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Application of artificial intelligence techniques in the aquaculture sector: Systematic review of the American context

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ABSTRACT. Aquaculture is an essential productive activity in food security, economy, and the sustainability of water resources globally. The study analyzes the application of artificial intelligence techniques in aquaculture on the American continent through a systematic review of 31 articles published between 2020 and 2024 in the Scopus and SciELO databases. Five key areas of application were identified: monitoring and control, organism identification and counting, biomass and mortality rate prediction, behavioral analysis, and production optimization. The most commonly used techniques include machine learning, deep learning, artificial vision, and genetic algorithms, with models such as Convolutional Neural Networks, Random Forest, and YOLO standing out, demonstrating high accuracy in aquaculture processes. However, research has focused mainly on fish, while other organisms, such as shellfish and shrimp, have received less attention. In addition, adopting these technologies faces challenges related to infrastructure, data availability, and staff training. It is concluded that the integration of AI in aquaculture has a high potential to improve the efficiency and sustainability of the sector. However, it is necessary to expand the study to other species and strengthen technological accessibility for small and medium-sized producers.

Keywords: aquaculture production, aquaculture, machine learning, deep learning, computer vision.

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Introduction

Aquaculture is the practice of cultivating organisms such as fish, mollusks, crustaceans and aquatic plants in controlled environments in fresh or salt water (Mizuta et al., 2023; Casado-del-Castillo & Fávaro, 2024). According to Iitembu et al. (2022), Partelow et al. (2023) and Mair et al. (2023), this activity seeks to optimize the production of aquatic species for human consumption, repopulation of ecosystems, ornamental production or industrial uses, contributing to food security and economic development sustainably, as long as it is appropriately managed to minimize environmental impacts.

Naylor et al. (2023) contextualize that global per capita fish consumption has doubled in the last five decades, reaching levels comparable to poultry and pork consumption in edible weight (Edwards et al., 2019; Zhang et al., 2023). Over the last 25 years, aquaculture production has grown faster than most food products, increasing approximately threefold in live weight and consolidating the aquaculture sector as an international industry with potential development (Garlock et al., 2022).

In this context, the Food and Agriculture Organization of the United Nations (Food and Agriculture Organization, 2022) points out that aquatic resources provide 17% of the essential amino acids consumed in the human diet, while the aquaculture industry contributes half of the world's fishery production. For its part, the International Center for Living Aquatic Resources Management (WorldFish Center, 2002) estimated that nearly 950 million people in the world depend on fish as their primary source of protein, highlighting the importance of the aquaculture sector for food security by providing fishery products as a primary source of protein (Arshad et al., 2022).

Now, with the advancement of information and communication technologies, especially in the field of Artificial Intelligence (AI) in the agricultural sector (Huanatico-Lipa & Coral-Ygnacio, 2024; Ormeño-Ayala & Zapata-Ttito, 2024; Parraga-Badillo & Coral-Ygnacio, 2024), the aquaculture industry has not remained oblivious to its incorporation. Various studies have demonstrated its impact on process optimization and increased productivity, such as the case of Hu et al. (2022), who achieved a 93.2% accuracy level by applying deep learning (computer vision) in recognizing the size of outdoor water waves caused by fish eating feed to determine whether to continue casting or stop feeding.

Another practical example was reported by Babu et al. (2023), who found that manual counts of juvenile fish are slightly more accurate (MAPE = 1.56) than the machine learning methods that explored Single Shot Detection (MAPE < 10%) and Faster Regions with convolutional neural networks (MAPE < 5%); however, the implementation of the models allows a faster evaluation of the counts and, therefore, facilitates higher performance. This optimization was also found by Guélac Gómez et al. (2022), who, when applying artificial vision to count fish larvae, obtained an accuracy of 92.65% and an average time of 61s, unlike the traditional method that had an accuracy of 64.44% and a time of 2009.3s.

As evidenced, AI has generated multiple benefits in the aquaculture sector. Recognizing that this field is constantly evolving, this article aims to analyze the application of AI techniques in the aquaculture sector through an exploratory systematic review of the last five years (2020-2024). The information presented can serve as a basis for academia and experts to work in synergy, promoting the integration of AI for the benefit of aquaculture, thus seeking to respond more efficiently to the growing demands for aquaculture development (Ismiño-Orbe et al., 2024).

It is essential to highlight that the review focuses on the context of the American continent due to the relevance of the aquaculture sector as a strategic economic activity in various regions of this territory (Del-Águila-Chávez et al., 2024; Peixoto-Lavajos et al., 2024; Sotelo-Lescano et al., 2024). According to Ramos Valladão et al. (2018) and Tiddens (2019), the American continent is home to a wide diversity of aquatic ecosystems and species, posing challenges and opportunities for the integration of AI in the production of the aquaculture sector. Therefore, the contextualized analysis seeks to provide a comprehensive view of the advances and challenges in the use of AI in aquaculture, highlighting how these technologies can contribute to sustainable and competitive development in America.

Materials and methods

We developed an exploratory systematic review, which consists of analyzing and synthesizing the scientific literature on a specific area of science (Codina, 2020). According to Ojeda-Mera et al. (2024), this type of review allows the identification of gaps in knowledge and the establishment of a solid basis for making informed decisions. Thus, the review was based on the phases established by Kitchenham and Charters (2007): planning, conducting the review and writing the report. This approach seeks to define the research questions, identify key terms and their synonyms for the search, select the appropriate databases and establish inclusion and exclusion criteria. Once the relevant material has been identified, a detailed analysis is conducted to extract information and report the findings (García-Alba et al., 2022). Based on this definition, we present the phases developed in this review:

Research questions

We pose the following questions:
Q1: In what specific aquaculture processes are AI techniques implemented?
Q2: What aquatic organisms have been studied in implementing AI techniques in aquaculture processes?
Q3: What AI techniques are applied at each stage of aquaculture processes?
Q4: What AI models are used in the different methods applied in aquaculture?
Q5: What is the accuracy level of AI models in aquaculture processes?

