Review

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Research Progress of Artificial Intelligence in Intelligent Fisheries Breeding in Prediction and Health Management Systems

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Review

Research Progress of Artificial Intelligence and Sensors in Intelligent Fishery Aquaculture Prediction and Health Management System

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Abstract: The research in this review emphasizes the crucial importance of integrating artificial intelligence (AI) into aquaculture to improve efficiency, sustainability, and fish health management. The current aquaculture practices face significant challenges, such as data quality issues, incomplete and noisy data, and the complexity of managing various environmental and biological factors that affect fish health. To address these challenges, this review explores advanced artificial intelligence methods, including deep learning, the Internet of Things (IoT), and sensor fusion technologies, to develop powerful predictive and health management (PHM) systems in aquaculture. This study summarizes various methods based on artificial intelligence for real-time monitoring, disease detection, and optimizing feeding strategies, which improve the overall management of aquaculture operations. These methods involve the use of high-precision sensors, automatic image and acoustic data acquisition, as well as complex data preprocessing and integration techniques. Overall, these technologies aim to ensure accurate and real-time monitoring and predictive analysis of fish health and environmental conditions. The research results indicate that the fusion technology of artificial intelligence and sensors has achieved success in significantly improving fish growth rate, reducing environmental impact, and enhancing operational efficiency. The integration in aquaculture provides a transformative approach, offering valuable insights and practical solutions for sustainable and intelligent fish farming. This study emphasizes the value of integrating artificial intelligence and sensors in improving predictive capabilities, optimizing resource utilization, and ensuring the ecological sustainability of aquaculture practices, thereby promoting the growing global demand for efficient and sustainable fish production systems.

Keywords: aquaculture; artificial intelligence; predictive health management; sensors; data integration; Internet of Things; real-time monitoring

1. Introduction

Over the past decade, predictive health management (PHM) systems have been implemented across various industrial sectors, revolutionizing maintenance approaches and enhancing operational efficiency. A PHM system encompasses seven key components: data collection, data processing, health indicator construction, fault detection, diagnosis, prediction, and decision-making [1]. This system leverages condition monitoring data and insights from operational staff to assess system health, identify potential anomalies, diagnose impending faults, and predict the remaining useful life (RUL). The insights and directives generated by the PHM guide the scheduling of maintenance tasks, thereby ensuring the system's availability, reliability, and safety[2].

Since the early 2010s, the advent of data science and cloud computing has transformed numerous sectors, including predictive maintenance, into mainstream industries while serving as catalysts for forecasting technological advancements. In response to these developments, Sindre et al. (2022) categorized modern data-driven prediction methods into three distinct groups: model-based or physics-based methods, data-driven methods, and hybrid methods[3]. This classification has gained popularity and is now broadly applicable to predictive health management (PHM) systems.

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Modern industry aims not only to enhance the safety of work environments but also to demand higher availability and reliability of production systems. One approach to meet these requirements is the development of autonomous systems from a system health management perspective. Autonomous PHM systems continuously monitor multiple connected devices via IoT and cloud-driven databases. These systems automatically utilize the acquired data for remaining useful life (RUL) prediction through advanced analytics and intelligent algorithms[1]. Beyond prediction, decision-making is crucial, with advanced algorithms enabling real-time, autonomous decisions based on predictive outcomes. Consequently, transitioning from traditional PHM systems to those driven by artificial intelligence (AI) is advisable.

In fisheries and aquaculture, the integration of Predictive Health Management (PHM) systems represents a leading-edge innovation, enhancing productivity and promoting the sustainability of farming practices. Within aquaculture, PHM encompasses the entire breeding cycle, from data collection and processing to health indicator development, fault detection, diagnosis, prediction, and decision-making. These elements collectively facilitate the intelligent management of aquatic resources.

The emerging field of artificial intelligence (AI) plays a pivotal role in enhancing the automation of Predictive Health Management (PHM) systems, from data analysis to decision-making. AI-driven PHM systems show great potential to revolutionize aquaculture practices by enabling autonomous systems that allow for continuous monitoring and real-time decision-making through predictive analytics. Despite the extensive literature on AI applications across various fields, there remains a noticeable absence of a comprehensive review that outlines state-of-the-art AI methods utilized within the PHM domain, specifically in the context of smart fisheries and aquaculture.

