ARTIFICIAL INTELLIGENCE IN AQUACULTURE: APPLICATIONS, RESEARCH GAPS, AND IMPLICATIONS FOR PROFESSIONAL EDUCATION AND GOVERNANCE — A SYSTEMATIC LITERATURE REVIEW

INTELIGÊNCIA ARTIFICIAL NA AQUICULTURA: APLICAÇÕES, LACUNAS DE PESQUISA E IMPLICAÇÕES PARA A FORMAÇÃO PROFISSIONAL E A GOVERNANÇA — UMA REVISÃO SISTEMÁTICA DA LITERATURA

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Abstract. Artificial intelligence (AI) is increasingly used in aquaculture to support monitoring, prediction, automation, and production management, while also creating new requirements for professional competence, ethical oversight, and governance. This systematic literature review, conducted under an integrative approach and reported in accordance with PRISMA 2020, examined practical applications of AI and their implications for professional education and governance in aquaculture. Searches in Scopus, Web of Science, PubMed, and Google Scholar identified 877 records, of which 97 met the eligibility criteria and were included in the qualitative synthesis. The evidence was concentrated on technical applications, particularly fish detection and biomass estimation, water and environmental monitoring, automated production systems, health and biosecurity, and feeding and growth optimization. Direct educational evidence was scarce: only one study examined aquaculture professionals' knowledge and interest in AI, and no included study evaluated formal curricular interventions or learning outcomes in Fisheries Engineering. The synthesis also identified concerns involving data quality, algorithmic bias, technological exclusion, privacy, standardization, and accountability. These findings indicate that responsible adoption requires locally representative data, transparent validation, digital and data literacy, human oversight, and coordinated governance. AI has substantial potential to support aquaculture, but its contribution to professional education remains an important and insufficiently investigated research field.

Keywords: artificial intelligence; aquaculture; higher education; fisheries engineering education; ethics.

Resumo. A inteligência artificial (IA) é cada vez mais utilizada na aquicultura para apoiar o monitoramento, a predição, a automação e a gestão produtiva, criando também novas exigências de competência profissional, supervisão ética e governança. Esta revisão sistemática da literatura, conduzida sob uma abordagem integrativa e relatada de acordo com o PRISMA 2020, examinou aplicações práticas da IA e suas implicações para a formação profissional e a governança na aquicultura. As buscas realizadas na Scopus, Web of Science, PubMed e Google Scholar identificaram 877 registros, dos quais 97 atenderam aos critérios de elegibilidade e foram incluídos na síntese qualitativa. As evidências concentraram-se em aplicações técnicas, especialmente detecção de peixes e estimativa de biomassa, monitoramento hídrico e ambiental, automação da produção, saúde e biossegurança, e otimização da alimentação e do crescimento. A evidência educacional direta foi escassa: apenas um estudo examinou o conhecimento e o interesse de profissionais da aquicultura em relação à IA, e nenhum avaliou intervenções curriculares formais ou resultados de aprendizagem em Engenharia de Pesca. A síntese também identificou preocupações relacionadas à qualidade dos dados, ao viés algorítmico, à exclusão tecnológica, à privacidade, à padronização e à responsabilização. A adoção responsável requer dados localmente representativos, validação transparente, letramento digital e de

dados, supervisão humana e governança coordenada. A IA apresenta elevado potencial para apoiar a aquicultura, mas sua contribuição para a formação profissional permanece um campo de pesquisa importante e ainda insuficientemente investigado.

Palavras-chave: inteligência artificial; aquicultura; educação superior; formação em Engenharia de Pesca; ética.

1. INTRODUCTION

Aquaculture has become increasingly important to global food production, livelihood generation, and food security (FAO, 2026). At the same time, the sector faces persistent challenges related to production efficiency, feed management, aquatic animal health, water quality, environmental sustainability, and the capacity to respond to biological and climatic variability. These interconnected challenges have accelerated the adoption of data-intensive technologies capable of supporting monitoring, prediction, and decision-making. Within this context, artificial intelligence (AI) has emerged as a potentially transformative component of contemporary aquaculture (Li et al., 2021; Sun et al., 2020; Yang et al., 2024).

Machine learning, deep learning, computer vision, predictive modeling, and intelligent sensor systems are being applied to fish detection and counting, biomass estimation, feeding optimization, disease diagnosis, behavioral monitoring, water-quality prediction, and production automation (Fjorden et al., 2025; Grandez-Yoplac et al., 2025; Kilinc et al., 2025; Nuangpirom et al., 2025; Wang et al., 2026). These applications can improve the consistency and timeliness of management decisions, reduce resource waste, support non-invasive animal monitoring, and strengthen the capacity to identify environmental and health risks. However, the expansion of AI in aquaculture should not be understood solely as a technological transition. It also changes the knowledge, skills, and responsibilities expected of the professionals who design, operate, evaluate, and regulate aquaculture systems (Yu, 2023; Zhai et al., 2021).

Fisheries engineers, aquaculture technicians, farm managers, researchers, and extension professionals are increasingly expected to interpret sensor-generated data, evaluate algorithmic outputs, interact with automated systems, and recognize the limitations of computational models. Professional education must therefore respond to production environments in which biological and engineering knowledge is progressively combined with data literacy, computational reasoning, environmental monitoring, and evidence-based decision-making. In higher education, AI can support personalized learning, rapid feedback, access to specialized information, and the development of educational materials, but its pedagogical value depends on appropriate training, critical use, and meaningful human oversight (Bhutoria, 2022; Montenegro-Rueda et al., 2023; Rahman & Watanobe, 2023).

The capacity to operate an AI-enabled system does not necessarily imply the capacity to evaluate it critically. Models may generate inaccurate or contextually inappropriate outputs when they are trained with limited, unrepresentative, or geographically concentrated datasets. This concern is particularly relevant in aquaculture because environmental conditions, cultivated species, production scales, infrastructure, and management practices vary substantially among regions. Similarly, educational AI may reproduce biases embedded in its training data and disadvantage learners whose linguistic, cultural, or socioeconomic contexts are insufficiently represented (Arora et al., 2023; Baker & Hawn, 2022).

Unequal access to digital infrastructure may consequently deepen existing disparities in both aquaculture and higher education. Large companies and research-intensive institutions are generally better positioned to invest in sensors, cloud platforms, automated equipment, connectivity, and specialized personnel. Small-scale producers, public educational institutions, and communities in disadvantaged regions may instead face barriers related to implementation costs, technical support, digital literacy, and access to representative data. Without inclusive

policies, AI adoption may reinforce technological exclusion and increase dependence on systems developed for production and educational contexts that differ from local realities (Risco, 2020; Rotz et al., 2019; Salas-Pilco & Yang, 2022).

AI adoption also raises questions concerning data privacy, ownership, transparency, accountability, cybersecurity, and the preservation of human judgment. Automated recommendations can influence feeding, animal-health interventions, environmental management, student assessment, academic production, and professional decision-making. Regulatory frameworks and institutional policies must therefore ensure that AI systems remain explainable, auditable, context-sensitive, and subject to human supervision. Education has a central role in this process because future professionals must understand not only how these technologies operate, but also when their outputs should be questioned, independently verified, or rejected (Chen, 2024; Schiff, 2022; Yu, 2023).

Although the literature on AI applications in aquaculture and higher education has expanded rapidly, evidence remains fragmented regarding how technological applications, educational practices, ethical risks, unequal access, and regulatory gaps interact in the preparation of professionals for increasingly automated technical-scientific fields. This fragmentation is particularly relevant to Fisheries Engineering, where professional practice requires the integration of biological sciences, production engineering, environmental management, data analysis, and responsibility for decisions affecting animals, ecosystems, producers, students, and communities.

Against this background, this systematic literature review aims to analyze the practical applications of artificial intelligence in aquaculture and higher education and to critically examine their implications for professional training in technical-scientific fields, particularly Fisheries Engineering. The review integrates evidence concerning technological applications, educational practices, ethical challenges, inequalities in access, and regulatory gaps. By connecting these dimensions, the study seeks to identify how professional education and public policy can respond to the increasing adoption of AI while preserving human oversight, social inclusion, environmental sustainability, and responsible decision-making.

2. METHODOLOGY

2.1 Study design

This study is a systematic literature review (SLR) conducted under an integrative approach, designed to map, synthesize, and critically analyze the current and prospective applicability of Artificial Intelligence (AI) technologies in the training of technical, academic, and scientific professionals working in Aquaculture. This systematic review was chosen for its ability to provide a comprehensive and replicable overview, allowing for a critical analysis of existing evidence. The SLR followed the PRISMA 2020 statement (Page et al., 2021) to ensure methodological transparency and reproducibility, while the integrative synthesis framework proposed by Kutcher & LeBaron (2022) was adopted to allow the combination of empirical studies with distinct methodological designs (quantitative, qualitative, and mixed methods). This methodology guarantees the academic robustness of the study and aligns with best scientific research practices.

