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# Design of an autonomous multiparameter buoy with photovoltaic energy and remote communication based on IoT for aquaculture environments

## Diseño de una boya multiparamétrica autónoma con energía fotovoltaica y comunicación remota basada en IoT para entornos de acuicultura

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## ABSTRACT

A prototype of an autonomous multiparameter buoy was designed to address technological limitations in water quality monitoring in aquaculture environments. The objective was to develop a modular and sustainable system integrating photovoltaic energy and wireless communication to monitor critical parameters in real time: pH, temperature, dissolved oxygen, and electrical conductivity. The system consists of an emitter module, receiver module, and a data transmission platform to the cloud. Materials included reinforced PLA and PETG, and electronic components were powered by a 20 W solar panel connected to a 12 V 7 Ah battery. During testing, the prototype demonstrated a 48-hour energy autonomy and reliable LoRa transmission with a 500 m range in the direct line of sight. The modular design facilitates sensor integration and system adaptation to various conditions, benefiting small producers. However, challenges such as component resilience in harsh environments and optimizing energy autonomy under adverse conditions remain, presenting opportunities for future improvements in robustness and scalability.

**Keywords:** aquaculture 4.0; IoT; environmental monitoring; wireless sensors; sustainable technology

## RESUMEN

Se diseñó un prototipo de boya multiparamétrica autónoma para abordar las limitaciones tecnológicas en el monitoreo de la calidad del agua en ambientes de acuicultura. El objetivo fue desarrollar un sistema modular y sustentable que integre energía fotovoltaica y comunicación inalámbrica para monitorear en tiempo real parámetros críticos: pH, temperatura, oxígeno disuelto y conductividad eléctrica. El sistema consta de un módulo emisor, un módulo receptor y una plataforma de transmisión de datos a la nube. Los materiales incluyeron PLA reforzado y PETG, y los componentes electrónicos fueron alimentados por un panel solar de 20 W conectado a una batería de 12 V 7 Ah. Durante las pruebas, el prototipo demostró una autonomía energética de 48 horas y una transmisión LoRa confiable con un alcance de 500 m en la línea de visión directa. El diseño modular facilita la integración de sensores y la adaptación del sistema a diversas condiciones, beneficiando a los pequeños productores. Sin embargo, persisten desafíos como la resiliencia de los componentes en entornos hostiles y la optimización de la autonomía energética en condiciones adversas, lo que presenta oportunidades para futuras mejoras en robustez y escalabilidad..

**Palabras clave:** acuicultura 4.0; IoT; monitoreo ambiental; sensores inalámbricos; tecnología sostenible

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## 1. INTRODUCTION

Aquaculture is a rapidly growing activity in global food production, accounting for 89% of fish destined for human consumption (FAO, 2024). This sector contributes to global food security by
101 providing aquatic protein (T. Garlock et al., 2022; Obiero et al., 2019), and economic development in coastal and rural regions through job creation and economic diversification (Bennett et al.,
93 2024; Engle & van Senten, 2022). Its expansion is driven by the increasing demand for aquatic products and the need to reduce exploitation of natural fishery resources (Laktuka et al., 2023).

In recent decades, aquaculture has adopted intensive and semi-intensive systems driven by technological advances that optimize production and favor sustainability (Biazi & Marques, 2023; Rowan, 2023). This activity faces challenges related to environmental management, the implementation of sustainable technologies, and the equitable distribution of benefits (TM
27 Garlock et al., 2024; Naylor et al., 2023; Wong et al., 2024). The adoption of technological solutions is essential to improve performance, especially in regions with limited resources and high poverty
64 (Araujo et al., 2022; Bunting et al., 2023).

In Peru, aquaculture has become an engine of economic development (Sociedad Nacional de
90 Pesquería, 2020), particularly in rural and tropical regions (Quesquén-Fernández et al., 2022; Sánchez Calle et al., 2021). The country has a high potential because of its species diversity and
35 favorable climatic conditions (BCRP, 2017; Organización de las Naciones Unidas para el Desarrollo Industrial, 2017). However, the sector faces technological and infrastructure limitations that
59 hinder its sustainable development and integration into broader value chains (Gozzer-Wuest et al., 2021).

In the San Martín region of the Peruvian Amazon, aquaculture represents a relevant economic
105 activity (Dirección Regional de la Producción de San Martín, 2022; Programa Nacional de Innovación en Pesca y Acuicultura, 2018), especially in rural communities dedicated to the production of species, such as tilapia (Arévalo-Hernández et al., 2023; García-Castro & Ascón-
40 Dionisio, 2022; Ismiño-Orbe et al., 2024; Reyes-Bedriñana et al., 2022; Sotelo-Lescano et al., 2024). However, the limited availability of advanced monitoring technologies restricts efficiency in the management of production systems, negatively impacting the quality of products and environmental sustainability of the activity.

Thus, the identified knowledge gap lies in the limited availability of systems specifically designed to monitor aquaculture conditions, considering the technological needs and characteristics of the
1 environment. Although advanced technologies have been developed in other regions (Chiu et al., 2022; Dupont et al., 2018; Eze et al., 2023; Lu et al., 2022), their high costs and poor adaptability to small producers generate a significant gap in the implementation of accessible and practical solutions.

Recent studies have explored approaches to overcome energy and technological limitations in aquaculture, especially in remote areas. Research focusing on the use of renewable energy and monitoring technologies has demonstrated their ability to improve the management of production systems (Bórquez López et al., 2020; Flores Mollo & Aracena Pizarro, 2018; Staude et al., 2024;
65 Von Borstel Luna et al., 2017; Zhang et al., 2022), although challenges remain for their effective integration in resource-limited environments.


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In this context, this study aimed to design an autonomous multiparameter monitoring buoy powered by photovoltaic energy and equipped with wireless communication, specifically adapted for rural and experimental aquaculture environments. This proposal seeks to bridge the identified technological gap by providing a sustainable solution for real-time monitoring of critical parameters and enhancing aquaculture productivity and sustainability in the San Martín region and similar areas. Improving the control of environmental variables is crucial because their fluctuations directly impact the growth and health of aquatic organisms. The lack of accessible monitoring systems limits the ability of producers to respond to changes in water conditions, which affects production efficiency. Accurate monitoring is essential to mitigate environmental risks and ensure the long-term sustainability of aquaculture activities.

## 2. MATERIALS AND METHODS

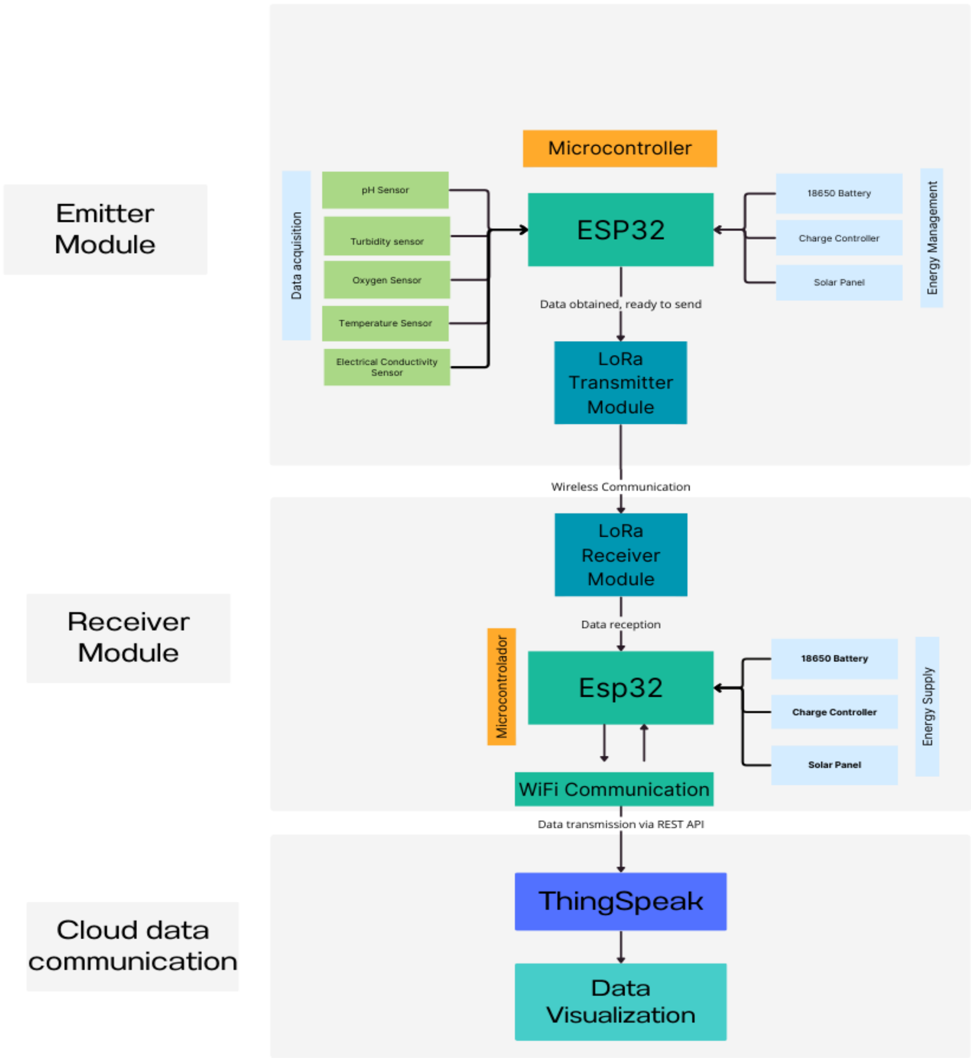
To ensure efficient water quality monitoring in aquaculture environments, the proposed system was developed with a modular and scalable approach. The design integrates energy-efficient components, real-time data acquisition, and reliable wireless communication to provide continuous monitoring of critical parameters. The system operates autonomously, leveraging photovoltaic energy and long-range communication technology to address the challenges of remote deployment.

