable for high-speed dynamic conveyors.	(Ali et al., 2026)
Phenotype & weight (Scylla paramamosain)	YOLOv11-DYPF + SVR	12 keypoints; 7 body dimensions	SVR mean weight error: 4.90%	High	Robustness: High precision in controlled lighting environments. Trade-off: Vulnerable to irregular target postures and carapace damage.	(Wu et al., 2025)
Molting recognition (Soft-shell crab)	YOLOF (based on YOLOv5)	Shedding crab images	shedding_crab AP: +1.7%; end unshell AP: +16.3%	28 FPS	Robustness: Effectively tracks distinct morphometric changes. Trade-off: Requires specific, unobstructed viewing angles to detect shell separation.	(Zhang Z. et al., 2024)
UAV-based monitoring (Hermit crab)	CRAB-YOLO + Super-Resolution (SRR)	Intertidal UAV aerial imagery	mAP improvement over YOLOv5 (Edge GPU)s: +5.4%	Moderate to High	Robustness: Capable of reconstructing low-resolution targets from high altitudes against complex intertidal backgrounds.	(Zhao et al., 2025)

Performance values should not be directly compared across studies because datasets, tasks, evaluation protocols, target species, environmental conditions, and metrics differ.

(Zhu et al., 2024; Luo et al., 2026; Sun C. et al., 2026). Technical routes include image enhancement and dehazing, data augmentation, spatial feature fusion, cross-frame aggregation, and post-detection identity association. These modules act on input restoration, sample coverage, single-frame representation, and temporal compensation, respectively, and cannot replace one another. The robustness problem can be further contextualized by studies on weak-signal detection, disease and bruise recognition, canopy recognition, obstacle detection, all-day detection, and instance segmentation under degraded visual conditions (Zhang Z. et al., 2023; Ma et al., 2024; Zhou et al., 2024; Zhang Z. et al., 2025).

Studies on cross-frame mud crab detection, partially occluded soft-shell crab recognition, crab seedling counting, low-light dehazing, and illumination-adaptive intertidal behavior analysis all treat illumination or occlusion as model-training and application conditions (Zhang Z. et al., 2024; Aini et al., 2025; Yu et al., 2025; Li X. et al., 2026). Robustness should be verified by separating degradation types: water turbidity and low contrast, local occlusion, overlapping individuals, moving blur, and lighting switching. Random splits over mixed data can report overall performance, whereas scene-level, species-level, and time-based splits are needed to test whether a module restores image appearance, supplements temporal information, or merely adapts to a particular data distribution (Siripattanadilok and Siriborvornratanakul, 2024; Sun Y. et al., 2024; Li et al., 2025; Tian et al., 2026).

In continuous operation, a correct single frame does not guarantee a correct process. After a target reappears from occlusion, the system must maintain identity; after enhancement of a low-quality frame, it must avoid false boundaries and false detections; after illumination switching, it must check for systematic output shifts. Detection, tracking, and abnormal-frame review should therefore be evaluated as one chain.

3.2.4 Lightweight detection and edge deployment

The core of edge deployment is not simply shrinking a network. It is maintaining perception outputs matched to operational rhythm under camera, processor, storage, power, and communication constraints. Lightweight routes in crab scenarios include model-structure compression, backbone replacement, front-end image enhancement, and task-scope reduction. Each affects the detectable range and the treatment of abnormal targets.

Deploying these models aboard commercial fishing vessels introduces severe hardware constraints absent in laboratory workstations. Edge devices on sorting decks are strictly limited by power availability, thermal management in corrosive environments, and onboard memory. Achieving real-time inference under these conditions requires deep algorithmic optimizations, such as parameter pruning, knowledge distillation, and precision quantization (e.g., INT8 or FP16). The necessity of these lightweight adaptations is fundamentally driven by the requirement to keep inference latency strictly lower than the mechanical cycle time of the processing conveyor.

Lightweight deployment studies on navigation, variable-rate actuation, target-oriented detection, point-cloud perception, and

remote-sensing segmentation provide transferable evaluation dimensions for edge inference in crab-harvesting scenarios (Liu et al., 2021; Lv et al., 2025; Xu et al., 2025; Ren et al., 2026). Real-time river crab detection, feeding-platform monitoring, precocious crab recognition, residual-feed detection, critical-part detection, and low-power fisheries video capture all treat model size and processing speed as application constraints (Ji et al., 2023; Gu et al., 2024; Sun Y. et al., 2026). Dehazing, channel compensation, and multi-scale enhancement improve low-contrast input but increase front-end latency. Lightweight backbones or detection heads reduce inference burden but may weaken output stability for small, occluded, or background-confused targets. Deployment evaluation must therefore connect input resolution, model size, inference speed, hardware use, continuous operation, target density, and throughput (Hu H. et al., 2023; Toé et al., 2023; Fang and Zhao, 2024).

Reliable lightweight systems require a branch for abnormal inputs. When images are too dark, targets overlap, or communication fails, directly outputting a class allows errors to enter downstream control. Confidence, image quality, and target motion state should trigger caching, repeated sampling, or manual verification. Edge deployment thus serves both computing control and long-term data governance.

To improve detection accuracy under complex backgrounds and small-object scenarios, recent studies have incorporated lightweight convolutional modules and attention mechanisms into the YOLO architecture. By introducing additional detection heads together with GSConv and Efficient Channel Attention (ECA) modules, the network achieves enhanced feature extraction and multi-scale representation while maintaining computational efficiency. As illustrated in Figure 2, the CRAB-YOLO framework provides an example of how architectural optimization can improve the perception capability of UAV-based crab detection systems, offering an effective reference for intelligent visual perception in sustainable crab fisheries.

3.3 Individual identity, attribute recognition, and quality assessment

3.3.1 Sex identification driven by abdominal morphology

Abdominal sex identification mainly observes gonopores, pleopods, abdominal segment width, abdominal-plate contour, and proportional relationships. Direct sexual characters are suitable for clear and posture-controlled individuals; geometric parameters support classification within the same species, developmental stage, and view; deep-learning classifiers can learn integrated morphological differences from ventral or dorsal images. If ventral visibility, flipping state, and developmental stage are not distinguished, models may confuse view or maturity differences with sex information.

Morphological studies of early developmental stages show that sex differences emerge with ontogeny and that body-size variables do not have constant discriminative value (Kajimoto et al., 2024; Jin et al., 2025). Explainable classification of giant crabs and dorsal morphology studies of horsehair crab indicate that dorsal carapace variables or image features can supplement sex discrimination when the ventral surface is not visible (Ueki et al., 2023; Chen Y. et al., 2025; Ebata et al., 2025). These results support organizing sex identification as a sequence of posture assessment, visible-body-region selection, and sex classification rather than as a universal abdominal-size threshold.

In equipment applications, sex identification is usually a preceding variable for quality grading, size management, or manual diversion. To maintain traceability, systems should store the body region used for judgment, image quality, and individual stage, and should treat low-confidence individuals as a separate state. This prevents incorrect sex labels from contaminating later variables and helps analyze errors across posture and developmental stages.

3.3.2 Quality grading by integrating shell color, body size, and fatness

Integrating shell color, body size, and fatness means converting appearance, geometric scale, and condition into traceable variables for the same crab. Shell color depends on light source, camera response, and carapace surface state; body size depends on posture and scale calibration; fatness requires body-size and body-weight relationships or defined condition factors. These variables have different origins and cannot be treated as direct equivalents of quality grade.

Analogous nondestructive quality-assessment studies show that optical variables should be linked to calibrated quality indicators rather than treated as direct quality labels (Shi et al., 2017; Huang et al., 2019; Xu M. et al., 2023; Sun J. et al., 2024; Tian et al., 2025; Li H. et al., 2026).

Comprehensive grading frameworks demonstrate that integrating multiple variables-such as sex, fatness, weight, and shell color-yields a more robust quality assessment for river crabs than single-feature analysis (Wang et al., 2023). Nevertheless, because carapace morphology and size-weight relationships vary significantly with origin, sex, and developmental stage (Kao et al., 2023; Aneesa et al., 2025; Frazato et al., 2025; Jin et al., 2025; Peng et al., 2025a; Wang Q. et al., 2025; Zhang W. et al., 2025), visual features alone remain insufficient if decoupled from physical measurements. To ensure operational reliability, quality models must strictly preserve image-weighing pairing and validate body-size variables across different demographic and environmental factors. Furthermore, while dorsal morphology and deep-learning sex recognition can enrich individual attribute profiling, they act as supplementary indicators and should not be treated as direct substitutes for actual fatness or calibrated quality grades (Ueki et al., 2023; Ebata et al., 2025).

Fusion-model evaluation should include shell-color acquisition conditions, size calibration, weighing ground truth, grade criteria, and cross-population validation. If images and weights are not obtained from the same individual, or if the training set mixes regional morphology differences into grade labels, the model output cannot be interpreted as individual quality status.

3.3.3 Potential of individual re-identification and weight estimation

Individual re-identification, morphological measurement, and weight estimation represent distinct hierarchical tasks in automated

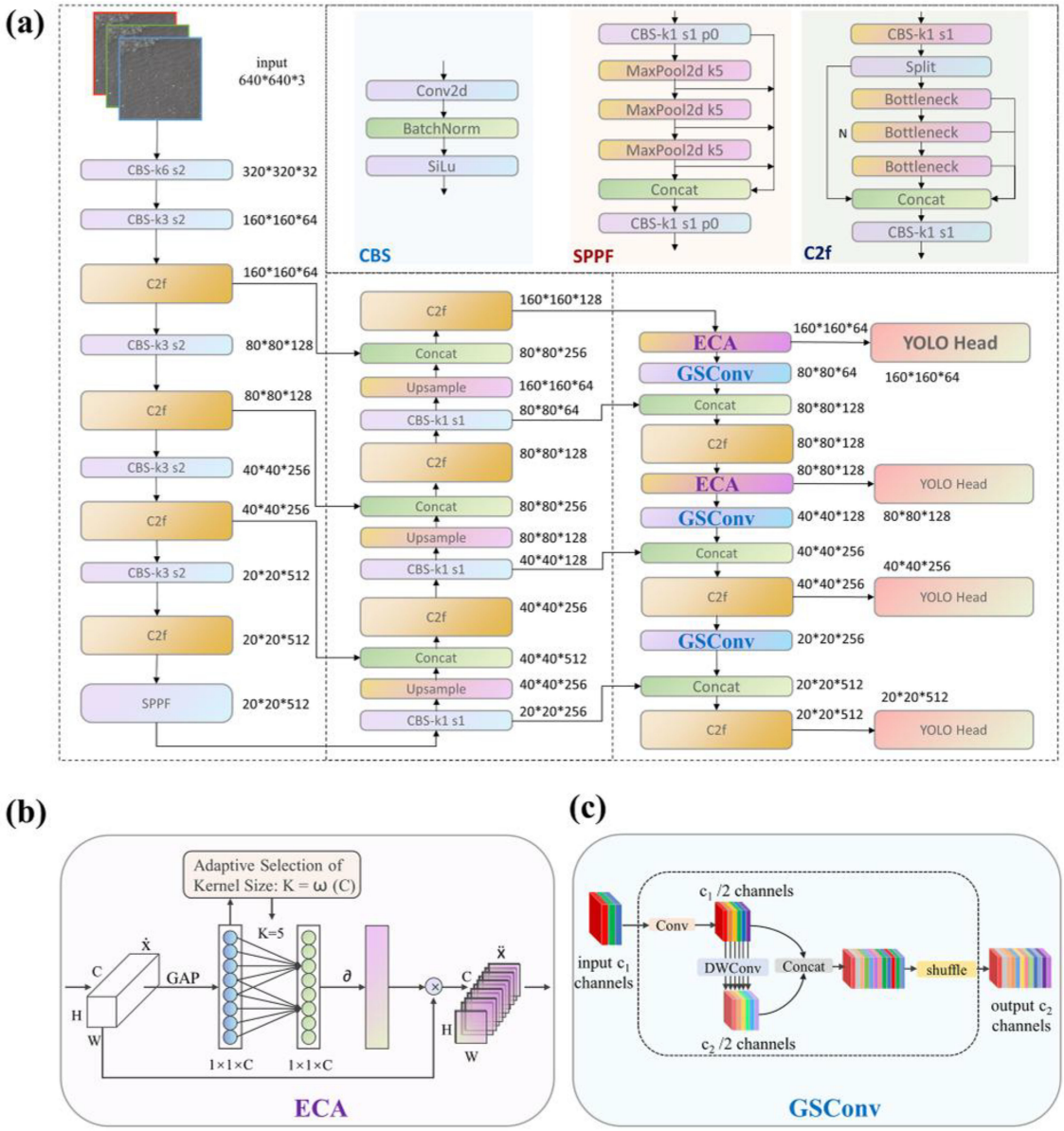


FIGURE 2
Architecture of the CRAB-YOLO network for UAV-based crab detection, adapted from Zhao et al. (2025). **(a)** Detailed architecture of the overall network; **(b)** Structure of the ECA module; **(c)** Structure of the GSConv module.

monitoring. While re-identification maintains identity continuity across observations and morphological measurement extracts geometric proportions, weight estimation strictly requires synchronized physical weighing to establish numerical baselines. Consequently, image records can only support individual-level weight monitoring when both identity association and weighing pairing are simultaneously maintained.

