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Review

Artificial Intelligence-Based Aquaculture System for Optimizing the Quality of Water: A Systematic Analysis

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Abstract: The world population is expected to grow to around 9 billion by 2050. The growing need for foods with high protein levels makes aquaculture one of the fastest-growing food industries in the world. Some challenges of fishing production are related to obsolete aquaculture techniques, overexploitation of marine species, and lack of water quality control. This research systematically analyzes aquaculture technologies, such as sensors, artificial intelligence (AI), and image processing. Through the systematic PRISMA process, 753 investigations published from 2012 to 2023 were analyzed based on a search in Scopus and Web of Science. It revealed a significant 70.5% increase in the number of articles published compared to the previous year, indicating a growing interest in this field. The results indicate that current aquaculture technologies are water monitoring sensors, AI methodologies such as K-means, and contour segmentation for computer vision. Also, it is reported that K means technologies offer an efficiency from 95% to 98%. These methods allow decisions based on data patterns and aquaculture insights. Improving aquaculture methodologies will allow adequate management of economic and environmental resources to promote fishing and satisfy nutritional needs.

Keywords: machine learning; artificial vision; feed managment; aquaculture; physical–chemical parameters; real-time detection

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1. Introduction

In recent years, aquaculture has gained greater importance due to concern that livestock farming, agriculture, and fishing are no longer sufficient activities to provide certainty in the demand for the food necessary for the population. Therefore, this technique can provide an option that includes food security, reduces food shortages, alleviates poverty, and reduces exploitation of the global fishing market. There has been a substantial increase in the consumption of aquaculture protein, reaching 3.1% worldwide, and its consumption also increased by 2.1% concerning other commonly consumed proteins of animal origin, such as meat and dairy products, to name a few [1]. Aquaculture products are globalized foods and the focus of the Global Value Chain. Europe, North America, and Japan require around 60% and 70% of aquaculture production [2]. The availability of fish was due to the proliferation of development of aquaculture systems that had an average annual growth of 6% from 2001 to 2018 [1]. Due to this, aquaculture became one of the most globalized foods, concentrating interest of agroindustries, civil society organizations (CSOs), and non-governmental organizations (NGOs). Preserving the proper physicochemical parameters contributes to the preservation of health and development in the density of the species. On the other hand, it is concluded that having poor-quality pond water will cause a severe problem for the fish since it will contribute to reducing the defenses against viral and bacterial infections and more diseases that could cause the death of the biological entity [3]. Therefore, maintaining the physicochemical parameters that preserve water quality and contribute to protecting the species represents a challenge for technology. The solution will consist of applying current technological devices, such as sensors, to obtain the data required to implement artificial intelligence (AI) and artificial vision methodologies. The technologies mentioned above will provide an opportunity to improve natural resource management practices, increase food certainty, reduce fishing efforts, and preserve food security. One of the challenges of this article, from the engineering application approach, is to identify the trends of all the technologies developed for aquaculture systems in the last ten years. The use of artificial intelligence and artificial vision will also be emphasized from the perspective of applying these methodologies to establish a path toward future challenges in fish production. This food of maritime origin is a notable provider of protein since it contains essential elements for the development of human beings, in addition to being part of nutritional balance [2]. Due to the proliferation of consumption of marine products, it has been essential to perpetuate fish health through semi-intensive and intensive techniques in aquaculture farms [4]. Maintaining water quality control and timely identification of any disease in the fish is a priority in aquaculture processes. Real-time monitoring serves to prevent and specify the treatment of the biological entity, avoiding diseases and deaths. It has been shown that the insertion of technological innovation in the timely diagnosis of fish contributes to increased production and decreased environmental impact. The objective of this article is to analyze the trends of sensors for data collection, artificial vision, and AI methodologies in aquaculture issues to improve fishery production and adequately manage water resources. Through the above, the following research questions could be answered:

- What current technologies are applied in smart aquaculture systems?
- What instrumentation systems are used for water control and monitoring?
- What image processing and artificial intelligence methodologies are applied in intelligent aquaculture systems?
- What is the future trend of aquaculture systems?

This article is divided as follows. Section 1 presents the introduction, where a brief context is provided on the generalities about aquaculture and its impact as an option in the need to provide food. Section 2 presents the methodology and tools used to obtain and analyze the data. Section 3 mentions the taxonomy that provides a hierarchical framework for aquatic species. Section 4 presents the technologies and innovations currently applied in aquaculture systems to control and monitor water quality. Section 5 shows the variety of sensors used to obtain water data in ponds and lakes. Section 6, the discussion section, presents the findings about the articles presented and the methodologies used in aquaculture systems, and scope and limitations are discussed. Finally, Section 7 presents the conclusion and future works.

2. Methodology

For the research of this article, publications from 2012 to 2023 were taken into account; more than 753 investigations were found based on the search in Scopus and Web of Science with the keywords "aquaculture and intelligent systems". Figure 1 presents the information selection process. The objective of this article is to provide a general review of the technological instruments and artificial intelligence methods that are currently used.