Recent advances in data science, cloud computing, and the Internet of Things (IoT) are propelling the development of predictive maintenance within aquaculture, aligning with the overarching goals of Industry 4.0. These technological breakthroughs facilitate the collection and analysis of extensive data sets from interconnected aquaculture systems, offering fresh insights into Predictive Health Management (PHM) systems. However, they also introduce substantial challenges to the current implementation of PHM[4].

Intelligent fishery farming, utilizing the Predictive Health Management (PHM) system and artificial intelligence technology, actively monitors, manages, and addresses real-time farming challenges, as depicted in Figure 1. In reaction to fish disease outbreaks, the PHM system continuously monitors the breeding environment and fish health, employing data analysis and pattern recognition to facilitate early disease diagnosis and warnings. This capability enables farmers to implement timely preventative and control measures, significantly reducing disease outbreak risks and impacts. Furthermore, by analyzing disease patterns and causes, the PHM system assists farmers in optimizing disease prevention strategies, thereby enhancing the efficiency and effectiveness of epidemic prevention. In terms of water quality management, the PHM system constantly tracks water quality parameters and autonomously adjusts water treatment equipment to ensure optimal conditions, fostering a favorable growth environment for fish and diminishing disease risks. The extensive water quality data collected serves as a scientific foundation for making precise and efficient water quality management decisions. Feed management, a critical aspect of fish farming, benefits from algorithms that assess the real-time nutritional needs of fish populations, enabling precise feeding that meets dietary requirements while minimizing overfeeding and feed waste, thus reducing costs. Additionally, in an era of rising labor costs, the PHM system reduces the need for daily manual operations and reliance on skilled technicians by requiring only routine system maintenance, thereby significantly enhancing breeding efficiency and economic returns through the automation and intelligent upgrading of fish farming operations.

This article comprehensively reviews research on intelligent fishery breeding prediction and health management systems powered by artificial intelligence. Section 2 discusses key factors influencing feeding strategies. Section 3 outlines the architecture and functionality of intelligent fish farming prediction and health management systems driven by AI. Sections 4 and 5 provide a detailed analysis of the principal technologies used for collecting and processing data on farmed fish. Section

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6 details the development of an overall fish health index (HI). Section 7 explores the challenges and potential solutions associated with smart feeding techniques. Section 8 concludes the paper.

This review addresses a gap in existing literature by offering a holistic overview of AI-based methodologies for fish farming PHM systems, providing a unique perspective that encompasses the entire PHM process from data collection to decision support. It aims to enhance understanding and interest in AI applications within fishery farming, aiding academics and industry professionals in fostering sustainable and intelligent advancements in fisheries and aquaculture.

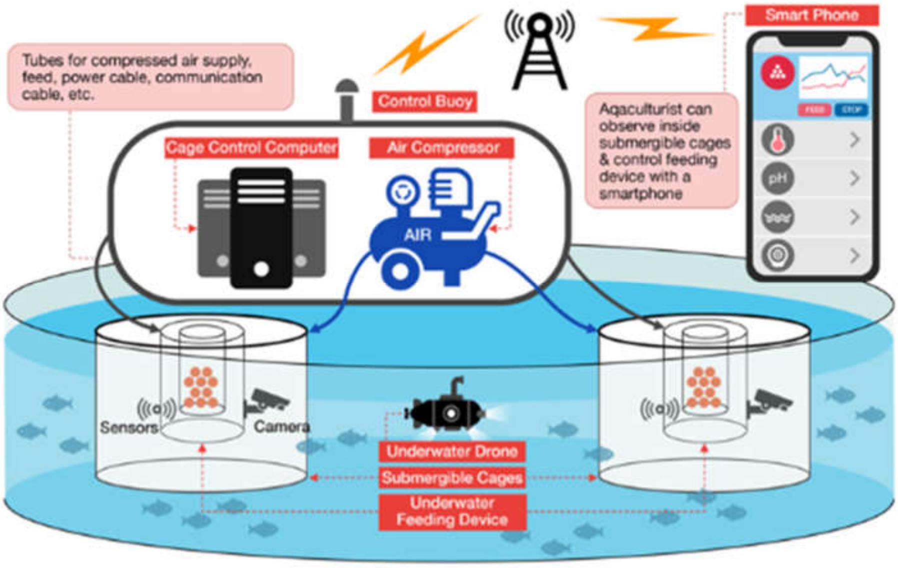

Figure 1. Fishery breeding prediction and health management system model.