Search strategy

We used the key terms: Artificial Intelligence, Machine Learning, Deep Learning, Computer Vision, Natural Language Processing, Expert Systems, Robotics, Genetic Algorithms, Aquaculture, Fish Farming and Fish Farming, from which the search strings were constructed according to Table 1. The selected databases were Scopus and SciELO due to their broad coverage of scientific literature at international and regional levels and the ease they offer for performing searches and applying manual filters.

Table 1. Database search string.

Database	Chain
Scopus	('Artificial Intelligence' OR 'Machine Learning' OR 'Deep Learning' OR 'Artificial Vision' OR 'Natural Language Processing' OR 'Expert Systems' OR 'Robotics' OR 'Genetic Algorithms') and ('Aquaculture' OR "Fish Farming' OR 'Fish Breeding')
SciELO	((artificial intelligence) OR (machine learning) OR (deep learning) OR (computer vision) OR (natural language processing) OR (expert systems) OR (robotics) OR (genetic algorithms)) and ((aquaculture) OR (fish farming)) OR (fish farming))

We carried out the article selection process by applying the search string in the advanced search tools of each database, considering the title, keywords, and abstract fields (1st classification). Subsequently, we applied manual filters based on the inclusion and exclusion criteria, such as the year range (2020-2024), language (Spanish and English), type of document (original article), source (scientific journal), and the country of the American continent (2nd classification). Then, the metadata was imported and organized in Excel, where duplicates were eliminated using the Scopus database as a reference (3rd classification). Next, from the complete reading of the articles, we selected those related to implementing AI techniques in aquaculture processes (4th classification). Table 2 presents the number of articles obtained at each stage of the selection process.

Table 2. Number of items according to classification.

Database	Classification			
	1st	2nd	3rd	4th
Scopus	1751	112	112	30
SciELO	5	3	3	1
			Total	31

Inclusion and exclusion criteria

Inclusion and exclusion criteria ensure the rigor and relevance of the selected studies to answer the research questions. They allow the delimitation of the scope of the analysis, ensure the quality of the sources, avoid biases in the selection of information and establish a coherent framework to compare and synthesize the findings (Ojeda-Mera et al., 2024).

This review included original articles published between 2020 and 2024 in English and Spanish from scientific journals and countries in the American continent whose objective was related to the implementation of AI techniques in aquaculture processes. Secondary sources, duplicate documents, and articles from conferences, reviews, and book chapters were excluded.

Data extraction

The articles were organized in an Excel sheet with the fields code, title, journal, year, DOI, aquaculture process, aquatic organism, AI technique, AI model, and accuracy. The database is available upon request to the corresponding author. Table 3 presents the list of extracted articles and their assigned codes, which are used as a reference in the results and discussion section.

Table 3. Coding of selected articles.

Code	Authors
A1	Guélac Gómez et al. (2022)
A2	Arboleda Patiño et al. (2021)
A3	Ranjan et al. (2024)
A4	Kunapinun et al. (2024)
A5	Souza et al. (2024)
A6	Navarro et al. (2024)
A7	Ramírez-Coronel et al. (2024)
A8	Hemal et al. (2024)
A9	Iqbal et al. (2024)
A10	Bowman et al. (2024)
A11	Salako et al. (2024)
A12	Gutierrez et al. (2023)
A13	Slonimer et al. (2023)
A14	Ranjan et al. (2023b)
A15	Costa et al. (2023)

A16	Davis et al. (2023)
A17	Ranjan et al. (2023a)
A18	Freitas et al. (2023)
A19	Lee et al. (2023)
A20	Kaur et al. (2023)
A21	Lopez-Tejeida et al. (2022)
A22	Brito Pache et al. (2022)
A23	Gonçalves et al. (2022)
A24	Nguyen et al. (2022)
A25	Graham et al. (2022)
A26	Zambrano et al. (2021)
A27	Lopes et al. (2021)
A28	O'Donncha et al. (2021)
A29	Bell et al. (2020)
A30	Fernandes et al. (2020)
A31	Armstrong and Verhoeven (2020)

Results and discussion

After a thorough analysis of each selected article, we answer the research questions below:

- Q1: In what specific aquaculture processes are AI techniques implemented?

According to the review, AI techniques are implemented in various aquaculture processes that we group into specific categories (Table 4). They are applied to growth monitoring, water quality, and farm management in monitoring and control. In identification and counting, they facilitate larval counting, species classification, zooplankton enumeration, and stomach fullness measurement. In prediction, they estimate weight dispersion, mortality rates, morphometric measurements, biomass in fry, water quality, benthic disturbance, and genomic aspects. In behavioral analysis, they focus on the study of feeding and the general behavior of fish. Specific measurements allow for the detection of fillet color, the assessment of water quality, and the measurement of bodies, weight, and length. In production and growth, they optimize production and determine fish sex, comprehensively improving aquaculture processes.

Table 4. Specific aquaculture processes where AI techniques are implemented.