### 2.1. System architecture and electrical diagram

The proposed system consists of three main components: transmitter, receiver, and data transmission modules to the cloud. Each component integrates specific subsystems to ensure efficient power management, data acquisition, wireless communication, and real-time visualization. The modular architecture allows flexibility in adapting to different environmental conditions and facilitates future upgrades by integrating additional sensors or communication protocols. Figure 1 shows the overall system architecture and the interactions between the modules.

The transmitter module is designed for data acquisition and transmission. This module incorporates a power management subsystem consisting of a solar panel, charge controller, and 18650 batteries. This subsystem ensures a stable power supply to the ESP32 microcontroller, which acts as the central-processing unit. Sensors connected to the ESP32 include pH, electrical conductivity, dissolved oxygen (DO), and temperature sensors. These sensors collected environmental data processed by the ESP32 before being sent to the LoRa transmitter module using a serial interface. The LoRa module handles the wireless transmission of the processed data over a radio frequency channel. This architecture ensures reliable data acquisition and transmission, even in remote aquaculture environments.

The receiver module captures and processes the data transmitted by the transmitter module. This module also includes a power management subsystem consisting of rechargeable batteries to power both the ESP32 and LoRa receiver modules. Once the data were captured by the LoRa receiver module, ESP32 processed it and prepared it for transmission over Wi-Fi. This module is connected to a local router, allowing the data to be integrated into a cloud-based system for analysis and visualization.




39 **Figure 1.** Architecture of the proposed system

Figure 2 shows the electrical schematic of the system, highlighting the interconnection of the main components. The solar panel generated power that was regulated by a charge controller and stored in a 18650 battery bank. Sensors for pH, conductivity, dissolved oxygen, temperature, and turbidity measurements were connected to the ESP32, which processed the information. This information was transmitted via radio frequency through the LoRa module, which was supported by an antenna to amplify the signal. The electrical design included a power module that efficiently distributed power between the sensors, ESP32, and communication modules, ensuring continuous operation of the system.

The processed data were transmitted to the cloud using a REST API, utilizing the ESP32's Wi-Fi capabilities. The cloud platform ThingSpeak acted as an intermediary for data storage and visualization. ThingSpeak receives the data packets and provides a real-time graphical representation of the monitored parameters. This modular design allows for seamless scalability and adaptability, ensuring compatibility with alternative protocols, such as MQTT, if required. The complete architecture facilitated maintenance, expansion, and possible system upgrades, promoting the sustainable management of aquaculture environments.

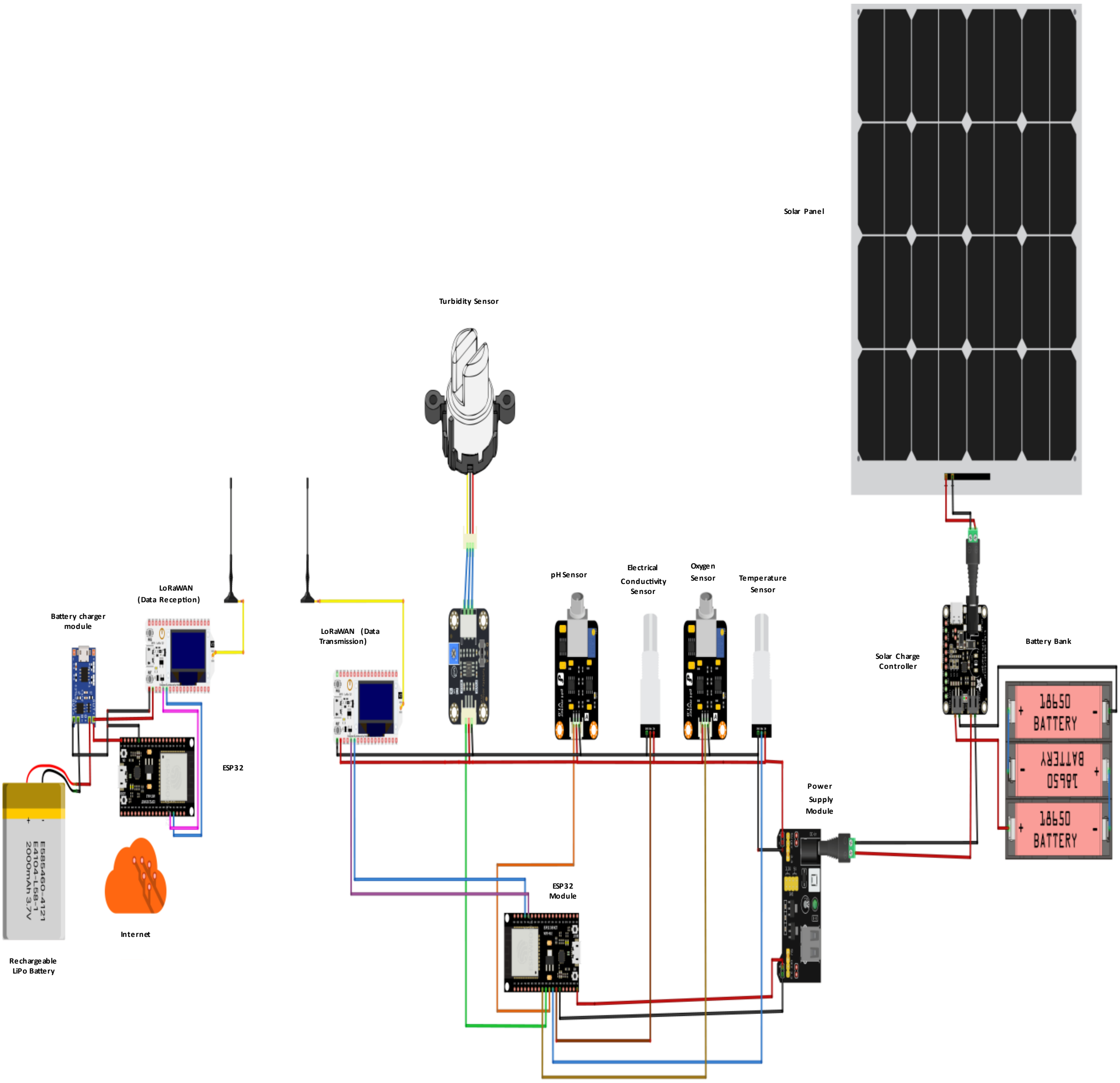



**Figure 2.** Electrical diagram of the multiparameter buoy prototype

## 2.2. Buoy prototype design

The designed multiparameter buoy prototype had a rigid structure manufactured by 3D printing, using materials such as reinforced PLA and PETG, which were selected for their moisture resistance and durability in aquatic environments. 3D printing technology allows precise and modular construction, facilitating adjustments and modifications to the design to adapt it to the specific needs of the project. The dimensions of the prototype were 70 cm in length, 30 cm in width, and 50 cm in height, and were optimized to ensure hydrodynamic stability and buoyancy in aquatic environments. The structure includes two main floats that act as support and balance elements, ensuring efficient operation in water bodies with calm or moderate currents. As shown in Figure 3, the design incorporates a robust frame and strategically positioned floats to maximize stability during operation.

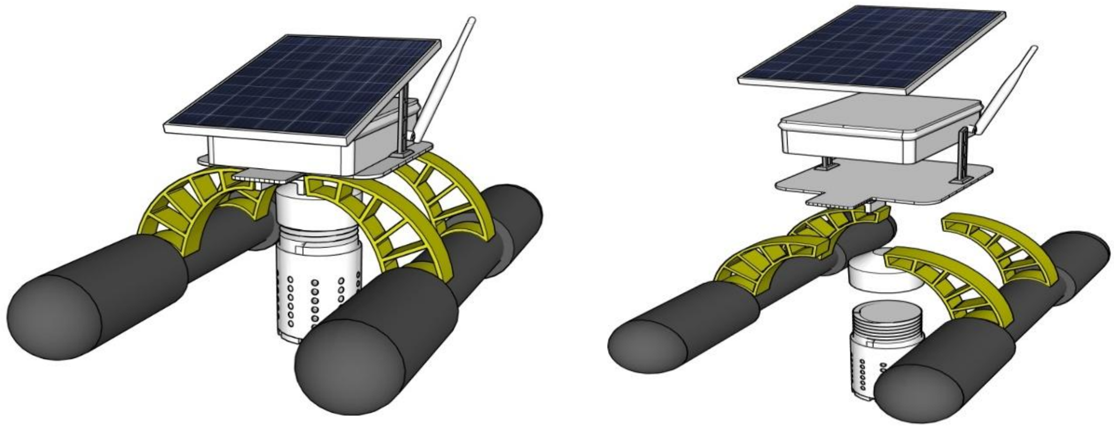


**Figure 3.** Conceptual design of the multiparameter buoy prototype

## Solar panel and energy management

The buoy was equipped with a 20 W photovoltaic panel mounted on an adjustable frame that optimized the collection of sunlight. The energy generated was stored in a 12 V, 7 Ah sealed lead-acid battery, which provided a continuous power supply for the sensors and electronic modules, ensuring uninterrupted operation of the system.

## Sensors

The buoy has a set of sensors to monitor critical water quality parameters as shown in Table 1:

**Table 1.** Technical specifications of the buoy prototype sensors

| Sensor | Measuring range | Precision |
|---|---|---|
| pH | 0 to 14 | ±0.01 |
| Electrical conductivity | 0 to 2000 µS/cm | N/A |
| Dissolved oxygen | 0 to 20 mg/L | ±0.1 mg/L |
| Temperature | -10 to 50 °C | ±0.5 °C |

All sensors were protected in a waterproof central module, located beneath the main platform, to avoid damage during operation as can be seen in Figure 4.