Recent advancements in re-identification demonstrate that leveraging global and local carapace textures-such as through pyramidal feature-fusion-can effectively maintain continuous identity association even when carapaces are incomplete (Zhang et al., 2022). However, robust identity tracking does not inherently translate to accurate weight prediction. Because crustacean morphology fluctuates significantly with seasonal, environmental, and developmental conditions (Ogburn et al., 2011), geometric visual cues are unreliable estimators of mass on their own. Therefore, operational weight models must rigorously align visual inputs with corresponding ground-truth weights under strictly controlled conditions (species, stage, season, and posture), treating variables like occlusion, molting, and carapace damage as explicit sources of error.

The practical value of re-identification is also to prevent repeated observations from inflating population indicators. If the same crab appears in the field of view at multiple moments without identity association, counts, body-size records, or quality changes may be treated as multiple samples. Re-identification creates a basis for de-duplication before linking records with weighing or tagging data.

Crucially, the visual perception outputs discussed in this section-ranging from bounding boxes to precise keypoints and

tracking identities-are not analytical endpoints; they are functional inputs for downstream physical execution. The ability to visually extract these parameters remains purely academic unless these data streams are seamlessly integrated with the physical gear capturing the crabs (as explored in Section 4) and the robotic systems processing them on deck (as discussed in Section 5).

Therefore, evaluating intelligent crab harvesting systems requires shifting the paradigm from purely algorithmic metrics to fisheries-aligned outcomes. High detection accuracy (e.g., mAP) alone does not guarantee sustainable harvesting if the specific operational and ecological downstream consequences are ignored.

Specifically, the translation of AI outputs into physical actions carries distinct ecological risks:

1. Localization to Mechanical Damage: While bounding boxes provide rough presence detection, imprecise keypoint or mask segmentation can lead to incorrect robotic grasping postures. In actual operations, this physical misalignment frequently causes mechanical damage, such as limb loss, which not only degrades the commercial value of the crab but significantly reduces the post-release survival probability of non-target bycatch.
2. Latency to Missed Ecological Opportunities: In dynamic marine environments with constant fluid disturbances, algorithmic processing delay is not merely a computational metric; it is a physical constraint. A latency of even 500 milliseconds (low FPS) may mean an undersized crab has drifted past an actively controlled escape vent, directly resulting in unintended retention and undermining the size-selectivity goal.
3. Tracking to Quota Management: Conversely, algorithmic failures in Multi-Object Tracking (e.g., identity switches caused by deck occlusions) do not just lower tracking metrics; they physically lead to double-counting on the processing conveyor. This directly distorts real-time catch statistics, thereby undermining the macro-level stock assessments and strict quota management policies essential for sustainable fisheries.

Consequently, future AI models for marine harvesting must be optimized and penalized not just for pixel-level errors, but for their direct impact on bycatch mortality, gear execution delays, and stock estimation accuracy.

4 Trapping behavior and intelligent crab pot/trap design

4.1 Bait-searching behavior and entry efficiency

Bait attraction is not equivalent to catch. It consists of chemical-cue release, oriented movement, approach to the entrance, entry through the opening, and later retention. Bait can alter alertness, grasping, and feeding, but entry in open water is also constrained by tidal activity, gear location, entrance visibility, and escape structures. Bait evaluation should separately record behavioral stimulation, number of approaches, and final retention.

Derby et al. showed that synthetic bait can stimulate blue crab behavior in the laboratory while not necessarily matching natural bait in field pot catch (Derby et al., 2024). Hewitt et al. showed that giant mud crab foraging varies with tidal stage, indicating that deployment period changes the proportion of individuals able to respond to bait cues (Hewitt et al., 2023a). Entrance color, mesh size, and soak time affect approach, escape opportunity, and selectivity (Olsen et al., 2022; Yu et al., 2024a; Susanto et al., 2025). Bait type itself should therefore be treated as an operational variable rather than as a background condition (Liu et al., 2024; Vu et al., 2025).

Bait assessment should distinguish release characteristics, behavioral response, and capture outcome. Release characteristics determine the spatial-temporal range of chemical cues; behavioral response describes whether individuals orient or approach; capture outcome further includes entry and retention. Comparing only hauled catch makes it difficult to determine whether a treatment changes long-range attraction, near-field recognition, or in-pot escape.

4.2 Relationships between light trapping and bait trapping

Light sources primarily modify visual cues near the gear and entrance, whereas bait creates chemical cues in the water. They may act at different stages of capture. Their combined effect depends on whether individuals have entered the light-influenced area, whether the light changes entrance recognition or retention, and whether it also changes the catch composition of target and associated species.

Nguyen et al. found that luminescent netting in snow crab pots has soak-time-dependent effects, and that short-term and long-term treatments do not necessarily produce the same catch differences (Nguyen et al., 2019). Lee et al. compared red, green, and blue LEDs in portunid trap fisheries and found relatively higher positive effects of blue and green light on CPUE, although differences among treatments and species responses were limited (Lee et al., 2026). Naimullah et al. showed that unbaited LED traps for orange mud crabs could not directly replace chemical attraction under the field conditions tested (Naimullah et al., 2022a). Luminescent-material evaluation should therefore record brightness decay, visible distance, source location relative to the entrance, and actual soak period.

The efficacy of light trapping is highly conditional and should not be viewed as a standalone replacement for traditional chemical baiting. Field evaluations demonstrate that artificial illumination, such as luminescent netting, exhibits strong soak-time-dependent effects, meaning that short-term attraction does not necessarily translate into long-term retention (Nguyen et al., 2019). Furthermore, while specific wavelengths can yield marginally higher Catch Per Unit Effort (CPUE) in certain trap fisheries, the overall performance differences across spectral treatments and

species responses often remain limited (Lee et al., 2026). Crucially, unbaited light sources have proven insufficient to directly replace the chemical cues required for successful capture under field conditions (Naimullah et al., 2022a). Consequently, evaluating luminescent materials requires treating brightness decay, visible distance, source placement relative to the entrance, and actual soak periods as critical operational variables.

Beyond initial attraction, the interpretation of color effects must be parsed by specific behavioral stages-ranging from distant approach to the selection of illuminated structures and final capture. Because different gears (e.g., gillnets, pots, and shelters) interact with crabs at distinct behavioral stages, isolated spectral variables are poor predictors of overall catchability. Synthesized evidence across various gear configurations indicates that spectral conditions, light intensity, placement, bait presence, gear type, and size composition must be evaluated as interconnected variables rather than isolated treatments to accurately assess capture performance (Kawamura et al., 2020; Naimullah et al., 2022a; Yu et al., 2023; Lee et al., 2026).

The synergy between light and bait should be tested within the same gear, soak time, and fishing ground by comparing empty controls, light-only treatments, bait-only treatments, and combined light-bait treatments. If combined treatments exceed the range explainable by either single factor, synergy can be discussed; otherwise, the result may reflect substitution, saturation, or failure of adjacent capture stages to connect (Naimullah et al., 2022a; Naimullah et al., 2022b; Yu et al., 2023; Becker et al., 2025; Cerbule et al., 2025a). Synergy between light and bait should be tested as an interaction effect in a factorial design rather than inferred only from a higher combined catch.

4.3 Pot structure and retention control

Pot structure regulates the guiding stage before entrance, passage through the entrance, and retention or escape inside the pot. Entrance color, passage boundary, mesh, and escape vents are not independent parameters; together they determine whether individuals approach, how they pass, and whether they leave during soaking. Structural evaluation should connect terminal catch with approach, entry, and escape events.

The structural layout in Figure 3 places the main pot-design variables in the same visual frame. The entrance funnel, mesh size, slit entrance, and escape gap correspond to the approach, passage, retention, and escape stages discussed in this section, linking geometric design with selectivity outcomes.

Entrance angle and passage shape should be assessed through approach direction, entrance localization, passing posture, and reasons for failed entry. Current abstract-level evidence mainly supports entrance color, mesh, and bait response rather than direct comparisons of entrance angle or passage shape. Future experiments should compare entrance angle, passage length, and opening direction within the same pot type and use approach, entry attempts, successful entry, and leaving events as continuous indicators (Hewitt et al., 2023a; Susanto et al., 2025).

Pot geometry inherently constrains the capture pathway by dictating the internal activity space, netting boundaries, the route from the entrance to the bait, and the strategic location of escape structures. The physical dimensions of these structures, such as ring size or vent shape, directly alter retention probabilities and shift size selectivity curves, often interacting with species- or sex-specific morphological differences (Olsen et al., 2022; Zhang, 2025).

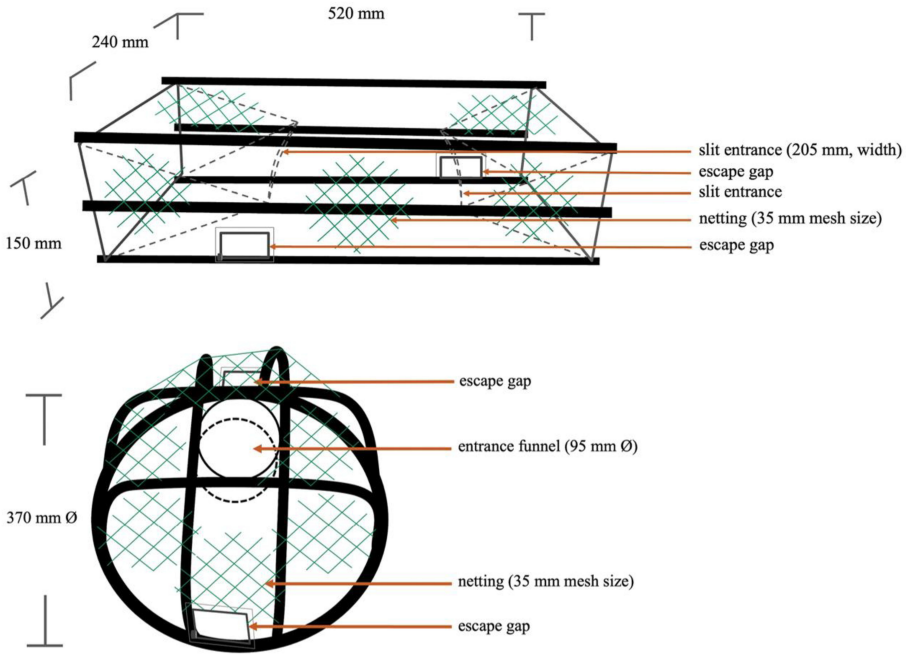


FIGURE 3
Structural configuration of escape-gap crab pots for size-selective retention, adapted from Picoy-Gonzales et al. (2025).

Furthermore, structural variables do not act in isolation; factors like entrance color and mesh size jointly dictate the ultimate catch composition (Susanto et al., 2025). Therefore, robust gear validation must move beyond simple catch totals to report specific pot types, entrance configurations, and precise escape-vent dimensions, ideally utilizing video or marking techniques to track exactly where geometric constraints act within the capture pathway.

Crucially, these physical constraints are modulated by soak time, which dictates not only the duration of bait efficacy but also the cumulative opportunities for target approach, entry, and eventual contact with escape structures. Prolonged soaking periods significantly increase the probability that undersized individuals will locate and successfully navigate escape openings, thereby reducing unintended retention (Yu et al., 2024a). In fact, the performance differences between various escape-vent geometries and the influence of environmental variables often only manifest over the full duration of a soak period (Naimullah et al., 2022b; Anders et al., 2023; Hewitt et al., 2023b; Zhang J. et al., 2023; Cerbule et al., 2024a; Zhang J. et al., 2024; Cerbule et al., 2026). Consequently, optimizing soak time requires evaluating dynamic shifts in catch composition and escapement rates rather than merely assessing the total retained catch.

4.4 Escape-vent design and release of undersized crabs

Escape vents create size selectivity through clear dimensions, shape, stiffness, and installation position, but this geometric constraint becomes actual release only through approach, turning, and passage. Evaluation should compare not only the reduction of undersized crabs, but also the retention of legal-sized crabs, release of associated species, and passage behavior of different body shapes.

The effectiveness of escape vents is not merely a function of their static dimensions; rather, it is deeply intertwined with crab morphology, behavior, and gear dynamics. Passage success depends heavily on a crab's orientation, size, and sex-specific body shape, which can significantly alter retention thresholds even under identical opening dimensions-such as the distinct male-female retention gaps observed across standardized escape-ring sizes of 60.3 mm, 63.5 mm, and 66.7 mm, or specific rectangular vent height configurations (Olsen et al., 2022; Zhang J. et al., 2024; Cerbule et al., 2026). Furthermore, release opportunities are continuously modulated by operational factors, including the internal navigation paths within different pot types, bait depletion over prolonged soaks, and the physical deformation of flexible materials such as hinged gaps (Anders et al., 2023; Picoy-Gonzales et al., 2025).

A critical synthesis of these studies reveals a fundamental ecological and operational trade-off in selective gear design: while maximizing vent dimensions or mesh sizes facilitates the escapement of sublegal crabs and bycatch, it inherently risks the unacceptable loss of legal-sized target catches if not precisely calibrated. Consequently, optimal escape-vent parameters cannot be generalized; they must be rigorously derived from species-specific target size thresholds and empirically validated across sex and carapace-width groups within the same pot type.

To manage this trade-off effectively, equipment evaluation must standardize its reporting. Rigid structures require clear documentation of exact dimensions and installation positions, whereas flexible components demand records of their opening geometry following prolonged soaking. Ultimately, as illustrated by the *in-situ* behavior in Figure 4, static vent geometry only translates into actual selective release when a crab can successfully orient, approach, and navigate the opening under dynamic field conditions. Establishing this clear link between physical gear parameters and behavioral escape processes is essential for integrating selective capture with downstream automated processing and resource conservation.