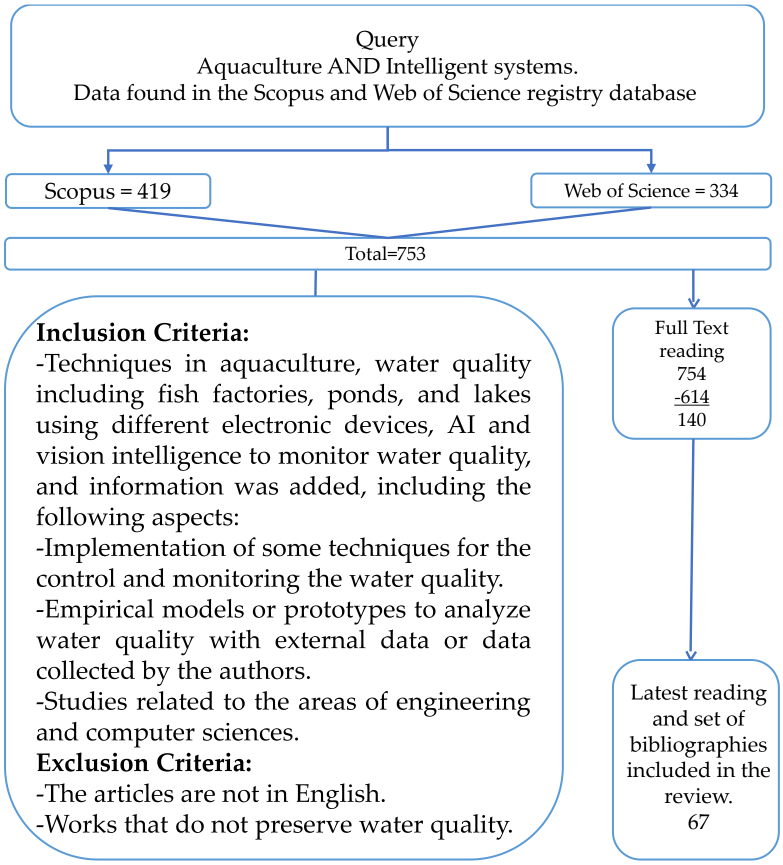


Figure 1. Systematic process for selecting review information.

In the following subsections, the specific discussions of each aquaculture hierarchy are analyzed, thus delimiting the topic to be addressed concerning other titles that could coincide in some keywords but that are not the object of study of this article. The aquaculture taxonomy is shared in Figure 2.

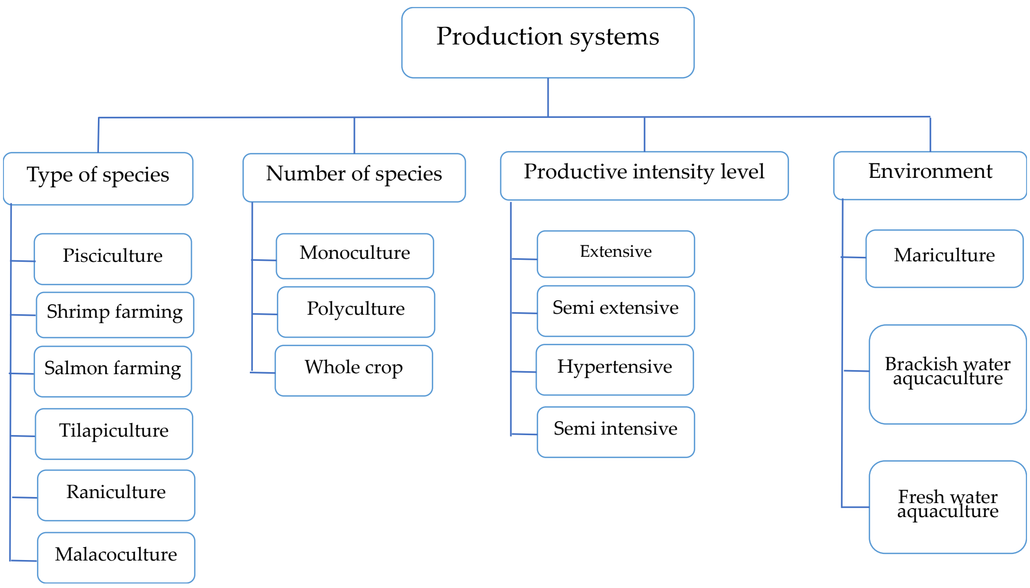
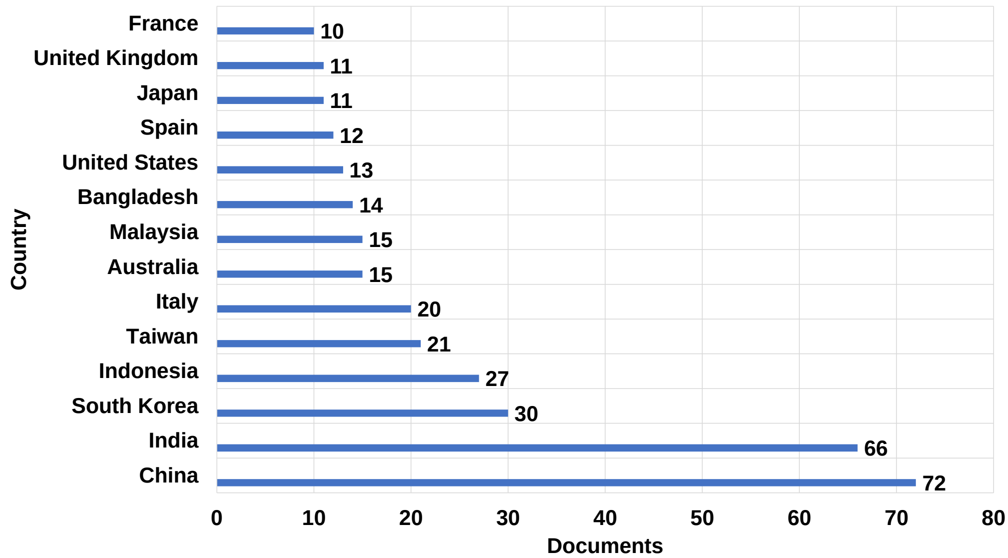


Figure 2. Taxonomy for keyword research in Scopus and Web of Science databases.

The research identifies the scope, capabilities, biases, and challenges of intelligent aquaculture systems. The articles' interest analysis was also carried out based on the year and country of each publication; this information is shared in Figure 3.