2. Materials and Methods

AI-based Prognostic Health Management (PHM) systems are spearheading the transformation of the aquaculture industry by orchestrating the entire farming process to manage the complex interactions that influence fish farming. These systems harness data from aquaculture operations to monitor the health and nutritional status of fish, facilitating early disease detection and the implementation of effective feeding strategies[5]. Artificial intelligence algorithms are employed to optimize fish stocking density, balance resource allocation, and alleviate breeding pressure. Moreover, the AI-driven PHM systems devise optimal feeding plans based on satiety, enhancing feed conversion efficiency to support growth and minimize waste. By analyzing extensive data sets, these systems offer a comprehensive view of the health and productivity of aquaculture operations, enabling timely interventions. The integration of artificial intelligence into PHM systems ensures that aquaculture management is data-driven, adaptable, and consistent with conservation priorities. This strategy not only preserves ecological sustainability but also boosts operational productivity to meet the escalating global demand for fish and fosters robust, sustainable aquaculture ecosystems.

During the breeding phase, the PHM system executes precise breeding based on the unique conditions of the fish, significantly impacting their growth. As illustrated in Figure 2, fish growth is influenced not only by intrinsic factors but also by external environmental changes, feed quality, and other variables. Consequently, this section primarily examines the effects of the fish's intrinsic characteristics, external environmental factors, and feed on their growth.

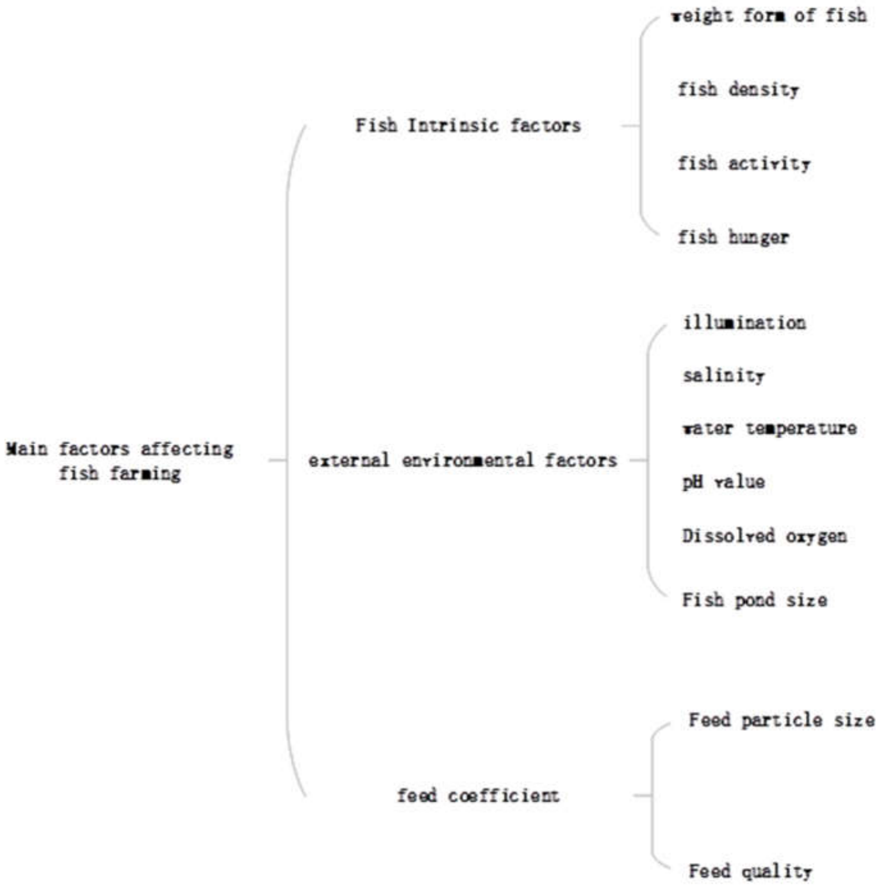

Figure 2. Main factors affecting fish farming.

2.1. Fish intrinsic factors

The intrinsic factors of the fish are the primary determinants of feeding. Should the total mass of the fish in the nursery change, or their individual conditions alter, their dietary requirements will consequently adapt.