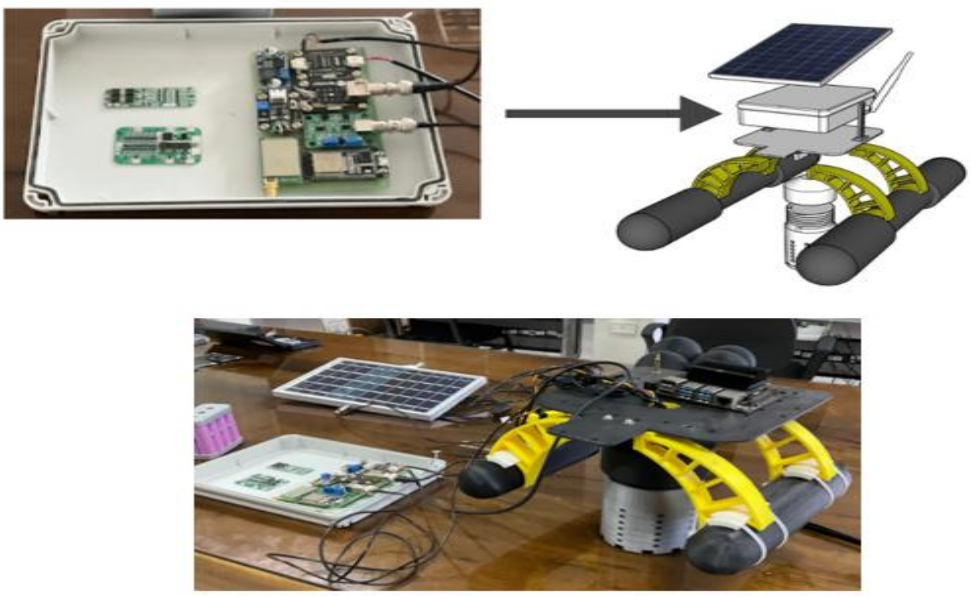


**Figure 4.** Location and protection of sensors in the central module

### Wireless communication

The system uses LoRa modules for data transmission via radio frequency, with a range of up to 500 m in the direct line of sight. The data collected by the ESP32 in the transmitter module were sent to the LoRa transmitter module, which communicates with a receiver module connected to a Wi-Fi network. The processed data were then transmitted to the cloud via a REST API using the ThingSpeak platform for storage and real-time visualization.

As shown in Figure 5, the system architecture enables efficient communication between the transmitter modules and the central receiver module, thereby optimizing the monitoring of critical parameters. Each transmitter module, equipped with a photovoltaic receiver, autonomously collects and transmits data, whereas the receiver module consolidates the information before sending it to the cloud for analysis. This modular configuration ensured a robust data flow that was adaptable to the needs of the aquaculture environment.


**Figure 5.** Conceptual design for sending data to the cloud

## 3. RESULTS

### Applications and functionalities

The buoy was designed to collect real-time multiparameter water quality data, enabling efficient, data-driven management of aquaculture environments. Monitored parameters include pH, dissolved oxygen, temperature, and electrical conductivity, with the sampling frequency adjustable based on operational requirements. This flexible approach ensured that the system could adapt to various environmental conditions and specific monitoring requirements. Furthermore, the modular architecture of the buoy makes it easy to maintain, allowing for scalable integration of additional sensors in the future, increasing the versatility of the system.

### Operation simulation

Initial testing of the prototype confirmed that the structure could support up to 200 g of additional weight, including electronics and sensors, without compromising its stability. The floats provided an adequate balance under moderate wind conditions, ensuring reliable operation in aquatic environments. The power management system proved to be efficient, guaranteeing autonomy for up to 48 hours in the absence of direct sunlight. As shown in Figure 6, the prototype was tested in a real aquatic environment, demonstrating its ability to operate effectively and collect multiparameter data in real time.

**Figure 6.** Testing of the buoy prototype in a real aquatic environment

## Data visualization

Figure 7 presents examples of data collected by the buoy sensors, including temperature, dissolved oxygen, turbidity, and conductivity levels. These data were recorded and visualized in real time using the ThingSpeak platform, allowing immediate analysis of the monitored parameters. This real-time visualization capability validates the functionality of the system to generate actionable and decision-relevant information for aquaculture management.

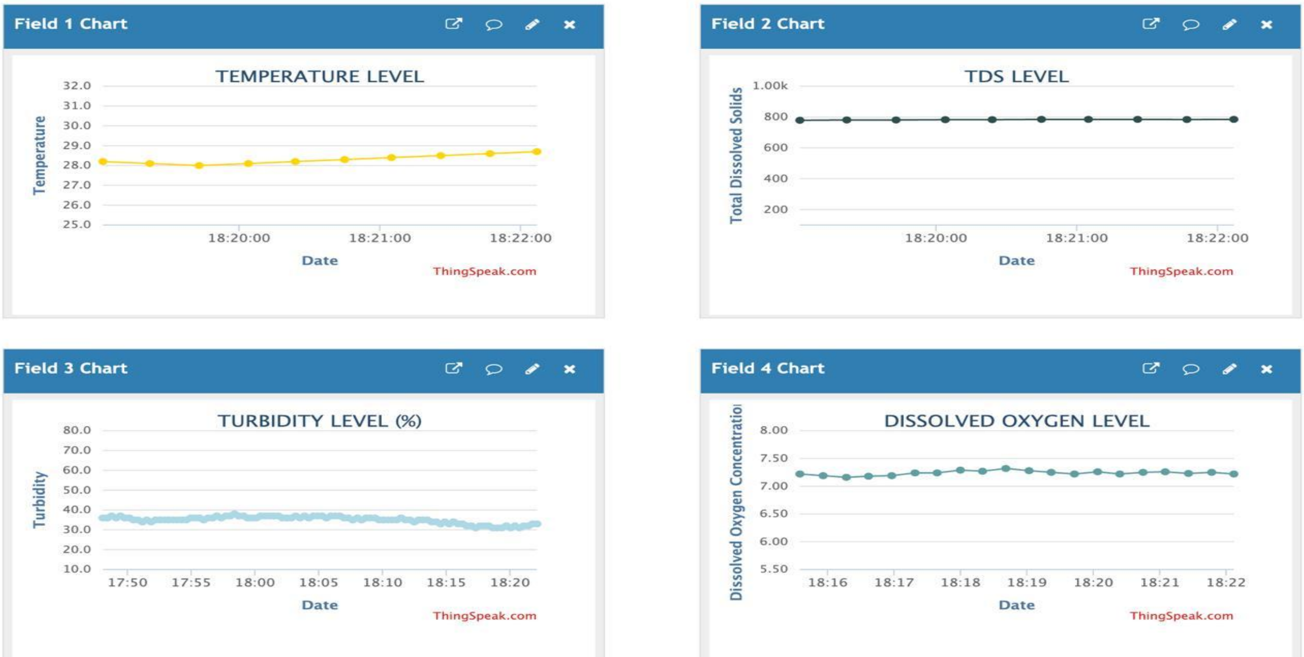



**Figure 7.** Visualization of real-time data obtained by the buoy sensors

## System challenges and discussion

The designed prototype demonstrated adequate energy autonomy for operation in remote aquaculture environments, lasting up to 48 h, without direct sunlight. This result is consistent with the findings of López et al. (2020); Zhang et al. (2022) highlighted the importance of optimizing renewable energy generation and storage in autonomous systems. However, under conditions of prolonged high cloud cover, autonomy could be limited, highlighting the need to explore complementary options such as the integration of hybrid energy generation systems. This challenge is critical for ensuring continuous operation in regions with significant climatic variability, such as San Martín.

The sensors installed on the buoy met the measurement ranges required for aquaculture monitoring and provided reliable data on pH, dissolved oxygen, temperature, and electrical conductivity. This aligns with studies such as that of Mollo and Pizarro (2018), who emphasized the need for robust and accurate sensors to cope with the changing conditions of water bodies. However, in scenarios with high sediment concentrations or extreme temperature fluctuations, the accuracy of the sensors can be compromised, suggesting the implementation of automatic calibration systems to mitigate this problem.

The LoRa modules in the system enabled reliable line-of-sight transmission up to 2 km, validating its effectiveness in rural and remote environments. This approach was consistent with that reported by Staude et al. (2024); Von Borstel Luna et al. (2017), who highlighted the usefulness of LoRa for environmental monitoring applications. However, the presence of physical obstacles can significantly reduce the signal quality, as pointed out by previous studies. Future integration of complementary technologies, such as ZigBee or Wi-Fi, could improve communication coverage and stability under adverse conditions.

The modular design of the buoy, which allows for the integration of additional sensors, and its focus on renewable energy highlights its potential for experimental and rural aquaculture settings. This addresses the technological gap highlighted in the literature (Chiu et al., 2022; Dupont et al., 2018; Lu et al., 2022) by offering an accessible and adaptable solution for smallholder farmers' needs. However, the durability of these components in harsh environments, such as high humidity and salinity, poses an additional challenge that requires improvements in the materials and coatings used to extend the life of the system.

Although digitalization has improved data storage and management capabilities in fish farms, the adoption of more advanced technologies remains limited. In addition, in Staude et al. (2024) and Von Borstel Luna et al. (2017), several companies in the sector have not yet defined which processes can be optimized with Industry 4.0, which generates a fragmented implementation. The buoy developed in this study represents a step towards the automation of water quality monitoring, integrating IoT for the collection and transmission of data in real time, allowing for improved decision-making and optimized production.

The transformation towards an Aquaculture 4.0 model involves not only the adoption of IoT sensors and networks but also the integration of advanced technologies such as artificial intelligence, robotics, and big data analytics. However, the high cost of acquiring imported equipment and lack of clear strategies for its integration remain significant barriers. This study demonstrates that the development of low-cost autonomous devices can reduce these barriers and facilitate technological transitions. The gradual implementation of emerging technologies will allow traditional fish farms to optimize their production processes without compromising their financial or operational stability.