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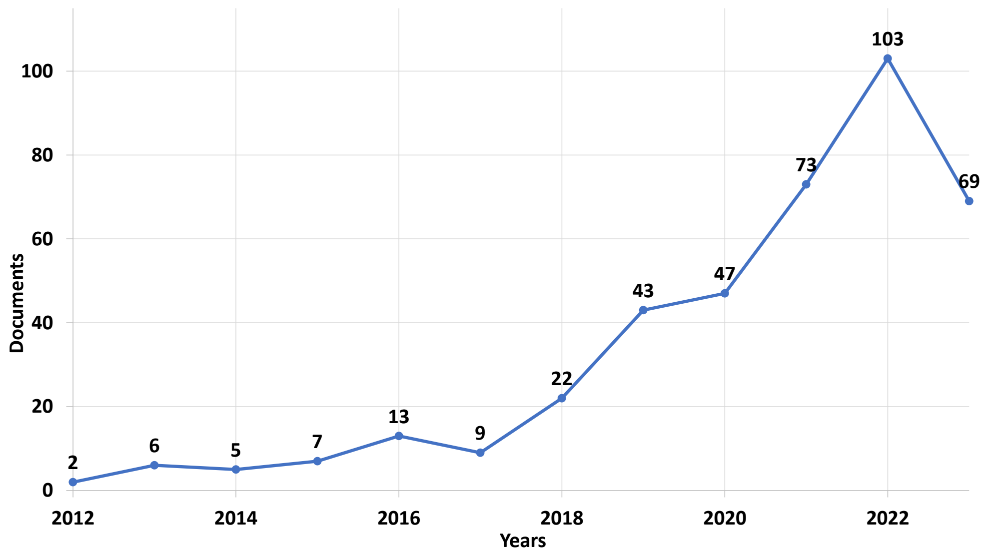

(**b**)

Figure 3. Report of publications from 2012 to 2022, where (**a**) displays the documents published by country and (**b**) presents the documents published by year.

Figure 3a shows that China had an increase in scientific publications derived from the fact that aquaculture production increased by 40.89% in 2021 compared to 2012. This increase led to the evaluation of sustainable and ecological development by identifying the different modes of cultivation [5]. The technology was applied to encourage traditional aquaculturists to adopt advanced techniques to promote the quality of the aquatic product [6]. Figure 3b shows the increase in scientific publications worldwide, with a rise of 70.5% from 2021 to 2022 derived from the need to satisfy food needs through obtaining maritime food. Aquaculture techniques reduce the environmental impact, preserve marine species, and provide high-protein, nutritious food. Aquaculture research also aims to optimize fishery production and protect water resources and land use.

Figure 4 shows publications about aquaculture systems by subject area. It is seen that 20.3% of the publications are made in computer sciences and 19.6% in engineering. The explanation of these percentages can be derived from the fact that it is challenging to introduce computational methodologies to the application of the entire engineering project. Some issues, such as limited resources, non-transparent objectives, unrealistic expectations, and a schedule preparation deficiency, result in the failure of most projects.

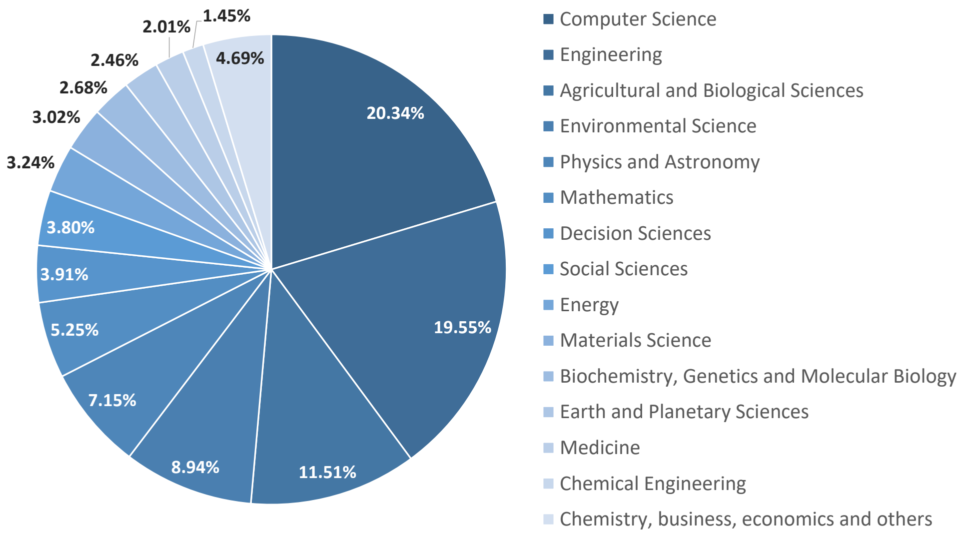

Figure 4. Documents published with the keywords "smart aquaculture" and their contributions for each research area.

3. Aquaculture Taxonomy

From an engineering point of view, aquaculture is approached from the activities related to the use of technologies applied in hydrobiological production processes. Technology also implies the proper management of natural resources and aquaculture species. The innovative development of new processes that will be incorporated into aquaculture methodologies means sustainability in cultivating maritime species. Aquaculture can be hierarchized into different production systems according to the habitat, the species, the type of facility, and the level of intensification, among others [7]. For this article, classification by environment and species will be the focus.

3.1. Taxonomic Classification According to Environment

This section briefly introduces the division of aquaculture by the environment in which the cultivation of the species is practiced.

- Mariculture or marine aquaculture refers to the breeding and reproduction of oysters, shrimp, clams, salmon, and bivalves, to name a few. It regularly develops in the ocean in saline water with at least 30 PSU (practical salinity units).
- Aquaculture in freshwater: This activity takes place on the continent, with water that has less than 0.5 PSU. This practice refers to the reproduction and rearing of aquatic animals in ponds, rivers, lakes, and continental bodies of water; some species are shrimp, tilapia, and crabs, to name a few.
- Aquaculture in salty water uses a mixture of seawater and freshwater in coastal areas, containing a salinity between 0.5 and 30 practical salinity units.

Figure 5 focuses on the hierarchy by type of environment.