2.1.1. Weight Form of Fish

In aquaculture, fish weight and morphology are widely regarded as critical indicators of their growth and health. Accurate data on these parameters are essential for effective breeding management, reflecting breeding outcomes and forming the foundation for enhancing breeding efficiency. Body weight serves as a direct measure of fish growth rate and feed conversion efficiency. According to the Food and Agriculture Organization of the United Nations (FAO), the feed conversion ratio (FCR) for farmed fish typically ranges from 1.1 to 1.5, implying that 1.1 to 1.5 kilograms of feed are needed to produce one kilogram of fish. Regular monitoring of fish weight allows farmers to track growth progress and assess the quality and efficacy of the feed. Should the weight gain fall short of expectations, farmers can promptly modify the feed formula or feeding strategy to optimize FCR, minimize feed wastage, and cut breeding costs[6]. Moreover, morphological features, particularly abnormal changes, often signal health issues. The prevalence of morphological abnormalities in fish, as noted in a study published by SPRINGER LINK, can indicate the quality of water and stress levels in the culture environment. Abnormalities such as scoliosis, fin damage or deformity, and anomalies in skin, scales, or eyes might suggest issues such as infectious diseases, parasite infestations, poor nutrition, or exposure to environmental toxins. Prompt identification and treatment of these issues are crucial for disease prevention and maintaining the health of the fish population. Thus, by integrating these indicators with regular monitoring and analysis, farmers can refine management practices, adjust breeding strategies promptly, and enhance both the economic returns and ecological sustainability of the breeding operations[7].

2.1.2. Density of Fish Schools

Fish density is a critical factor as it influences both fish behavior and health. Excessively high densities can precipitate competition among fish, leading to inadequate food and space. Research indicates that overly dense aquaculture conditions exacerbate stress responses in fish, impair immune system functionality, and thereby increase disease prevalence. Conversely, excessively low densities result in resource wastage. In a given breeding area, if fish are sparsely distributed, space and feed resources are underutilized, diminishing breeding efficiency. Consequently, the proportion of breeding costs attributed to each unit of output escalates, resulting in diminished economic returns[8]. Therefore, maintaining optimal densities is vital for both fish welfare and the economic sustainability of aquaculture operations. This requires a delicate balance, taking into account the species-specific behaviors and needs of the fish.

2.1.3. Fish Activity

Fish activity is a dynamic indicator of the state of the aquaculture environment and can provide insight into fish health. Healthy fish typically display certain activity patterns, including foraging, swimming, and social behaviors. By observing changes in these behavioral patterns, farmers can obtain important information about the health of fish stocks and the quality of the environment. Behavioral studies have shown that abnormalities in fish activity patterns, such as reduced swimming distances, reduced speeds, or excessive aggregation, may be due to environmental stress, deterioration of water quality, or signals of underlying disease. Additionally, water quality parameters such as ammonia nitrogen and nitrite Increased levels can also lead to reduced fish activity[9]. By using a PHM system, farmers can monitor the movement and behavior of fish stocks in real time, allowing them to quickly identify health problems or environmental stress and take appropriate management measures. This active surveillance can help improve the efficiency of early diagnosis and intervention and reduce the risk of disease outbreaks.

2.1.4. Hunger of Fish

The hunger level of fish significantly influences their feeding behavior, which subsequently affects their growth rate and feed utilization efficiency[10]. Effectively understanding and managing hunger is crucial for optimizing feed inputs, minimizing waste, and meeting the nutritional needs of fish. This task necessitates meticulous observation and fine-tuning of feeding strategies to align with the fluctuating appetites of fish, influenced by factors such as water temperature, quality, and health. Thus, timely detection of issues is essential. AI-based Prognostic Health Management (PHM) systems facilitate the monitoring and rapid decision-making required to adjust feeding or cleaning schedules appropriately, thereby precisely managing the hunger of fish and maximizing operational benefits.

2.2. External Environmental Factors

As aquatic organisms, the growth and development of fish are intricately linked to their environmental conditions, making them highly sensitive to various environmental factors. These factors encompass light, water temperature, dissolved oxygen content, and salinity, among others. Fluctuations in these environmental parameters prompt adjustments in fish activity and behavior, which in turn can significantly impact their growth rate and overall health.