Category	Process	Code
Monitoring-and-control	Growth-monitoring	A4
	Water-quality-monitoring	A8, A16
	Crop-production-monitoring	A29
Identification-and-counting	Larvae-counting	A1, A15
	Species-identification-and-counting	A5
	Identification-and-enumeration-of-zooplankton	A10
	Counting-and-measuring-stomach-fullness	A19
	Classification-of-species	A13
Prediction	Weight-dispersion-prediction	A6
	Predicting-mortality-rates	A14
	Prediction-of-morphometric-measurements	A18
	Water-quality-prediction	A26
	Biomass-prediction-in-fry	A22
	Genomic-prediction	A24
	Mortality-prediction	A27
	Prediction-of-benthic-disturbance-levels	A31
Behavioral-analysis	Feeding-behavior-analysis	A9
	Stress-analysis	A28
Specific-measurements	Fillet-color-detection	A3
	Species-detection	A17
	Water-quality-detection	A20
	Body-measurement-and-body-weight	A21, A30
Increased-production-and-growth	Increase-in-production	A2
	Growth-and-sex-determination	A12

- Q2: What aquatic organisms have been studied in implementing AI techniques in aquaculture processes?

According to Table 5, fish have been the most researched set of aquatic organisms, with 23 studies identified. Seaweed is next with three studies, shrimp with three mentions, and shellfish with only one reference. In addition, one study addressed aquatic organisms in a general way. This suggests that the application of AI in aquaculture has focused mainly on fish, while other organisms, such as shellfish and shrimp, have received less attention in comparison.

Table 5. Specific aquaculture organizations where AI techniques are implemented.

Body	Code
Fish	A1, A2, A3, A5, A6, A7, A8, A9, A11, A12, A13, A14, A15, A17, A18, A21, A22, A23, A25, A27, A28, A30, A31
Seaweed	A4, A10, A29
Seafood	A16
Shrimp	A19, A20, A24
General	A26

- Q3: What AI techniques are applied at each stage of aquaculture processes?

Table 6 shows that machine learning is the most widely used technique, with 33% of applications, and dominates in biological predictions and water quality control. Deep learning accounts for 23%, focusing on species classification and behavioural analysis. With 20%, artificial vision outperforms machine learning in visual detection and morphological measurement. Although less frequent (17%), genetic algorithms are essential in growth optimisation and species selection. With 13%, IoT stands out in real-time ecosystem monitoring and organism development. Integrating these technologies improves aquaculture's efficiency and sustainability by providing more accurate data and optimising decision-making.

Table 6. AI techniques used by each aquaculture process.

Technique	Process	Code
Genetic algorithm	Increase in production	A2
Machine learning	Species identification and counting	A5
	Weight dispersion prediction	A6
	Water quality monitoring	A8
	Identification and enumeration of zooplankton	A10
	Growth and sex determination	A12
	Prediction of benthic disturbance levels	A31
	Farm monitoring	A29
	Behavioral analysis	A28
	Genomic prediction	A24
	Obtaining weight and length	A21
	Species detection	A17
	Larvae counting	A15
	Water quality control	A20
	Ultrasound image classification of ovarian development	A25
	Water quality prediction	A26
	Mortality prediction	A27
Deep learning	Feeding behavior analysis	A9
	Counting fry	A23
	Classification of species	A13
	Water quality monitoring	A16
	Species detection	A17
	Counting and measuring stomach fullness	A19
	Biomass prediction in fry	A22
	Genomic prediction	A24
	Body measurement and body weight	A30
Internet of Things (IoT)	Growth monitoring	A4
Machine vision	Water quality monitoring	A8
	Biomass estimation	A7
	Body measurement and body weight	A30
	Fillet color detection	A3
	Prediction of morphometric measurements	A18
	Mortality rate detection	A14
	Monitoring and control	A11
	Identification and enumeration of zooplankton	A10
	Larvae counting	A1

- Q4: What AI models are used in the different techniques applied in aquaculture?

Based on the analysis carried out, we grouped the AI models into five sections (Table 7), highlighting machine learning as the most used, with models such as Random Forest, Decision Tree, SVM, K-NN, Logistic Regression, Naive Bayes, AdaBoost, Haar Cascade, Conventional Neural Networks and Deep Neural Networks, along with k- fold cross-validation. MaskRCNN, YOLOv8, Faster R-CNN, YOLOv7 and classical approaches such as Linear Regression, Power Model and Multilayer Perceptron, and SVM stand out in computer vision. For genetic algorithms, no model is specified. In the Internet of Things (IoT), LSTM is used. U-Net, Involutional Neural Networks, and Multilayer Perceptron are applied in deep learning. Perceptron, Convolutional Neural Networks, HAUCS Path Planning, YOLOv5 and AR-YOLOv5. These models optimize image analysis, data prediction and decision making.

Table 7. AI models in different techniques applied in aquaculture.

Technique	Model	Code
Machine vision	MaskRCNN	A1, A18
	YOLOv8	A3
	Linear regression (RL) Power Model (PM) Multilayer Perceptron (MLP)	A7
	Support Vector Machines (SVM)	A10
	Faster R-CNN	A11
	YOLOv7	A14
	Conventional Neural Network (CNN)	A30
Genetic algorithm	Not specified	A2
IoT	LSTM	A4
Machine learning	YOLOv4—Darknet	A5
	Random Forest (RF)	A6, A8, A20, A24
	Support Vector Machine (SVM)	A8, A10, A20, A25, A26, A29, A31
	Decision tree (DT)	A8, A20
	K-Nearest Neighbors (KNN)	A8, A12, A20, A25
	Logistic regression (LR)	A8
	Conventional Neural Network (CNN)	A15, A25
	Neural Networks (NN) Naive Bayes (NB) AdaBoost	A20
	Hair Cascade	A21
	Linear regression (RL) ANN	A26
	k-fold cross-validation	A27
	Deep Neural Networks (DNN)	A28
Deep learning	Involutional Neural Network (INN)	A9
	U-Net	A13
	HAUCS Path Planning (HPP)	A16
	YOLOv5 Faster R-CNN	A17
	AR-YOLOv5	A19
	Linear regression (RL)	A22
	Conventional Neural Network (CNN)	A23
	Multilayer Perceptron (MLP)	A24

- Q5: What is the accuracy level of AI models in aquaculture processes?