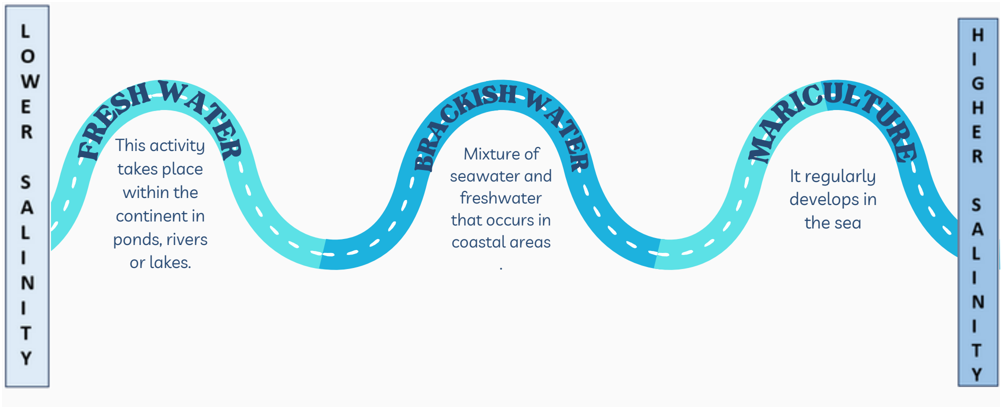

Figure 5. Aquaculture is divided by type of environment.

3.2. Classification According to the Type of Species

It is important to divide aquaculture by species to apply monitoring technologies, system control, and appropriate good practices so that the organism is cultured efficiently and optimized for its production. The taxonomic classification by species division is shared in Figure 6.

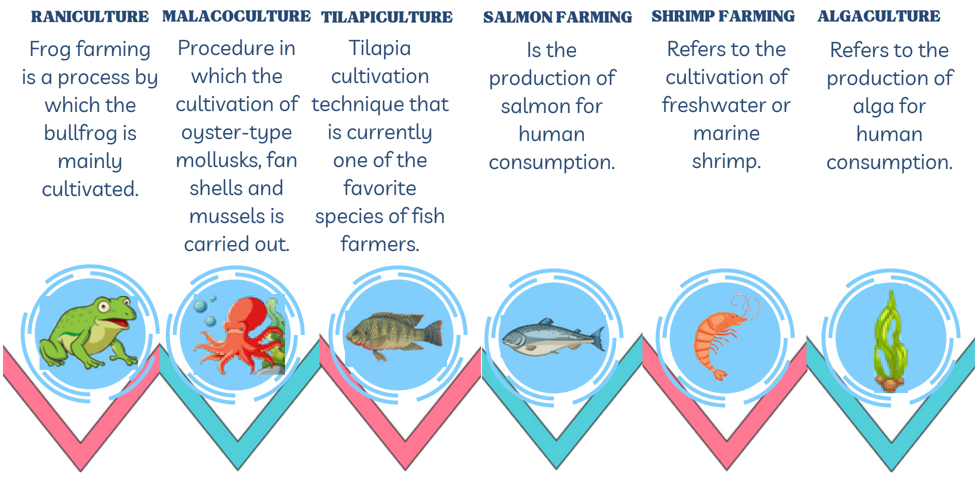

Figure 6. Taxonomic division by species in aquaculture.

4. Aquaculture Technologies

Current aquaculture systems employ applied technologies such as data acquisition sensors, AI, and machine vision. These devices allow the control and monitoring of water quality to maintain the appropriate physicochemical parameters for use within an aquaculture system [8–14]. Preserving the variables of the aquatic habitat allows increasing the growth rates of fish, improving food, and preserving adequate habitat parameters to provide certainty in fishery production.Water quality must be maintained in optimal ranges of potential hydrogen (pH), ammonia, nitrate (NO_3), temperature, nitrite (NO_2), water level in the pond, dissolved oxygen (DO), salinity (SL), electrical conductivity (EC), and water hardness. In the case of controlling optimal parameters, it is necessary to prioritize water quality through constant monitoring and the execution of actuators that help preserve the desirable habitat to produce the species. Table 1 presents the minimum concentrations or optimal ranges for aquaculture systems.

Table 1. Minimum concentrations or optimal ranges of water quality for aquaculture system.

Parameter	Minimum or Optimal Concentrations	Reference
pH Nitrite nitrogen	6.5–8.0 0.25–1.0 mg NO_2-N/L	[8]
Temperature Dissolved Oxygen	17–34 °C >4 mg/L	[9]
Flow Total Dissolved Solids Salinity Relative Humidity	1–2 L/min <1000 mg/L 0–2 ppt 60–80%	[10]
CO_2 Alkalinity Electro-Conductivity	340–1300 ppm 50–150 mg/L $CaCO_3$ 30–5000 μ-mhos/cm	[11]
Total ammonia	<2 mg NH_3-N/L	[12]
Nitrate nitrogen	50–100 mg NO_3-N/L	[13]
Light Intensity	600–900 PPFD	[14]

It is worth mentioning that depending on the species to be cultivated, a specific concept is labeled that will serve to identify the type of culture that is going to be carried out, for example, tilapia farming, shrimp farming, salmon farming, and malacoculture. Fish farming, part of aquaculture, focuses on fish farming in general. In fish production, it should be mentioned that production has grown by 46% from 2016 to 2018, compared to 45.1% from 2011 to 2015. However, technology is still required to help with disease problems, water contamination, fry production, and poor process management practices. To solve part of these problems, it is necessary to include innovations applicable to these systems, such as aquaculture sensors, artificial vision, artificial intelligence, and data analysis. In [15], the authors propose a buoy system in which affordable AI is applied to measure water quality and provide real-time information to predict temperature, salinity, dissolved oxygen, and water velocity to establish the ideal place where aquaculture cages will be installed in the coastal zone and thus optimize the fishing production of certain maritime species. Another example of the contribution in the control and monitoring of water conditions to preserve marine ecosystems that will allow fishing for maritime food is established in the study carried out on the coasts of the Mediterranean, where space images, remote sensing, satellites, and machine learning were used. With this, the results yielded a method to evaluate ecological quality and environmental management [16]. In [17], the use of remote sensors is shared, which allows data to be obtained about the quality of the water in the coastal lagoon of the Mar Menor in the Southeast of Spain, where water parameters are measured for the purpose of making strategic decisions to provide preventive assistance in the event of ecological disasters that condition the environmental balance that compromises the continued provision of ecosystem services such as aquaculture, fishing, and some industrial activities in the area.