2.2 Research questions

Three research questions (RQs) guided the review protocol:

RQ1: What are the main practical applications of AI in the Aquaculture sector and in Higher Education, and how do these tools impact educational practices and professional training in technical-scientific areas such as Fisheries Engineering?

RQ2: What are the ethical challenges associated with the use of AI in Aquaculture and Education — including data privacy, algorithmic bias, and technological exclusion — and how can unequal access to technology affect small-scale aquaculture producers and educational institutions in disadvantaged regions?

RQ3: What regulatory gaps hinder the ethical and sustainable use of AI in Aquaculture and Higher Education, and how can public policies be structured to democratize access to AI in these sectors?

2.3 Information sources and search strategy

Four scientific databases were consulted between May and June 2026: Scopus, Web of Science, and PubMed — selected for their peer-reviewed indexing and reproducibility — and Google Scholar was included as a complementary search source to identify potentially relevant studies not indexed in the primary databases and to increase retrieval sensitivity, following the recommendation by Haddaway et al. (2015). The search string combined three conceptual blocks connected by Boolean operators:

("artificial intelligence" OR "machine learning" OR "deep learning" OR "computer vision") AND ("aquaculture" OR "fish farming" OR "fisheries engineering") AND ("education" OR "higher education" OR "vocational training" OR "professional training" OR "ethics" OR "public policy" OR "regulation")

The search was replicated in English, Portuguese, and Spanish to reduce language-related bias. For Google Scholar, the first 100 results returned in each language were screened.

2.4 Eligibility criteria

Inclusion criteria: (i) peer-reviewed empirical articles published from January 2018 to June 2026; (ii) studies addressing the application of artificial intelligence, machine learning, deep learning, computer vision, or related technologies within aquaculture, fisheries engineering, higher education, vocational education, or their intersection; (iii) studies reporting practical applications, educational outcomes, ethical implications, governance issues, regulatory frameworks, public policy considerations, or socio-economic impacts associated with AI adoption; and (iv) full-text articles available in English, Portuguese, or Spanish.

Exclusion criteria were: (i) duplicate records across databases; (ii) non-peer-reviewed publications, including editorials, conference abstracts, technical notes, and preprints; (iii) studies focused exclusively on algorithmic development without a clearly defined application to aquaculture, fisheries engineering, education, ethics, governance, regulation, or socioeconomic outcomes; (iv) studies unrelated to any of the three research questions; (v) studies that did not provide empirical evidence or a substantive analytical discussion; and (vi) narrative reviews whose findings substantially overlapped with those of a more recent review already included in the corpus.

Given the integrative scope of the review, eligibility for the final synthesis required each document to provide relevant evidence addressing at least two of the three research questions. This criterion was defined *a priori* to ensure that the included documents contributed to the integration of technological applications with educational, ethical, socioeconomic, or governance dimensions. Documents addressing only one research question were excluded during full-text assessment, and the corresponding reason for exclusion was recorded separately.

2.5 Selection process

All records retrieved from the selected databases were exported to Rayyan™ (Ouzzani et al., 2016), where duplicate records were identified and removed. The subsequent selection

process was conducted independently by two reviewers using the platform's blinded-screening function. Disagreements between the reviewers were resolved through discussion and, when consensus could not be reached, by consultation with a third reviewer.

The selection process comprised four sequential stages. First, duplicate records were removed, and the remaining records were verified according to publication type and retrievability. Editorials, conference abstracts, preprints, technical notes, non-scientific documents, and records lacking sufficient bibliographic information for verification or full-text retrieval were excluded.

Second, the titles and abstracts of the remaining records were screened against the eligibility criteria described in Section 2.4. At this stage, studies were assessed for thematic relevance, alignment with the review objectives, and potential contribution to the research questions. Records that clearly did not address artificial intelligence in aquaculture, higher education, professional training, ethics, governance, regulation, or related socioeconomic implications were excluded.

Third, the full texts of all potentially eligible reports were sought and independently assessed. Studies were excluded when the full text could not be obtained after institutional and complementary searches or when the complete article did not satisfy the predefined eligibility criteria.

Fourth, the studies that remained eligible after full-text assessment were evaluated according to their contribution to the integrative synthesis. This assessment considered their capacity to provide evidence concerning the practical applications of AI, associated ethical and social challenges, inequalities in technological access, regulatory gaps, public-policy implications, or professional training in technical-scientific fields. Studies with an excessively narrow scope and insufficient contribution to the research questions were excluded.

For each report excluded after full-text assessment, the principal reason for exclusion was recorded. The results of the selection process, including the number of records retained and excluded at each stage, are presented in Section 3.1 and in the PRISMA 2020 flow diagram (Figure 1).

2.6 Data extraction and evidence synthesis

Data extraction was independently performed by two reviewers using a standardized extraction form specifically developed for this review. Any disagreements were resolved through discussion until consensus was reached.

For each of the 97 included studies, the following information was extracted: (a) bibliographic characteristics; (b) country; (c) application domain; (d) principal findings; (e) contribution to RQ1, RQ2 and RQ3, (f) limitations.

For the geographical analysis, each document was assigned to a single country according to the institutional affiliations of the majority of its authors. When authors reported affiliations in different countries, the country represented by the largest number of author affiliations was assigned to the document. Thus, country refers to the predominant institutional affiliation of the authors rather than to the study location, data origin, or authors' nationality.

The extracted information was organized into a structured evidence matrix, which served as the primary analytical framework for this review. This matrix enabled systematic comparisons among studies and supported the descriptive analyses presented in the Results section.

Subsequently, the studies were grouped according to their contribution to the three research questions and compared to identify recurrent technological approaches, application domains, ethical concerns, governance issues, methodological trends, and research gaps. Because this review adopted an integrative perspective, evidence was synthesized across multiple analytical dimensions rather than according to methodological design alone.

The evidence matrix also served as the basis for the preparation of the summary tables and thematic synthesis presented in Section 3. A complete version of the extraction matrix is provided as Supplementary Table S1 to ensure transparency and reproducibility.

3. RESULTS

The database searches identified 877 records, comprising 141 records from Scopus, 337 from Web of Science, 99 from PubMed, and 300 from Google Scholar. After the removal of 135 duplicate records, 742 records remained for screening. A further 155 records were excluded because they were non-peer-reviewed publications or ineligible publication types. Consequently, 587 records underwent title and abstract screening, of which 331 were excluded for not meeting the eligibility criteria.

A total of 256 reports were sought for full-text retrieval. Of these, 33 reports could not be retrieved, resulting in 223 reports assessed for eligibility. Following full-text assessment, 126 reports were excluded: 63 because they did not address the review objectives, 40 because they addressed only one of the three research questions, and 23 because they made an insufficient contribution to the integrative synthesis. The remaining 97 documents fulfilled the eligibility criteria and were included in the qualitative synthesis (Figure 1).

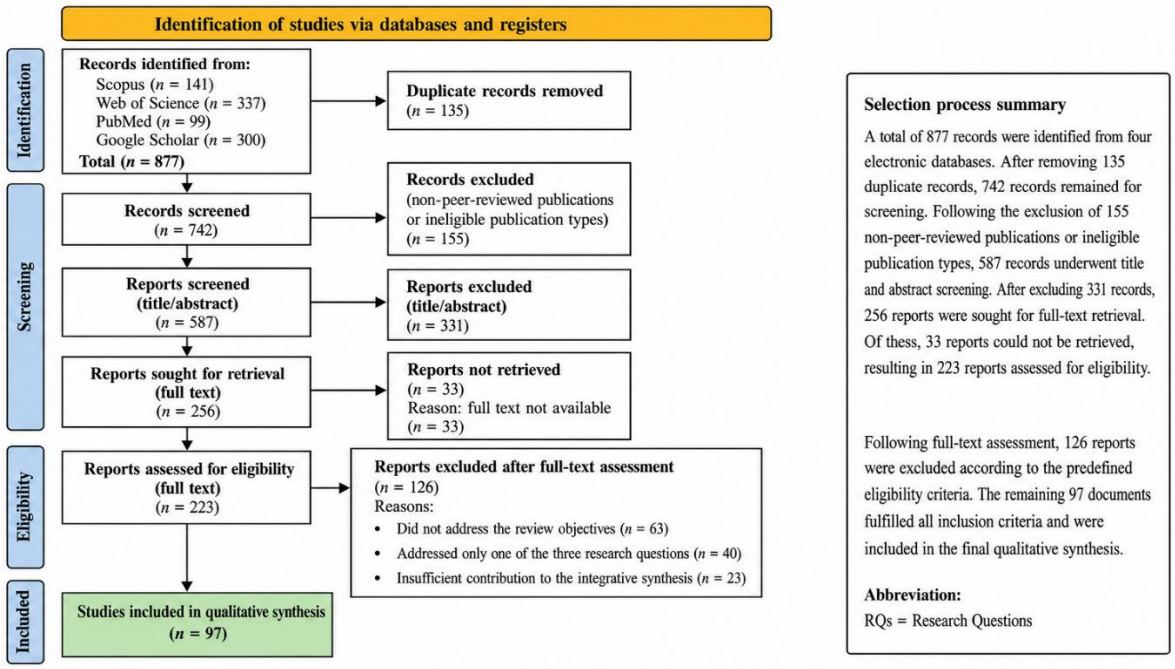


Figure 1. PRISMA 2020 flow diagram of the study selection process.