2.2.1. Lighting

Light is a key external factor affecting fish physiological and behavioral processes. Research shows that light not only affects the circadian rhythm of fish, but also significantly affects their feeding patterns and reproductive cycles. Proper lighting conditions cannot be ignored to simulate the natural environment and thereby promote the health and growth of fish. According to a paper in

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the journal Aquaculture, artificial light sources can increase the growth rate of some fish species by up to 25% by extending daylight hours or adjusting photoperiods[11]. Optimizing the growth conditions of farmed fish and supporting their natural behavior requires strict control of light, so the corresponding PHM system is indispensable. Factors such as light intensity, duration and spectrum have varying effects on different species and should be adjusted according to the specific needs of the cultured species. Taking tilapia as an example, an experiment showed that using an artificial light source with an intensity of 200 lx can increase the growth rate of tilapia by 20% compared to natural light. Reasonable control of light conditions is an important part of ensuring breeding efficiency.

2.2.2. Water Temperature

Water temperature is a crucial environmental factor influencing fish health and aquaculture production. It directly impacts fish metabolism, growth rates, and immune system function. The ecological model of Adam et al. shows that even small, gradual changes in body size in a fish population can have large effects on natural mortality, biomass, and catch. Although growth was relatively insensitive to changes in temperature, the model results suggested that a fish aged 20 in 2099 would have an otolith about 10% larger and a body size about 5% larger than a fish aged 20 in 1977[12]. Fish thrive within an optimal temperature range; deviations from this range cause physiological stress, reduce immunity, and increase disease susceptibility. Regular monitoring, combined with intelligent prediction and response systems, is essential under natural conditions with temperature fluctuations. This integrated approach provides farmers with real-time data and forecasts potential risks, enabling them to take proactive measures to protect fish from temperature extremes.

2.2.3. PH and Calcium

The combined effect of Ca and pH on fish and fisheries is considered for both laboratory and field studies. It can be seen that at concentrations less than 100 μeq l−1, Ca can exert a significant influence on survival times of fish, and similarly in the field, the number of fishless lakes and the number of fish species found in lakes are less dependent on H+ concentration at low concentrations of Ca than at high Ca levels. The limited historical field data available suggest that alongside any increase there may have been in surface water acidity, Ca concentrations have also increased, and the latter may have offset to some extent the deleterious biological effects of this increased acidity. Nevertheless, details of seasonal and spatial variations in these important water quality factors will need to be considered before a full understanding of the response to acidity of a fishery can be reached[13].

2.2.4. Salinity

Development and growth (continuous in fish) are controlled by 'internal factors' including CNS, endocrinological and neuroendocrinological systems. Among vertebrates, they also are highly dependent on environmental conditions. Among other factors, many studies have reported an influence of water salinity on fish development and growth. In most species, egg fertilization and incubation, yolk sac resorption, early embryogenesis, swimbladder inflation, larval growth are dependent on salinity. In larger fish, salinity is also a key factor in controlling growth. Do the changes in growth rate, that depend on salinity, result from an action on: (1) standard metabolic rate; (2) food intake; (3) food conversion; and/or (4) hormonal stimulation? Better growth at intermediate salinities (8–20 psu) is very often, but not systematically, correlated to a lower standard metabolic rate. Numerous studies have shown that 20 to >50% of the total fish energy budget are dedicated to osmoregulation. However, recent ones indicate that the osmotic cost is not as high (roughly 10%) as this. Data are also available in terms of food intake and stimulation of food conversion, which are both dependent on the environmental salinity. Temperature and salinity have complex interactions. Many hormones are known to be active in both osmoregulation and growth regulation, e.g. in the control of food intake. All of these factors are reviewed. As often, multiple causality is likely to be at

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work and the interactive effects of salinity on physiology and behaviour must also be taken into account[14].