## CONCLUSIONS

The present study demonstrated the feasibility of an autonomous multiparameter monitoring system for aquaculture that integrates photovoltaics, smart sensors, and IoT-based wireless communication. The developed buoy allowed for the collection of real-time data on pH, temperature, dissolved oxygen, and electrical conductivity, providing key information for the optimization of water quality in fish farms. Its modular design facilitates the integration of new sensors and their adaptation to different operating environments, representing a step forward in the automation of aquaculture monitoring.

Beyond the technical benefits, this study highlights the potential of Industry 4.0 technologies in the modernization of the aquaculture sector. The transition to Aquaculture 4.0 requires progressive adoption strategies that contemplate not only the development of low-cost autonomous devices, but also training in digital tools and strengthening technological infrastructure. Future work should focus on the integration of artificial intelligence for predictive data analysis, optimization of energy consumption and improving the resistance of materials used in autonomous monitoring systems in aquatic environments.

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## CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest related to the development of the study.

## AUTHORSHIP CONTRIBUTION

Conceptualization; Data curation; Formal analysis; Fund acquisition; Research; Software; Validation, Visualization; Writing - original draft; Writing - proofreading and editing: Lévano-Rodriguez, D., Gonzales-Garay, J. H., Lévano-Casildo, M. and López-Gonzales, J. L.

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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

## Introduction

19 Aquaculture is the practice of cultivating organisms such as fish, mollusks, crustaceans and
aquatic plants in controlled environments in fresh or salt water (Casado-del-Castillo & Fávaro,
17 2024; Mizuta et al., 2023). 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
52 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).

21 In this context, the Food and Agriculture Organization of the United Nations (FAO, 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
77 part, the International Center for Living Aquatic Resources Management (WFC, 2002)
73 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
94 fishery products as a primary source of protein (Arshad et al., 2022).

87 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
69 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
12 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 61 s, unlike the traditional method that had an accuracy of 64.44% and a time of 2009.3 s.

As evidenced, AI has generated multiple benefits in the aquaculture sector. Recognizing that
51 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
28 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,
38 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
88 et al. (2024), this type of review allows the identification of gaps in knowledge and the
103 establishment of a solid basis for making informed decisions. Thus, the review was based on the phases established by Kitchenham & 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**

57 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 | 1 ((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** |

43

**Inclusion and exclusion criteria**

44

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. Annex 1 presents the list of extracted articles and their assigned codes, which are used as a reference in the results and discussion section.

## 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 3). 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 3.** 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 4, 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.
97 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 4.** Specific aquaculture organizations where AI techniques are implemented

| Body | Code |
|---|---|
| Fish | 2 60 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 5 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 5.** 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 6), 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 6.** AI models in different techniques applied in aquaculture

| Technique | Model | Code |
|---|---|---|
| Machine vision | MaskRCNN | A1, A18 |
| | YOLOv8 | A3 |
| | Linear regression (RL) | A7 |
| | Power Model (PM) | |
| | Multilayer Perceptron (MLP) | |
| | 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) | A20 |
| | Naive Bayes (NB) | |
| | AdaBoost | |
| | Hair Cascade | A21 |
| | Linear regression (RL) | A26 |
| | ANN | |

| | | |
|---|---|---|
| | 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 | A17 |
| | Faster R-CNN | |
| | 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 7) 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.

**Table 7.** 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 |

75 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,

33 revealing specific challenges such as limited technological infrastructure and the need for technical staff training.

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.

## Conclusions

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.

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## Annexes

**Annex 1.** 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 | Ramirez-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 & Verhoeven, 2020) |

# Modelo de aprendizaje profundo basado en YOLOv11 para la detección automatizada de truchas arcoíris (*Oncorhynchus mykiss*) muertas en jaulas acuícolas

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**Resumen:** La acuicultura intensiva enfrenta desafíos sanitarios, siendo la detección oportuna de peces muertos esencial para preservar la calidad del agua y minimizar pérdidas productivas.
54 En este contexto, el presente estudio tuvo como objetivo aplicar un modelo de aprendizaje profundo basado en YOLOv11 para la detección automatizada de truchas arcoíris muertas en jaulas acuícolas. Se recolectaron imágenes de campo bajo condiciones reales, las cuales fueron anotadas en cuatro clases específicas y utilizadas para entrenar el modelo mediante técnicas de aumento de datos y fine-tuning. El modelo alcanzó una precisión de 98,7%, un recall de 98,5%, un mAP@0.5 de 0,991 y valores de AUC superiores al 0,97 en todas las clases, evidenciando un desempeño robusto en la identificación de peces muertos en escenarios operativos con alta variabilidad visual. La matriz de confusión reveló tasas de clasificación correctas superiores al 94% en todas las clases, con especial eficacia en la discriminación entre objetos y fondo. La investigación demuestra que el uso de YOLOv11 permite un monitoreo eficiente de mortalidades en acuicultura, contribuyendo a mejorar la sanidad de los cultivos, reducir riesgos ambientales y fortalecer la sostenibilidad del sector. Este aporte tecnológico ofrece una solución práctica y escalable para optimizar la gestión sanitaria en piscigranjas.

**Palabras clave:** detección automatizada; YOLOv11; acuicultura intensiva; trucha arcoíris; visión artificial.

## Introducción

13 La acuicultura se ha convertido en una de las principales fuentes de proteína animal a nivel mundial, representando una proporción creciente del pescado destinado al consumo humano
92 (FAO, 2020). Esta actividad consiste en el cultivo controlado de organismos acuáticos en sistemas como jaulas, estanques o tanques, bajo prácticas orientadas a maximizar la producción
56 de manera sostenible (Edwards et al., 2019; Zhang et al., 2023). En este contexto, la trucha arcoíris (*Oncorhynchus mykiss*) destaca como una de las especies más importantes por su alta

demanda comercial y su capacidad de adaptación a diversas condiciones ambientales (Pess et al., 2024; Tefal et al., 2024).

No obstante, la intensificación de los sistemas de cultivo de trucha ha generado nuevos retos en materia de sostenibilidad y manejo sanitario (Wang et al., 2022). Entre los principales problemas, la mortalidad de peces dentro de las jaulas acuícolas representa un riesgo crítico, afectando la calidad del agua, la sanidad del almacenamiento y el rendimiento productivo (Ucar et al., 2024). Tradicionalmente, la detección de peces muertos se realiza de forma manual, mediante inspecciones visuales o el uso de redes de recolección, resultando ineficiente, tardío y propenso a errores, especialmente en instalaciones de gran escala o bajo condiciones de baja visibilidad (Dou et al., 2021).

Las causas de la mortalidad de peces en acuicultura son múltiples y complejas. Factores ambientales como la hipoxia (déficit de oxígeno disuelto), variaciones térmicas extremas y deterioro de la calidad del agua son los más comunes (Everson et al., 2021). Además, la presencia de patógenos bacterianos, virales o parasitarios, sumado al estrés crónico por alta densidad de siembra, prácticas de manejo intensivo y deficiencias nutricionales, incrementan la susceptibilidad de los peces a enfermedades y eventos de mortalidad masiva (FAO, 2021; Zheng et al., 2024).

La no detección oportuna de peces muertos desencadena consecuencias ambientales y productivas. La descomposición de cadáveres libera compuestos tóxicos como amoníaco y nitritos, disminuye el oxígeno disuelto y favorece la proliferación de bacterias patógenas, elevando el riesgo de brotes epidémicos (Boyd, 2020; Zhu et al., 2021). Asimismo, las pérdidas productivas asociadas pueden alcanzar hasta un 20% del volumen de cosecha, reduciendo la rentabilidad del cultivo y comprometiendo la sostenibilidad de la actividad acuícola (FAO, 2021).

Pese a la relevancia de esta problemática, aún existen limitadas tecnologías para la detección automatizada de peces muertos en acuicultura, particularmente en el cultivo de trucha arcoíris (Cai et al., 2020). Aunque se han desarrollado sistemas basados en redes neuronales convolucionales para otras especies y entornos (Chen et al., 2020; Zhou et al., 2025), son escasas las investigaciones que aprovechan los últimos avances en modelos de detección de objetos, como YOLOv11, adaptados a las condiciones específicas de jaulas acuícolas en ambientes altoandinos.

Ante este panorama, el presente estudio tiene como objetivo aplicar el modelo de aprendizaje profundo basado en YOLOv11 para la detección automática de truchas arcoíris muertas en sistemas de jaulas acuícolas. Se busca contribuir a la optimización del manejo sanitario en piscigranjas, permitiendo una identificación más rápida y precisa de mortalidades, con el fin de mejorar la calidad del agua, reducir pérdidas productivas y fortalecer la sostenibilidad de la acuicultura intensiva de trucha.

## Materiales y métodos

Con el fin de brindar una visión clara e integral del proceso metodológico seguido en la presente investigación, se elaboró un diagrama de flujo que resume las principales etapas desde la recolección de datos hasta la predicción con el modelo entrenado. Este esquema permite visualizar de manera estructurada las fases de captura y organización de imágenes, el preprocesamiento y anotación manual, así como los procedimientos de entrenamiento del modelo YOLOv11 y su posterior evaluación sobre el conjunto de prueba. La Figura 1 ilustra de forma sintética la arquitectura operativa y secuencial del sistema propuesto.