Note: Records were identified from four electronic databases (Scopus, Web of Science, PubMed and Google Scholar) and managed using Rayyan™ software. Of the 877 records initially identified, 97 studies fulfilled the eligibility criteria and were included in the final qualitative synthesis. Adapted from Page et al., (2021).

The included documents were published between 2020 and 2026. Experimental studies predominated, accounting for 71 documents (73.2%), whereas review articles represented 26 documents (26.8%). Because the corpus included both primary studies and review articles, the frequencies reported in this review represent the number of included documents rather than fully independent empirical evidence. Some primary studies may also have been represented within the included reviews; therefore, the reported frequencies should be interpreted as document-level occurrences. The temporal distribution showed a marked increase in scientific production during the most recent years. Studies published in 2025 constituted the largest group

(n = 27; 27.8%), followed by publications from 2024 (n = 25; 25.8%) and 2026 (n = 19; 19.6%). Together, these three years accounted for 71 documents (73.2%) in the final corpus. The remaining documents were published in 2023 (n = 11; 11.3%), 2022 (n = 8; 8.2%), 2020 (n = 4; 4.1%), and 2021 (n = 3; 3.1%).

Based on the predominant institutional affiliation of the authors, the corpus comprised documents assigned to 26 countries. China accounted for 44 documents (45.4%), followed by India with 10 documents (10.3%). Malaysia and Taiwan contributed four documents each, while Brazil, Japan, and Spain contributed three documents each. The remaining 26 documents were distributed across 19 countries, each represented by one or two publications. China and India together accounted for 54 documents (55.7%) of the included corpus.

The studies employed a heterogeneous range of artificial intelligence methods, from conventional machine-learning algorithms to deep neural networks and multimodal architectures. Frequently identified approaches included random forests, support vector machines, decision trees, artificial neural networks, convolutional neural networks, recurrent neural networks, long short-term memory networks, gradient-boosting methods, and different versions of the YOLO object-detection architecture. Several studies combined these techniques with attention mechanisms, ensemble learning, explainable AI, Internet of Things platforms, cloud and edge computing, remote sensing, automated sensor networks, blockchain, and federated learning.

The application categories were not mutually exclusive because individual studies frequently addressed more than one production or management problem. Fish detection, classification, counting, biomass estimation, or phenotyping constituted the largest thematic category (n = 43). These applications included species and individual recognition, body-size and weight estimation, larvae or stock counting, behavioral monitoring, and non-invasive phenotypic assessment.

Water quality and environmental monitoring represented another prominent category (n = 36). Applications in this group involved dissolved oxygen, temperature, pH, salinity, ammonia, effluent characteristics, water-quality forecasting, harmful algal blooms, and environmental changes in aquaculture areas. Smart systems, automation, sensor networks, or Internet of Things applications were identified in 30 studies. Health, disease, welfare, stress, or biosecurity applications appeared in 27 studies, while feeding, growth, aeration, or production optimization was addressed in 23 studies. Sustainability, governance, technological adoption, or socioeconomic considerations were identified in 19 studies, and nine studies employed remote sensing or spatial mapping for the identification and monitoring of aquaculture areas. Because these categories overlapped, their frequencies exceeded the total number of included studies.

Evidence directly concerning aquaculture education and professional training was substantially less frequent than evidence concerning production applications. Only one of the 97 included studies (1.0%) directly examined aquaculture professionals' knowledge, attitudes, and interest in learning about artificial intelligence (Gkikas et al., 2024). None of the studies empirically evaluated formal curricular interventions, classroom practices, course design, student performance, or learning outcomes specifically within Fisheries Engineering or aquaculture education.

Educational content in the remaining corpus was indirect and was primarily associated with the implementation of AI-enabled technologies. Training, digital literacy, data interpretation, sensor calibration, equipment maintenance, and collaboration with research or educational institutions were identified as requirements for technology adoption. The educational dimension was therefore predominantly related to professional preparedness and implementation capacity rather than to the evaluation of formal educational interventions.

Ethical and social evidence was organized into three interconnected categories: data-related risks, unequal technological access, and limitations in human capacity to evaluate AI-supported

decisions. Data-related issues included restricted access to representative datasets, variable data quality, privacy and security concerns, limited transparency, and difficulties in transferring models among species, production systems, and geographical contexts. Technical conditions in aquatic environments, including turbidity, inadequate illumination, occlusion, sensor limitations, and restricted computational capacity, were also identified as factors affecting data quality and model performance (Li & Du, 2022)

Access-related evidence included implementation and maintenance costs, limited internet connectivity, insufficient technical support, low digital literacy, and unequal access to sensors, automated equipment, cloud platforms, and specialized personnel. These conditions were especially relevant to small-scale farms, artisanal production systems, and remote communities. Some studies described comparatively low-cost, decentralized, or participatory technological arrangements designed for resource-constrained production systems (Ramanathan et al., 2023; Saba et al., 2026).

Governance-related evidence was less frequent than evidence concerning technical applications. The identified governance content was classified into five categories: data privacy and security; standardization of monitoring procedures; transparency and traceability; institutional coordination; and policies supporting technology adoption. Privacy and security were addressed in connection with farm-generated data, centralized and distributed data storage, cloud platforms, digital twins, federated learning, and control over commercially sensitive information (Cheng et al., 2024).

Standardization-related content included the selection of environmental parameters, acceptable measurement ranges, sensor calibration, maintenance procedures, data interoperability, and validation of information used by predictive models. Transparency and traceability were associated with blockchain, digital supply chains, product certification, data integrity, fraud prevention, and technologies for identifying illegal, unreported, and unregulated fishing activities. Institutional and policy-related content included access to finance, digital infrastructure, training programs, information about technological benefits, stakeholder collaboration, and government support for the adoption of intelligent systems (Beg et al., 2024; Sen et al., 2026).

The included studies more frequently identified governance requirements and implementation barriers than empirically evaluated formal regulations, public policies, accountability mechanisms, or institutional governance frameworks specifically designed for artificial intelligence in aquaculture. Evidence concerning professional education and governance was therefore less extensive than evidence concerning technological development and production applications.

4. DISCUSSION

The findings demonstrate that artificial intelligence is becoming an important component of contemporary aquaculture, particularly in production systems that depend on continuous monitoring, rapid data processing, and automated decision support. The recent increase in publications indicates an expanding research field driven by advances in machine learning, computer vision, sensor networks, Internet of Things platforms, and cloud and edge computing. Nevertheless, technological development has progressed more rapidly than research concerning professional education, social inclusion, governance, and the long-term consequences of AI adoption. This imbalance is central to understanding both the transformative potential of AI and the conditions required for its responsible implementation.

The continental distribution of the evidence reveals a pronounced concentration of research in Asia, which accounted for 74 of the 97 included studies (76.3%), followed by Europe with 14 studies (14.4%), South America with five (5.2%), Africa with three (3.1%), and North America with one (1.0%) (Figure 2). This distribution reflects the substantial participation of

Asian countries, particularly China and India, in aquaculture production and investment in digital farming technologies. Nevertheless, it limits the geographical representativeness of the evidence and raises questions regarding the transferability of models across distinct environmental, socioeconomic, and infrastructural contexts.