5. Aquaculture Sensors

Various sensors can extract information from the parameters existing in the external environment and within the aquaculture system. This water quality monitoring is critical for assembling a database that will be analyzed using AI technologies. The purpose of the analysis will be to explain the events that occurred at the time and so that patterns can be established that can predict future events in the control of the fish care process. Pattern prediction will lead to optimal, economically viable, and sustainable production. Figure 7 shows how information about the aquaculture system and its external environment is acquired. Aquaculture sensors, transmission processes, collection, analysis, and application of the data obtained to execute water quality management processes, preservation of the biological entity, and determined biomass forecasts are mentioned.

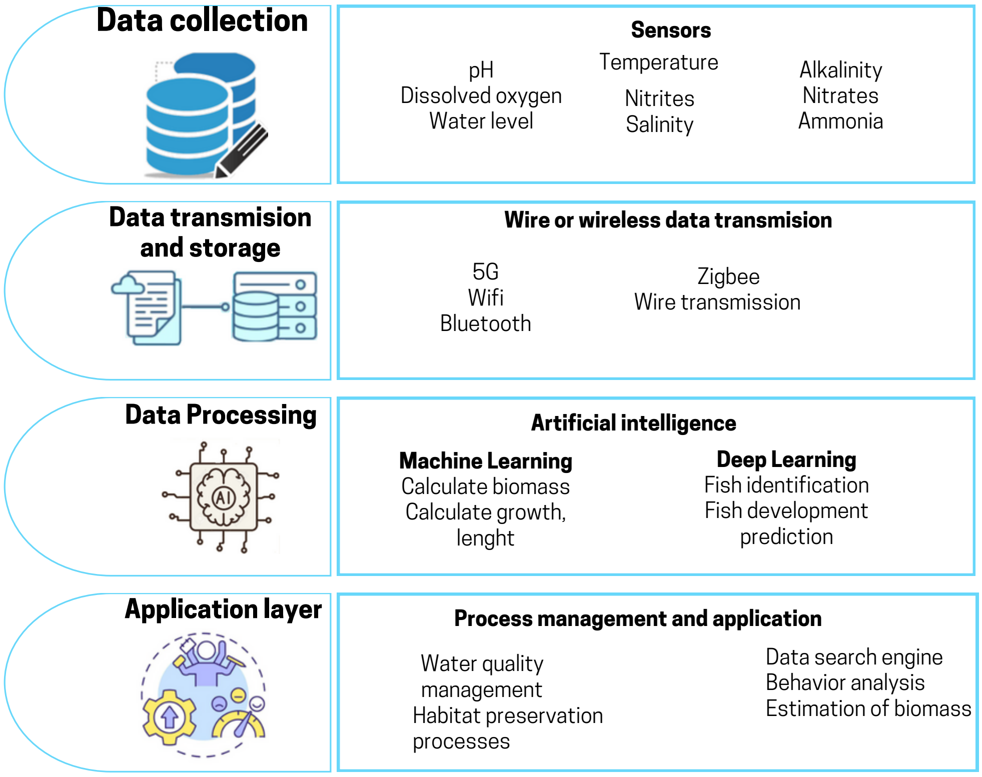

Figure 7. Sensors, transmission, and data processing are applied to different tasks in aquaculture systems.

The main objective of aquaculture systems is the control and monitoring of aquaculture systems, so innovative applications have been developed and applied to smart devices with computing devices where the aquarium system interacts with a remote user interface [18]. In [19], the authors implement the Internet of Things (IoT). Essential data in an aquarium system are the ammonia level and water temperature. This paper proposes a robust aquarium control system using the decision tree regression (DTR) algorithm. In [20], it is explained that aquaculture is one of the most important sources of food for humans. This paper proposed a sustainable fish farming system prototype, which can, through the application of IoT, reduce the need for energy to control the environment; LED lighting is used to support photosynthesis during the night. In [21], the integration of intelligent systems with applications in aquaculture that include water recirculation, biological flocculation technology, automation, and continuous monitoring that guarantees water quality and transcends a high percentage of growth and development of the fish is mentioned.

One aquaculture system that controls and collects data in real time was developed in Taiwan to solve the problems faced by the aquaculture sector in that country. Since there is a large population of senile people and little labor participation by young adults, this system is configured with sensors for pH, water temperature, turbidity, and dissolved oxygen. It proposes monitoring and adjusting water parameters remotely. Data are acquired to apply AI to predict increased California bass biomass. The intelligent aquaculture system and artificial intelligence can be used as an autonomous system that will reduce costs, increase species production, and support aquaculturists [22]. Another aquaculture system emerged due to the problem of typhoons, lack of labor, outdated traditional techniques, and cold waves that harm aquaculture in Taiwan. For this system, temperature, pH, water level, dissolved oxygen, and wireless data transmission sensors were used to monitor the optimal parameters of the fish's habitat. The pH sensor used for this system cannot be in continuous contact with water, so a system with a robot arm was designed. This implementation made it possible to correct the problem above and reduce costs due to handling errors, material resources, and labor savings [23,24]. Obtaining environmental data and transmitting the information wirelessly to the computer is essential. The data will then be analyzed, processed, and presented through LabView software 2012 version or superior and the GSM (Global System for Mobile module) [25].