Figure 4 links escape-vent geometry with the behavioral passage process. To extend that mechanism to pot-level design and ecological performance, Table 2 compares representative factors affecting crab-pot efficiency, selective release, bycatch control, and gear-loss risk.

Table 2 indicates that intelligent crab-pot design should not optimize catch efficiency as a single endpoint. Bait, light, entrance color, mesh, escape openings, soak time, bycatch-reduction devices, and gear-loss management act at different stages of the capture pathway; therefore, future systems should integrate behavioral observation, size-selective release, catch-composition assessment, and post-deployment ecological-risk control.

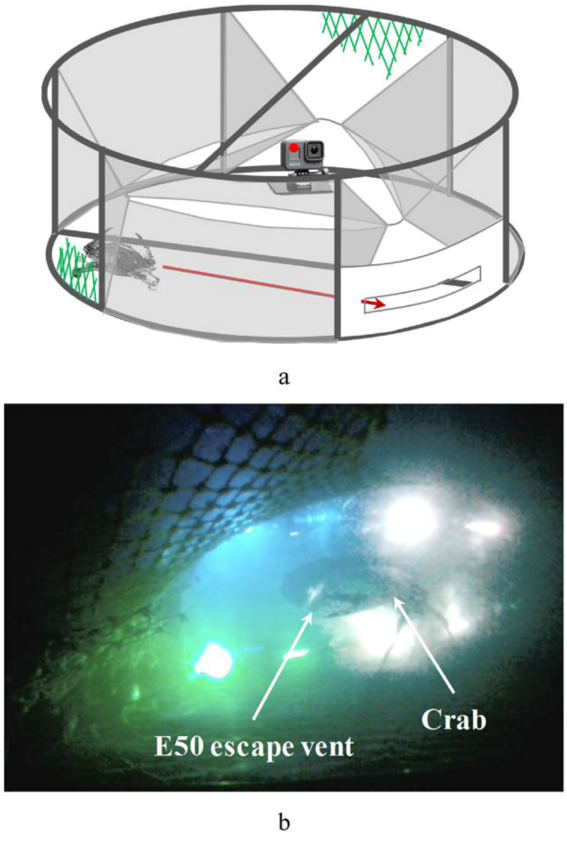


FIGURE 4
Behavioral passage mechanism of swimming crabs through pot escape vents, adapted from Zhang et al (Zhang J. et al., 2023).

TABLE 2 Representative factors affecting crab-pot capture efficiency, size-selective release, bycatch control, and derelict-gear risk.

Factor	Setting	Variable	Result	Reference
Soak time + escape	Swimming crab pots	Circular/rectangular openings; 2, 5, 7 days	Undersized-crab retention decreased as soak time increased. Selective contact after 7 days: >90% Escape openings reduced bycatch capture. Circular vs rectangular openings: no significant selectivity difference.	(Yu et al., 2024a)
Escape vent	East China Sea swimming crab pots	Rectangular; elliptic; circular vents	Escape vents reduced sublegal crabs. Sublegal threshold: <49 mm CL or <116 mm CW Rectangular vents produced steeper selectivity curves. First underwater observation period: 2.5 h	(Zhang J. et al., 2023)
Escape ring	Texas blue crab pots	60.3, 63.5, 66.7 mm rings	CW50 increased with escape-ring size. Male-female CW50 gap at 60.3 mm: 4.4 mm Male-female CW50 gap at 63.5 mm: 5.0 mm Male-female CW50 gap at 66.7 mm: 7.2 mm	(Olsen et al., 2022)
Entrance color + mesh	Blue swimming crab pots	Yellow/dark-green/red entrances; mesh size	Yellow entrances caught more crabs than dark-green or red entrances. Mesh size affected size selectivity. Mesh size >75 mm released crabs with CW <100 mm.	(Susanto et al., 2025)
Bait type	Swimming crab pots	Squid; trash fish+squid; synthetic bait	Squid alone significantly increased crab catch. Trash fish+squid also significantly increased crab catch. Synthetic bait caught fewer blue crabs than menhaden in the field test.	(Derby et al., 2024; Vu et al., 2025)
Soak time + bycatch	Taiwan Strait traps	2011–2016 logbook/VDR data; soak time	Optimal target CPUE: 48 h Crab-trap bycatch increased after 48 h. Fish-trap bycatch was not affected by soak time.	(Naimullah et al., 2022b)
LED wavelength	Portunidae traps	Red, green, and blue LEDs	Positive CPUE effect: blue > green > red Differences among LED colors were small. Effects on catch rate and crab size were limited. Species differences were not statistically significant.	(Lee et al., 2026)
Unbaited LED	Scylla olivacea	Green/blue/white/red LEDs; baits	Captivity test: green, blue, and white LEDs attracted crabs. Red LED showed no attraction relative to controls. CPUE gain vs empty trap: green LED + 2.18% CPUE gain vs empty trap: chicken head +4.52% CPUE gain vs empty trap: mackerel +7.28% Average CPUE: mackerel 0.66, chicken head 0.38, green LED 0.13 per trap.	(Naimullah et al., 2022a)
Noctilucent pot	Yellow Sea crab pots	Control; stick; net; net+stick	10 min solar charge produced 6 h emission. Net+stick catch efficiency: +63.84% vs control Crab proportion in net+stick pots: 86.35% Crab weight in net+stick pots: 61.5 g Weight gain vs control: +38.30% W50: net 53.01 g; net+stick 54.49 g	(Liu W. et al., 2025)
Bycatch device	Virginia tidal-creek blue crab pots	Four BRDs; control	Terrapin CPUE differed among treatments: p=0.003 Control terrapin CPUE: 0.97 +/- 0.18 All BRDs significantly reduced terrapin capture. Blue-crab CPUE did not differ among treatments: p=0.392 Legal crab size did not differ: p=0.216	(Reinsel et al., 2023)
Gear loss	Seribu Islands trap fishery	Field survey; fisher interviews	Estimated lost traps: 64,272 per year Share of traps lost: 18% Replacement cost: USD 195,082 Main causes: gear conflict, buoy loss, theft, and damage.	(Riyanto et al., 2025)

5 Vision-guided handling, sorting, and processing automation

5.1 Visual localization requirements in crab processing automation

Once the selective gear configurations (discussed in Section 4) successfully bring a curated catch to the surface, the operational bottleneck immediately shifts to shipboard processing. Although processing automation occurs post-capture, it serves as the critical physical nexus where the visual perception outputs from Section 3 are actively converted into precise mechanical actions.

Although processing automation occurs after capture, it tests whether visual outputs can be converted into physical actions, which is also central to intelligent harvesting systems. Visual localization in processing equipment must convert target position, posture, key regions, and operational state in images into information callable by mechanisms. Detection and counting only state whether an object appears. Without conversion between camera coordinates and operation coordinates, temporal target position, and abnormal-state feedback, results cannot become grasping, cutting, or sorting instructions.

Studies on intelligent production, robotic harvesting, hand-eye coordination, and visual servo systems further show that recognition outputs must be converted into robot coordinates, picking points, or actuator commands before they can support automation (Wu and Gu, 2017; Xu Z. et al., 2023; Guan et al., 2024; Guan et al., 2025; Tai et al., 2025; Chen Z. et al., 2026).

Sun Y. et al., 2026 integrated image enhancement, multi-object detection of crabs and feed, environmental sensing, and information processing in a river crab feeding-platform monitoring system. This proves that object and environmental information can be organized in one sensing system, but its output is monitoring and counting rather than processing localization. Processing scenarios require additional camera calibration, actionable-region definition, localization-error reporting, and post-action verification.

Visual localization should distinguish detection coordinates from execution coordinates. Image coordinates describe where a target lies in the camera field; execution coordinates describe where a tool can reach. Conversion requires camera intrinsic and extrinsic parameters, the operation plane, and mechanism kinematics. If the target moves between acquisition and execution, time compensation based on conveyor speed or mechanism state is required.

5.2 Visual localization and end-effector guidance

Vision guidance aims to transform individual boundaries, keypoints, posture, and scale information into actionable coordinates. The perception layer expresses targets and local regions; the geometric layer determines scale, direction, and relative position; the execution layer forms gripper or cutting paths. If the three layers are not linked by the same object and timestamp, visual-model performance cannot be interpreted as operation performance.

Crab morphology segmentation and key-region localization are fundamental for defining precise operational sites, such as the carapace, abdomen, and specific appendages. However, executing these tasks in processing environments is severely complicated by posture variations, appendage occlusions, and boundary discontinuities caused by wet surface reflections. A critical bottleneck in advancing automated processing is the absence of dedicated, large-scale crab segmentation datasets. While current studies draw on proxy evidence from crab-like robotic motion models to justify dynamic region localization (Hu et al., 2025), the lack of standardized benchmarks prevents the direct, rigorous comparison of competing segmentation algorithms.

Beyond 2D boundary extraction, generating effective cutting or grasping trajectories demands multi-dimensional inputs. Safe tool approach directions require the integration of depth mapping, 3D keypoints, and posture estimation, particularly when selecting upper-layer targets from densely piled catches (Ali et al., 2026). Concurrently, coarse-to-fine segmentation, real-time carapace measurement, and the physiological screening of targets (e.g., identifying molting states prior to handling) are essential for establishing scale references and confirming the operational state before any mechanical interaction occurs (Tang et al., 2020; Cao et al., 2021; Toé et al., 2023; Chen K. et al., 2025).

Ultimately, bridging the gap between visual perception and physical execution requires strict error management. Path generation algorithms must translate visual uncertainties directly into physical safety boundaries. When keypoints or instance masks fluctuate, end-effectors must not move rigidly along estimated borders; instead, controllers must dynamically reserve avoidance distances based on established error margins, target thickness, and holding states. To prevent irreversible product damage, systems must incorporate built-in fallback protocols-such as mechanical repositioning, flipping, or diversion to manual review-whenever targets present low visual confidence or severe occlusion.

5.3 Dynamic conveying, sorting, and measurement control

Dynamic conveying requires distinguishing repeated appearances of the same target from sequential passage of different targets and pairing image records with size or weight information. Single-frame detection answers whether a target exists; tracking answers whether identity is continuous; weight estimation requires ground-truth weighing for the same object.

Work on sorting systems, visual density estimation, grading, behavior classification, and maturity quantification provides cross-domain references for linking continuous visual records to identity tracking and downstream decision chains (Chen et al., 2020; Pan et al., 2023; Jiang et al., 2024; Peng et al., 2025c).

Towed-sledge video systems for snow crab estimate survey area and population density from continuously moving observations (Watanabe, 2002a; Watanabe, 2002b). As an analogy rather than direct conveyor evidence, their experience shows that moving-platform image records must be interpreted with track and coverage; however, these systems do not provide identity tracking or weight estimation on a conveyor. Processing conveyors must further record target speed, trajectory interruption, duplicate counting, identity switches, image-measurement error, weighing error, and sorting rhythm.

Dynamic sorting organizes detection, tracking, size judgment, and actuator action into a continuous control chain. Vision must complete identity and attribute judgment before the target reaches the execution zone; the controller must output the corresponding action when the target arrives; and post-action verification must confirm allocation. Counts, positions, and quality information must be bound to the same trajectory to avoid repeated processing or incorrect diversion.

Shipboard detection is constrained by deck-background variation, illumination fluctuation, occlusion, device computing power, and continuous power supply. Iftikhar et al. used benchmark single-stage detectors on crab and lobster fishery datasets to support detector selection and input configuration (Iftikhar et al., 2024), but shipboard systems still require records of detection timestamps, deck position, target trajectories, and communication state to turn single-frame recognition into real-time input for sorting or measurement.

Multi-object tracking is essential for maintaining consistent identity labels across continuous frames, particularly when mitigating dynamic occlusion, close physical contact, and short-term target disappearance amidst debris. The integration of advanced object detectors with robust tracking algorithms has proven effective for dynamic counting and identity recovery following severe occlusion events (Tian et al., 2026). However, sustaining continuous association remains heavily contingent on raw image quality; environmental factors such as dehazing efficiency, rapid contour deformation, and the availability of high-quality frames critically constrain tracking stability (Aguzzi et al., 2009; Lu et al., 2020). Consequently, the evaluation of dynamic sorting systems must extend beyond static detection accuracy to explicitly report metrics on identity switches, track interruptions, re-identification rates, arrival-time prediction accuracy, and protocols for handling abnormal objects, all synchronized seamlessly with mechanical actuator responses.

Furthermore, coupling visual measurement with weight estimation demands that image dimensions, target identities, and physical weight data are strictly synchronized within the exact same temporal chain. Because crustacean morphology fluctuates significantly depending on the developmental stage and seasonal variations (Ogburn et al., 2011), geometric visual dimensions are fundamentally unreliable if interpreted independently of the sampling period and biological state. To establish robust numerical models, weight-estimation frameworks must synchronously acquire calibrated images and ground-truth physical weights. Evaluation metrics should subsequently stratify prediction errors across multiple biological and environmental axes, specifically documenting variances caused by sex, size, seasonal shifts, posture irregularities, and abnormal carapace states.

5.4 From single-machine automation to system intelligence

The transition from single-machine automation to system coordination fundamentally depends on traceable data links spanning perception, data fusion, decision-making, mechanical execution, and human interaction. A standalone recognition module cannot independently verify whether a mechanical action successfully engaged the intended target. Therefore, robust systems must seamlessly bind target identity, environmental state, spatial mechanism coordinates, and control commands across a unified spatiotemporal axis.