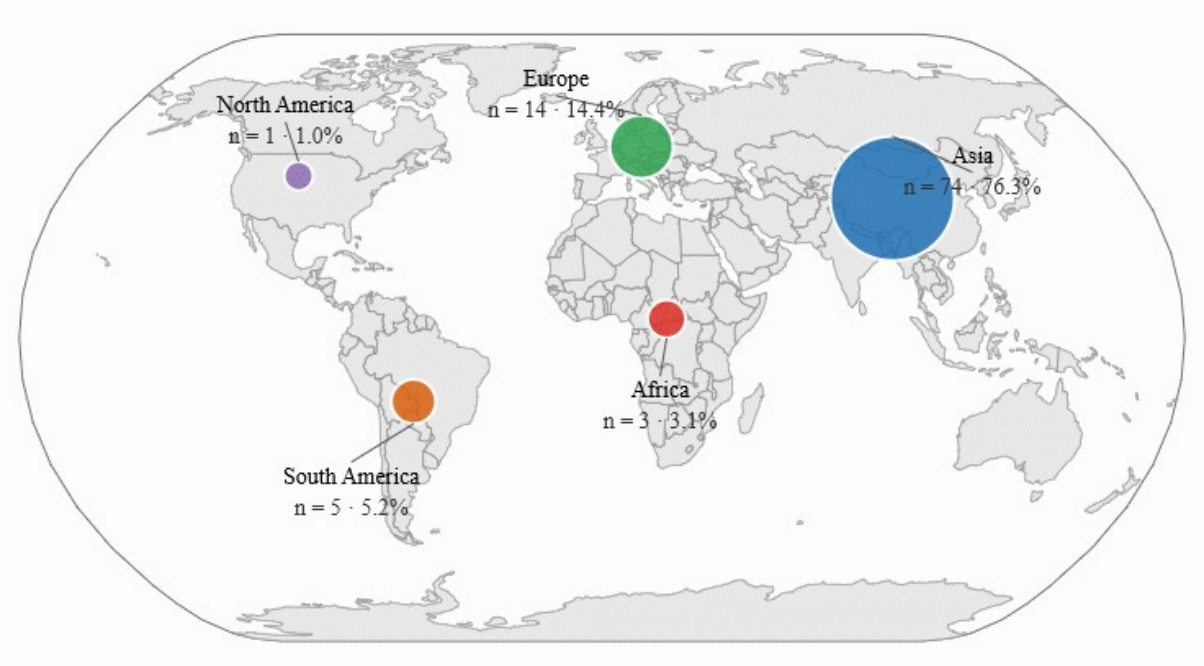


Figure 2. Continental distribution of the 97 studies included in the systematic review.

Note: Circle size is proportional to the number of documents assigned to each continent. Each document was geographically classified according to the country representing the majority of its authors' institutional affiliations. Continental classification follows the United Nations M49 standard.

The limited representation of Africa, Latin America, and North America is particularly relevant because AI models are sensitive to the characteristics of their training and validation data. Aquaculture systems differ considerably in cultivated species, water conditions, climate, production scale, management practices, connectivity, equipment availability, and access to specialized personnel. Consequently, an algorithm validated in an intensive Asian production system cannot automatically be assumed to perform equally well in artisanal, small-scale, or geographically distinct aquaculture systems. This continental imbalance reinforces the need for locally representative datasets, external model validation, multicenter studies, participatory technology development, and stronger research capacity in underrepresented regions.

The evidence also indicates that AI-enabled aquaculture operates as an interconnected technological system rather than through isolated algorithms (Figure 3). Machine learning, deep learning, computer vision, predictive modeling, and emerging multimodal architectures constitute the main analytical branches. Their practical operation, however, depends on enabling infrastructure such as sensors, IoT platforms, remote sensing, edge and cloud computing, federated learning, and blockchain. These elements connect data acquisition and processing to applications involving fish detection, biomass estimation, environmental monitoring, feeding, health management, automation, sustainability, and governance.

Computer vision and deep learning were particularly prominent in applications involving fish detection, counting, behavior recognition, biomass estimation, and phenotyping. These technologies can reduce direct animal handling and enable continuous and non-invasive monitoring. Li & Du (2022) demonstrated the breadth of deep-learning applications in aquaculture machine vision while also identifying persistent challenges involving underwater illumination, turbidity, occlusion, image quality, dataset size, and model performance. These

limitations are important because high accuracy under controlled experimental conditions does not necessarily guarantee reliable performance in commercial production environments.

Predictive and time-series models were more frequently associated with water quality, environmental changes, feeding, aeration, growth, and disease risk. Sensor networks can identify changes in dissolved oxygen, temperature, pH, salinity, ammonia, animal behavior, and other indicators before they become evident through conventional observation. Sen et al. (2026) associated these developments with improvements in feeding optimization, biomass estimation, disease surveillance, energy use, and operational efficiency. However, the effectiveness of predictive systems depends on sensor reliability, calibration, data continuity, appropriate model selection, and the capacity of users to interpret alerts and predictions.

Traditional machine-learning methods, including random forests, support vector machines, decision trees, and gradient-boosting algorithms, remain relevant because they can provide robust performance with structured datasets and may require fewer computational resources than complex deep-learning architectures. In contrast, deep neural networks and multimodal models can process images, sensor measurements, text, and temporal data simultaneously but generally require larger datasets, greater computational capacity, and more complex validation. Liu et al. (2026) emphasized that multimodal models introduce challenges related to data acquisition, model performance, security, governance, and industrial implementation.

The boundaries among these technological branches are therefore not rigid. Many studies combined computer vision with IoT sensors, predictive analytics with cloud platforms, or deep learning with automated control systems. IoT, blockchain, remote sensing, and cloud computing should not themselves be classified as branches of artificial intelligence. They operate as enabling digital infrastructures that collect, transmit, process, protect, or document the data used by AI systems. Federated learning occupies an intermediate position because it is a machine-learning strategy implemented through distributed infrastructure to allow collaborative model development without centralizing sensitive farm data.

This distinction has direct implications for professional education. Fisheries engineers and aquaculture professionals increasingly need to understand both analytical models and the infrastructures through which those models operate. Their role is not limited to activating automated equipment or reading software dashboards. Professionals must assess data quality, recognize uncertainty, evaluate whether a model was validated under comparable biological and environmental conditions, and determine when automated recommendations require independent verification.

Lindholm‑Lehto (2023) observed that advanced water-quality monitoring systems require competent users, regular maintenance, calibration, and context-sensitive interpretation. (Li et al., 2025) similarly described aquaculture digitalization as a process that combines traditional production knowledge with digital and analytical skills, contributing to new forms of professional practice. These observations indicate that AI does not eliminate the need for specialized human knowledge. Instead, it changes the nature of professional competence and increases the importance of combining biological judgment with data literacy.

The limited educational evidence identified in the corpus is therefore significant. Gkikas et al. (2024) found that 64.4% of surveyed aquaculture professionals characterized their AI knowledge as limited or non-existent, although 67.1% expressed an interest in learning more. Knowledge of AI was positively associated with its use, while interest in learning was associated with expectations regarding its professional contribution. These findings indicate that technological availability alone is insufficient to ensure effective adoption. Professionals must also understand the principles, limitations, and appropriate uses of the systems with which they interact.

The absence of studies evaluating formal curricula, classroom interventions, student performance, or learning outcomes in Fisheries Engineering represents an important

educational gap. Existing research on AI in higher education indicates that these technologies can support access to information, personalized feedback, academic production, and the development of teaching materials (Bhutoria, 2022; Montenegro-Rueda et al., 2023). At the same time, generative AI and automated educational systems may encourage superficial learning, technological dependence, inappropriate authorship practices, and reduced critical engagement when their use is not accompanied by clear pedagogical objectives and human supervision (Rahman & Watanobe, 2023; Yu, 2023).

Aquaculture education must therefore move beyond teaching students how to operate specific software. A curriculum responsive to AI-enabled aquaculture should integrate aquatic sciences, engineering, statistics, data management, sensor technology, environmental monitoring, ethics, and governance. This does not imply transforming Fisheries Engineering programs into computer science degrees. Instead, students should acquire sufficient computational and data literacy to collaborate with technology specialists, understand how models are developed and validated, and retain professional responsibility for decisions affecting animals, ecosystems, producers, and communities.

Practical educational activities could include interpreting water-quality time series, evaluating computer-vision outputs, validating biomass estimates, identifying biased or incomplete datasets, comparing model predictions with field observations, and analyzing the environmental and social consequences of automated decisions. Students should also learn how to document uncertainty, communicate technological limitations, and determine when an AI recommendation should be accepted, adjusted, or rejected. These competencies would position AI as a decision-support resource rather than an unquestionable replacement for professional judgment.

Figure 3 emphasizes that professional competence connects the different levels of AI-enabled aquaculture. Data literacy is needed to assess the quality and representativeness of information; computational reasoning is needed to understand how models generate predictions; biological knowledge is necessary to interpret outputs within real production systems; and ethical competence is required to evaluate the consequences of automated decisions. Human oversight should therefore be incorporated throughout system design, validation, implementation, and evaluation.