Innovative aquaculture has been promoted exponentially in recent years, and excess production has been required because of the high density of aquaculture practices. This contributes to the appearance of diseases in fish, and the reduction in production quality has undermined the balance of the aquatic habitat. Current technologies have been integrated to support smart fish farming to solve problems such as cost-effective labor. When the appropriate parameters of the aquaculture habitat are maintained, the efficiency of feeding the fish is increased, in addition to preventing diseases. Intelligent equipment based on IoT, 5G connections, and AI, with its algorithms and computing, will aim to find and solve aquaculture problems. Therefore, optimized module designs that will serve as construction for a smart fish farm [26–31] are proposed. Figure 8 shows a typical aquaculture system with actuators, sensors (turbidity, pH, salinity, dissolved oxygen, etc.), storage of the data obtained by the sensors, data analysis, the visual user interface, and, in several of the aquaculture systems, process control to enable the actuators and preserve water quality.

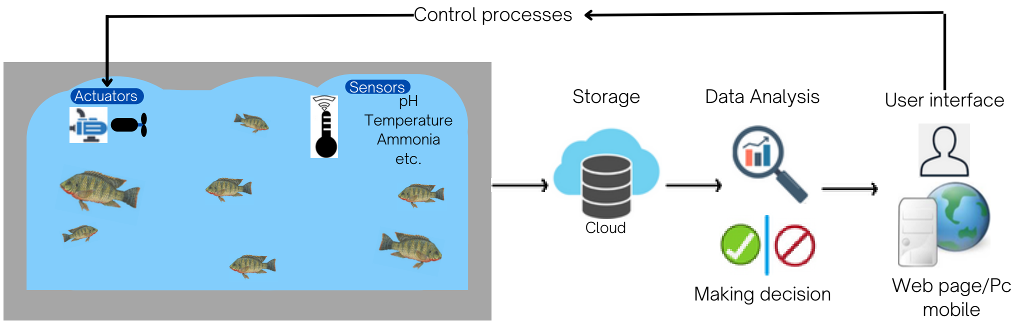

Figure 8. A standard aquaculture system includes communication protocol, actuators, sensors, storage, data analysis, decision making by the data system, and notification to the user.

In [30], the aquaculture system describes a series of sensors for water monitoring that, unlike the other systems compared in the following table, adds sensors for ammonia, fish mobility, salinity, and nitrate. This review identified different articles on aquaculture that share the use of sensors. The synthesis of the systems is shown in Table 2.

Table 2. General overview of aquaculture systems.

Ref	System	Connection	Tb	DO	Ca	WL	WQ	Wt	Server
[22]	Fishpond	Wi-Fi	X		X				Cloud
[24]	Fish farm	Wi-Fi/LoRa				X	X		Web
[25]	Fishpond	Wi-Fi		X	X				PC
[26]	Fishpond	Wi-Fi	X			X			Cloud
[27]	Fishpond	Wire Network	X					X	Web
[28]	Fishpond	Wireless	X	X					Cloud
[29]	Fish farm	Lora Wan		X		X			Cloud
[30]	Fish farm	Wi-Fi/LoRa/5G			X	X	X	X	Cloud

X = Apply.

Table 2 describes the network protocols and servers most commonly used in aquaculture systems. The aquaculture systems [22,25] were applied for a prototype compared with the other aquaculture systems used in fish farms. It should be noted that the aquaculture project [25] turned out to be more energy-efficient and less costly compared to the one [31] that required more excellent economic investment in addition to having the limitation of presenting instability in the system. According to the monitoring of water through the sensors, the particular objectives of each project can be achieved, as shown in Table 3.

Table 3. Water monitoring, objectives, benefits, and limitations.

Reference	Mainboard	Objective	Benefits
[22]	Arduino Mega 2560	Predict growth, autonomous feeding	Reduce excess feeding, fish monitoring and control, optimize production, reduce production costs
[24]	Plc for the robot, Arduino Mega 2560 for sensors	Problem detection	24 h processes, high reliability and stability in measurements, parameter change notice, the robotic arm can perform maintenance work, remote monitoring, real-time water notification
[31]	Microcontrollers	Measurement and control of production, continuous monitoring, biomass estimation	Remote monitoring, real-time water notification, disease prevention, 24 h processes, robot process operators, precise and automatic food distribution, reduce operating costs, improve food management
[25]	Atmega 16, Labview for visualization	Water monitoring and network control	Monitoring in 3 min time intervals, user notification

Artificial Vision and Image Processing in Aquaculture System

Artificial vision allows computers and systems to extract important data from videos or digital images, actions can be taken, and processes can be executed. Aquaculture has been used to recognize fish and monitor and extract information that allows proper management, effective feeding, and disease prevention. The activities carried out through AI are summarized in the recognition and counting of individuals, biomass measurement, behavioral monitoring, and classification of the species and factors around the fish's habitat. Within sustainable development trends, machine learning is a subdivision of artificial intelligence that can recognize and learn the observed data characteristics by applying algorithmic models. In the application of this article, data such as size, weight, temperature, and pH measurement can be focused on. It is essential to mention that aquaculture represents a continuously growing global production, mainly in species such as carp, catfish, bivalves, and tilapia, representing 75% of aquaculture production [32]. There is a significant diversity of species in aquaculture, and it is estimated that 40% of the different categories belong to shellfish, fish, and algae produced in various aquatic habitats such as freshwater, brackish water, and marine water [33]. For an approach in innovative aquaculture, a range of instruments are proposed that can monitor the parameters of the aqueous habitat in real time and thus make decisions based on the data obtained [34]. Innovative aquaculture production includes automated and remote control and IoT. Through collecting information on temperature, humidity, dissolved oxygen, light, and pH, data transmission to the monitoring center, data analysis, and decision making for performance aquaculture systems can be carried out [35]. The application of AI and the IoT in aquaculture has resolved existing difficulties in traditional aquaculture [36]. These technologies have made it possible to carry out actions to control water quality in hatcheries, water troughs, and cages [37,38]; by monitoring the existing parameters in the ponds, the supply of the amount of food and the appropriate time for its nutrition is improved. The feeding period is also reduced, and this reduces labor, since the entire process is carried out under automation. Aquaculture presents several challenges, including preserving water quality, maintenance costs, food, and space. Due to this, biofloc technology, which uses food not consumed to convert it into organic matter, has been chosen. This allows the reuse of the food. The patterns are analyzed by obtaining data from the sensors, and an AI model is proposed to generate learning models and decisions for proper food management [39].