Advancements in multi-task learning, multimodal fusion, and multi-sensor evaluation demonstrate that heterogeneous signals can be effectively integrated provided the target variables and decision pathways are explicitly defined (Zhu et al., 2020; Deng et al., 2023; Elsherbiny et al., 2025; Huang et al., 2025). Recent foundational work has successfully demonstrated isolated components of this integration, such as pairing visual detection with environmental sensors (Sun Y. et al., 2026), spatially aligning multi-modal underwater imaging (Chang et al., 2022), and establishing responsive human-machine interfaces to keep operators in the control loop (Hui et al., 2024). However, a critical maturity gap remains: these proof-of-concept systems do not yet encompass the full complexity of shipboard crab harvesting or deck-processing workflows. To bridge this gap, future engineering efforts must prioritize cross-sensor calibration, stringent data synchronization, automated abnormal-event alarms, and seamless human-takeover protocols during long-term continuous operation.

Ultimately, true system intelligence is not achieved merely by adding more sensors; it is defined by the reliable exchange of contextual information around a singular object and operational event. Visual, acoustic, environmental, and kinematic data must operate on a unified time base, ensuring that target identity remains unbroken from the moment of perception to final execution. When anomalies occur, this data must automatically feed back into the decision loop to correct subsequent actions. Without this rigorous spatiotemporal correspondence, interconnected modules will remain functionally isolated parallel machines rather than an intelligent, cohesive harvesting system.

Ultimately, a highly coordinated, intelligent shipboard sorting system does more than simply replace manual labor; it functions as a continuous, high-fidelity biological sampling station. The granular data generated seamlessly across the automated conveyor belt-comprising continuous species counts, precise sex ratios, and paired weight-size dimensions-forms the exact foundational dataset required for the macro-level resource monitoring, catchability calibration, and ecological impact assessments discussed in Section 6.

6 Resource monitoring, selective harvesting, and impact assessment

6.1 Underwater video monitoring for crab resource assessment

Translating visible individuals in underwater video into reliable resource assessment indicators requires linking raw counts with survey area, time, and detection probability. A raw video record does not inherently equate to resource density. Recorded counts are heavily biased by the camera's field of view, platform trajectory,

target posture, and dynamic water visibility. Therefore, accurately interpreting these visual records demands robust community-scale baseline references to account for broader ecological shifts, rather than relying solely on isolated imagery (Yang et al., 2024).

To prevent 'sustainability' from becoming a hollow technological claim, intelligent crab harvesting operations must ultimately be evaluated against established, measurable ecological indicators. Moving forward, technological success should not only be measured by precision and speed, but must be explicitly correlated with biological metrics. Key measurable indicators include:

1. Bycatch Reduction Rate (BRR): Quantifying the percentage decrease in non-target species retention due to intelligent selectivity.
2. Post-Release Mortality (PRM): Tracking the physical condition and survival probability of discarded crabs following robotic handling.
3. Size-Selection Parameters (e.g., L50): Using the length at 50% retention to statistically verify that the integration of AI perception and escape vents effectively protects juvenile cohorts.
4. Benthic Footprint Reduction: Measuring the reduction in bottom-contact duration (soak time) and the prevention of ghost fishing through gear loss monitoring.

Furthermore, visual monitoring cannot be evaluated in a vacuum; it must be cross-calibrated with physical survey tools, which carry their own inherent biases. For example, telemetry data demonstrates that a crab's approach to a pot does not guarantee capture, as retention is heavily constrained by initial distance and behavioral responses (Becker et al., 2025), while comparative gear studies highlight distinct size selectivities between traps and trawls (Hanamseth et al., 2022). Because environmental states and operational conditions fundamentally alter both physical catch rates and mobile imaging effectiveness (Hewitt et al., 2023b; Bodine et al., 2026), underwater video surveys must rigorously document platform tracks, camera height, field width, illumination, turbidity, and explicit duplicate-counting rules to serve as reliable management-scale data.

Ultimately, the fundamental unit of a video survey must be a spatially contextualized observation within a known range, rather than a disembodied frame count. For static deployments, this requires strict field-boundary definitions and protocols for identifying repeated individuals; for mobile platforms, it necessitates continuous logging of track, speed, altitude, and swept width. To prevent visibility fluctuations from being misinterpreted as biological scarcity, the probability of false negatives (missed targets) must be dynamically quantified across varying substrates, turbidity levels, and lighting conditions.

6.2 Catchability and calibration of survey results

Catchability links true resource status with catch or survey records and is jointly affected by environment, behavior, gear structure, and fishing practice. The same resource density can produce different terminal catches under different temperature, hydrology, illumination, soak time, and gear conditions. Resource assessment must therefore record these variables together with effort and survey position.

Water temperature, water flow, and light affect catchability by changing individual activity, movement, and opportunity to approach gear. They also change imaging and observation conditions. Hewitt et al. showed that giant mud crab catch rates are related to water temperature, river flow, wind speed, lunar phase, and soak time (Hewitt et al., 2023b). Telemetry and behavior studies demonstrate temporal and tidal constraints on approach to baited pots and foraging (Hewitt et al., 2023a; Becker et al., 2025). Artificial-light studies further suggest that light may alter behavior or merely observation conditions (Naimullah et al., 2022a; Cerbule et al., 2025a; Lee et al., 2026).

Underwater video can decompose terminal catch into approach, entrance passage, escape, and retention, providing process explanations for pot selectivity. Behavioral records of Japanese rock crab toward collapsible baited pots, comparisons of Japanese mitten crab pot and hand-net surveys, and trawl groundrope video of snow crab all show that video can expose individuals that were not captured and identify where escape occurred (Archdale et al., 2003; Fujita et al., 2006; Kobayashi and Vazquez-Archdale, 2016). Fixed underwater camera studies of crab-tile habitats also show that remote video can reveal responses of mobile benthic animals during tidal immersion (Sheehan et al., 2010).

Fishery data used in resource assessment reflect crab distribution and catchability, but also fishers' choices of area, time, bait, and gear. If capture probability differs by sex, size, or region, the relationship between catch per unit effort (CPUE) and true density changes. Skerritt et al. demonstrated through continuous mark-recapture work on lobster that sex-specific catchability can alter density estimates (Skerritt et al., 2023). Studies of seasonal effort, environmental catch variation, mesh size, entrance structure, and escape devices further show that operational strategies alter spatial and temporal coverage of observation data (Naimullah et al., 2022b; Olsen et al., 2022; Hewitt et al., 2023b; Yu et al., 2024c; Greenberg and Mcallister, 2025; Susanto et al., 2025).

Fishing behavior is not simply the amount of effort. It includes where vessels work, when pots are hauled, what gear is used, and how recent information changes strategy. Wang et al. modeled the Alaskan snow crab fishery and showed that vessels adjust fishing areas according to abundance, distribution, weather risk, cost, and information, and that spatial strategies differ among vessels (Wang T. et al., 2024). Long-term studies of portunid catch variability and governance comparisons in swimming crab fisheries also show that environment, fisher behavior, monitoring institutions, and enforcement structure shape data quality and management response (Schilling et al., 2023; Macario et al., 2026).

6.3 Selective harvesting and resource conservation

Selective harvesting reduces unintended impacts on undersized individuals, associated species, and protected animals by adjusting entry, retention, escape, and spatial-temporal operating conditions. Its performance should not be evaluated only through target catch. It should connect size composition, release process, derelict-gear risk, and line-risk outcomes.

Escape-vent shape and height, soak time, mesh, and entrance adjustment can change size selectivity and bycatch composition

(Naimullah et al., 2022b; Madhu et al., 2023; Zhang J. et al., 2023; Zhang J. et al., 2024; Cerbule et al., 2025b; Susanto et al., 2025; Cerbule et al., 2026; Yu et al., 2026). Bycatch-reduction devices for non-target animals, pot-structure studies, and derelict-pot risk studies show that structural measures must be verified together with target retention, non-target exclusion, and operating conditions (Wilson et al., 2022; Cerbule et al., 2023; Moore et al., 2023; Reinsel et al., 2023; Cerbule et al., 2024a). Environmental catchability and effort changes also influence how conservation measures perform across seasons and fishing grounds (Anders et al., 2023; Hewitt et al., 2023a; Hewitt et al., 2023b).

The synergy of selective technologies should not be understood as simple addition of devices. Entrance and stimulus parameters affect which individuals approach and enter; escape vents and mesh affect which are retained; soak time and location affect how long these processes operate. If measures act on the same stage, marginal effects may decline; if they act on consecutive stages, they may form a more complete control chain for size and species composition.

6.4 Abandoned fishing gear and marine-animal protection

Derelict crab pots and vertical lines create different risk pathways: ghost fishing focuses on continued capture and mortality inside or around the pot, whereas vertical-line risk depends on spatial overlap and encounter probability outside the pot. The former requires evaluation of entry, death, escape, and material failure; the latter requires evaluation of line distribution, marine-animal movement space, and overlap with fishing effort. Pengsakun et al. (2026) showed in studies of abandoned, lost, and discarded fishing gear in the Gulf of Thailand that habitat damage, including coral tissue necrosis, breakage, algal cover, and sediment accumulation, should be considered in addition to ghost catch.

Derelict pots may continue to capture after baiting and hauling cease. Their persistence depends on entry, escape opportunity, whether dead individuals create further attraction cues, material durability, and exposure time. Ghost-pot studies in swimming crab and snow crab show that abandoned gear can retain target and associated species and that self-baiting is not a fixed-strength mechanism (Cerbule et al., 2023; Cerbule et al., 2024b; Yu et al., 2024b). Studies on derelict pots, escapement, and retrieval operations further show that long-term risk depends on whether escape channels remain functional after material aging (Antonelis et al., 2023; Vodopia et al., 2024; Serrano et al., 2026).

Biodegradable escape devices are useful only if material failure creates an unobstructed and appropriately sized passage that crabs can actually use. Failure includes degradation that is too slow, openings blocked by structure, doors that still require pushing, and insufficient opening size. Retrieval records and escape-gap observations indicate that improvement should verify failure timing, opening geometry after long soaking, biofouling, and actual escape behavior rather than relying on material name or laboratory degradation time (Antonelis et al., 2023; Vodopia et al., 2024; Vodopia et al., 2025; Cerbule et al., 2026).

Vertical lines between pot buoys and pots can overlap with marine-animal movement space. Risk depends on line number, deployment position, line tension, and seasonal animal distribution. Riekkola et al. (2023) showed through retrospective analysis of Dungeness crab measures in Washington State that reducing gear numbers changes the trade-off between whale risk and fishery economics. Ehnert-Russo et al. showed that seasonal migration can concentrate offshore blue crab pot effort in specific Florida areas, so risk assessment must first understand the spatial distribution of effort (Ehnert-Russo et al., 2022).

Welch et al. showed that dynamic management can reduce vertical-line risk, but the size of planning units changes the spatial trade-off between risk avoidance and fishing activity (Welch et al., 2024). Peck et al. provided direct engineering observations by measuring rope tension during snow crab hauling (Peck et al., 2024), while protected-shark bycatch and derelict-gear retrieval records show that conservation measures should be evaluated with gear configuration and recovery management (Pillans et al.,

TABLE 3 Consolidation of current research gaps and proposed technological solutions in intelligent crab harvesting.

Operational domain	Identified research gaps (current limitations)	Proposed solutions & future directions
1. Visual Perception & AI	Fragmented datasets: Lack of large-scale, standardized public underwater image datasets. Insufficient metadata: Datasets often lack critical environmental tags (e.g., turbidity, lighting). Computational limits: Heavy models struggle with low-power edge deployment on ships.	Establish open-source, multi-species benchmark datasets with standardized metadata protocols. Develop lightweight edge-computing models (e.g., via pruning or knowledge distillation) suited for vessel deployment.
2. Selective Catch Operations	Limited field trials: Over-reliance on controlled laboratory/tank tests rather than *in-situ* marine validation. Passive gear bias: Current escape vents are static and dimension-fixed, lacking dynamic adaptability to diverse bycatch profiles.	Execute long-term, commercial-scale field trials under variable marine conditions. Design active-sorting gear mechanisms driven by real-time sensor feedback.
3. Deck Processing Automation	Mechanical damage risks: Rigid robotic end-effectors increase post-release mortality for non-target species. Tracking instability: Severe occlusions on deck conveyors lead to identity switches in multi-object tracking.	Integrate soft robotics and multi-modal sensory feedback (tactile + visual) for zero-harm handling. Develop robust 3D tracking algorithms optimized for dense, overlapping biological targets.
4. Macro-Level Resource Monitoring	Lack of ecological validation: Algorithmic metrics are rarely translated into quantifiable ecological parameters (e.g., BRR, L50). Economic barriers: Insufficient Life-Cycle Assessments (LCA) and socio-economic cost-benefit analyses for small-scale fisheries.	Bridge data streams directly to quota management systems. Conduct comprehensive socio-economic feasibility studies and LCAs to support technology adoption policies.

2022; Vodopia et al., 2025). Ropeless or reduced-line approaches must also preserve reliable localization and retrieval to avoid creating new derelict-gear risks.

7 Conclusions

While significant individual technological advancements have been made, the transition to fully integrated intelligent crab harvesting is hindered by several systemic limitations. To avoid redundant descriptions and provide a clear roadmap for researchers and industry stakeholders, Table 3 systematically consolidates the primary research gaps identified across the four operational domains of this review, alongside their proposed solutions.