The accuracy levels of AI models applicable to aquaculture processes (Table 8) vary depending on the technique used. In high accuracy (⩾95%), the YOLOv8 (99.50%), MaskRCNN (92.65%) and AR-YOLOv5 (97.70%) models indicate their effectiveness in detection and classification tasks. In medium accuracy, there are Neural Networks (84%), Naive Bayes (84%) and SVM (84%). Other models, such as linear regression and random forests, are in the unspecified accuracy category, suggesting fluctuation in their performance. In general, the most advanced models in computer vision and deep learning achieve higher levels of accuracy, highlighting their potential in optimizing aquaculture processes.

The study conducted by Aung et al. (2025) provides a global overview of the use of AI in various aquaculture applications through a systematic review of 57 articles, while our work focuses specifically on the context of the American continent, with 31 selected studies. This geographical and thematic distinction allows our study to highlight regional particularities in technological adoption, a key contribution for designing strategies adapted to the social, economic, and ecological conditions of the Americas. Unlike Aung et al. (2025) global approach, our study brings to light the lag in AI implementation in Latin American countries, revealing specific challenges such as limited technological infrastructure and the need for technical staff training.

Table 8. Accuracy of AI techniques applied in aquaculture processes.

Category	Model	Percentage	Code
High precision (≥95%)	YOLOv8	99.50%	A3
	YOLOv7	93.40%	A14
	YOLOv5	86.50%	A17
	YOLOv4 - Darknet	96.74%	A5
	Conventional Neural Network (CNN)	97.84%	A15, A23, A25, A30
	MaskRCNN	92.65%	A1, A18
	AR-YOLOv5	97.70%	A19
	K- Nearest Neighbors (KNN)	94%	A8
	Involutional Neural Network (INN)	97%	A9
	Logistic regression (LR)	94%	A8
	Decision Tree (DT)	94%	A8
	Random Forest (RF)	94.63%	A6, A8, A29
	HAUCS Path Planning (HPP)	98.5%	A16
	Support Vector Machine (SVM)	98%	A25
	Hair Cascade	92%	A21
Medium accuracy (80% - 94%)	AdaBoost	84%	A20
	Naive Bayes (NB)	84%	A20
	Neural Networks (NN)	84%	A20
	Faster R-CNN	86.28%	A11, A17
	U-Net	93%	A13
	Support Vector Machine (SVM)	86.13%	A10, A20, A25
	Decision Tree (DT)	84%	A20
	K-fold cross-validation	80%	A27
Not specific	LSTM	Not specific	A4
	Power Model (PM)		A7
	Linear regression (RL)		A7, A22, A26
	Random Forest (RF)		A24, A26, A31
	MaskRCNN		A18
	Deep Neural Networks (DNN)		A28
	ANN		A26
	Increase in production		A2
	Linear regression (RL)		A7, A22, A26
	Multilayer Perceptron (MLP)		A7, A24

Both studies agree on the wide range of AI applications in aquaculture. Aung et al. (2025) emphasize its use in environmental monitoring, disease detection, and feed optimization through techniques such as computer vision, machine learning, and predictive models. Our article complements these findings by categorizing processes into five specific areas: monitoring and control, identification and counting, prediction, behavioral analysis, and production optimization. This reaffirms that the use of techniques such as YOLO, CNN, and SVM is widespread across different regions and processes (Babu et al., 2023; Bowman et al., 2024).

A key differentiating aspect is the focus on the species studied. While Aung's article addresses various aquatic species, the attention is mainly directed toward fish and specific areas such as recirculating systems or oyster and shrimp hatcheries (Chang et al., 2022; Deng et al., 2023). In our analysis, a strong predominance of research on fish is evident, and we highlight the limited attention given to mollusks and crustaceans a critical issue considering the biodiversity in the Americas. This finding reveals the need to balance research efforts to cover a broader diversity of aquaculture species and production environments.

Regarding the models and techniques used, both studies agree on the predominance of machine learning and deep learning. However, our work contributes by showing the specific adoption of models such as Random Forest, YOLOv8, and MaskRCNN in Latin American scenarios, with high accuracy results in counting, classification, and biomass prediction tasks (Guélac Gómez et al., 2022; Hu et al., 2022). We also highlight the integration of emerging technologies such as IoT and computer vision, which are often absent or superficially addressed in the global study (Lévano-Rodriguez et al., 2025).

Finally, although both works acknowledge the challenges associated with AI implementation, such as costs, lack of representative data, and social acceptance, our study emphasizes the need to propose public policies and strategies for technological democratization aimed at small and medium producers. While Aung et al. (2025) stress the technical and financial obstacles to large-scale adoption, our article advocates for a more contextualized and participatory approach that promotes technology transfer to foster sustainable regional development.

One of the limitations of the present study is the selection of bibliographic sources exclusively from the Scopus and SciELO databases, which could restrict access to relevant research published on other scientific platforms. While these databases offer a broad coverage of scientific literature, including different sources, such as IEEE Xplore, Web of Science or repositories specialized in aquatic sciences, they could provide a more complete view of the state of the art in integrating AI in aquaculture. Other studies should expand the use of databases to obtain a greater representativeness of studies and avoid possible biases in selecting information.