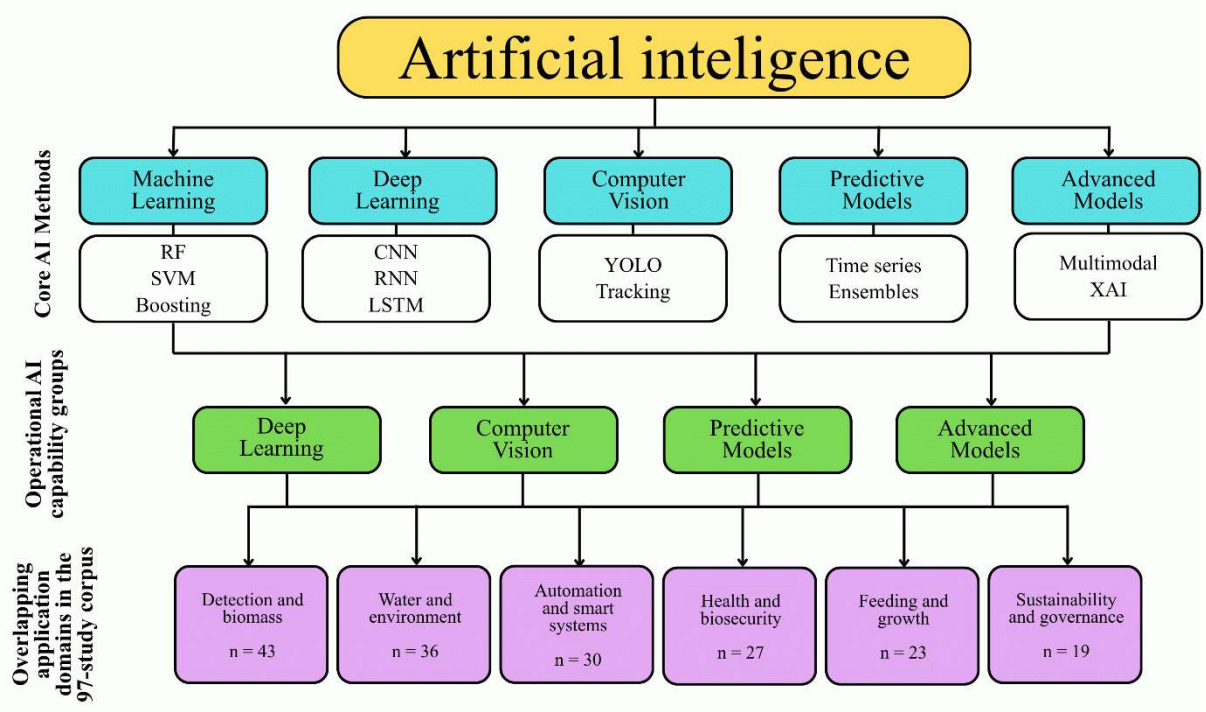


Figure 3. Conceptual organization of artificial intelligence methods and their principal application domains in the 97-study corpus.

Abbreviations: AI, Artificial Intelligence; CNN, Convolutional Neural Network; LSTM, Long Short-Term Memory; RF, Random Forest; RNN, Recurrent Neural Network; SVM, Support Vector Machine; XAI, Explainable Artificial Intelligence; YOLO, You Only Look Once; n, number of studies.

Note: Application domains were non-mutually exclusive because individual studies could address more than one category.

The findings also demonstrate that access to AI technologies is uneven. Small-scale producers and remote communities may face inadequate connectivity, limited access to equipment, insufficient technical support, high implementation costs, and low digital literacy. Saba et al. (2026) identified weak digital infrastructure, insufficient funding, limited training programs, and inadequate coordination among institutions as barriers to smart fisheries adoption. These difficulties concern not only technology but also the distribution of knowledge, resources, and decision-making power.

If technological development remains concentrated in large companies and research-intensive production systems, AI may reinforce existing inequalities rather than democratize access to sustainable aquaculture practices. Georgopoulos et al. (2023) showed that economic feasibility, reliable performance, access to information, education, training, infrastructure, and data protection influence decisions concerning AI adoption. These factors demonstrate that adoption is a sociotechnical process shaped by institutional, economic, and educational conditions.

Evidence from artisanal fish farming in southern Brazil provides a more inclusive perspective. Ramanathan et al. (2023) demonstrated that comparatively low-cost IoT systems could support water-quality monitoring and waste reduction when implementation involved collaboration among farmers, researchers, and educational institutions. This suggests that technological inclusion depends on participatory design, local training, technical support, and adaptation to users' knowledge and priorities. Public policies should therefore avoid assuming that technologies developed for intensive production can be transferred to small-scale systems without modification.

Algorithmic bias constitutes an additional concern. Models reproduce the characteristics and limitations of the data used during their development. If training datasets predominantly represent particular species, regions, farm sizes, or production conditions, model outputs may be less reliable elsewhere. Aung et al., (2025) identified restricted access to representative data, high costs, technical complexity, limited social acceptance, and privacy and security concerns as barriers to responsible AI adoption in commercial aquaculture.

Arora et al., (2023) describe the broader concentration of technological development and data control as a form of data colonialism. In aquaculture, this risk may arise when systems developed by organizations in technologically dominant regions marginalize local knowledge, traditional practices, or low-impact production models. Algorithms optimized for intensive systems may recommend practices that are economically inaccessible or environmentally inappropriate for small producers. Responsible innovation therefore requires diverse datasets, local validation, stakeholder participation, and recognition of context-specific knowledge.

Transparency is equally important. Professionals should be able to identify the origin of training data, the conditions under which a model was validated, its expected performance, and its known limitations. Explainable AI methods may assist in clarifying which variables influenced a prediction, but technical explainability alone does not guarantee accountability. Institutions must also define who is responsible when an automated recommendation causes economic loss, environmental damage, or adverse animal-welfare outcomes.

Privacy and cybersecurity are becoming increasingly relevant because intelligent aquaculture systems generate commercial and environmentally sensitive data. These may include production volumes, feeding strategies, disease events, water conditions, mortality, geographic locations, and financial indicators. Centralized storage can expose this information to unauthorized access, secondary use, or commercial exploitation. Saba et al., (2026) highlighted the absence of clearly defined policies concerning data ownership, consent, privacy, transparency, and accountability in smart fisheries.

Federated learning provides one possible technical response to these concerns. Cheng et al. (2024) proposed an edge-cloud architecture in which machine-learning models could be collaboratively trained without transferring raw farm data to a central repository. Cheng et al., (2025) subsequently applied a related framework to automated crayfish health assessment, preserving data privacy while reducing communication requirements. Such approaches may reduce exposure of sensitive information, but they do not eliminate the need for rules concerning ownership, consent, access, model responsibility, and secondary data use.

The governance evidence also indicates a need for standardization. Lindholm‑Lehto (2023) identified the absence of uniform requirements concerning which water-quality parameters should be measured in recirculating aquaculture systems and which ranges or fluctuations should be considered acceptable. Without standardized procedures for sensor calibration, data validation, interoperability, and model evaluation, comparisons among farms and studies remain difficult. Poorly standardized data may also undermine algorithms trained across multiple production systems.

Traceability technologies provide another example of the relationship between technical innovation and governance. Blockchain, digital supply-chain platforms, and intelligent monitoring can improve certification, data integrity, fraud prevention, and consumer access to production information (Li et al., 2025; Sen et al., 2026). Related technologies have also been used to identify illegal, unreported, and unregulated fishing activities (Klawikowska et al., 2022). Nevertheless, technological traceability does not automatically produce accountability. Governance frameworks must define who records information, who verifies its accuracy, who controls access, and how disputes or errors are addressed.

Regulatory inconsistency is not limited to AI-specific systems. Beg et al., (2024) identified inconsistent application of regulations in organic aquaculture, illustrating the difficulty of

harmonizing production standards, certification, economic feasibility, and local conditions. As AI becomes incorporated into monitoring and certification processes, existing regulatory inconsistencies may be transferred into digital systems unless standards are clearly defined and periodically reviewed.

Rowan (2023) emphasized the importance of digital innovation ecosystems capable of connecting producers, researchers, technology providers, educational institutions, financial organizations, and government agencies. Such ecosystems can support specialist training, technology testing, access to finance, cybersecurity, and knowledge exchange. This perspective is consistent with the evidence that AI adoption depends on coordinated institutional capacity rather than on isolated technological acquisition.

Governance should therefore be understood as a continuous process involving data management, system validation, professional education, infrastructure investment, public participation, and institutional accountability. Regulation should not be limited to prohibiting harmful applications. It should also create conditions for responsible experimentation, independent auditing, transparent reporting, and equitable access. Particular attention should be given to small-scale producers who may otherwise bear the costs of technological transitions without sharing equally in their benefits.

Several evidence gaps emerged from the synthesis. Greater geographical diversity is needed, particularly from Africa, Latin America, small island states, and other regions where small-scale aquaculture contributes substantially to food security and livelihoods. Research should evaluate AI systems using local species, environmental conditions, production scales, and infrastructure. Multicenter validation would help determine whether models can generalize beyond the farms or datasets used during their development.