To transition from conceptual frameworks to real-world impact, future research must move beyond generic objectives and adopt a structured, time-phased roadmap. Addressing these multifaceted challenges requires a clear timeline across short-, medium-, and long-term milestones:

1. Short-Term Goals (1–3 Years): Research must prioritize data governance and standardization. This involves establishing open-source, multi-species underwater image datasets that incorporate rigorous metadata (turbidity, illumination, and camera geometry) to overcome current data fragmentation and enable fair algorithmic benchmarking.
2. Medium-Term Goals (3–5 Years): Efforts should center on multimodal sensor integration and robust edge deployment. Integrating machine vision with acoustic tracking or tactile sensors will help compensate for visual limitations in turbid marine environments. Concurrently, lightweight model optimization must achieve real-time inference under the severe hardware and power constraints of commercial fishing vessels.
3. Long-Term Goals (5–10 Years): The focus must shift toward full system-level integration and socio-economic validation. This includes executing long-term field trials that link perception outputs directly to selective gear performance and resource dynamics, incorporating life-cycle assessments (LCAs) for biodegradable gear, and identifying and mitigating the socio-economic and financial barriers that hinder the adoption of intelligent harvesting technologies in small-scale fisheries.

Ultimately, the future of sustainable marine fisheries depends on bridging the gap between computational intelligence and ecological reality. By transitioning from highly controlled laboratory concepts to rigorous *in-situ* multi-modal integrations, and by strictly aligning AI performance with measurable resource-conserving indicators (such as bycatch reduction and post-release survival), intelligent harvesting technologies can profoundly transform crab fisheries from exhaustive resource extraction into dynamic, ecologically conscious management systems.

Author contributions

HZ: Supervision, Writing – review & editing, Funding acquisition, Software, Investigation, Writing – original draft, Resources, Validation, Project administration, Visualization, Data curation, Formal analysis, Conceptualization, Methodology. YC: Writing – original draft, Conceptualization, Software, Funding acquisition, Resources, Investigation, Project administration, Formal analysis, Visualization, Validation, Methodology, Supervision, Data curation. ZT: Data curation, Validation, Project administration, Conceptualization, Methodology, Supervision, Writing – original draft, Resources, Funding acquisition, Writing – review & editing, Software, Investigation, Formal analysis, Visualization.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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References

Aguzzi, J., Costa, C., Fujiwara, Y., Iwase, R., Ramirez-Llorda, E., and Menesatti, P. (2009). A novel morphometry-based protocol of automated video-image analysis for species recognition and activity rhythms monitoring in deep-sea fauna. *Sensors* 9, 8438–8455. doi: 10.3390/s91108438

Aini, M., Leong, S., Yong, Y., Lee, B., Zhao, X., Manaf, S., et al. (2025). Image enhancement for detection of underwater moulted crabs in greenhouse soft-shell crab farming using deep learning. *Smart. Agric. Technol.* 12, 15. doi: 10.1016/j.atech.2025.101223

Ali, M., Sadrieh, F., Wu, B., and Tao, Y. (2026). CrabFormer: RGB-D segmentation and pose estimation for front-End loading of piled Chesapeake blue crabs. *Comput. Electron. Agric.* 245, 14. doi: 10.1016/j.compag.2026.111588

Anders, N., Arnesen, K., Hustad, A., Jorgensen, T., Lokkeborg, S., Siikavuopio, S., et al. (2023). Improving size selection in the Norwegian red king crab (Paralithodes camtschaticus) fishery through modification to pot design and soak time. *Fish. Res.* 261, 10. doi: 10.1016/j.fishres.2023.106641

Aneesa, K., Chaithanya, E., and Varghese, S. (2025). Biometric indices of Scylla serrata (Forskal, 1775): Exploring gender-specific growth patterns from the Cochin Estuary, southwest coast of India. *Heliyon* 11, 13. doi: 10.1016/j.heliyon.2025.e42829

Antonelis, K., Drinkwin, J., Rudell, P., Morgan, J., Selleck, J., Velasquez, D., et al. (2023). Determining effectiveness of dungeness crab escapement in derelict traps. *Mar. Pol.* 149, 8. doi: 10.1016/j.marpol.2023.105499

Archdale, M., Anraku, K., Yamamoto, T., and Higashitani, N. (2003). Behavior of the Japanese rock crab 'Ishigani' Charybdis japonica towards two collapsible baited pots:: Evaluation of capture effectiveness. *Fish. Sci.* 69, 785–791. doi: 10.1046/j.1444-2906.2003.00689.x

avila-Thieme, M., Gelcich, S., Gephart, J., and Donlan, C. (2025). Brachyuran crab fisheries in Chile: challenges and opportunities for rising demand. *Rev. Fish. Biol. Fish.* 35, 775–788. doi: 10.1007/s11160-025-09933-y

Becker, A., Johnson, D., Pederson, H., and Taylor, M. (2025). Capture probability of blue swimmer crab (Portunus armatus) in baited traps and implications for trap survey design. *Fish. Manage. Ecol.* 32, 70–80. doi: 10.1111/fme.12784

Bodine, C., Baxevani, K., Abbasi, N., Wierzbicki, J., Christoph, O., Hughes, C., et al. (2026). GhostVision: Democratizing derelict gear detection using low-cost sonar and artificial intelligence. *J. Mar. Sci. Eng.* 14, 18. doi: 10.3390/jmse14100951

Cao, S., Zhao, D., Sun, Y., Liu, X., and Ruan, C. (2021). Automatic coarse-to-fine joint detection and segmentation of underwater non-structural live crabs for precise feeding. *Comput. Electron. Agric.* 180, 105905. doi: 10.1016/j.compag.2020.105905

Cerbule, K., Araya-Schmidt, T., Larsen, R., Winger, P., Bayse, S., Karlsen, I., et al. (2026). Applicability of different pot escape gaps to reduce bycatch of undersized snow crab (Chionoecetes opilio) based on laboratory observations. *Fish. Res.* 298, 14. doi: 10.1016/j.fishres.2026.107753

Cerbule, K., Herrmann, B., Brcic, J., Grimaldo, E., and Bak-Jensen, Z. (2024a). Selectivity in snow crab (Chionoecetes opilio) pot fishery: Effect of escape gap shape and size for conservation of fishery resources. *J. Nat. Conserv.* 79, 14. doi: 10.1016/j.jnc.2024.126616

Cerbule, K., Herrmann, B., Grimaldo, E., Brinkhof, J., Sistiaga, M., Larsen, R., et al. (2023). Ghost fishing efficiency by lost, abandoned or discarded pots in snow crab (Chionoecetes opilio) fishery. *Mar. pollut. Bull.* 193, 9. doi: 10.1016/j.marpolbul.2023.115249

Cerbule, K., Herrmann, B., Grimaldo, E., Grimsmo, L., and Karlsen, J. (2025a). Does soak time influence the effect of artificial light on catch efficiency in snow crab (Chionoecetes opilio) pot fishery? *Aquacult. Fish.* 10, 330–343. doi: 10.1016/j.aaf.2023.11.004

Cerbule, K., Herrmann, B., Larsen, R., and Yu, M. (2024b). Ghost fishing by self-baited lost, abandoned or discarded pots in snow crab (Chionoecetes opilio) fishery. *J. Nat. Conserv.* 82, 10. doi: 10.1016/j.jnc.2024.126764

Cerbule, K., Larsen, R., Araya-Schmidt, T., Winger, P., Tatone, I., and Langedal, G. (2025b). Use of escape gaps in Barents Sea snow crab (Chionoecetes opilio) fishery: Can it reduce bycatch of undersized crabs? *Fish. Res.* 290, 10. doi: 10.1016/j.fishres.2025.107516

Chang, C., Ubina, N., Cheng, S., Lan, H., Chen, K., and Huang, C. (2022). A two-mode underwater smart sensor object for precision aquaculture based on AIoT technology. *Sensors* 22, 29. doi: 10.3390/s22197603

Chatzievangelou, D., Thomsen, L., Doya, C., Purser, A., and Aguzzi, J. (2022). Transects in the deep: Opportunities with tele-operated resident seafloor robots. *Front. Mar. Sci.* 9, 20. doi: 10.3389/fmars.2022.833617

Chen, X., Bao, Y., Ying, Z., Xie, M., Li, T., Zou, J., et al. (2026). A UAV-based deep learning pipeline for intertidal macrobenthos monitoring: Behavioral and age classification in Tachypleus tridentatus. *Remote Sens. Ecol. Conserv.* 12, 242–259. doi: 10.1002/rse2.70036

Chen, K., Chen, Z., Wang, C., Zhou, Z., Xiao, M., Zhu, H., et al. (2025). Improved YOLOv8-based method for the carapace keypoint detection and size measurement of Chinese mitten crabs. *Animals* 15, 105905. doi: 10.3390/ani15070941

Chen, X., Xie, M., Feng, J., Zou, J., Shi, J., Zhuang, L., et al. (2025). A rapid bycatch assessment framework for small-scale fisheries: A case study on horseshoe crab (Tachypleus tridentatus) bycatch. *Ocean. Coast. Manage.* 266, 12. doi: 10.1016/j.ocecoaman.2025.107701

Chen, Y., Yang, W., Hadley, S., Leiva, R., Bai, Q., and Kang, B. (2025). A self-learning based explainable AI framework for giant crab sex classification. *Comput. Electron. Agric.* 239, 110989. doi: 10.1016/j.compag.2025.110989

Chen, Z., Yin, J., Farhan, S., Liu, L., Zhang, D., Zhou, M., et al. (2026). A comprehensive review of obstacle avoidance for autonomous agricultural machinery in multi-ope rational environment. *Artif. Intell. Agric.* 16, 139–163. doi: 10.1016/j.aiia.2025.10.001

Chen, C., Zhu, W., Steibel, J., Siegford, J., Han, J., and Norton, T. (2020). Classification of drinking and drinker-playing in pigs by a video-based deep learning method. *Biosyst. Eng.* 196, 1–14. doi: 10.1016/j.biosystemseng.2020.05.010

Coleman, M., Bloor, I., and Jenkins, S. (2024). Establishing the role of the North Atlantic Oscillation as a potential driver of brown crab Cancer pagurus density. *Fish. Res.* 279, 9. doi: 10.1016/j.fishres.2024.107120

Deng, J., Ni, L., Bai, X., Jiang, H., and Xu, L. (2023). Simultaneous analysis of mildew degree and aflatoxin B1 of wheat by a multi-task deep learning strategy based on microwave detection technology. *LWT. Food Sci. Technol.* 184, 9. doi: 10.1016/j.lwt.2023.115047

Derby, C., Mesape, K., Ngo-Vu, H., Gentit, L., and Fluech, B. (2024). Developing and field testing sustainable synthetic baits for the blue crab (Callinectes sapidus) fishery. *Fish. Res.* 276, 9. doi: 10.1016/j.fishres.2024.107042

Duan, Q., Feng, X., Kong, M., Fu, J., and Zhang, T. (2025). Crab species recognition method based on incremental learning. *Aquac. Int.* 33, 21. doi: 10.1007/s10499-025-01939-4

Ebata, K., Ueki, Y., Toyota, K., Takeuchi, K., and Satake, S. (2025). Morphometric parameters that reveal sex differences on the dorsal surface of the horsehair crab Erimacrus isenbeckii (Brandt, 1848) (Decapoda: Brachyura: Cheiragonidae). *J. Crustac. Biol.* 45, 6. doi: 10.1093/jcbiol/ruaf030

Ehnert-Russo, S., Crowley, C., and Becker, K. (2022). Assessing Northeast Florida offshore blue crab fishing effort within Florida's state waters. *North Am. J. Fish. Manage.* 42, 668–683. doi: 10.1002/nafm.10767

Elsherbiny, O., Gao, J., Guo, Y., Tunio, M., and Mosha, A. (2025). Fusion of the deep networks for rapid detection of branch-infected aeroponically cultivated mulberries using multimodal traits. *Int. J. Agric. Biol. Eng.* 18, 75–88. doi: 10.25165/j.ijabe.20251802.8666

Fang, G., and Zhao, Y. (2024). Detection of critical parts of river crab based on lightweight YOLOv7-SPSD. *Sensors* 24, 16. doi: 10.3390/s24237593

Frazato, P., Bezerra, A., Marçal, I., and Teixeira, G. (2025). Allometry, sexual maturity and intraspecific morphological variations in Aegla jacutinga Marçal and Teixeira, 2020 (Crustacea, Anomura). *Acta Zool.* 12. doi: 10.1111/azo.70016

Fujita, K., Watanabe, T., and Kitagawa, D. (2006). Behavioral responses of the snow crab Chionoecetes spp. to the groundrope of a bottom trawl. *Nippon. Suisan. Gakkaishi.* 72, 695–701. doi: 10.2331/suisan.72.695

Gao, X., Gao, J., and Qureshi, W. (2025). Applications, trends, and challenges of precision weed control technologies based on deep learning and machine vision. *Agronomy-Basel* 15, 54. doi: 10.3390/agronomy15081954

Grassian, B., Roman, C., Omand, M., Wishner, K., and Seibel, B. (2023). Multi-sensor observation of a rapidly dispersing micronekton thin layer. *Deep-Sea. Res. Part. I-Oceanogr. Res. Pap.* 191, 103924. doi: 10.1016/j.dsr.2022.103924