Data has been provided on the application of AI in aquaculture applied in feeding mechanisms, drones, aerial robotic systems, robotic fish, disease prevention, mobile phone applications, open sea fishing, and blockchain in shrimp supply [40,41]. In [42], it is mentioned that automated learning or machine learning aims to solve difficulties using algorithms and learning data to create mathematical models to optimize the aquaculture system. There are various models implemented in aquaculture, including decision tree (DT) [43], Naive Bayes [44], support vector machine (SVM) [45], artificial neural network (ANN) [46], K-neighbor nearest (KNN) [47], deep learning (DL) [48], and ensemble learning (EL) [49]. In [50], supervised, unsupervised, and semi-supervised learning is mentioned, and the four types of machine learning structures are mentioned. Supervised learning is used for classification and regression as a learning method with a model that maintains the object's value. Citing the theory of machine learning and its advantages, several theories have been implemented in aquaculture, for example, the detection of fish biomass [51,52], calculation of fish size [53] and weight [54–56], individual counting [57], fish recognition [58], age detection [59], sex detection [60], fish species classification [61–63], feeding behavior [64], univariate prediction [65,66], and multivariate prediction [67], with high accuracy. Regarding artificial vision processes, the documents that make intelligent diagnoses of possible fish diseases will be addressed, ensuring their well-being and health and thus preventing the death of the species. One of the main factors causing approximately 50% of the overall loss of fish production is disease, as it spreads rapidly and on a large scale in a short time [68]. Fish parasites can adversely affect humans to the extent of transmitting diseases such as salmonella [69]. These diseases are caused by bacteria, viruses, or contamination of their habitat, and conventional methods are slow, expensive, and require the dissection of fish tissue. Because of this, it is imperative to apply new technologies that can prevent and diagnose diseases in real time, which will keep fish disease-free and prevent the spread of diseases. Research in expert systems that began in the 70s and has had an increase in its application until the 90s has achieved progress in diagnosing disease in fish [70], although it should be mentioned that the precision in the diagnosis depends on experts most of the time. For the analysis of fish images, greater precision has been required, and more accurate images have been obtained by eliminating noise in the visual information. This generally includes blurring of the image area, a drop of water on the lens, or a section of the fish outside the angle of the camera lens. Appropriate techniques to solve these problems have been detailed based on contour methods and recovery of missing information through segmentations of representative contours by applying weighted least squares iteratively to recover information from missing or poorly segmented contour segments [71]. Smart aquaculture promotes decreased labor and supply costs, increased operational efficiency, greater productivity, and food certainty.

Due to the aforementioned, innovation is demonstrated in obtaining information corresponding to the preservation of fish and the diagnosis of diseases. Table 4 provides the methods currently used to obtain segmentation images, listing the steps that each of the described methodologies followed to extract information about the health of the fish in its aquatic environment.

The information in Table 5 compiles the methods applied for labeling the information obtained from the biological entity and which will later be used by the AI for data processing and application of the K means methodology. It can be seen that the weighted least squares method generates 95% efficiency and the deep neural network method generates 98%, these two being the procedures that represent the greatest reliability in their results. Table 5 shares the methodology for obtaining the image, the AI for data analysis processing, reference points, labeling, and process efficiency.

Table 4. Artificial vision methodology for image processing in aquaculture system.

Work	Object	Obtaining the Image	Advantages
[71]	Fish on fishmonger ramps	Contour segmentation: Coarse to acceptable level segmentation. Continuous iterative contour segmentation. Application of pre-trained shape models.	Does not require high volumes of datasets. Prior knowledge of the shape of the fish. More samples are needed for shape modeling. Segmentation can be performed on low-quality images. No human effort is required.
[72]		Contour segmentation: Separates the outline of the fish from the background image. Change the image to grayscale. Apply K means and segment the image. Adopt mathematical morphology to establish the limit of the fish.	High precision and stability. People's prior knowledge determines sample values.
[31]	Bank of fish	Image segmentation. The image obtained replaces the original.	Accurate and effective. Easy to understand and analyze. Prior knowledge of the characteristics of the fish. Complex noise reduction. Execution time reduction.
[73]	Underwater environments	Image segmentation: RGB image fusion. Application of the adaptive contrast histogram equalization method. Edge detection algorithm. Fusion of the image of points 2 and 3, body and edge.	No human intervention is required. Fast and effective, 4.27 s. Beats algorithms like Otsu, Chan, and Vese.
[74]	Underwater environments	Principal Component Analysis (PCA). Spatial Pyramid Programming (SPP).	The applied model obtains an accuracy of 98.64

Table 5. Artificial intelligence with labeled automatic and K means algorithms for data processing through artificial vision with contour segmentation methodology to improve aquaculture processes.

Reference	Object	Method	Measure	Points	Efficiency	Limitations
[71]	Fishmonger	Weighted least squares	Size	Tail–body	Greater than 95%	The method is optimal for flatfish; for other types of fish, more K-means would have to be applied.
			Length	Body inflection and mouth	583 masks	
[72]	-	Otsu algorithm/ histogram peaks	Disease diagnosis	Default cluster center	-	The result depends on adequately choosing the right cluster center.
				Calculate the distance of each sample from the default cluster	-	The use of other methods is required to ensure the correct choice of the cluster. This technique was applied only to carp.