Conclusion

According to the literature review, focusing on the American continent, we can observe that various investigations have been developed on the integration of AI in the aquaculture sector, highlighting the use in monitoring and control of growth and water quality, identification and counting of organisms, prediction of biomass and mortality rates, analysis of feeding behavior and optimization of production, improving operational efficiency and reducing production costs and environmental impacts.

The studies focused on fish, followed by seaweed, shrimp and shellfish. The most commonly used techniques include machine learning, deep learning, artificial vision, and genetic algorithms, which are applied according to the specific aquaculture process. As for the models, Random Forest, Convolutional Neural Networks and YOLO have demonstrated high accuracy in species identification, counting, and production predictions. However, there is still room for improvement in models applied to water quality and behavioural analysis.

In this regard, future research should address the lack of studies on other aquatic organisms, such as crustaceans and mollusks, which have received less attention than fish. Furthermore, it is necessary to evaluate the applicability and effectiveness of AI models in different aquaculture environments, considering environmental factors, biological variability and implementation costs. Likewise, the optimization of AI models for real-time monitoring and prediction could improve the sustainable management of the sector, allowing for more efficient decision-making and reducing environmental impact. Finally, it is essential to strengthen collaboration between researchers, producers and technology developers to promote innovative solutions that facilitate the integration of AI in aquaculture at a regional level.

Data availability

Not applicable.

References

Arboleda Patiño, M. T., Velastegui Córdova, M. E., & Toasa Espinoza, J. L. (2021). Algoritmos genéticos para el aumento de producción de Tilapia en planteles piscícolas del cantón Pastaza. *Dilemas Contemporáneos: Educación, Política y Valores*, *8*(31), 1-13. https://doi.org/10.46377/dilemas.v8i.2783

Armstrong, E., & Verhoeven, J. (2020). Machine learning analyses of bacterial oligonucleotide frequencies to assess the benthic impact of aquaculture. *Aquaculture Environment Interactions*, *12*(1), 131-137. https://doi.org/10.3354/aei00353

Arshad, N., Samat, N., & Lee, L. K. (2022). Insight into the relation between nutritional benefits of aquaculture products and its consumption hazards: a global viewpoint. *Frontiers in Marine Science*, *9*(1), 1-20. https://doi.org/10.3389/fmars.2022.925463

Aung, T., Abdul Razak, R., & Rahiman Bin Md Nor, A. (2025). Artificial intelligence methods used in various aquaculture applications: a systematic literature review. *Journal of the World Aquaculture Society*, *56*(1), e13107. https://doi.org/10.1111/jwas.13107

Babu, K. M., Bentall, D., Ashton, D. T., Puklowski, M., Fantham, W., Lin, H. T., Tuckey, N. P. L., Wellenreuther, M., & Jesson, L. K. (2023). Computer vision in aquaculture: a case study of juvenile fish counting. *Journal of the Royal Society of New Zealand*, *53*(1), 52-68. https://doi.org/10.1080/03036758.2022.2101484

Bell, T. W., Nidzieko, N. J., Siegel, D. A., Miller, R. J., Cavanaugh, K. C., Nelson, N. B., Reed, D. C., Fedorov, D., Moran, C., Snyder, J. N., Cavanaugh, K. C., Yorke, C. E., & Griffith, M. (2020). The utility of satellites and autonomous remote sensing platforms for monitoring offshore aquaculture farms: a case study for canopy forming kelps. *Frontiers in Marine Science*, *7*(1), 1-16. https://doi.org/10.3389/fmars.2020.520223

Bowman, M. N., McManamay, R. A., Perez, A. R., Hamerly, G., Arnold, W., Steimle, E., Kramer, K., Norris, B., Prangnell, D., & Matthews, M. (2024). Analysis of an optical imaging system prototype for autonomously monitoring zooplankton in an aquaculture facility. *Aquacultural Engineering*, *104*(1), 102389. https://doi.org/10.1016/j.aquaeng.2023.102389

Brito Pache, M. C., Sant'Ana, D. A., Araújo Rozales, J. V., Weber, V. A. M., Oliveira Junior, A. S., Garcia, V., Pistori, H., & Naka, M. H. (2022). Prediction of fingerling biomass with deep learning. *Ecological Informatics*, *71*(1), 101785. https://doi.org/10.1016/j.ecoinf.2022.101785

Casado-del-Castillo, S. P., & Fávaro, L. F. (2024). Características de vida e estrutura populacional de Citharichthys spilopterus (Paralichthyidae): espécie fauna acompanhante no Sul do Brasil. *Revista Peruana de Investigación Agropecuaria*, *3*(1), e55. https://doi.org/10.56926/repia.v3i1.55

Chang, C.-C., Ubina, N. A., Cheng, S.-C., Lan, H.-Y., Chen, K.-C., & Huang, C.-C. (2022). A two-mode underwater smart sensor object for precision aquaculture based on AIoT technology. *Sensors*, *22*(19), 7603. https://doi.org/10.3390/s22197603

Codina, L. (2020). Cómo hacer revisiones bibliográficas tradicionales o sistemáticas utilizando bases de datos académicas. *Revista ORL*, *11*(2), 139-153. https://doi.org/10.14201/orl.22977

Costa, C. S., Gonçalves, W. N., Zanoni, V. A. G., Santos de Arruda, M., Araújo Carvalho, M., Nascimento, E., Marcato Junior, J., Diemer, O., & Pistori, H. (2023). Counting tilapia larvae using images captured by smartphones. *Smart Agricultural Technology*, *4*(1), 100160. https://doi.org/10.1016/j.atech.2022.100160

Davis, A., Wills, P. S., Garvey, J. E., Fairman, W., Karim, M. A., & Ouyang, B. (2023). Developing and field testing path planning for robotic aquaculture water quality monitoring. *Applied Sciences*, *13*(5), 2805. https://doi.org/10.3390/app13052805