Greenberg, A., and Mcallister, M. (2025). Modeling seasonal variation in crabbing effort: Which potential drivers and constraints are most influential? *Mar. Coast. Fish.* 17, 10. doi: 10.1093/mcfafs/vtaf030

Gu, X., Chen, G., Capinha, C., Wang, W., Lu, X., and Wang, M. (2026). Automating coastal bioindicator acquisition with deep learning: crab community monitoring for enhanced wetland management. *Ecol. Indic.* 182, 13. doi: 10.1016/j.ecolind.2025.114577

Gu, H., Gan, D., Chen, M., and Feng, G. (2024). One-year-old precocious Chinese mitten crab identification algorithm based on task alignment. *Animals* 14, 15. doi: 10.3390/ani14142128

Guan, X., Shi, L., Ge, H., Ding, Y., and Nie, S. (2025). Development, design, and improvement of an intelligent harvesting system for aquatic vegetable Brasenia schreberi. *Agronomy-Basel* 15, 31. doi: 10.3390/agronomy15061451

Guan, X., Shi, L., Yang, W., Ge, H., Wei, X., and Ding, Y. (2024). Multi-feature fusion recognition and localization method for unmanned harvesting of aquatic vegetables. *Agriculture-Basel* 14, 24. doi: 10.3390/agriculture14070971

Guo, Z., Xiao, H., Dai, Z., Wang, C., Sun, C., Watson, N., et al. (2025). Identification of apple variety using machine vision and deep learning with Multi-Head Attention mechanism and GLCM. *J. Food Meas. Charact.* 19, 6540–6558. doi: 10.1007/s11694-025-03385-5

Hamamé, M., Aedo, G., Ortiz, P., Olguín, A., and Pardo, L. (2024). Biological and fishery indicators for the small-scale marble crab fishery in Northern Patagonia:

recommendations for improving a monitoring program and stock assessment of a data-limited fishery. *Front. Mar. Sci.* 11, 11. doi: 10.3389/fmars.2024.1392758

Hanamseth, R., Johnson, D., Schilling, H., Suthers, I., and Taylor, M. (2022). Evaluation of a novel research trap for surveys of blue swimmer crab populations. *Mar. Freshw. Res.* 73, 812–822. doi: 10.1071/mf21005

Hewitt, D., Johnson, D., Suthers, I., and Taylor, M. (2023a). Crabs ride the tide: incoming tides promote foraging of giant mud crab (Scylla serrata). *Mov. Ecol.* 11, 16. doi: 10.1186/s40462-023-00384-3

Hewitt, D., Taylor, M., Suthers, I., and Johnson, D. (2023b). Environmental drivers of variation in southeast Australian giant mud crab (Scylla serrata) harvest rates. *Fish. Res.* 268, 11. doi: 10.1016/j.fishres.2023.106850

Hilborn, R., Gilman, E., Hall, M., Marshall, C. T., Melvin, E., and Pons, M. (2026). Comparing effectiveness of experimental and implemented bycatch reduction measures: the ideal and the real. *Rev. Fish. Sci. Aquacult.* doi: 10.1080/23308249.2026.2637728

Hu, H., Tang, C., Shi, C., and Qian, Y. (2023). Detection of residual feed in aquaculture using YOLO and Mask RCNN. *Aquac. Eng.* 100, 8. doi: 10.1016/j.aquaeng.2022.102304

Hu, T., Wang, W., Gu, J., Xia, Z., Zhang, J., and Wang, B. (2023). Research on apple object detection and localization method based on improved YOLOX and RGB-D images. *Agronomy-Basel* 13, 17. doi: 10.3390/agronomy13071816

Hu, S., Xin, M., Li, S., Li, J., Wang, G., Zhang, S., et al. (2025). Analysis and experimental research on the coupled motion of the foot and paddle of crab-like robot based on biological observation. *Appl. Ocean. Res.* 158, 15. doi: 10.1016/j.apor.2025.104524

Huang, X., Du, L., Li, Z., Xue, J., Shi, J., Tahir, H., et al. (2023). A visual bi-layer indicator based on mulberry anthocyanins with high stability for monitoring Chinese mitten crab freshness. *Food Chem.* 411, 10. doi: 10.1016/j.foodchem.2023.135497

Huang, X., Li, Z., Li, Z., Shi, J., Zhang, N., Qin, Z., et al. (2025). Application of image computing in non-destructive detection of Chinese cuisine. *Foods* 14, 26. doi: 10.3390/foods14142488

Huang, X., Yu, S., Xu, H., Aheto, J., Bonah, E., Ma, M., et al. (2019). Rapid and nondestructive detection of freshness quality of postharvest spinaches based on machine vision and electronic nose. *J. Food Saf.* 39, 8. doi: 10.1111/jfs.12708

Hui, Z., Zhang, Z., Wang, Y., Zhang, R., Liu, X., Jiang, M., et al. (2024). Gradiently foaming ultrasoft hydrogel with stop holes for highly deformable, crack-resistant and sensitive conformal human-machine interfaces. *Adv. Mater.* 36, 11. doi: 10.1002/adma.202314163

Iftikhar, M., Neal, M., Hold, N., Dal Toé, S., and Tiddeman, B. (2024). Detection of crabs and lobsters using a benchmark single-stage detector and novel fisheries dataset. *Computers* 13, 29. doi: 10.3390/computers13050119

Ivanov, P. (2025). Features of the current red king crab Paralithodes camtschaticus (Tilesius, 1815) fishery off Western Kamchatka: A new fishery ground in Shelikhov Bay. *Russ. J. Mar. Biol.* 51, 525–534. doi: 10.1134/s1063074025700336

Ji, W., Pan, Y., Xu, B., and Wang, J. (2022). A real-time apple targets detection method for picking robot based on ShufflenetV2-YOLOX. *Agriculture-Basel* 12, 18. doi: 10.3390/agriculture12060856

Ji, W., Peng, J., Xu, B., and Zhang, T. (2023). Real-time detection of underwater river crab based on multi-scale pyramid fusion image enhancement and MobileCenterNet model. *Comput. Electron. Agric.* 204, 12. doi: 10.1016/j.compag.2022.107522

Jiang, Y., Wang, D., Wang, Z., Dai, H., Wang, C., and Wang, Y. (2025). Recent advances in spectroscopy and imaging techniques for nondestructive detection of meat quality and safety. *Food Sci. Nutr.* 13, 27. doi: 10.1002/fsn3.71303

Jiang, L., Wang, Y., Wu, C., and Wu, H. (2024). Fruit distribution density estimation in YOLO-detected strawberry images: A kernel density and nearest neighbor analysis approach. *Agriculture-Basel* 14, 16. doi: 10.3390/agriculture14101848

Jin, Y., Liu, J., Xu, Z., Yuan, S., Li, P., and Wang, J. (2021). Development status and trend of agricultural robot technology. *Int. J. Agric. Biol. Eng.* 14, 1–19. doi: 10.25165/j.ijabe.20211404.6821

Jin, X., Zhang, F., Ma, L., Liu, Z., Wang, W., Gou, Q., et al. (2025). Sex differences in growth and carapace traits in the juvenile-crab instars in the mud crab Scylla paramamosain Estampador, 1950 (Decapoda: Brachyura: Portunidae). *J. Crustac. Biol.* 45, 9. doi: 10.1093/jcbiol/ruaf058

Kajimoto, A., Toyota, K., Ohira, T., and Yusa, Y. (2024). Transcriptomic analysis of sexually dimorphic cypris larvae of the rhizocephalan barnacle Peltogasterella gracilis. *Comp. Biochem. Physiol. D-Genom. Proteomics* 52, 9. doi: 10.1016/j.cbd.2024.101342

Kao, W., Chang, P., Shih, C., Chen, P., Tzeng, T., Han, Y., et al. (2023). Morphometric differentiation of the swimming crab Portunus sanguinolentus (Herbst, 1783) populations in East Asia: Implications for stock identification and management. *Water* 15, 15. doi: 10.3390/w15193335

Kawamura, G., Yong, A., Roy, D., and Lim, L. (2020). Shelter colour preference in the purple mud crab Scylla tranquebarica (Fabricius). *Appl. Anim. Behav. Sci.* 225, 6. doi: 10.1016/j.applanim.2020.104966

Khan, Z., Shen, Y., and Liu, H. (2025). ObjectDetection in agriculture: A comprehensive review of methods, applications, challenges, and future directions. *Agriculture-Basel* 15, 36. doi: 10.3390/agriculture15131351

Kobayashi, S., and Vazquez-Archdale, M. (2016). Selectivity of two methods for surveying the Japanese mitten crab, Eriocheir japonica (de Haan, 1835), in a riverine environment. *J. Crustac. Biol.* 36, 1–11. doi: 10.1163/1937240x-00002399

Lee, W., Xu, H., Naimullah, M., Ikhwanuddin, M., Waiho, K., Fazhan, H., et al. (2026). The effect of LED wavelength variations on catch efficiency in Portunidae trap fisheries. *Fish. Sci.* 92, 33–45. doi: 10.1007/s12562-025-01944-9

Li, L., Ren, Z., Tang, C., Lu, S., and Liang, Y. (2025). A deep learning-based detection model and illumination-adaptive behavioral analysis for soldier crabs in the intertidal zone. *Ecol. Inform.* 90, 17. doi: 10.1016/j.ecoinf.2025.103338

Li, H., Wang, Y., Li, C., Nunekpeku, X., Chen, Y., Zhang, W., et al. (2026). Non-destructive visualization and prediction of surimi gel quality under atmospheric cold plasma via hyperspectral imaging and deep learning. *Food Control.* 183, 13. doi: 10.1016/j.foodcont.2025.111942

Li, D., Yu, J., Du, Z., Xu, W., Wang, G., Zhao, S., et al. (2024). Advances in the application of stereo vision in aquaculture with emphasis on fish: A review. *Rev. Aquac.* 16, 1718–1740. doi: 10.1111/raq.12919

Li, X., Yu, J., Li, D., Ren, N., Duan, Q., and Jin, J. (2026). Non-invasive crab gender detection based on carapace features using image enhancement and BLC-YOLOv8n. *Aquac. Int.* 34. doi: 10.1007/s10499-026-02573-4

Liang, J., Wang, Y., Shi, Y., Huang, X., Li, Z., Zhang, X., et al. (2023). Non-destructive discrimination of homochromatic foreign materials in cut tobacco based on VIS-NIR hyperspectral imaging. *J. Sci. Food Agric.* 103, 4545–4552. doi: 10.1002/jsfa.12528

Liu, J., Abbas, I., and Noor, R. (2021). Development of deep learning-based variable rate agrochemical spraying system for targeted weeds control in strawberry crop. *Agronomy-Basel* 11, 17. doi: 10.3390/agronomy11081480

Liu, X., Jia, W., Ruan, C., Zhao, D., Gu, Y., and Chen, W. (2018). The recognition of apple fruits in plastic bags based on block classification. *Precis. Agric.* 19, 735–749. doi: 10.1007/s11119-017-9553-2

Liu, H., Ma, X., Yu, Y., Wang, L., and Hao, L. (2023). Application of deep learning-based object detection techniques in fish aquaculture: A review. *J. Mar. Sci. Eng.* 11, 867. doi: 10.3390/jmse11040867

Liu, W., Min, M., Wang, Z., Liu, Y., Wang, L., and Zhang, X. (2025). Noctilucent crab pots in the Yellow Sea, China: Field evidence for catch efficiency enhancement and sustainable crab fishery practices. *Fishes* 10, 14. doi: 10.3390/fishes10100481

Liu, D., Wang, P., Zhang, Z., Lu, Y., Wang, B., and Hu, Y. (2025). Robust detection of dense small tea shoots across cultivars under occlusion and bud-leaf similarity for intelligent selective harvesting. *Sci. Hortic.* 353, 18. doi: 10.1016/j.scienta.2025.114499

Liu, D., Zhu, B., Liu, X., and Wang, F. (2024). Important but ignored: Research progress on crab foraging behaviour and its implications for aquaculture. *Rev. Aquac.* 16, 1798–1818. doi: 10.1111/raq.12923

Lu, H., Uemura, T., Wang, D., Zhu, J., Huang, Z., and Kim, H. (2020). Deep-sea organisms tracking using dehazing and deep learning. *Mobile. Netw. Appl.* 25, 1008–1015. doi: 10.1007/s11036-018-1117-9

Lucchetti, A., Virgili, M., Vasapollo, C., Petetta, A., Bargione, G., Li Veli, D., et al. (2021). An overview of bottom trawl selectivity in the Mediterranean Sea. *Mediterr. Mar. Sci.* 22, 566–585. doi: 10.12681/mms.26969

Luo, W., Li, Q., Zhang, H., Diao, Z., Guo, Z., Cai, Z., et al. (2026). Detection of early decay in dekopon fruit based on structured-illumination reflectance imaging combined with a comparison between traditional machine learning and deep learning models. *Postharvest. Biol. Technol.* 233, 12. doi: 10.1016/j.postharvbio.2025.114044

Lv, R., Hu, J., Zhang, T., Chen, X., and Liu, W. (2025). Crop-free-ridge navigation line recognition based on the lightweight structure improvement of YOLOv8. *Agriculture-Basel* 15, 16. doi: 10.3390/agriculture15090942

Ma, J., Zhao, Y., Fan, W., and Liu, J. (2024). An improved YOLOv8 model for lotus seedpod instance segmentation in the lotus pond environment. *Agronomy-Basel* 14, 15. doi: 10.3390/agronomy14061325