2.2.5. Dissolved Oxygen Content

With fisheries reaching a stagnating phase, the world will have to look to aquaculture in the future to provide fish products that will likely be needed. Oxygen is essential for the survival of living organisms, making dissolved oxygen content a crucial indicator in aquatic environments. A consideration of oxygen as a resource suggests that net oxygen gain per unit of energy expenditure will be the most useful currency for ecological models of breathing. In the process of oxygen uptake, fish always expend energy on perfusion, usually on ventilation and often on locomotion. These costs, and the risk of predation, will vary with oxygen availability and the type of behavioral response shown. The principal categories of behavioral response to reduced external availability of dissolved oxygen are (1) changes in activity, (2) increased use of air breathing, (3) increased use of aquatic surface respiration, and (4) vertical or horizontal habitat changes. Fish should choose whichever combination of responses minimizes the costs of meeting their oxygen demands. A small number of studies provides qualitative support for this prediction[15]. Low dissolved oxygen levels can cause breathing difficulties, slow growth, reduced immunity, and even death in fish. Therefore, maintaining adequate dissolved oxygen levels is a critical aspect of aquaculture management. To sustain sufficient dissolved oxygen, farms often employ aerators and oxygenation equipment. Aerators enhance the dissolution rate of oxygen in water by increasing the contact area between water and air, while oxygenation equipment delivers pure oxygen or oxygen-rich air directly into the water to quickly boost dissolved oxygen levels. Besides mechanical aeration, adjusting the breeding density is also important. Excessively high breeding density intensifies competition among fish, accelerates oxygen consumption, and can result in insufficient dissolved oxygen. Thus, monitoring water quality parameters, regularly checking dissolved oxygen levels, and adjusting breeding density according to fish growth conditions and seasonal changes are key measures to ensure healthy fish growth.

2.2.6. Fish Pond Size

The size and design of a pond directly determine its biocapacity, water quality stability, and the quality of the ecological environment for fish. Specifically, overcrowding in ponds can seriously affect fish health. Research indicates that the stress response caused by high-density farming can reduce fish growth by 20-25%. Additionally, crowded conditions increase the risk of disease transmission and deteriorate water quality. Key specifications for pond design include depth and surface area. Depth affects water temperature stability and dissolved oxygen distribution, while surface area relates to the space for gas exchange and photosynthesis. For example, deeper ponds maintain more stable temperatures but may require additional mechanical agitation to oxygenate the bottom water layer[16].

2.3. Feed Coefficient

The feed coefficient, or feed conversion ratio (FCR), is a key measure of how efficiently fish convert feed into weight gain. It is directly related to the growth rate, health status of fish, and the overall economic benefits of the fishery. Most fish breeding programs aim at improving growth rate and include feed conversion ratio (FCR) neither in the breeding goal nor in the selection index, although decreasing FCR is known to increase farm profit and decrease environmental impacts. This is because FCR is difficult to measure in fish that live in groups and FCR is assumed to have a favourable (negative) genetic correlation with growth, although the magnitude of this correlation is unknown[17]. To ensure efficient feed use, the quality, particle size, and formulation of the feed must precisely match the fish's nutritional needs, considering their specific dietary requirements at different life stages. An appropriate feed formula can significantly improve fish growth efficiency and health, reducing the FCR, thereby lowering feed costs and enhancing economic returns. The proportions of nutrients such as protein, fat, vitamins, and minerals in the feed should be optimized

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according to the fish species and growth stage, considering digestibility and energy conversion efficiency. The particle size should align with the feeding habits and mouthpart size of the fish to avoid feeding difficulties or inefficiencies caused by particles that are too large or too small. For example, young fish often require smaller feed particles for easier ingestion and digestion. Implementing a precise feeding program, including regular assessment of feed composition and adjustments to feeding techniques, feeding frequency, and schedules, can ensure maximum feed utilization and reduce waste due to overfeeding. Feeding times should consider the fish's natural feeding patterns and activity cycles, as well as environmental factors such as light changes and water temperature.

3. Intelligent Fishery Breeding Prediction and Health Management System Structure Based on Artificial Intelligence

Integrating artificial intelligence (AI) into predictive and health management (PHM) systems for smart fisheries represents a significant advancement towards sustainable aquaculture practices. This AI-enhanced PHM framework harnesses the synergy of data analytics, sensor technology, and AI innovation to oversee, manage, and promptly resolve the multifaceted issues inherent in aquaculture. Specifically, this AI-driven PHM infrastructure employs sophisticated data analytics and pattern recognition capabilities to provide real-time monitoring of aquaculture environments and fish health, particularly during disease outbreaks. This approach enables early detection and warning of potential health issues, allowing farmers to implement rapid and effective countermeasures to mitigate the incidence and impact of disease outbreaks. By profiling disease patterns and root causes, AI-enhanced PHM systems assist farmers in refining disease prevention and control methods, thereby enhancing the effectiveness of epidemic management strategies. In managing water quality, the system continuously monitors water parameters and automatically adjusts the water treatment process to maintain optimal conditions. This creates an ideal habitat for fish, reducing susceptibility to disease and leveraging extensive water quality data to support precise and efficient decision-making[4].