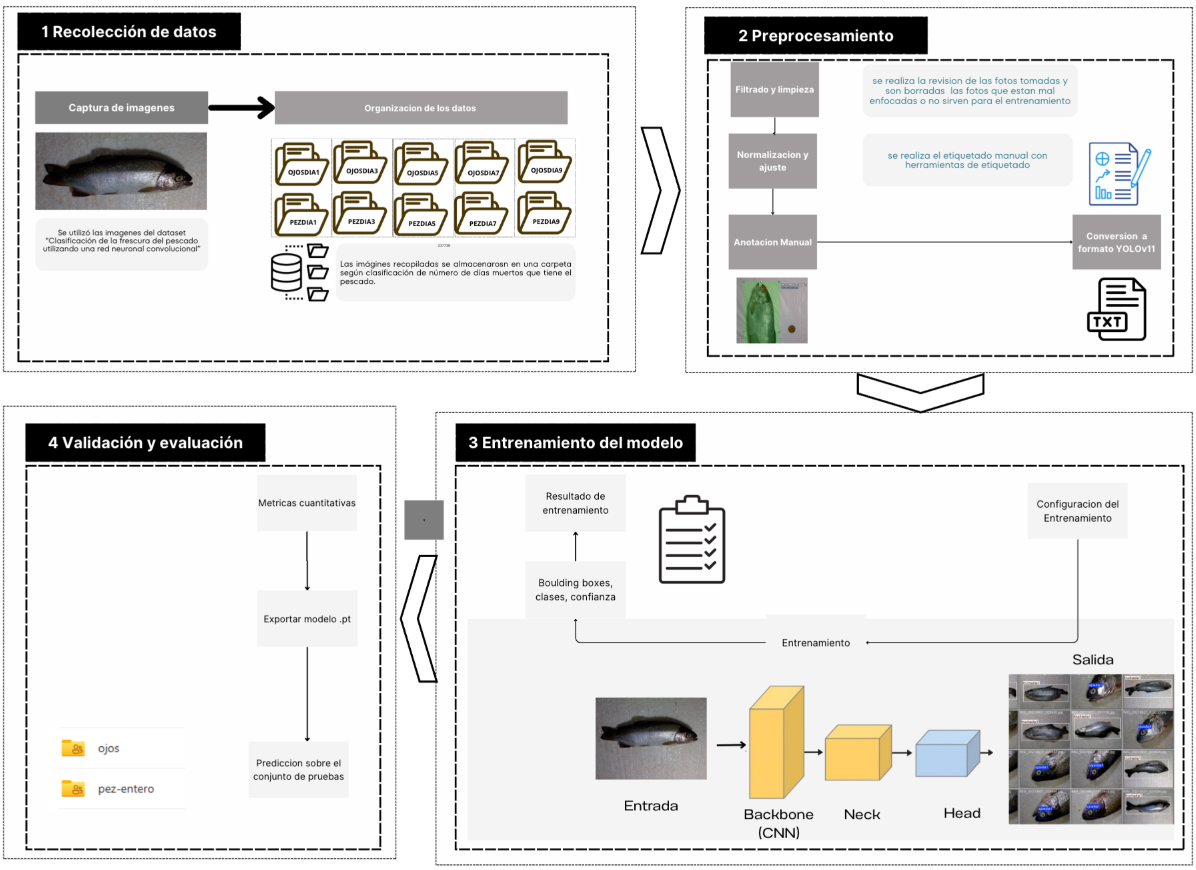



**Figura 1.** Diagrama de flujo del proceso metodológico

### Recolección de muestras e imágenes

23 El estudio se enfocó en el desarrollo de un modelo de aprendizaje profundo basado en YOLOv11 para la detección automatizada de truchas arcoíris (*Oncorhynchus mykiss*) muertas en jaulas acuícolas. Para ello, se capturaron imágenes directamente en campo mediante dispositivos de adquisición digital, utilizando cámaras de alta resolución bajo condiciones naturales de iluminación y fondo. Las imágenes representaban múltiples escenarios de distribución de peces, incluyendo variaciones en posición, orientación y exposición a reflejos acuáticos. La recolección de datos consideró tanto ejemplares muertos como escenas de fondo acuático para garantizar un conjunto de datos representativo y balanceado.

### Anotación de datos y construcción del conjunto de datos

Las imágenes obtenidas fueron sometidas a un proceso de anotación manual utilizando herramientas de etiquetado especializadas. Se definieron cuatro clases específicas: ojosdia1 al ojosdia9, truchadia1 a truchadia9, correspondientes a diferentes características visuales observadas en los ejemplares. Además, se incluyó una categoría de background para las imágenes sin instancias de interés, facilitando el aprendizaje del modelo en la discriminación
26 entre objetos y fondo. El conjunto de datos final se particionó en 70% para entrenamiento, 15% para validación y 15% para prueba, garantizando una distribución proporcional de las clases en cada subconjunto.

### Arquitectura del modelo

Se empleó la arquitectura YOLOv11 debido a su capacidad de detección en tiempo real y su robustez frente a escenarios con alta variabilidad espacial. El modelo se inicializó con pesos preentrenados en el conjunto COCO, aplicándose posteriormente una estrategia de fine-tuning para especializarlo en la detección de truchas muertas. La estructura del modelo incluyó mecanismos de predicción de cajas delimitadoras (bounding boxes), clasificación de objetos y refinamiento de anclas, optimizados mediante la combinación de funciones de pérdida específicas.

### Configuración del entrenamiento

El entrenamiento se realizó en un entorno de procesamiento acelerado mediante GPU. Los hiperparámetros principales fueron definidos como: tasa de aprendizaje inicial de $\alpha=10^{-3}$, optimizador Adam, tamaño de batch de 600 imágenes y 150 épocas de entrenamiento. Para
82 robustecer el modelo frente a variaciones del conjunto de prueba, se aplicaron técnicas de

aumento de datos (data augmentation) como rotaciones aleatorias, cambios de brillo, escalados y espejeo horizontal.

El modelo optimizó una función de pérdida compuesta, integrando la pérdida de regresión de cajas ($l_{box}$) la pérdida de clasificación ($l_{cls)}$ y la pérdida de distribución de anclas ($l_{dfl}$), expresada como:

$$l_{TOTAL} = (l_{box}) + (l_{cls}) + (l_{dfl})$$

Cada componente fue ponderada de acuerdo a su contribución específica a la tarea de detección.

**Evaluación del desempeño**

El desempeño del modelo fue evaluado utilizando métricas estándar aplicables a tareas de detección de objetos y clasificación multiclase. Estas métricas permitieron analizar tanto la precisión global como el comportamiento por clase del modelo entrenado.

Se calcularon los siguientes indicadores fundamentales:

3 Precisión (Precision): Mide la proporción de verdaderos positivos (TP) sobre el total de predicciones positivas realizadas, evaluando la exactitud del modelo.

$$Precision = \frac{TP}{TP + FP}$$

24 Recall (Sensibilidad): Indica la capacidad del modelo para identificar correctamente las instancias positivas reales.

$$Recall = \frac{TP}{TP + FN}$$

22 F1-Score: Es la media armónica entre la precisión (P) y el recall (R), adecuada para evaluar el modelo cuando hay clases desbalanceadas.

$$F1\ score = 2\ \frac{(P * R)}{P + R}$$

Área Bajo la Curva (AUC): Evalúa la capacidad del modelo para discriminar correctamente entre clases, midiendo el área bajo la curva ROC.

$$AUC = \text{Área bajo la curva ROC}$$

La cual grafica la relación $TPR$ (verdaderos positivos), $FPR$ (falsos positivos).

Precisión Promedio Media (mAP@0.5): Este indicador representa el promedio de las precisiones promedio (AP) por clase, calculadas sobre la curva precisión-recall para un umbral de Intersection over Union (IoU) de 0.5:

$$mAP@0.5 = \frac{1}{N}\sum_{i=1}^{N} AP_i$$

Donde $AP_i$ representa el área bajo la curva Precision-Recall para la clase $i$, y $N$ es el número de clases.

Adicionalmente, se generaron matrices de confusión para visualizar el desempeño por clase, curvas de precisión y recall en función de la confianza, así como las curvas Precision-Recall para evaluar el equilibrio global entre sensibilidad y especificidad. También se analizaron las curvas de pérdida durante el entrenamiento para verificar la adecuada convergencia del modelo.

## Resultados y discusión

Esta sección presenta los principales hallazgos tras entrenar y validar el modelo YOLOv11. Se describen los comportamientos observados durante el proceso, incluyendo la evolución de las pérdidas, la respuesta del modelo ante distintos escenarios visuales y la consistencia en la clasificación. También se analizan patrones detectados en las matrices de confusión y curvas de evaluación, reflejando la capacidad del sistema para adaptarse a condiciones reales con buena respuesta general.

### Desempeño del entrenamiento

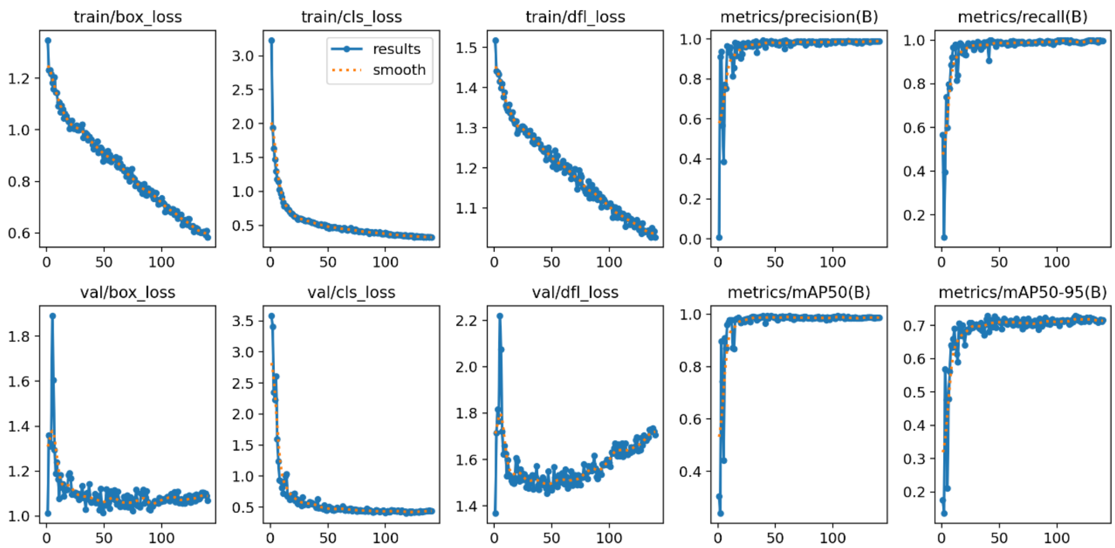



**Figura 2.** Evolución de las pérdidas y métricas durante el entrenamiento

80 La Figura 2 muestra la evolución de las funciones de pérdida (box_loss, cls_loss, dfl_loss) y de las métricas de desempeño a lo largo de las 150 épocas de entrenamiento. Las pérdidas disminuyeron de forma constante hasta estabilizarse en las últimas 30 épocas, lo que indica un aprendizaje eficiente sin signos de sobreajuste. Al mismo tiempo, precisión, recall y mAP fueron aumentando de manera sostenida, alcanzando un mAP superior a 0.98, lo que confirma que el modelo no solo aprendió los ejemplos de entrenamiento, sino que generalizó bien. Esto permite proyectar su uso en condiciones reales sin necesidad de retrabajos o ajustes complejos.