Del-Águila-Chávez, J., García-Meléndez, R. L., García-Ruiz, L., & Casado-del-Castillo, S. P. (2024). Diversidad de camarones de agua dulce (Crustacea: Palaemonidae) en afluentes de la cuenca alta del rio Itaya, Loreto, Perú. *Revista Peruana de Investigación Agropecuaria*, *3*(2), e73. https://doi.org/10.56926/repia.v3i2.73

Deng, J., Bai, Y., Chen, Z., Shen, T., Li, C., & Yang, X. (2023). A convolutional neural network for coastal aquaculture extraction from high-resolution remote sensing imagery. *Sustainability*, *15*(6), 5332. https://doi.org/10.3390/su15065332

Edwards, P., Zhang, W., Belton, B., & Little, D. C. (2019). Misunderstandings, myths and mantras in aquaculture: Its contribution to world food supplies has been systematically over reported. *Marine Policy*, *106*(1), 103547. https://doi.org/10.1016/j.marpol.2019.103547

Food and Agriculture Organization. (2022). *The state of world fisheries and aquaculture 2022*. FAO.

Fernandes, A. F. A., Turra, E. M., Alvarenga, É. R., Passafaro, T. L., Lopes, F. B., Alves, G. F. O., Singh, V., & Rosa, G. J. M. (2020). Deep Learning image segmentation for extraction of fish body measurements and prediction of body weight and carcass traits in Nile tilapia. *Computers and Electronics in Agriculture*, *170*(1), 105274. https://doi.org/10.1016/j.compag.2020.105274

Freitas, M. V., Lemos, C. G., Ariede, R. B., Agudelo, J. F. G., Neto, R. R. O., Borges, C. H. S., Mastrochirico-Filho, V. A., Porto-Foresti, F., Iope, R. L., Batista, F. M., Brega, J. R. F., & Hashimoto, D. T. (2023). High-throughput phenotyping by deep learning to include body shape in the breeding program of pacu (Piaractus mesopotamicus). *Aquaculture, 562*(1), 738847. https://doi.org/10.1016/j.aquaculture.2022.738847

García-Alba, J. R., Rodríguez-Franco, R., & Angélica-Cerdán, M. (2022). Sistemas expertos en agricultura de precisión: revisión sistemática de la literatura. *Revista Internacional de Desarrollo Regional Sustentable*, *7*(1-2), 247-264.

Garlock, T., Asche, F., Anderson, J., Ceballos-Concha, A., Love, D. C., Osmundsen, T. C., & Pincinato, R. B. M. (2022). Aquaculture: the missing contributor in the food security agenda. *Global Food Security*, *32*(1), 100620. https://doi.org/10.1016/j.gfs.2022.100620

Gonçalves, D. N., Acosta, P. R., Ramos, A. P. M., Osco, L. P., Furuya, D. E. G., Furuya, M. T. G., Li, J., Junior, J. M., Pistori, H., & Gonçalves, W. N. (2022). Using a convolutional neural network for fingerling counting: a multi-task learning approach. *Aquaculture*, *557*(1), 738334. https://doi.org/10.1016/j.aquaculture.2022.738334

Graham, C. A., Shamkhalichenar, H., Browning, V. E., Byrd, V. J., Liu, Y., Gutierrez-Wing, M. T., Novelo, N., Choi, J.-W., & Tiersch, T. R. (2022). A practical evaluation of machine learning for classification of ultrasound images of ovarian development in channel catfish (Ictalurus punctatus). *Aquaculture*, *552*(1), 738039. https://doi.org/10.1016/j.aquaculture.2022.738039

Guélac Gómez, J., Sánchez Calle, J. E., Valles Coral, M. Á., Nakagawa Valverde, N., & Chichipe Puscan, A. K. (2022). Conteo automático de larvas de peces utilizando visión por computadora basado en redes neuronales. *Scientia Agropecuaria*, *13*(2), 159-166. https://doi.org/10.17268/sci.agropecu.2022.014

Gutierrez, A. P., Selly, S.-L. C., Pountney, S. M., Taggart, J. B., Kokkinias, P., Cavrois-Rogacki, T., Fernandez, E. J., Migaud, H., Lein, I., Davie, A., & Bekaert, M. (2023). Development of genomic markers associated to growth-related traits and sex determination in lumpfish (Cyclopterus lumpus). *Genomics*, *115*(6), 110721. https://doi.org/10.1016/j.ygeno.2023.110721

Hemal, M. M., Rahman, A., Nurjahan, Islam, F., Ahmed, S., Kaiser, M. S., & Ahmed, M. R. (2024). An integrated smart pond water quality monitoring and fish farming recommendation aquabot system. *Sensors*, *24*(11), 3682. https://doi.org/10.3390/s24113682

Hu, W.-C., Chen, L.-B., Huang, B.-K., & Lin, H.-M. (2022). A computer vision-based intelligent fish feeding system using deep learning techniques for aquaculture. *IEEE Sensors Journal*, *22*(7), 7185-7194. https://doi.org/10.1109/JSEN.2022.3151777

Huanatico-Lipa, J. C., & Coral-Ygnacio, M. A. (2024). Librerías informáticas utilizadas en análisis de imágenes dermatológicas con visión computacional: una revisión de literatura. *Revista Científica de Sistemas e Informática*, *4*(1), e590. https://doi.org/10.51252/rcsi.v4i1.590

Iitembu, J. A., Gabriel, N. N., Tjipute, M., Asino, H., & Hamukwaya, J. (2022). The governance of aquaculture in Namibia as a vehicle for food security and economic growth. In H. A. Mupambwa, A. D. Nciizah, P. Nyambo, B. Muchara, & N. N. Gabriel (Eds), *Food security for african smallholder farmers* (pp. 391-403). Springer.