More studies are also needed under real commercial conditions. Algorithmic accuracy measured using controlled datasets provides limited information about long-term reliability, maintenance costs, energy requirements, sensor degradation, connectivity interruptions, producer acceptance, or economic return. Future research should combine technical performance with environmental, economic, animal-welfare, and social indicators.

Educational research constitutes another priority. Studies should evaluate curriculum models, teaching strategies, professional-development programs, and digital-literacy initiatives designed specifically for Fisheries Engineering and aquaculture education. Outcomes should include not only technical competence but also critical thinking, ethical reasoning, understanding of uncertainty, and the capacity to challenge inappropriate algorithmic recommendations.

Governance research should move beyond conceptual recommendations and evaluate actual policies, standards, accountability mechanisms, data-sharing arrangements, and institutional frameworks. Comparative studies across countries and production systems could identify which governance approaches support innovation while protecting producers, workers, animals, ecosystems, and consumers. Research should also examine how AI affects employment, professional autonomy, traditional ecological knowledge, and the distribution of economic benefits.

This review has limitations. Searches were restricted to four databases and to studies available in English, Portuguese, or Spanish. Google Scholar screening was limited to the first 100 results in each language, which may have introduced ranking bias. The requirement that studies contribute to at least two research questions strengthened the integrative character of the synthesis but may have excluded specialized studies providing relevant evidence on a single dimension. The inclusion of both experimental studies and reviews introduced methodological heterogeneity and prevented direct comparison of all reported outcomes. Furthermore, the rapid pace of AI development means that technologies and regulatory debates may evolve after the search period.

Despite these limitations, the synthesis indicates that the principal question is no longer simply whether artificial intelligence can be applied to aquaculture. The more important issue is how these technologies can be integrated into production, education, and governance without weakening professional responsibility, excluding vulnerable producers, or transferring inappropriate models across distinct environmental and social contexts. The future contribution of AI to aquaculture will depend on the quality of its data and algorithms, but equally on the professionals, institutions, policies, and educational systems responsible for directing its use.

5. CONCLUSIONS

Artificial intelligence is becoming an important component of contemporary aquaculture, particularly in applications involving fish detection and biomass estimation, environmental monitoring, automated production, health and biosecurity, and feeding and growth optimization. Nevertheless, the available evidence is geographically concentrated and is dominated by technical performance studies, frequently conducted under controlled conditions or with locally restricted datasets. The transferability of these systems across species, production scales, and environmental contexts therefore remains uncertain.

The review identified a substantial imbalance between technological development and educational evidence. Although AI-enabled aquaculture requires professionals capable of interpreting data, validating models, recognizing uncertainty, and maintaining responsibility for automated decisions, only one included study directly investigated aquaculture professionals' knowledge and interest in AI. No study evaluated formal curricular interventions or learning outcomes in Fisheries Engineering. Professional education should consequently integrate biological and engineering knowledge with data literacy, computational reasoning, ethics, and governance, while preserving human judgment as the basis of professional accountability.

Responsible adoption also depends on conditions that extend beyond algorithmic accuracy. Representative datasets, transparent validation, data protection, interoperability, technical support, digital infrastructure, and participation by small-scale producers are necessary to prevent AI from reinforcing existing technological and socioeconomic inequalities. Public policies and institutional arrangements should support local validation, professional training, independent auditing, and equitable access rather than treating technological acquisition as sufficient for digital transformation.

Future research should prioritize multicenter and real-world validation, assessment of economic and environmental performance, evaluation of educational interventions, and comparative analysis of governance mechanisms. Within the limitations of the search strategy and the heterogeneous corpus, this review indicates that AI can strengthen aquaculture decision-making, but its sustainable contribution will depend equally on the quality of its technologies and on the educational, ethical, and institutional capacity governing their use.

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Supplementary Table S1. Characteristics of the 97 studies included in qualitative synthesis.

Country	Author (Year)	Study type	AI Technique	Application Domain
Bangladesh	(Saba et al., 2026)	Review	-	Smart fisheries, precision aquaculture, fish detection and recognition, disease diagnosis, water quality monitoring, fish quality assessment, intelligent fisheries management
Bangladesh	(Ahmed & Jeba, 2024)	Experimental	None	SalmonScan image dataset development; fish disease detection resources; computer vision and deep-learning training data.
Brazil	(Costa et al., 2023)	Experimental	CNN	Larvae counting; fish larvae detection; computer vision; precision aquaculture; aquaculture automation.
Brazil	(Souza et al., 2024)	Experimental	CNN; Batch Normalization	Pirapitinga fingerling detection and counting; stocking and harvesting management; aquaculture automation.
Brazil	(Ramanathan et al., 2023)	Experimental	None	IoT adoption in artisanal fish farming; waste reduction; water quality monitoring; feeding optimization; sustainability and technology acceptance.
China	(Cai et al., 2020)	Experimental	Modified YOLOv3 + MobileNetv1	Fish detection and counting
China	(Gao et al., 2024)	Experimental	Mask R-CNN + SE-ResNext101 + Multi-scale CNN	Individual fish recognition
China	(Deng et al., 2023)	Experimental	CNN (CANet/DeepLabV3+)	Environmental monitoring
China	(L. Wang et al., 2026)	Review	-	Aquaculture effluent treatment
China		Experimental	CV, DL, IoT	Smart aquaculture
China	(Tao et al., 2026)	Experimental	Deep Learning (CNN-LSTM)	Environmental monitoring
China	(Qin et al., 2025)	Experimental	Ensemble Machine Learning (XGBoost, GBDT, Random Forest, ANN, SVR, GPR, DT, MLR)	Aquaculture environmental monitoring/Water quality prediction / Harmful algal bloom prediction
China	(Xie et al., 2024)	Experimental	XGBoost, RF, ANN, KNN, GNB	Aquaculture pond detection and mapping
China	(W. Jia & Hu, 2026)	Experimental	Randon Forest	Sustainable aquaculture; carbon emission assessment; carbon removal assessment; carbon neutrality; environmental management; decision support.
China	(X. Song et al., 2023)	Experimental	SOM	Fish nutrition; carbohydrate metabolism; genotype classification; growth performance analysis; precision aquaculture.

Country	Author (Year)	Study type	AI Technique	Application Domain
China	(L. Wang et al., 2026)	Experimental	SVR; LightGBM; KNN; ANN; LM-BPNN; XGBoost	Aquaculture wastewater treatment; coagulation process optimization; water quality prediction; soft sensor development; intelligent process control.
China	(J. Wang & Zhang, 2025)	Experimental	CNN; DNN; RNN	Water quality monitoring; multispectral sensing; optical sensing; water quality prediction; precision aquaculture; shrimp farming.
China	(X. Yang et al., 2021)	Review	-	Smart fish farming; fish identification; species classification; behavior analysis; feeding decision; biomass estimation; water quality prediction.
China	(J. Yang et al., 2024)	Experimental	Modified VGG16; Swin Transformer; BPNN	Recirculating Aquaculture Systems (RAS); Intelligent Aeration Control; Oxygen Consumption Prediction; Fish Behavior Monitoring; Water Quality Management
China	(F. Chen et al., 2021)	Experimental	BPNN; ELM; PNN; LSTM; SVM	Recirculating Aquaculture Systems (RAS); intelligent flow control; water quality management; process control; intelligent aquaculture automation.
China	(Zhou et al., 2022)	Experimental	ELM; AdaBoost; PSO	Dissolved oxygen prediction; Aeration control; Water quality monitoring; Recirculating Aquaculture Systems (RAS); Intelligent aquaculture automation.
China	(H. Wang et al., 2022)	Experimental	YOLOv5; MHA	Fish behavior detection; Cannibalism detection; Computer vision; Precision aquaculture; Fish welfare.
China	(Gao et al., 2022)	Experimental	YOLOv4; ResNeXt50; CBAM	Fish individual recognition; Fish identification; Object detection; Computer vision; Precision aquaculture.
China	(L. Zhang et al., 2026)	Experimental	MAFA-YOLOv11n; CBAM; FASFF-Head	Pond fish detection and counting; stocking density assessment; precision feeding; intelligent aquaculture management.
China	(Luo et al., 2025)	Experimental	FishMambaNet; Selective State Space Model (SSM); CNN; MSCA	Fish disease detection and diagnosis; aquatic animal health monitoring; real-time edge deployment.
China	(Duan et al., 2025)	Experimental	FiVOS; Interactive Video Object Segmentation; Space-Time Memory Network	Fish video segmentation; fish behavior analysis; individual tracking; intelligent aquaculture monitoring.