Macario, A., Errabo, D., Liao, L., Sailadjan, S., and Tomiyama, T. (2026). Comparative governance and fishing practices in swimming crab fisheries in the Philippines and Japan: Inputs toward sustainable management. *Sustain. Sci.* 15. doi: 10.1007/s11625-026-01855-3

Madhu, V., Anand, S., Cerbule, K., and Herrmann, B. (2023). Simple pot modification improves catch efficiency and species composition in a tropical estuary mud crab (Scylla serrata) fishery. *Estuar. Coast. Shelf. Sci.* 288, 8. doi: 10.1016/j.ecss.2023.108369

Matzen, E., Fuller, E., Asmutis-Silvia, R., Milliken, H., Amico, M., Galvez, B., et al. (2025). Working with Northeastern United States lobster harvesters to develop acoustic trap retrieval in place of buoys and persistent vertical lines to reduce whale entanglements. *ICES. J. Mar. Sci.* 82, 11. doi: 10.1093/icesjms/fsaf015

Memon, M., Chen, S., Shen, B., Liang, R., Tang, Z., Wang, S., et al. (2025). Automatic visual recognition, detection and classification of weeds in cotton fields based on machine vision. *Crop Prot.* 187, 11. doi: 10.1016/j.cropro.2024.106966

Moore, A., Heney, C., Lincoln, H., Colvin, C., Newell, H., Turner, R., et al. (2023). Bycatch in northeast Atlantic lobster and crab pot fisheries (Irish Sea, Celtic Sea and Bristol Channel). *Fish. Res.* 265, 13. doi: 10.1016/j.fishres.2023.106745

Naimullah, M., Lan, K., Ikhwanuddin, M., Amin-Safwan, A., and Lee, W. (2022a). Unbaited light-emitting diode traps performance for catching orange mud crabs. *J. Mar. Sci. Technol.-Taiwan.* 30, 48–62. doi: 10.51400/2709-6998.2565

Naimullah, M., Lee, W., Wu, Y., Chen, Y., Huang, Y., Liao, C., et al. (2022b). Effect of soaking time on targets and bycatch species catch rates in fish and crab trap fishery in the southern East China Sea. *Fish. Res.* 250, 15. doi: 10.1016/j.fishres.2022.106258

Nguyen, K., Winger, P., Wood, J., Donovan, M., Humborstad, O., Lokkeborg, S., et al. (2019). Application of luminescent netting in traps to improve the catchability of the snow crab Chionoecetes opilio. *Mar. Coast. Fish.* 11, 295–304. doi: 10.1002/mcf2.10084

Ogburn, M., Stuck, K., Heard, R., Wang, S., and Forward, R. (2011). Seasonal variability in morphology of blue crab, Callinectes sapidus, megalopae and early juvenile stage crabs, and distinguishing characteristics among co-occurring Portunidae. *J. Crustac. Biol.* 31, 106–113. doi: 10.1651/09-3241.1

Olsen, Z., Topping, D., Wagner, T., Anderson, J., Gelpi, C., Sutton, G., et al. (2022). Differential effects of three crab trap escape ring sizes on retention of male and female blue crabs. *North Am. J. Fish. Manage.* 42, 270–276. doi: 10.1002/nafm.10743

Pan, Y., Zhang, Y., Wang, X., Gao, X., and Hou, Z. (2023). Low-cost livestock sorting information management system based on deep learning. *Artif. Intell. Agric.* 9, 110–126. doi: 10.1016/j.aiia.2023.08.007

Peck, G., Araya-Schmidt, T., and Winger, P. (2024). Hauling snow crab traps in Eastern Canada: A study documenting tension in ropes. *Fishes* 9, 11. doi: 10.3390/fishes9050154

Peng, Y., Lu, J., Li, R., Xu, C., Zheng, S., Ren, Z., et al. (2025a). The characteristics of sex differentiation based on morphological traits during the early development stage of the swimming crab Portunus trituberculatus and sex prediction model comparison. *Fishes* 10, 14. doi: 10.3390/fishes10010008

Peng, Y., Sun, J., Wu, Z., Gao, J., Shi, L., and Shi, Z. (2025b). A vision-based information processing framework for vineyard grape picking using two-stage segmentation and morphological perception. *Horticulturae* 11, 21. doi: 10.3390/horticulturae11091039

Peng, Y., Sun, J., Wu, Z., Shi, L., Ji, X., Jia, Y., et al. (2025c). Apple maturity quantification based on fine-grained coloration analysis using deep learning and computer vision. *J. Food Meas. Charact.* 19, 9637–9653. doi: 10.1007/s11694-025-03652-5

Peng, Y., Zhao, S., and Liu, J. (2021). Fused deep features-based grape varieties identification using support vector machine. *Agriculture-Basel* 11, 16. doi: 10.3390/agriculture11090869

Pengsakun, S., Yeemin, T., Sutthacheep, M., Jungrak, L., Klinthong, W., Aunkhongthong, W., et al. (2026). Environmental effects of plastic pollution from lost, discarded, and abandoned fishing gear on underwater pinnacles in the Gulf of Thailand. *Front. Mar. Sci.* 12, 20. doi: 10.3389/fmars.2025.1670284

Petetta, A., Virgili, M., Guicciardi, S., and Lucchetti, A. (2021). Pots as alternative and sustainable fishing gears in the Mediterranean Sea: an overview. *Rev. Fish. Biol. Fish.* 31, 773–795. doi: 10.1007/s11160-021-09676-6

Picoy-Gonzales, R., Añasco, N., Lizada, J., Anraku, K., and Monteclaro, H. (2025). Simple fix: The potential of escape gaps in enhancing the capture performance of crab pots used in the fishery of blue swimming crab, Portunus pelagicus (Crustacea, Decapoda, Portunidae), in the Philippines. *Acta Ichthyol. Piscat.* 55, 101–113. doi: 10.3897/aiep.55.149577

Pillans, R., Fry, G., Carlin, G., and Patterson, T. (2022). Bycatch of a critically endangered shark Glyphis glyphis in a crab pot fishery: Implications for management. *Front. Mar. Sci.* 9, 16. doi: 10.3389/fmars.2022.787634

Qiu, D., Guo, T., Yu, S., Liu, W., Li, L., Sun, Z., et al. (2024). Classification of apple color and deformity using machine vision combined with CNN. *Agriculture-Basel* 14, 14. doi: 10.3390/agriculture14070978

Reggiannini, M., and Moroni, D. (2021). The use of saliency in underwater computer vision: A review. *Remote Sens.* 13, 22. doi: 10.3390/rs13010022

Reinsel, M., Gibson, M., Klesch, N., and Chambers, R. (2023). Bycatch reduction devices exclude diamondback terrapins and maintain blue crab catch in two Virginia tidal creeks. *Mar. Coast. Fish.* 15, 9. doi: 10.1002/mcf2.10263

Ren, Q., Wu, Y., Zeng, Q., and Yang, N. (2026). Deep learning based agricultural remote sensing image segmentation: a review. *J. Agric. Eng.* 57, 20. doi: 10.4081/jae.2025.1954

Riekkola, L., Liu, O., Feist, B., Forney, K., Abrahms, B., Hazen, E., et al. (2023). Retrospective analysis of measures to reduce large whale entanglements in a lucrative commercial fishery. *Biol. Conserv.* 278, 14. doi: 10.1016/j.biocon.2022.109880

Riyanto, M., Fajri, R., Yuwandana, D., Wahju, R., Purbayanto, A., Richardson, K., et al. (2025). Estimates of gear loss and contributing factors in trap fisheries in coastal waters: A case study from the Seribu Islands, Indonesia. *Fish. Res.* 289, 10. doi: 10.1016/j.fishres.2025.107500

Schilling, H., Johnson, D., Hanamseth, R., Suthers, I., and Taylor, M. (2023). Long-term drivers of catch variability in south-eastern Australia's largest portunid fishery. *Fish. Res.* 260, 11. doi: 10.1016/j.fishres.2022.106582

Serrano, R., Repp, J., Regan, K., Trembanis, A., Oliver, M., and Hale, E. (2026). Examining the impact of derelict pots on blue crab (Callinectes sapidus) catch and harvest within a recreational fishery. *Fish. Manage. Ecol.* 16. doi: 10.1111/fme.70083

Sheehan, E., Coleman, R., Attrill, M., and Thompson, R. (2010). A quantitative assessment of the response of mobile estuarine fauna to crab-tiles during tidal immersion using remote underwater video cameras. *J. Exp. Mar. Biol. Ecol.* 387, 68–74. doi: 10.1016/j.jembe.2010.02.008

Shi, J., Hu, X., Zou, X., Zhao, J., Zhang, W., Holmes, M., et al. (2017). A rapid and nondestructive method to determine the distribution map of protein, carbohydrate and sialic acid on Edible bird's nest by hyper-spectral imaging and chemometrics. *Food Chem.* 229, 235–241. doi: 10.1016/j.foodchem.2017.02.075

Siripattanadilok, W., and Siriborvornratanakul, T. (2024). Recognition of partially occluded soft-shell mud crabs using Faster R-CNN and Grad-CAM. *Aquac. Int.* 32, 2977–2997. doi: 10.1007/s10499-023-01307-0

Skerritt, D., Bell, M., Lees, K., Mill, A., Polunin, N., and Fitzsimmons, C. (2023). Estimating catchability and density of the European lobster Homarus gammarus from continuous, short-term mark-recapture data. *Mar. Ecol. Prog. Ser.* 715, 79–89. doi: 10.3354/meps14351

Slizkin, A., Borilko, O., Borisovets, E., Chernienko, I., and Tkacheva, O. (2025). The history of the stock status and fishery management for the red king crab Paralithodes camtschaticus in waters of Primorye. *Russ. J. Mar. Biol.* 51, 599–612. doi: 10.1134/s1063074025700397

Sun, Y., Li, Z., Yang, Z., Yuan, B., Zhao, D., Ren, N., et al. (2026). Design of monitoring system for river crab feeding platform based on machine vision. *Fishes* 11, 21. doi: 10.3390/fishes11020088

Sun, J., Yang, F., Cheng, J., Wang, S., and Fu, L. (2024). Nondestructive identification of soybean protein in minced chicken meat based on hyperspectral imaging and VGG16-SVM. *J. Food Compos. Anal.* 125, 12. doi: 10.1016/j.jfca.2023.105713

Sun, Y., Yuan, B., Li, Z., Liu, Y., and Zhao, D. (2024). Rethinking underwater crab detection via defogging and channel compensation. *Fishes* 9, 18. doi: 10.3390/fishes9020060

Sun, C., Zhang, L., Zhai, L., Shen, T., Cai, J., Zou, X., et al. (2026). Automatic early bruise detection in strawberry fruit by hyperspectral imaging and deep learning techniques. *Postharvest. Biol. Technol.* 232, 12. doi: 10.1016/j.postharvbio.2025.113966

Susanto, A., Suuronen, P., Purbayanto, A., Nurdin, H., Jayanudin, Syafrie, H., et al. (2025). Adjusting trap mesh size and entrance color to increase capture efficiency of blue swimming crabs. *Fish. Manage. Ecol.* 32, 570–580. doi: 10.1111/fme.70001

Tai, S., Tang, Z., Li, B., Wang, S., and Guo, X. (2025). Intelligent recognition and automated production of chili peppers: A review addressing varietal diversity and technological requirements. *Agriculture-Basel* 15, 26. doi: 10.3390/agriculture15111200

Tang, C., Zhang, G., Hu, H., Wei, P., Duan, Z., and Qian, Y. (2020). An improved YOLOv3 algorithm to detect molting in swimming crabs against a complex background. *Aquac. Eng.* 91, 102115. doi: 10.1016/j.aquaeng.2020.102115

Tao, J., Quagrainie, K., Foster, K., and Widmar, N. (2024). A regional analysis of climate change effects on global snow crab fishery. *Nat. Resour. Model.* 37, 21. doi: 10.1111/nrm.12406

Tian, C., Che, X., Ge, L., Qu, Z., and Han, M. (2026). Design and performance verification of crab seedling automatic counting equipment based on improved YOLOv11+DeepSORT. *Aquac. Eng.* 113, 12. doi: 10.1016/j.aquaeng.2025.102680

Tian, Y., Sun, J., Zhou, X., Cong, S., Dai, C., and Shi, L. (2025). Nondestructive detection of soluble solids content in apples based on multi-attention convolutional neural network and hyperspectral imaging technology. *Foods* 14, 16. doi: 10.3390/foods14223832

Toé, S., Neal, M., Hold, N., Heney, C., Turner, R., Mccoy, E., et al. (2023). Automated video-based capture of crustacean fisheries data using low-power hardware. *Sensors* 23, 7897. doi: 10.3390/s23187897

Ueki, Y., Toyota, K., Ohira, T., Takeuchi, K., and Satake, S. (2023). Gender identification of the horsehair crab, Erimacrus isenbeckii (Brandt, 1848), by image recognition with a deep neural network. *Sci. Rep.* 13, 8. doi: 10.1038/s41598-023-46606-x

Venables, S., Drerup, C., Powell, S., Marshall, N., Herbert-Read, J., and How, M. (2022). Polarization vision mitigates visual noise from flickering light underwater. *Sci. Adv.* 8, eabq2770. doi: 10.1126/sciadv.abq2770

Vodopia, D., Verones, F., Askham, C., and Larsen, R. (2024). Retrieval operations of derelict fishing gears give insight on the impact on marine life. *Mar. pollut. Bull.* 201, 8. doi: 10.1016/j.marpolbul.2024.116268