Table 5. *Cont.*

Reference	Object	Method	Measure	Points	Efficiency	Limitations
[31]	Bank of fish	Adaptive fast clustering	Color	Grayscale databases	56% lower execution time of Adaptive Fast Clustering algorithm compared to K-means	This technique was applied only to carp.
			Behavior	Default grayscale cluster center	71% lower execution time of fast adaptive clustering algorithm compared to fuzzy clustering algorithm	The result depends on adequately choosing the right cluster center. Image pixel loss
[73]	Underwater environments	Active contour	Identify the sea cucumber.	-	120 samples	This technique was applied only to sea cucumbers.
[74]	Underwater environments	Deep neural network	Fish Identification Color Texture	-	98.64%	-

6. Discussion

This article frames current technologies and their application in aquaculture, especially in preserving the physicochemical parameters necessary to conserve the habitat of the biological entity and thus provide certainty in its production. The most used sensors in aquaculture systems control variables such as pH, temperature, NO_2, NO_3, DO, and SL. It is shown that 60% of aquaculture systems use free access cards. Process execution times are reduced, and data are monitored 24 h daily. Wireless connections are used in 90% of systems and connect to a cloud server. In recent years, maritime industrial production has increased worldwide, impacting the overexploitation of lakes, lagoons, and seas throughout the planet. In [75], it is mentioned that monitoring water is an essential process to provide certainty in controlling the parameters of aquaculture processes, allowing decisions to be made promptly and in real time. In this case study, a system was implemented based on open-source hardware that measures temperature, pH, and dissolved oxygen through sensors for each parameter, and a database was obtained that allows relating the control of the aquaculture environment with the growth of the cultivated species. The application of the aforementioned system demonstrated that it is precise, reliable, and accurate in water measurement processes. In [76], the authors propose a closed-loop control that includes a Raspberry Pi card, Python programming, an ammoniacal nitrogen sensor, and solenoid valves to carry out a process of removing ammoniacal nitrogen resulting from the excretion of fish and that contributes to the proliferation of diseases and deaths in the biological entity. It was shown to have energy and water savings of more than 95%, which allows for optimizing the preservation of fish in aquaculture systems and promoting water quality in fish farms. Intelligent systems based on sensors, in conjunction with automatic control through AI, will obtain the necessary diagnoses to gather information about the health of the fish. Artificial vision, in conjunction with artificial intelligence, will provide a real-time, non-invasive diagnosis of the biological entity and will be a technique that will promote the care of the fish to maximize its production. Artificial vision will also be able to detect some changes in the fish biomass, but it has limitations concerning image acquisition mainly in that there is no database to make comparisons between one image and another, so it can be necessary to provide initially programmed parameters, give a greater quantity and quality of images with high resolution so that there is systematic training, and achieve a higher level of precision in its processes. To obtain a better artificial vision technique, it is necessary to apply the K means methodology for use by AI, add a database with images that serve as a comparison between those that have already been obtained and those that are going to be obtained, apply a contour segmentation methodology, and capture higher-quality images of the fish being analyzed. The findings show that 60% of the research used the technique of obtaining the image through contour segmentation because large amounts of data are not required to obtain image processing. In addition, the fast adaptive data clustering method is 56% shorter in execution time compared to K-means.

One of the goals of water monitoring through AI is that it can analyze and prevent changes in water quality that affect fish habitat. Real-time information allows you to make the necessary decisions to preserve the ideal parameters of the aquaculture system. Likewise, AI plays an important role in analyzing different mass data that require efficient management and the identification of trends and models that are generally not detected using conventional techniques. This provides results that prevent abnormal events such as sudden changes in water quality. An early reaction prevents the spread of diseases, the presence of pathogenic microorganisms, and contamination, and provides certainty in aquaculture production.

The combined use of the methodologies mentioned in this article can maximize the certainty of the information since more incredible details of the information on the biological entity and its environment will be provided. After analyzing several publications, it is proposed that the ideal system should be composed of pH, DO, NO_2, NH_3, and temperature sensors to capture the required data to provide information to the AI. The K means methodology and the contour segmentation of artificial vision will be able to analyze water quality patterns and prevent any anomaly in its habitat or disease that could harm aquaculture production. The systematic review found that, using a least squares methodology and body-to-tail segmentation of the fish, an efficiency of 95% was obtained. On the other hand, applying neural networks and segmentation based on the fish's physical characteristics, a result of 98% was obtained. Therefore, by combining neural networks and body-to-tail segmentation, an efficiency greater than 98% could be achieved.

7. Conclusions

The trend in the future will focus on the improvement of intelligent systems, mainly on the optimization of the methodologies that are applied through AI. The timely forecast in the control of water quality and the prevention of diseases in fish will optimize economic and environmental resources to achieve certainty in production for human consumption. Likewise, artificial vision will provide AI with data for the timely detection of any fish condition, preventing the spread of a disease in the aquatic environment. The importance of aquaculture production forms the backbone of the social and economic development of the world through the exploitation of fishing resources. This represents a guaranteed food source for the coming years and impacts poverty reduction and the proliferation of direct and indirect jobs. However, there is an urgent need for continuous scientific contributions that will challenge improving the control and preservation of the aquatic environment by properly managing water resources to avoid negative environmental impacts, inadequate exploitation of flora and fauna, and adequate management of fishery production. This will allow sustainable development by conserving natural resources and meeting the food needs of future generations since, according to the FAO, the aquaculture sector currently represents 50% of the world's diet. Aquaculture production had an average annual growth of 6% from 2001 to 2018, producing more than 82 million tons. It is one of the animal proteins that increased its consumption by 2.1% compared to other animal proteins. Aquaculture provides the most consumed protein worldwide and is primarily of interest to NGOs and CSOs. It also includes food and nutritional certainty and stands out as being goal 14 within the 2030 Agenda for Sustainable Development. One main challenge is the proper and sustainable management of marine resources. Food security for the population will be one of the main challenges technology must solve by implementing the devices mentioned in this scientific review. The combined application of AI methodologies, machine learning, and image capture is the intelligent solution to preserving the marine entity for human consumption, and these technologies will also serve in the responsible and appropriate management of maritime resources.

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