Iqbal, U., Li, D., Du, Z., Akhter, M., Mushtaq, Z., Qureshi, M. F., & Rehman, H. A. U. (2024). Augmenting aquaculture efficiency through involutional neural networks and self-attention for Oplegnathus Punctatus feeding intensity classification from log mel spectrograms. *Animals*, *14*(11), 1690. https://doi.org/10.3390/ani14111690

Ismiño-Orbe, R. A., Fernández-Méndez, C., Ramírez-Arrarte, P., Alván -Aguilar, M., & Murrieta-Morey, G. A. (2024). Crecimiento poblacional de Brachionus quadridentatus Hermann, 1783 (Rotífera) aplicando tres dietas. *Revista de Veterinaria y Zootecnia Amazónica*, *4*(2), e868. https://doi.org/10.51252/revza.v4i2.868

Kaur, G., Braveen, M., Krishnapriya, S., Wawale, S. G., Castillo-Picon, J., Malhotra, D., & Osei-Owusu, J. (2023). Machine learning integrated multivariate water quality control framework for prawn harvesting from fresh water ponds. *Journal of Food Quality*, *2023*, 1-9. https://doi.org/10.1155/2023/3841882

Kitchenham, B., & Charters, S. M. (2007). *Guidelines for performing systematic literature reviews in software engineering – versión 2.3.* Keele University and University of Durham.

Kunapinun, A., Fairman, W., Wills, P. S., Hanisak, D., & Ouyang, B. (2024). Advancing seaweed cultivation: integrating physics constraint in machine learning for enhanced biomass forecasting in IMTA Systems. *Remote Sensing*, *16*(23), 4418. https://doi.org/10.3390/rs16234418

Lee, Y.-K., Lin, B.-Y., Weng, T.-H., Huang, C.-K., Liu, C., Liu, C.-C., Lin, S.-S., & Wang, H.-C. (2023). Counting and measuring the size and stomach fullness levels for an intelligent shrimp farming system. *Connection Science*, *35*(1), 2268878. https://doi.org/10.1080/09540091.2023.2268878

Lévano-Rodriguez, D., Gonzales-Garay, J. H., Lévano-Casildo, M., & López-Gonzales, J. L. (2025). Design of an autonomous multiparameter buoy with photovoltaic energy and remote communication based on IoT for aquaculture environments. *Revista Científica de Sistemas e Informática*, *5*(1), e866. https://doi.org/10.51252/rcsi.v5i1.866

Lopes, B. D. M., Silva, L. C. B., Blanquet, I. M., Georgieva, P., & Marques, C. A. F. (2021). Prediction of fish mortality based on a probabilistic anomaly detection approach for recirculating aquaculture system facilities. *Review of Scientific Instruments*, *92*(2). https://doi.org/10.1063/5.0045047

Lopez-Tejeida, S., Soto-Zarazua, G. M., Toledano-Ayala, M., Contreras-Medina, L. M., Rivas-Araiza, E. A., & Flores-Aguilar, P. S. (2022). An improved method to obtain fish weight using machine learning and NIR camera with haar cascade classifier. *Applied Sciences*, *13*(1), 69. https://doi.org/10.3390/app13010069

Mair, G. C., Halwart, M., Derun, Y., & Costa-Pierce, B. A. (2023). A decadal outlook for global aquaculture. *Journal of the World Aquaculture Society*, *54*(2), 196-205. https://doi.org/10.1111/jwas.12977

Mizuta, D. D., Froehlich, H. E., & Wilson, J. R. (2023). The changing role and definitions of aquaculture for environmental purposes. *Reviews in Aquaculture*, *15*(1), 130-141. https://doi.org/10.1111/raq.12706

Navarro, L. C., Azevedo, A., Matos, A., Rocha, A., & Ozório, R. (2024). Predicting weight dispersion in seabass aquaculture using Discrete Event System simulation and Machine Learning modeling. *Aquaculture Reports*, *38*(1), 102315. https://doi.org/10.1016/j.aqrep.2024.102315

Naylor, R., Fang, S., & Fanzo, J. (2023). A global view of aquaculture policy. *Food Policy*, *116*(1), 102422. https://doi.org/10.1016/j.foodpol.2023.102422

Nguyen, N. H., Vu, N. T., Patil, S. S., & Sandhu, K. S. (2022). Multivariate genomic prediction for commercial traits of economic importance in Banana shrimp Fenneropenaeus merguiensis. *Aquaculture*, *555*(1), 738229. https://doi.org/10.1016/j.aquaculture.2022.738229

O'Donncha, F., Stockwell, C. L., Planellas, S. R., Micallef, G., Palmes, P., Webb, C., Filgueira, R., & Grant, J. (2021). Data driven insight into fish behaviour and their use for precision aquaculture. *Frontiers in Animal Science*, *2*(1), 1-19. https://doi.org/10.3389/fanim.2021.695054

Ojeda-Mera, C., Injante, R., Valles-Coral, M., Pinedo, L., Tejada, K., & García-Bautista, A. (2024). Estado actual de la accesibilidad web en Latinoamérica: una revisión exploratoria de las evaluaciones y herramientas utilizadas. *Revista Española de Documentación Científica*, *47*(1), e378. https://doi.org/10.3989/redc.2024.1.1464

Ormeño-Ayala, Y. I., & Zapata-Ttito, A. G. (2024). Aplicación de la red convolucional Mask R-CNN para la estimación del peso corporal del cuy. *Revista Científica de Sistemas e Informática*, *4*(1), e614. https://doi.org/10.51252/rcsi.v4i1.614