Country	Author (Year)	Study type	AI Technique	Application Domain
China	(Tong et al., 2026)	Experimental	LMFF-YOLO; YOLOv8n-seg	Floating residual feed detection and segmentation; feed waste estimation; intelligent feeding; water quality management in RAS.
China	(S. Liu et al., 2026)	Review	-	Multimodal large models in aquaculture; water quality management; precision feeding; behavior detection; disease diagnosis; intelligent breeding; energy management; aquaculture robotics.
China	(Shi et al., 2026)	Experimental	DS-DDPM; MambaVision-MDF; Multi-Head Acoustic Attention	Acoustic monitoring of fish anesthetic recovery; generative data augmentation; aquaculture transportation; real-time decision support.
China	(Zhu & Zhou, 2025)	Experimental	Improved YOLOv8	Glass eel capture equipment detection; satellite-image monitoring; small-target detection; IUU fishing surveillance; eel resource management.
China	(J. Zhang et al., 2025)	Experimental	YOLOv8; ByteTrack; Kalman Filter	Shrimp detection and multi-object tracking; behavior analysis; water-velocity assessment; precision feeding in RAS.
China	(M. Xu et al., 2023)	Experimental	Random Forest; SVM; XGBoost; CCDC	Mangrove area mapping; aquaculture impact assessment; soil carbon stock estimation; coastal environmental management.
China	(W. Xu et al., 2023)	Experimental	DT-YOLOv5; Coordinate Attention; BiFPN	Sea cucumber disease recognition; abnormal behavior detection and tracking; aquatic animal welfare monitoring.
China	(W. Liu et al., 2024)	Experimental	PCA-ISSA-DAM-Bi-GRU	Dissolved oxygen prediction; marine ranching; water quality monitoring; early warning and intelligent regulation.
China	(H. Song et al., 2026)	Experimental	Random Forest; Kernel Ridge Regression; XGBoost; GBLUP	Sturgeon genomic selection; trait prediction; candidate gene identification; caviar and body-weight breeding.
China	(Liang et al., 2024)	Experimental	K-means; Multiple Linear Regression; SVM	Swimming crab aggressiveness assessment; cannibalism reduction; behavioral phenotyping; selective breeding.
China	(Bai et al., 2024)	Experimental	U-Net; CNN; Threshold Segmentation	Disease-related spleen phenotyping; genomic prediction; genome-wide association; disease resistance in large yellow croaker.
China	(X. Liu et al., 2024)	Experimental	Ridge Regression; XGBoost; CatBoost; Random Forest; Stacking	Freshwater aquaculture pond water quality estimation; chlorophyll-a and turbidity mapping; UAV multispectral monitoring.

Country	Author (Year)	Study type	AI Technique	Application Domain
China	(Dong et al., 2026)	Experimental	Aqua-HybridNet; CNN; Transformer Self-Attention	Freshwater aquaculture pond detection and mapping; multi-source remote sensing; sustainable regional aquaculture management.
China	(H. Zhang et al., 2026)	Experimental	Random Forest; Ridge Regression; Kernel Ridge Regression; Stacking; SHAP	Antibiotic ecological-risk assessment; dissolved organic matter analysis; comparison of RAS and traditional aquaculture systems.
China	(D. Li & Du, 2022)	Review	-	Aquaculture machine vision; fish classification, detection, counting, behavior recognition and biomass estimation; image preprocessing.
China	(Ren et al., 2020)	Experimental	Deep Belief Network; Variational Mode Decomposition	Dissolved oxygen prediction; recirculating aquaculture systems; water quality early warning and control.
China	(P. Li et al., 2025)	Review	-	Digital intelligent fisheries; IoT; precision feeding; traceability; aquaculture process automation and management.
China	(Y. Yang et al., 2025)	Experimental	YOLOv8-FA; ByteTrack	ROV-assisted sea cucumber detection, tracking, counting and density estimation; precision aquaculture; ecological monitoring.
China	(Miao et al., 2024)	Experimental	ISUNet; U-Net	Water-body extraction and spatiotemporal mapping; coastal resource management; assessment of aquaculture-related land-use change.
China	(Mustapha et al., 2021)	Review	-	Cloud computing, IoT and AI in aquaculture; feeding; traceability; disease detection; growth prediction; environmental and market monitoring.
China	(R. Jia et al., 2023)	Experimental	Improved YOLOv8; InceptionNeXt; SEAM	Underwater organism detection; marine ranching monitoring; small and overlapping target detection; resource-density assessment.
China	(Jiang et al., 2024)	Experimental	WBi-YOLOSF; YOLOv5; Artificial Rabbits Optimization	Underwater aquatic-product detection and classification; small-target recognition; aquaculture automation and real-time monitoring.
China	(J. Li et al., 2025)	Experimental	YOLOv8-BaitScan; YOLOv8n	Underwater bait residue detection and counting; feed-waste reduction; water pollution prevention; intelligent feeding.

Country	Author (Year)	Study type	AI Technique	Application Domain
Colombia	(Fandiño Pelayo et al., 2025)	Experimental	None (PID control only)	Aquaponics water quality regulation; long-term sensor-data validation; sustainable production; preparation of datasets for future AI models.
Egypt	(Aly & Fathi, 2024)	Review	-	Aquaculture biosecurity
Egypt	(Hussein et al., 2025)	Experimental	PCA; Linear Discriminant Analysis	Heavy-metal contamination assessment; ecological and human health risk; Nile tilapia and surface-water monitoring.
Finland	(Lindholm-Lehto, 2023)	Review	-	Water quality monitoring in recirculating aquaculture systems; sensors; IoT; real-time warnings; fish behavior monitoring.
Greece	(Gkikas et al., 2024)	Experimental	None	AI adoption; AI perception; Fish health management; Mediterranean aquaculture; Technology acceptance.
Greece	(Debroy et al., 2025)	Review	-	AI adoption; Technology adoption; Agriculture; Livestock farming; Aquaculture; Adoption barriers and drivers.
India	(Georgopoulos et al., 2023)	Review	-	Smart aquaponics / Precision aquaculture
India	(Gladju et al., 2022)	Review	-	General aquaculture / Fisheries AI applications
India	(Sen et al., 2026)	Review	-	Sustainable aquaculture; water quality monitoring; biomass estimation; disease management; feeding optimization; autonomous systems
India	(Roy et al., 2024)	Review	-	Smart aquaculture; water quality monitoring; automated feeding; fish health monitoring; disease prediction; fish species classification; fish counting; biomass estimation; weight estimation; fish measurement; fish behavior monitoring; precision aquaculture; decision support; offshore aquaculture; environmental monitoring; sustainable aquaculture.
India	(Gandh et al., 2024)	Experimental	DL; RNN; LSTM; GRU; Attention Mechanism (Attention-based LSTM e Attention-based GRU); Adam Optimizer	Smart aquaculture; water quality prediction; water quality monitoring; dissolved oxygen prediction; temperature prediction; salinity prediction; pH prediction; precision aquaculture; decision support.

Country	Author (Year)	Study type	AI Technique	Application Domain
India	(Krishnan et al., 2023)	Experimental	Random Forest	White spot syndrome virus comparative genomics; virulence-related gene identification; shrimp disease research.
India	(Beg et al., 2024)	Review	-	Organic aquaculture regulation; certification; production; marketing; socioeconomic and sustainability governance.
India	(Kumar et al., 2024)	Review	-	Solar energy and AI integration; aquaculture monitoring; fish health; post-harvest processing; energy efficiency and sustainability.
India	(Mandal & Ghosh, 2024)	Review	-	Fish growth and health monitoring; feeding optimization; disease detection; predictive analytics; sustainable aquaculture.
India	(Athiraja et al., 2026)	Experimental	SLCAM-AquaNet; ResNet; MobileNetV2	Aquaculture disease classification; fish health monitoring; lightweight real-time disease diagnosis.
Indonesia	(Supria et al., 2025)	Experimental	XGBoost; SMOTE; GridSearchCV	Dissolved oxygen classification; low-cost IoT sensing; real-time aquaponics monitoring and oxygen management.
Indonesia	(Suasono et al., 2026)	Experimental	Multi-Layer Perceptron (MLP); Analytic Hierarchy Process	Shrimp pond water quality classification; critical-state detection; decision support for conventional aquaculture.
Ireland	(Rowan, 2023)	Review	-	Digital transformation across fisheries and aquaculture supply chains; sustainability; monitoring; food processing; traceability.
Italy	(Lattanzi et al., 2026)	Experimental	Decision Tree; Random Forest; XGBoost; Logistic Regression; SHAP	Small-scale vessel activity classification; fishing-effort estimation; vessel tracking; fisheries monitoring.
Italy	(Previti et al., 2025)	Review	Text Mining; Latent Dirichlet Allocation Topic Modeling	Fish welfare; antimicrobial use and resistance; aquaculture research mapping; One Health policy.
Japan	(Lin et al., 2025)	Experimental	DL; CV; Mask R-CNN; CNN; Image Processing; GBLUP	Precision aquaculture; automated phenotyping; genomic selection; fish breeding; body size estimation; computer vision for aquaculture.
Japan	(Abe et al., 2021)	Experimental	SegNet	Fish detection; Fish counting; Fish tracking; Semantic segmentation; Aquaculture net cages; Aquaculture monitoring.