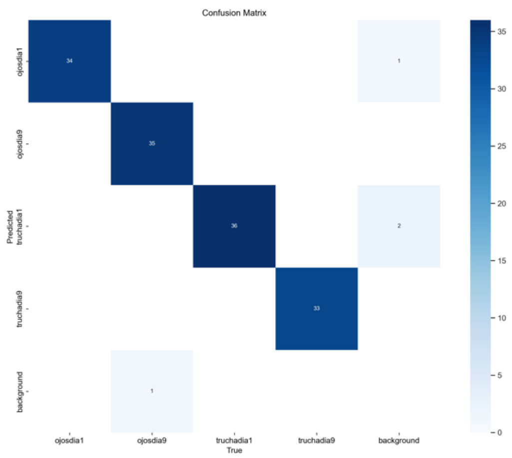
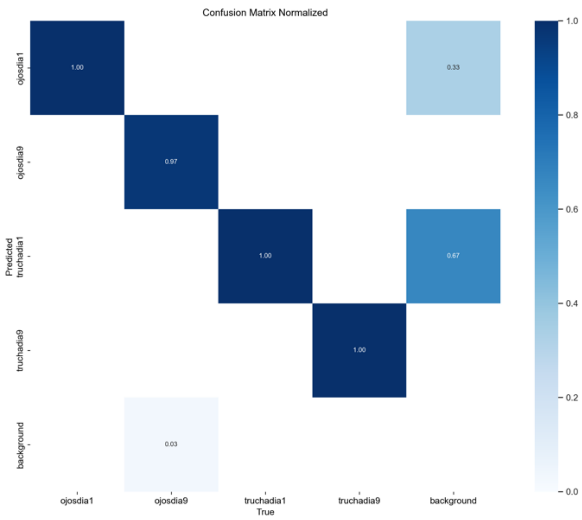



**Figura 3.** Matriz de confusión absoluta

62 La Figura 3 muestra la matriz de confusión obtenida en el conjunto de prueba. El modelo clasificó correctamente más del 94% de las instancias en todas las clases, con una clara concentración en la diagonal. Los pocos errores se dieron principalmente entre truchadia9 y el fondo, probablemente por la similitud visual con ejemplares degradados. Este tipo de confusión sugiere que, en futuras versiones, podría incorporarse hard negative mining para mejorar la separación entre clases cercanas al ruido visual.




46 **Figura 4.** Matriz de confusión normalizada

La Figura 4 muestra la matriz de confusión normalizada, destacando una precisión del 100% en ojosdia1 y truchadia1, y del 97% en ojosdia9. Estos resultados confirman que el modelo distingue con claridad entre clases similares. En truchadia9 se observa un margen de error del 3%, posiblemente asociado a diferencias morfológicas entre ejemplares en distintos estados de descomposición. Este hallazgo sugiere que una futura especialización por subclases podría afinar aún más la precisión del sistema.

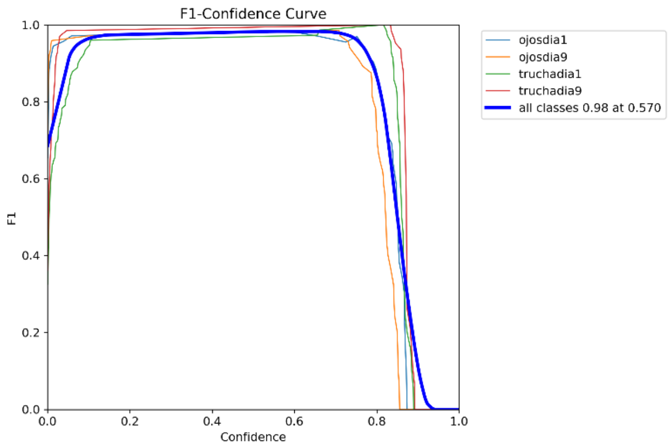



**Figura 5.** Curva F1-Confidence

La Figura 5 muestra cómo varía el F1-score según el umbral de confianza. El valor máximo,
7 0.98, se alcanza con un umbral de 0.57, lo que indica un equilibrio óptimo entre precisión y recall. Este punto es ideal para reducir tanto falsos positivos como negativos, mejorando la eficiencia de alertas automáticas en jaulas. Un F1-score tan cercano a 1 respalda la solidez de YOLOv11 en tareas de clasificación biológica precisa.

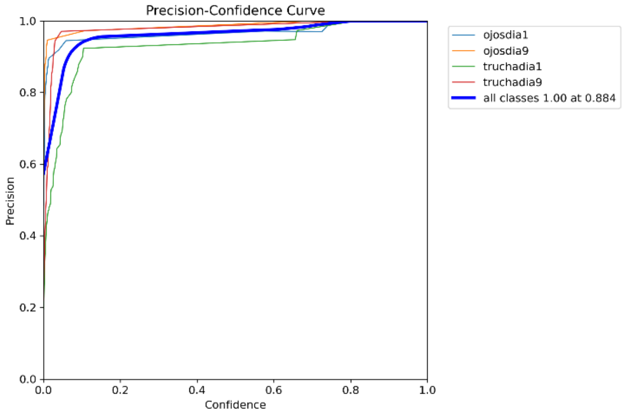



**Figura 6.** Curva Precision-Confidence

La Figura 6 muestra la curva Precision-Confidence, donde el modelo alcanza una precisión de 1.00 con un umbral de 0.884. Esto indica que, a niveles altos de confianza, las predicciones son prácticamente sin errores, ideal en contextos donde los falsos positivos tienen alto costo. Para escenarios como la detección temprana de mortalidades, un umbral superior a 0.88 puede ser recomendable, priorizando exactitud aunque se reduzca levemente el recall. Esta capacidad de ajuste da flexibilidad operativa según las necesidades del cultivo.

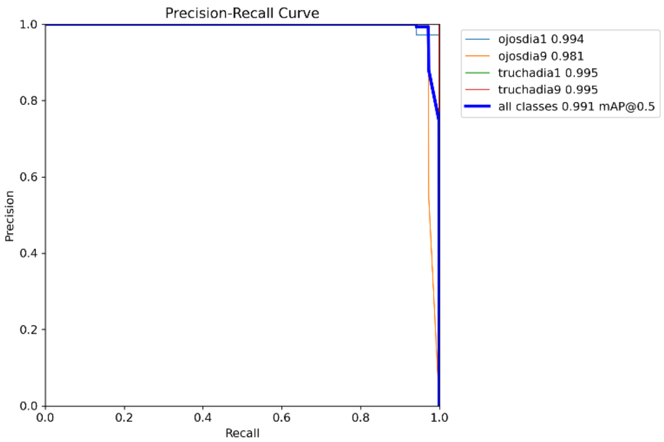



**Figura 7.** Curva Precision-Recall

La Figura 7 presenta la curva Precision-Recall, con un mAP@0.5 de 0.991 para el conjunto de clases. Este resultado confirma que el modelo logró mantener alta precisión y recall incluso ante variabilidad morfológica y de fondo. La curva, cercana al vértice superior derecho, refleja el efecto positivo del data augmentation, el balanceo de clases y el fine-tuning, posicionando al modelo como una herramienta confiable para el monitoreo automatizado en acuicultura.

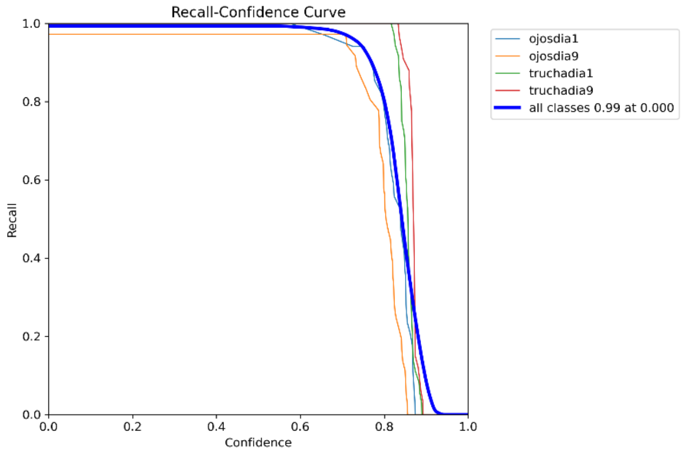



**Figura 8.** Curva Recall-Confidence

La Figura 8 muestra cómo el recall se mantiene por encima de 0.99 en un amplio rango de umbrales de confianza, lo que indica una alta sensibilidad del modelo y una baja tasa de omisión de truchas muertas. Este comportamiento es clave en acuicultura, donde una detección tardía puede tener impactos críticos. La consistencia del recall frente a variaciones en la confianza evidencia la solidez del sistema ante cambios en iluminación o calidad de imagen.