Vodopia, D., Verones, F., Askham, C., and Larsen, R. (2025). Ghost fishing catch estimates based on annual retrieval operations in Norwegian waters. *Fish. Res.* 292, 9. doi: 10.1016/j.fishres.2025.107599

Vu, N., Nguyen, K., and Nguyen, L. (2025). The effect of bait types on catch performance in the Vietnamese swimming crab trap fishery. *J. Mar. Sci. Technol.-Taiwan.* 33, 24. doi: 10.51400/2709-6998.2764

Wang, J., Gao, Z., Zhang, Y., Zhou, J., Wu, J., and Li, P. (2022). Real-time detection and location of potted flowers based on a ZED camera and a YOLO V4-Tiny deep learning algorithm. *Horticulturae* 8, 14. doi: 10.3390/horticulturae8010021

Wang, Y., Gou, S., Wang, C., Zhang, G., Uchman, A., and Wetzel, A. (2024). The crab Macrophthalmus japonicus burrows on a tidal flat of the Yellow River Delta in China: Their 3D morphological variability in relation to physicochemical conditions and palaeoichnological perspective. *Palaeogeogr. Palaeoclimatol. Palaeoecol.* 638, 112037. doi: 10.1016/j.palaeo.2024.112037

Wang, W., Li, C., Xi, Y., Gu, J., Zhang, X., Zhou, M., et al. (2025). Research progress and development trend of visual detection methods for selective fruit harvesting robots. *Agronomy-Basel* 15, 31. doi: 10.3390/agronomy15081926

Wang, T., Szuwalski, C., Punt, A., and Hilborn, R. (2024). Diversity of fishing strategies and high spatial adaptivity in the Alaskan snow crab fishery. *ICES. J. Mar. Sci.* 81, 929–943. doi: 10.1093/icesjms/fsae052

Wang, D., Vinson, R., Holmes, M., Seibel, G., and Tao, Y. (2018). Convolutional neural network guided blue crab knuckle detection for autonomous crab meat picking machine. *Opt. Eng.* 57, 12. doi: 10.1117/1.Oe.57.4.043103

Wang, Q., Wang, Z., Shan, H., Ding, C., Wu, D., Jiang, M., et al. (2025). The construction of migration crab passageways and the carapace length-weight relationships of migratory Eriocheir sinensis H. Milne Edwards, 1853 (Decapoda: Brachyura: Varunidae) in the Yangtze River, China. *J. Crustac. Biol.* 45, 7. doi: 10.1093/jcbiol/ruaf012

Wang, Y., Zhang, Y., Gou, S., and Zhang, G. (2025). 3D morphology of crab (Macrophthalmus japonicus) burrows from the Pearl River Delta front, China: The physicochemical factors, with implications for the rock record. *J. Palaeogeography-English.* 14, 203–220. doi: 10.1016/j.jop.2024.09.004

Wang, H., Zhu, H., Bi, L., Xu, W., Song, N., Zhou, Z., et al. (2023). Quality grading of river crabs based on machine vision and GA-BPNN. *Sensors* 23, 19. doi: 10.3390/s23115317

Watanabe, T. (2002a). Development of the deep-sea video monitoring system on a towed sledge to estimate the population density of the snow crab chionoecetes opilio. *Fish. Sci.* 68, 101–104. doi: 10.2331/fishsci.68.sup1_101

Watanabe, T. (2002b). Method to estimate the population density of the snow crab Chionoecetes opilio using a deep-sea video monitoring system on a towed sledge. *Jarq. - Jpn. Agric. Res. Q.* 36, 51–57. doi: 10.6090/jarq.36.51

Welch, H., Liu, O., Riekkola, L., Abrahms, B., Hazen, E., and Samhouri, J. (2024). Selection of planning unit size in dynamic management strategies to reduce human-wildlife conflict. *Conserv. Biol.* 38, 12. doi: 10.1111/cobi.14201

Willse, N., Ober, C., Chang, H., Harlisa, H., Ernawati, T., Kembaren, D., et al. (2024). Linking crustacean life history to fishery management controls and reference points. *Fish. Manage. Ecol.* 31, 13. doi: 10.1111/fme.12691

Wilson, L., Romano, S., and Williard, A. (2022). Efficacy of fisheries-sourced bycatch reduction solutions in preventing capture of diamond-backed terrapins (Malaclemys terrapin) in blue crab pots. *Herpetol. Conserv. Biol.* 17, 76–84.

Wu, Q., and Gu, J. (2017). Design and research of robot visual servo system based on artificial intelligence. *Agro. Food. Ind. Hi-Tech.* 28, 125–128.

Wu, C., Zhang, S., Wang, W., Wu, Z., Yang, S., and Chen, W. (2025). Computation and analysis of phenotypic parameters of Scylla paramamosain based on YOLOv11-DYPF keypoint detection. *Aquac. Eng.* 111, 14. doi: 10.1016/j.aquaeng.2025.102571

Xi, Q., Chen, Q., Ahmad, W., Pan, J., Zhao, S., Xia, Y., et al. (2025). Quantitative analysis and visualization of chemical compositions during shrimp flesh deterioration using hyperspectral imaging: A comparative study of machine learning and deep learning models. *Food Chem.* 481, 10. doi: 10.1016/j.foodchem.2025.143997

Xie, H., Zhang, Z., Zhang, K., Yang, L., Zhang, D., and Yu, Y. (2024). Research on the visual location method for strawberry picking points under complex conditions based on composite models. *J. Sci. Food Agric.* 104, 8566–8579. doi: 10.1002/jsfa.13684

Xu, Y., Chen, Q., Liu, Y., Sun, X., Huang, Q., Ouyang, Q., et al. (2018). A novel hyperspectral microscopic imaging system for evaluating fresh degree of pork. *Korean. J. Food. Sci. Anim. Resour.* 38, 362–375. doi: 10.5851/kosfa.2018.38.2.362

Xu, J., Liu, H., and Shen, Y. (2025). Image and point cloud-based neural network models and applications in agricultural nursery plant protection tasks. *Agronomy-Basel* 15, 34. doi: 10.3390/agronomy15092147

Xu, Z., Liu, J., Wang, J., Cai, L., Jin, Y., Zhao, S., et al. (2023). Realtime picking point decision algorithm of trellis grape for high-speed robotic cut-and-catch harvesting. *Agronomy-Basel* 13, 24. doi: 10.3390/agronomy13061618

Xu, M., Sun, J., Cheng, J., Yao, K., Wu, X., and Zhou, X. (2023). Non-destructive prediction of total soluble solids and titratable acidity in Kyoho grape using hyperspectral imaging and deep learning algorithm. *Int. J. Food Sci. Technol.* 58, 9–21. doi: 10.1111/ijfs.16173

Yang, Z., Feng, G., Yang, G., Zhang, T., Zhao, F., Geng, Z., et al. (2024). The spatiotemporal changes of crab community in the Yangtze River Estuary after the fishing ban. *Front. Mar. Sci.* 11, 14. doi: 10.3389/fmars.2024.1476392

Yao, K., Sun, J., Chen, C., Xu, M., Zhou, X., Cao, Y., et al. (2022). Non-destructive detection of egg qualities based on hyperspectral imaging. *J. Food Eng.* 325, 10. doi: 10.1016/j.jfoodeng.2022.111024

Yao, K., Xu, Y., Sun, J., Zhou, B., Zhang, B., Du, X., et al. (2026). Simultaneous detection and visualization of lipid and protein oxidation in frozen-thawed chicken meat using hyperspectral imaging. *Food Res. Int.* 229, 9. doi: 10.1016/j.foodres.2026.118463

Yu, M., Herrmann, B., Brcic, J., Sistiaga, M., Yang, Y., Liang, H., et al. (2026). Guidelines to make swimming crab (Portunus trituberculatus) pot fishery size selective. *Fish. Manage. Ecol.* 14. doi: 10.1111/fme.70056

Yu, M., Herrmann, B., Cerbule, K., Liu, C., Dou, Y., Zhang, L., et al. (2024a). The effect of soak time on pot escape opening selectivity in swimming crab (Portunus trituberculatus) fishery. *Fish. Res.* 275, 13. doi: 10.1016/j.fishres.2024.107020

Yu, M., Herrmann, B., Cerbule, K., Liu, C., Dou, Y., Zhang, L., et al. (2024b). Ghost fishing efficiency in swimming crab (Portunus trituberculatus) pot fishery. *Mar. pollut. Bull.* 201, 12. doi: 10.1016/j.marpolbul.2024.116192

Yu, M., Herrmann, B., Cerbule, K., Liu, C., Zhang, L., and Tang, Y. (2023). Effect of artificial lights on catch efficiency and capture patterns in Asian paddle crab (Charybdis japonica) gillnet fishery. *Reg. Stud. Mar. Sci.* 65, 12. doi: 10.1016/j.rsma.2023.103101

Yu, M., Herrmann, B., Cerbule, K., Liu, C., Zhang, L., and Tang, Y. (2024c). Effect of gillnet mesh size on the capture probability and capture patterns in the Asian paddle crab (Charybdis japonica) fishery. *Heliyon* 10, 16. doi: 10.1016/j.heliyon.2024.e25771

Yu, M., Xie, Z., Ye, Y., and Shi, C. (2025). TMAE-YOLO: precision detection of mud crabs in underwater environments. *Aquac. Int.* 33. doi: 10.1007/s10499-025-02149-8

Zhang, J. (2025). Effect of escape vents on retention and size selectivity of crab pots for swimming crab Portunus trituberculatus in the East China Sea (vol 6, pg 340, 2021). *Aquacult. Fish.* 10, 734–734. doi: 10.1016/j.aaf.2020.04.008

Zhang, Z., Liu, F., He, X., Wu, X., Xu, M., and Feng, S. (2024). Soft-shell crab detection model based on YOLOF. *Aquac. Int.* 32, 5269–5298. doi: 10.1007/s10499-024-01426-2

Zhang, Z., Lu, Y., and Liu, P. (2025). Training strategy optimization of a tea canopy dataset for variety identification during the harvest period. *Agriculture-Basel* 15, 21. doi: 10.3390/agriculture15192027

Zhang, Z., Lu, Y., Zhao, Y., Pan, Q., Jin, K., Xu, G., et al. (2023). TS-YOLO: An all-day and lightweight tea canopy shoots detection model. *Agronomy-Basel* 13, 18. doi: 10.3390/agronomy13051411

Zhang, J., Shi, X., He, P., and Shi, J. (2023). Effectiveness of escape vent shape in crab pots for releasing swimming crab Portunus trituberculatus in the East China sea. *Aquacult. Fish.* 8, 332–340. doi: 10.1016/j.aaf.2021.12.007

Zhang, K., Xin, Y., Shi, C., Xie, Z., and Ren, Z. (2022). A pyramidal feature fusion model on swimming crab Portunus trituberculatus re-identification. *Front. Mar. Sci.* 9. doi: 10.3389/fmars.2022.845112

Zhang, W., Xue, J., Ma, L., and Yang, J. (2025). Carapace morphological characteristics of Chinese mitten crab (Eriocheir sinensis) from emerging origins revealed via geometric morphometrics. *Animals* 15, 12. doi: 10.3390/ani15091300

Zhang, J., Zhang, H., He, P., Fei, J., Chu, W., and Shi, J. (2024). Selectivity of crab pots with escape vents and the optimal vent height for reducing the catch of sublegal swimming crab in the East China Sea pot fishery. *Fish. Res.* 274, 10. doi: 10.1016/j.fishres.2024.107002

Zhao, F., Chen, Y., Xi, D., Liu, Y., Wang, J., Tabeta, S., et al. (2025). Enhanced hermit crabs detection using super-resolution reconstruction and improved YOLOv8 on UAV-captured imagery. *Mar. Environ. Res.* 210, 14. doi: 10.1016/j.marenvres.2025.107313

Zhou, X., Chen, W., and Wei, X. (2024). Improved field obstacle detection algorithm based on YOLOv8. *Agriculture-Basel* 14, 26. doi: 10.3390/agriculture14122263

Zhou, P., Zhou, Z., Yang, C., Fang, Y., Bu, Y., Wang, C., et al. (2025). Development of a multi-modal deep-learning-based web application for image classification of marine decapods in conservation practice. *Front. Mar. Sci.* 12, 7. doi: 10.3389/fmars.2025.1496831

Zhu, J., Cai, J., Sun, B., Xu, Y., Lu, F., and Ma, H. (2023). Inspection and classification of wheat quality using image processing. *Qual. Assur. Saf. Crop Foods.* 15, 43–54. doi: 10.15586/qas.v15i3.1220

Zhu, W., Li, J., Li, L., Wang, A., Wei, X., and Mao, H. (2020). Nondestructive diagnostics of soluble sugar, total nitrogen and their ratio of tomato leaves in greenhouse by polarized spectra-hyperspectral data fusion. *Int. J. Agric. Biol. Eng.* 13, 189–197. doi: 10.25165/j.ijabe.20201302.4280

Zhu, H., Wang, D., Wei, Y., Zhang, X., and Li, L. (2024). Combining transfer learning and ensemble algorithms for improved citrus leaf disease classification. *Agriculture-Basel* 14, 20. doi: 10.3390/agriculture14091549

Zhu, Y., Zhang, S., Tang, S., and Gao, Q. (2025). Research progress and applications of artificial intelligence in agricultural equipment. *Agriculture-Basel* 15, 34. doi: 10.3390/agriculture15151703