Country	Author (Year)	Study type	AI Technique	Application Domain
Japan	(Wang et al., 2026)	Experimental	MultiTask-Fish; ResNet34; FPN; Channel Attention	Fish counting in complex aquaculture scenes; density estimation; instance segmentation; stocking and feeding management.
Malaysia	(Stofa et al., 2025)	Review	-	Smart aquaculture
Malaysia	(Aung et al., 2025)	Review	-	Disease detection; fish behavior monitoring; feeding optimization; water quality monitoring; biomass and growth estimation; fish counting; shrimp seed counting; aquaculture area extraction and mapping; remote sensing; environmental monitoring; phytoplankton identification; seaweed monitoring; fish disease diagnosis; decision support systems; precision aquaculture; sustainable aquaculture management.
Malaysia	(Cheng et al., 2024)	Experimental	Federated Learning; YOLOv7; Faster R-CNN (ResNet50/101); SSD-ResNet101; CenterNet-Hourglass104	Precision aquaculture; prawn growth monitoring; water quality monitoring; privacy-preserving edge-cloud decision support for small-scale farms.
Malaysia	(Cheng et al., 2025)	Experimental	Federated Learning; YOLOv11	Crayfish health assessment; density estimation; growth-stage classification; disease detection; privacy-preserving smart aquaculture.
Nigeria	(Akinsorotan et al., 2024)	Review	-	Smart aquaculture; water quality and fish health monitoring; feeding management; biosensors; sustainability and technology adoption.
Norway	(Fjorden et al., 2025)	Experimental	YOLOv8n; YOLOv8n-seg; Transfer Learning	Fish scale-loss detection and quantification; salmon welfare assessment; skin segmentation; underwater monitoring.
Norway	(Knausgård et al., 2022)	Experimental	YOLO; CNN with Squeeze-and-Excitation; Transfer Learning	Temperate fish detection and species classification; underwater video monitoring; marine ecology and fisheries assessment.
Peru	(Grandez-Yoplac et al., 2025)	Review	-	Rainbow trout recirculating aquaculture systems; IoT integration; water treatment; intelligent and sustainable aquaculture.
Poland	(Klawikowska et al., 2022)	Review	-	Illegal, unreported and unregulated fishing detection; ghost fishing; vessel tracking; marine surveillance; fisheries enforcement.

Country	Author (Year)	Study type	AI Technique	Application Domain
Slovenia	(Marzidovšek et al., 2024)	Experimental	DT; RF; SVM; MLP	Harmful algal bloom (HAB) prediction; Diarrhetic Shellfish Poisoning (DSP) prediction; Shellfish safety monitoring; Early Warning System (EWS); Mussel aquaculture.
South Korea	(Kim et al., 2026)	Experimental	MIL; Autoencoder	Digital twin; Smart aquafarm monitoring; Water quality monitoring; Dissolved oxygen prediction; Temperature prediction; Risk assessment; Metaverse-based aquaculture.
Spain	(Rocruz et al., 2025)	Experimental	ML	Environmental monitoring
Spain	(Peiró-Signes et al., 2022)	Experimental	XGBoost	Consumer behavior analysis; sustainable aquaculture; seafood labeling; sustainability assessment; market analysis; decision support.
Spain	(Molares-Ulloa et al., 2026)	Experimental	DoME; Symbolic Regression	Harmful algal bloom prediction; DSP risk management; shellfish safety; explainable early-warning systems.
Switzerland	(Pietsch et al., 2024)	Experimental	Random Forest	Zebrafish stress classification; brain gene-expression analysis; fish welfare and stress biomarker identification.
Taiwan	(Kao & Chen, 2024)	Experimental	YOLO	Fish recognition
Taiwan	(H. Wang et al., 2022)	Experimental	Faster R-CNN, YOLOv4, EfficientDet-D1	Fish behaviour monitoring
Taiwan	(Lai et al., 2024)	Experimental	Linear Regression; SVM; Random Forest; LSTM; Hybrid ensemble	Aquatic product price prediction; wholesale market forecasting; market decision support; fisheries and aquaculture management.
Taiwan	(Negi & Chen, 2026)	Review	-	Shrimp gut microbiome; probiotics; immune modulation; disease resistance; sustainable shrimp aquaculture.
Thailand	(Nuangpirom et al., 2025)	Experimental	Multiple Linear Regression; Decision Tree Regression; Random Forest Regression	Real-time water quality prediction; edge AIoT; autonomous dissolved oxygen and pH regulation; small-scale tilapia aquaculture.
Türkiye	(Çakir et al., 2023)	Experimental	SVM	Disease prediction
Türkiye	(Kilinc et al., 2025)	Review	-	Food quality and safety in agriculture, fisheries and aquaculture; intelligent processing; traceability; disease prediction; post-harvest monitoring.
United States	(Raposo et al., 2025)	Experimental	CV	Fish welfare monitoring

Country	Author (Year)	Study type	AI Technique	Application Domain
Vietnam	(Quang et al., 2025)	Experimental	DT; Random Forest; Gradient Boosting Regression; AdaBoost Regression	Coastal and brackish water quality mapping; remote sensing; aquaculture and environmental impact monitoring.

Abbreviations: ABR, AdaBoost Regression; AHP, Analytic Hierarchy Process; AI, Artificial Intelligence; ANN, Artificial Neural Network; BiFPN, Bidirectional Feature Pyramid Network; Bi-GRU, Bidirectional Gated Recurrent Unit; BN, Batch Normalization; BPNN, Backpropagation Neural Network; CA, Coordinate Attention; CBAM, Convolutional Block Attention Module; CCDC, Continuous Change Detection and Classification; CNN, Convolutional Neural Network; CV, Computer Vision; DAM, Dual Attention Mechanism; DBN, Deep Belief Network; DDPM, Denoising Diffusion Probabilistic Model; DL, Deep Learning; DNN, Deep Neural Network; DS-DDPM, Domain-Specific Denoising Diffusion Probabilistic Model; DT, Decision Tree; ELM, Extreme Learning Machine; FASFF, Four-Head Adaptive Spatial Feature Fusion; FL, Federated Learning; FPN, Feature Pyramid Network; GBDT, Gradient-Boosted Decision Tree; GBLUP, Genomic Best Linear Unbiased Prediction; GBR, Gradient Boosting Regression; GNB, Gaussian Naive Bayes; GPR, Gaussian Process Regression; GridSearchCV, Grid-Search Cross-Validation; GRU, Gated Recurrent Unit; IoT, Internet of Things; ISSA, Improved Sparrow Search Algorithm; KNN, K-Nearest Neighbors; KRR, Kernel Ridge Regression; LightGBM, Light Gradient-Boosting Machine; LM-BPNN, Levenberg-Marquardt Backpropagation Neural Network; LSTM, Long Short-Term Memory; MDF, Multi-Domain Fusion; MHA, Multi-Head Attention; MIL, Multiple-Instance Learning; ML, Machine Learning; MLP, Multilayer Perceptron; MLR, Multiple Linear Regression; MSCA, Multi-Scale Context Aggregation; PCA, Principal Component Analysis; PID, Proportional-Integral-Derivative; PNN, Probabilistic Neural Network; PSO, Particle Swarm Optimization; R-CNN, Region-based Convolutional Neural Network; ResNet, Residual Network; RF, Random Forest; RNN, Recurrent Neural Network; RR, Ridge Regression; SE, Squeeze-and-Excitation; SHAP, SHapley Additive exPlanations; SMOTE, Synthetic Minority Over-sampling Technique; SOM, Self-Organizing Map; SSD, Single Shot Detector; SSM, State Space Model; SVM, Support Vector Machine; SVR, Support Vector Regression; TL, Transfer Learning; VGG, Visual Geometry Group; VMD, Variational Mode Decomposition; XGBoost, Extreme Gradient Boosting; YOLO, You Only Look Once.Abbreviations.

Note: Architecture-specific model names and labels (e.g., Aqua-HybridNet, CANet, DoME, FiVOS, ISUNet, LMFF-YOLO, MAFA-YOLO, SEAM, SLCAM-AquaNet, and WBi-YOLOSF) were retained as reported in the source studies and were not treated as general AI-method abbreviations. The AI Technique column was completed only for experimental research articles. Review articles synthesize multiple AI methods and were therefore classified as not applicable.