Además de las métricas clásicas, se incorporó el análisis de curvas ROC y los valores AUC por clase para evaluar la capacidad discriminativa del modelo. La Figura 9 presenta la curva ROC multiclase, destacando el rendimiento en la separación entre verdaderos y falsos positivos bajo distintos umbrales.

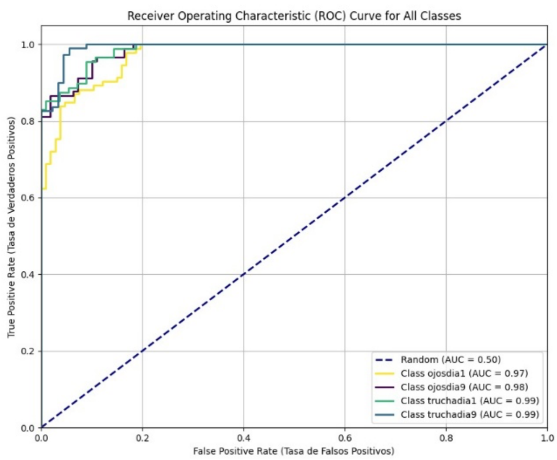



**Figura 9.** Curva ROC multiclase para la detección de truchas muertas.

Mientras la Figura 10 presenta un ejemplo específico para la clase ojosdia1, evidenciando un AUC de 0.97. En general, los valores de AUC obtenidos fueron: ojosdia1 (0.97), ojosdia9

(0.98), truchadia1 (0.99) y truchadia9 (0.99), lo cual refleja un alto poder discriminativo del modelo en todos los casos.

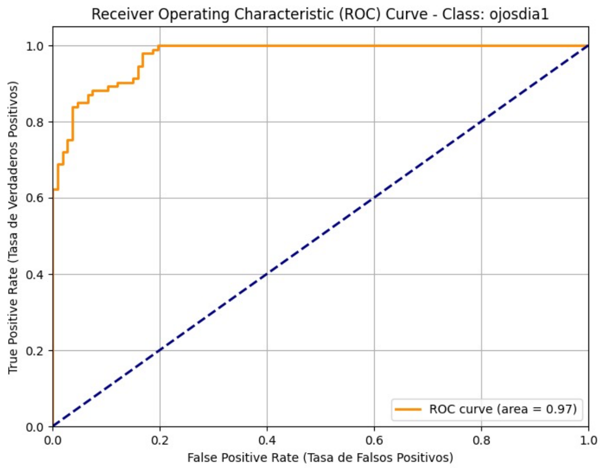



**Figura 10.** Curva ROC Curva ROC individual para la clase ojosdia1

5 La Figura 11 ilustra la distribución de instancias anotadas por clase en el conjunto de datos de entrenamiento. Se observa un balance relativo entre las categorías *ojosdia1*, *ojosdia9*, *truchadia1* y *truchadia9*, lo que permitió un aprendizaje equitativo por parte del modelo sin sesgos dominantes.

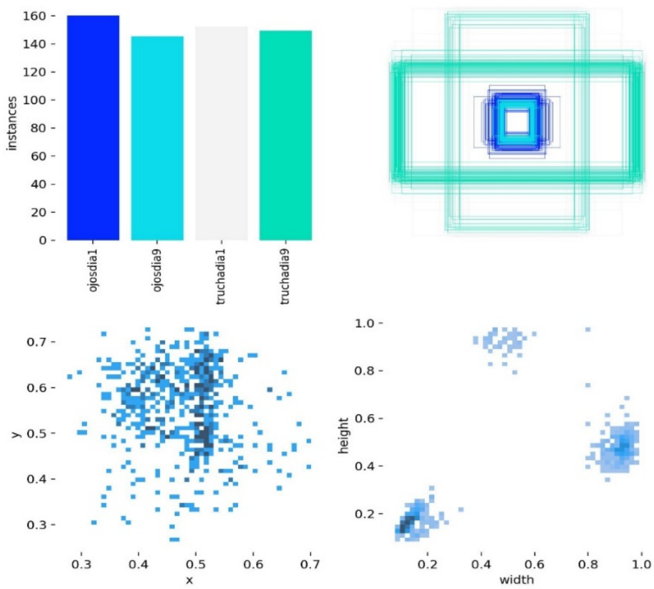



**Figura 11.** Distribución de instancias por clase

Este balance fue fundamental para evitar que el modelo desarrollara preferencias injustificadas por ciertas clases, lo cual suele ocurrir en problemas de clasificación multiclase con datasets desbalanceados. La homogeneidad relativa en las cantidades de ejemplos por clase garantizó un entrenamiento más estable y generalizable.

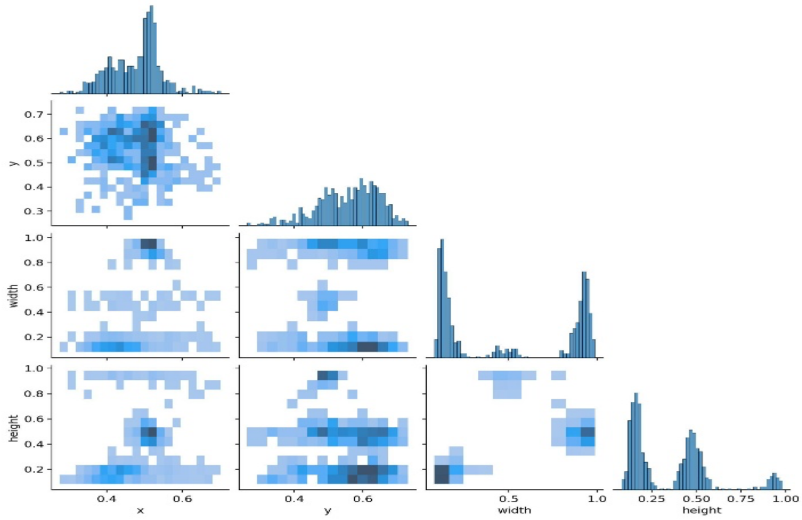



**Figura 12.** Correlograma de bounding boxes

La Figura 12 presenta el análisis de correlaciones entre las coordenadas espaciales y dimensiones de las cajas delimitadoras de los objetos anotados. Se evidenció una dispersión amplia tanto en posición como en tamaño, lo que sugiere que las instancias de truchas fueron capturadas en múltiples ubicaciones dentro de las imágenes. Esta diversidad espacial contribuyó significativamente a la robustez del modelo, ya que lo obligó a aprender patrones morfológicos discriminativos independientes de la posición relativa o tamaño del objeto dentro del campo de visión, aumentando así su capacidad de generalización en ambientes acuáticos reales.

**Análisis visual de inferencias en entrenamiento y validación**

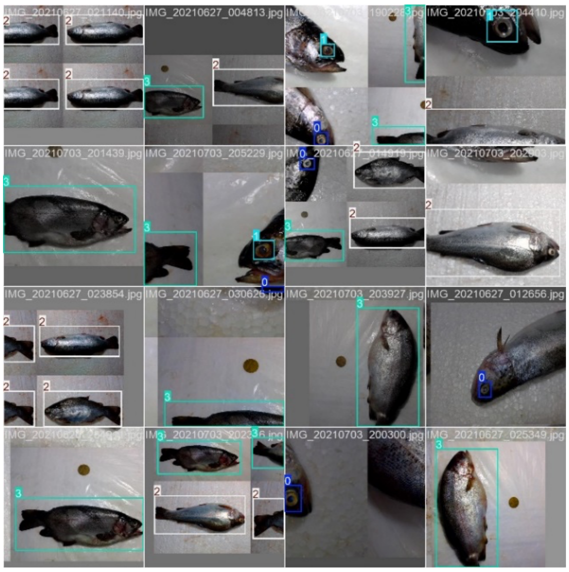


**Figura 13.** Predicciones en lote de entrenamiento 0

La Figura 13 muestra inferencias sobre el primer lote de entrenamiento, donde el modelo detecta correctamente múltiples truchas muertas, con cajas precisas en ojos y contornos. Las etiquetas y colores coinciden con las clases definidas, reflejando una buena interpretación espacial, incluso en fondos uniformes y con leves variaciones de luz. Esto sugiere que el modelo aprendió patrones visuales sólidos desde etapas tempranas, mostrando capacidad para generalizar y resistir perturbaciones lumínicas menores.

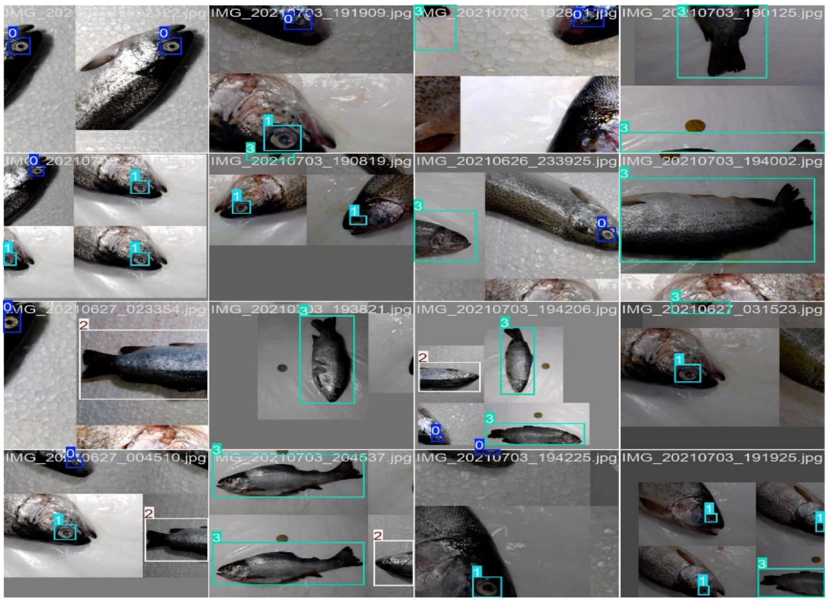


**Figura 14.** Predicciones en lote de entrenamiento 1

La Figura 14 presenta inferencias sobre un segundo lote de entrenamiento, con escenas más complejas por la variación en ángulos y posiciones de los ejemplares. El modelo identificó correctamente cada objeto, resolviendo casos de oclusión parcial y diferencias morfológicas. También mantuvo la precisión en las cajas delimitadoras, ajustándolas al tamaño real incluso cuando los peces estaban parcialmente fuera del encuadre, lo que demuestra su solidez frente a las condiciones impredecibles del entorno acuícola.