Feed management, a crucial element of fish farming, greatly benefits from AI-integrated PHM systems. The system analyzes the real-time nutritional needs of fish groups through algorithms to achieve precise feeding, meeting the dietary needs of the fish while preventing overfeeding, resulting in less feed waste and lower operating costs. Furthermore, in an era of rising labor costs, PHM systems require minimal daily maintenance and upkeep, reducing reliance on manual labor and professionals. This simplification of operations significantly improves the efficiency and profitability of aquaculture enterprises, marking a transformative step towards automation and intelligence in fish farming. As shown in Table 1 integrating AI intelligence into fish farming PHM systems heralds a new era of aquaculture efficiency, sustainability, and economic viability.

In summary, the integration of AI into fishery breeding prediction and health management systems provides a comprehensive and intelligent approach to aquaculture. By leveraging AI for real-time monitoring, early disease detection, optimal water quality management, and precise feed management, these systems significantly enhance the sustainability and profitability of fish farming operations.

4. Fish Farming Data Collection

In aquaculture, accurate and comprehensive collection of data on fish species is critical to the successful implementation of prediction and health management systems (PHM). These data are not only of great significance for developing optimized feeding strategies, but are also critical for ensuring the overall health of aquatic organisms. Because depending on the type and requirements of the collected data, the following three collection methods can be used.

4.1. Image Acquisition

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Image collection is crucial in the aquaculture sector, particularly for identifying and counting fish stocks. High-quality image data significantly enhances the management efficiency of fish farming, especially in developing intelligent feeding mechanisms and assessing health status. As shown in Table 2, this method enables farmers to monitor and manage aquatic life more accurately, thereby optimizing the breeding environment and increasing production efficiency.

Key challenges in implementing image acquisition include developing robust models capable of accurately identifying different fish species and behaviors, as well as processing and analyzing large volumes of image data. Successful image analysis depends on high-quality, representative image sets that depict various fish states, appearances under different lighting conditions, and scenes with different backgrounds. To build a robust and generalizable model, image data must be collected from diverse sources. As illustrated in Figure 3, these sources include, but are not limited to, public databases, online resources, and experimental collection data, each with its unique value and limitations[18].

Table 1. Integrating AI intelligence into fish farming PHM systems heralds a new era of aquaculture efficiency, sustainability, and economic viability.

Reference	equipment	Farming management method	Research goal	Experimental results
Sanz et al. (2024)[19]	Load cells, current meters, oceanographic buoy	Dynamic stress analysis for offshore aquaculture infrastructure	Reduce breakage risk in sea cages	Improved R2 by 0.8 for better stress insights
Sung et al. (2023)[20]	RTD PT100, SEN 0161, SEN 0189	Real-time monitoring using data fusion and deep reinforcement learning	Develop a low-cost, accurate aquaculture monitoring system	Achieved 5% lower error rate
Zhang et al. (2023)[21]	IoT devices, underwater wireless sensors, drones,	Automated monitoring with AI, IoT, and blockchain	Enhance efficiency and sustainability in marine aquaculture	Improved monitoring and control, advanced automation
Ma et al. (2023)[22]	Advanced water filtration, specialized feeding, real-time water quality monitoring	Sustainable practices using advanced technology	Develop efficient, sustainable aquaculture for large species	Enhanced growth, reduced environmental impact
Zhang et al. (2023)[23]	pH, temperature, salinity, dissolved oxygen, light intensity	IoT-based anomaly detection with 4G DTU	Comprehensive anomaly monitoring for sustainable aquaculture	High detection accuracy (87.71%) and 92.08% communication succes
Bu et al. (2023)[24]	Acoustic and optical sensors	AUV-aided data collection using deep reinforcement learning	Minimize AoI and energy consumption in underwater networks	Reduced AoI and energy consumption effectively

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Alselek et al. (2022)[25]	pH, temperature, dissolved oxygen, water level, TDS, EC, ion-selective sensors	IoT monitoring system using LoRa, LTE-M, NB-IoT	Cost-effective, comprehensive monitoring for aquaponics and fisheries	Reduced energy consumption by 70%, efficient communication
Chang et al. (2022)[26]	Sonar imaging device and stereo camera	Real-time monitoring using a two-mode underwater surveillance camera system	Develop a smart underwater imaging device for monitoring freely swimming fish	The proposed system achieved accurate fish length and weight estimation
Cheng et al. (2021)[27]	pH, dissolved oxygen, ammonia nitrogen	UAV-based real-time water quality monitoring	Integrate UAV and IoT for real-time monitoring	High prediction accuracies (92%-99%) for water quality
Daniela et al. (2019)[28]	pH, electrical conductivity, turbidity, ultrasonic, IMU, GPS, UV, liquid level, dissolved oxygen	Use of unmanned surface vehicles (USVs) and buoys for real-time monitoring and data collection in aquaculture environments	Develop an IoT-based platform for continuous, real-time monitoring of water quality parameters in aquaculture	The platform achieved efficient data collection and transmission,

Table 2. Image collection in the aquaculture.