Parraga-Badillo, S. R., & Coral-Ygnacio, M. A. (2024). Implementaciones de selección visual en frutas: revisión sistemática de literatura. *Revista Científica de Sistemas e Informática*, *4*(1), e591. https://doi.org/10.51252/rcsi.v4i1.591

Partelow, S., Asif, F., Béné, C., Bush, S., Manlosa, A. O., Nagel, B., Schlüter, A., Chadag, V. M., Choudhury, A., Cole, S. M., Cottrell, R. S., Gelcich, S., Gentry, R., Gephart, J. A., Glaser, M., Johnson, T. R., Jonell, M., Krause, G., Kunzmann, A., … Turchini, G. M. (2023). Aquaculture governance: five engagement arenas for sustainability transformation. *Current Opinion in Environmental Sustainability*, *65*(1), 101379. https://doi.org/10.1016/j.cosust.2023.101379

Peixoto-Lavajos, J. A., Navas-Vásquez, M. E., Tuesta-Rojas, C. A., & Murrieta-Morey, G. A. (2024). Identificación de monogeneos parásitos de Pterigoplichthys pardalis (Castelnau, 1855) 'carachama común' procedentes del Mercado Belén, Iquitos – Perú. *Revista Agrotecnológica Amazónica*, *4*(1), e540. https://doi.org/10.51252/raa.v4i1.540

Ramírez-Coronel, F. J., Rodríguez-Elías, O. M., Esquer-Miranda, E., Pérez-Patricio, M., Pérez-Báez, A. J., & Hinojosa-Palafox, E. A. (2024). Non-invasive fish biometrics for enhancing precision and understanding of aquaculture farming through statistical morphology analysis and machine learning. *Animals*, *14*(13), 1850. https://doi.org/10.3390/ani14131850

Ramos Valladão, G. M., Umeda Gallani, S., & Pilarski, F. (2018). South American fish for continental aquaculture. *Reviews in Aquaculture*, *10*(2), 351-369. https://doi.org/10.1111/raq.12164

Ranjan, R., Sharrer, K., Tsukuda, S., & Good, C. (2023a). Effects of image data quality on a convolutional neural network trained in-tank fish detection model for recirculating aquaculture systems. *Computers and Electronics in Agriculture*, *205*(1), 107644. https://doi.org/10.1016/j.compag.2023.107644

Ranjan, R., Sharrer, K., Tsukuda, S., & Good, C. (2023b). MortCam: an artificial intelligence-aided fish mortality detection and alert system for recirculating aquaculture. *Aquacultural Engineering*, *102*(1), 102341. https://doi.org/10.1016/j.aquaeng.2023.102341

Ranjan, R., Shroff, H., Sharrer, K., Tsukuda, S., & Good, C. (2024). FilletCam AI: a handheld tool for precise fillet color profiling of Atlantic salmon and rainbow trout. *Journal of Agriculture and Food Research*, *18*(1), 101461. https://doi.org/10.1016/j.jafr.2024.101461

Salako, J., Ojo, F., & Awe, O. O. (2024). Fish-NET: advancing aquaculture management through ai-enhanced fish monitoring and tracking. *Agris On-Line Papers in Economics and Informatics*, *16*(2), 121-131. https://doi.org/10.7160/aol.2024.160209

Slonimer, A. L., Dosso, S. E., Albu, A. B., Cote, M., Marques, T. P., Rezvanifar, A., Ersahin, K., Mudge, T., & Gauthier, S. (2023). Classification of herring, salmon, and bubbles in multifrequency echograms using u-net neural networks. *IEEE Journal of Oceanic Engineering*, *48*(4), 1236-1254. https://doi.org/10.1109/JOE.2023.3272393

Sotelo-Lescano, L. O., Campos-Baca, L. E., Del-Águila-Chávez, J., & Casado-del-Castillo, S. P. (2024). Biología reproductiva de Hypophthalmus edentatus (Pimelodidae) y Brycon amazonicus (Bryconidae) en la cuenca del Putumayo, región Loreto, Perú. *Revista Peruana de Investigación Agropecuaria*, *3*(2), e71. https://doi.org/10.56926/repia.v3i2.71

Souza, A. S., Costa, A. C., França, H. F. C., Nuvunga, J. J., Ferreira de Melo, G. A., Lima, L. C., Kretschmer, V. V., Oliveira, D. Á., Horn, L. D., Rezende, I. R., Fernandes, M. P., Reis Neto, R. V., Freitas, R. T. F., Oliveira, R. F., Viadanna, P. H., Vitorino, B. M., & Minafra, C. S. (2024). Identification and counting of Pirapitinga Piaractus brachypomus fingerlings fish using machine learning. *Animals*, *14*(20), 2999. https://doi.org/10.3390/ani14202999

Tiddens, A. (2019). *Aquaculture in America: the role of science, government, and the entrepreneur*. Routledge.

WorldFish Center. (2002). *Fish: an issue for everyone*. WorldFish Center. https://hdl.handle.net/20.500.12348/2262

Zambrano, A. F., Giraldo, L. F., Quimbayo, J., Medina, B., & Castillo, E. (2021). Machine learning for manually-measured water quality prediction in fish farming. *PLOS ONE*, *16*(8), e0256380. https://doi.org/10.1371/journal.pone.0256380

Zhang, R., Chen, T., Wang, Y., & Short, M. (2023). Systems approaches for sustainable fisheries: a comprehensive review and future perspectives. *Sustainable Production and Consumption*, *41*(1), 242-252. https://doi.org/10.1016/j.spc.2023.08.013

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