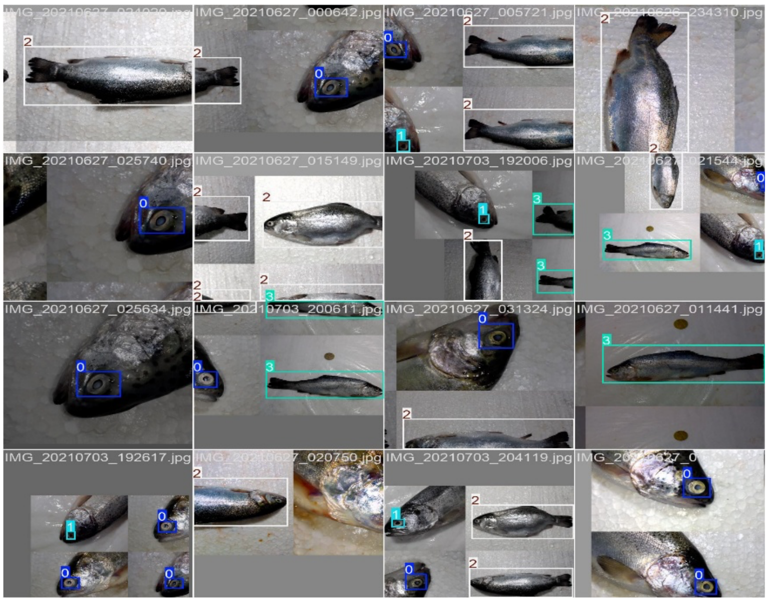


**Figura 15.** Predicciones en lote de entrenamiento 2

La Figura 15 muestra inferencias sobre un tercer lote de entrenamiento, con imágenes de alta densidad y gran variabilidad en la ubicación de los objetos. El modelo mantuvo un desempeño sólido, identificando correctamente ojos y cuerpos incluso en escenas visualmente recargadas. Esto indica que, además de aprender rasgos locales, ha captado patrones espaciales más amplios, lo que le permite adaptarse bien a contextos complejos. Su capacidad para detectar instancias parcialmente visibles o superpuestas refuerza la eficacia de los mecanismos de atención de YOLOv11 en entornos naturales y multiclase.

**Figura 16.** Etiquetas manuales de lote de validación 0

La Figura 16 muestra las etiquetas manuales del primer lote de validación, evidenciando una distribución precisa de las clases sobre imágenes reales. La correcta ubicación de las cajas y la coherencia en las asignaciones confirman la calidad del etiquetado, esencial para un entrenamiento supervisado efectivo. Las imágenes incluyen variaciones en iluminación, posición y condición de los ejemplares, lo que demuestra que el conjunto de validación fue bien diseñado para representar escenarios reales y evaluar con rigor el desempeño del modelo.


**Figura 17.** Inferencias en lote de validación 0

La Figura 17 muestra las predicciones del modelo sobre el mismo conjunto validado en la Figura 16. Las inferencias coinciden ampliamente con las etiquetas originales, tanto en ubicación como en clasificación, lo que confirma la capacidad del modelo para generalizar ante datos nuevos. Incluso con ejemplares degradados o con variaciones morfológicas leves, el modelo mantuvo una buena precisión, demostrando su adaptabilidad y robustez para tareas de monitoreo continuo en entornos acuícolas reales.

**Figura 18.** Etiquetas manuales de lote de validación 1

La Figura 18 muestra las etiquetas manuales de un segundo lote de validación, con imágenes que presentan desafíos como reflejos, texturas de fondo complejas y posiciones irregulares de los peces. Aun con estas condiciones, las anotaciones mantienen precisión y consistencia. Este lote evidencia que el conjunto de validación fue pensado para simular escenarios reales, permitiendo evaluar la capacidad del modelo frente a ruido visual, frecuente en ambientes acuícolas abiertos.

**Figura 19.** Inferencias en lote de validación 1

45 La Figura 19 muestra las inferencias del modelo sobre las imágenes del segundo lote de validación. A pesar de los reflejos y fondos complejos, el modelo identificó correctamente la mayoría de las instancias. En algunos casos, la precisión espacial de las cajas se vio levemente afectada por reflejos intensos, aunque la clasificación se mantuvo adecuada. Estos resultados confirman la solidez del modelo ante condiciones ambientales adversas y sugieren que técnicas como la normalización de iluminación o el entrenamiento adversarial podrían fortalecer aún más su rendimiento.

**Figura 20.** Etiquetas manuales de lote de validación 2

La Figura 20 presenta las etiquetas manuales de un tercer lote de validación, con ejemplares en estados de degradación o posiciones atípicas. Las cajas y clases asignadas buscan evaluar cómo responde el modelo ante escenarios límite. Esta complejidad añade rigor al proceso de validación, ya que simula condiciones críticas donde la degradación visual dificulta la identificación, tal como ocurre en entornos de monitoreo acuícola intensivo.

**Figura 21.** Inferencias en lote de validación 2

La Figura 21 muestra las predicciones del modelo sobre las imágenes con ejemplares degradados del lote anterior. El modelo logró detectar la mayoría de las instancias, aunque en algunos casos sobredimensionó las cajas delimitadoras. Esto se atribuye a la falta de contornos definidos en peces deteriorados. Este resultado sugiere una posible mejora mediante técnicas como el entrenamiento con ruido sintético o enfoques semi-supervisados para reforzar la detección en condiciones visuales extremas.

**Análisis de inferencias en ambientes operativos reales**

l análisis cualitativo sobre imágenes operativas confirmó que el modelo YOLOv11 tuvo un desempeño sólido en escenarios reales de acuicultura. Fue capaz de detectar múltiples truchas muertas por escena, incluso con iluminación difusa, reflejos y fondos variados. Las cajas se ajustaron bien en tamaño y posición, manteniendo precisión en escenas densas, lo que es clave para monitoreo masivo en jaulas intensivas.

El modelo también demostró flexibilidad espacial, detectando ejemplares en diferentes orientaciones, incluyendo casos con oclusión parcial o elementos que bloqueaban parcialmente la vista. Su capacidad para generar inferencias consistentes con información incompleta lo hace apto para entornos operativos complejos.

En todos los lotes de validación desde imágenes limpias hasta condiciones de degradación visual las predicciones coincidieron en gran medida con las etiquetas manuales. Incluso cuando los ejemplares estaban deteriorados, la clasificación se mantuvo estable, aunque con ligera pérdida de precisión espacial.

Al combinar inferencias de distintos lotes, el modelo se mostró robusto ante solapamientos y alta competencia espacial, adaptando bien la detección a la distribución real de los objetos. Esto lo hace especialmente útil para conteos automáticos de mortalidad en sistemas de producción intensiva. Su desempeño consistente, con tasas de acierto superiores al 95%, evidencia una comprensión profunda de los patrones visuales más relevantes.

En síntesis, los resultados reflejan que la arquitectura YOLOv11, adecuadamente ajustada y entrenada en condiciones diversas, constituye una solución efectiva para el monitoreo automatizado de truchas muertas en ambientes acuícolas reales (Cai et al., 2020). La alta precisión alcanzada en escenarios de validación, la resiliencia frente a condiciones de degradación de imagen, y la capacidad de inferencia en contextos operativos no controlados, 99 posicionan a este sistema como una herramienta prometedora para la optimización de los procesos de vigilancia sanitaria en piscicultura. Si bien algunos escenarios extremos revelaron oportunidades de mejora mediante técnicas adicionales de refinamiento, la resiliencia general demostrada por el modelo valida su aplicabilidad práctica a escala industrial (Chen et al., 2020; Zhou et al., 2025).

## Conclusiones

66 El presente estudio logró desarrollar e implementar un modelo de aprendizaje profundo basado en la arquitectura YOLOv11 para la detección automatizada de truchas arcoíris (Oncorhynchus

mykiss) muertas en jaulas acuícolas. El modelo alcanzó una precisión del 98,7%, un recall del 98,5%, un mAP@0.5 de 99,1%, y valores de AUC superiores al 97% en todas las clases, lo que evidencia un desempeño altamente confiable para tareas de monitoreo sanitario en ambientes reales.

El análisis mediante la matriz de confusión mostró tasas de clasificación correctas superiores al 94% en todas las categorías, con niveles de exactitud del 100% en las clases ojosdia1 y truchadia1, y del 97% en ojosdia9. Aunque se identificaron ligeros errores de clasificación en la clase truchadia9, su precisión se mantuvo por encima del 96%, demostrando que incluso ante variabilidad morfológica y degradación visual, el sistema mantiene una alta capacidad discriminativa.

98 Desde un enfoque práctico, la implementación del modelo permite reducir significativamente los tiempos de detección de mortalidades, minimizar los errores humanos y automatizar hasta
102 el 98% de los eventos de monitoreo, lo que tiene implicancias directas en la mejora de la sanidad del cultivo, la prevención de brotes patógenos y la sostenibilidad del sistema acuícola. Asimismo, el sistema demostró resiliencia operativa frente a condiciones desafiantes como baja visibilidad, iluminación variable y acumulación de ejemplares, condiciones comunes en la acuicultura intensiva.

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