Reference	Image segmentation algorithm	Target counting method	Research target	Results
Zhang et al. (2024)[29]	BoTS-YOLOv5s-seg	Object detection and counting using the improved YOLOv5s-seg model	Farmed fish in aquaculture environments	model size: 7.1 MB, GFLOPs: 25.4
Manikanta et al. (2024)[30]	Hybrid VGG16 and Darknet	Detection and classification using bounding boxes around fish	Fish classification and detection in various underwater environments	Achieved precision of 0.7, recall of 0.8, F1 score of 0.66
Liu et al. (2023)[31]	EfficientNet-B5 with GeM pooling for feature extraction	fish individual recognition	Individual fish recognition in underwater environments for precision aquaculture	Improved Rank1 accuracy by 2.60% on DlouFish dataset and 3.12% on WideFish dataset
Gori et al. (2023)[32]	OpenCV and rembg libraries	focus on species recognition	Saltwater fish species found in Indian seas	accuracy of 94% on a test dataset
Banno et al. (2022)[33]	YOLOv4 real-time object detector framework	Automatic detection and counting by AI, compared with manual human count	Wild fish aggregations around aquaculture sites	False positive rate: >7%, False negative rate: acceptable

Zhang et al. (2022)[34]	Multiscale and multicolumn convolution group network	Generation of density maps using a multiscale multicolumn convolution group network, asymmetric convolution, and spatial pyramid structure	High-density fish in breeding ponds or fixed waters	5.36 (Test Set A) and 23.67 (Test Set B); MSE (Mean Squared Error)
Abdul et al. (2022)[6]	Otsu thresholding, morphological operations, edge detection	Using IR sensor module and image processing in MATLAB	Post-larvae (PL) fish in aquaculture systems	small mean absolute error for large and small PLs
Teh et al. (2022)[35]	Mask R-CNN	Object detection and counting using a robotic eye camera and improved Mask R-CNN model	Shrimp detection and counting in aquaculture	accuracy rate of up to 97.48%; Precision increased to 95.79%
Zhang et al. (2020)[36]	MCNN and DCNN	Hybrid neural network model with density maps to estimate fish population	Atlantic salmon in far offshore mariculture	Accuracy: 95.06%; MAE: 4.29; RMSE: 5.57
Jose and Kumar (2020)[37]	Image segmentation for background elimination using landmark marking software	focus on species and genus classification	Wrasse fishes (family Labridae) in coral reefs	Genus-level classification accuracy: 96.65%

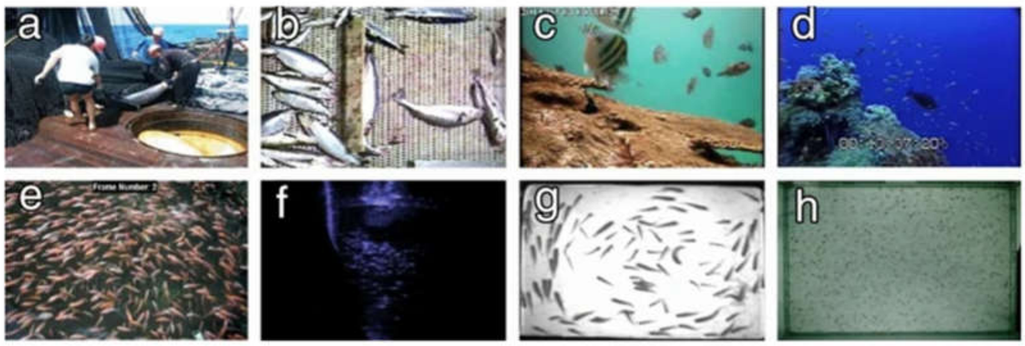

Figure 3. Main factors affecting fish farming.

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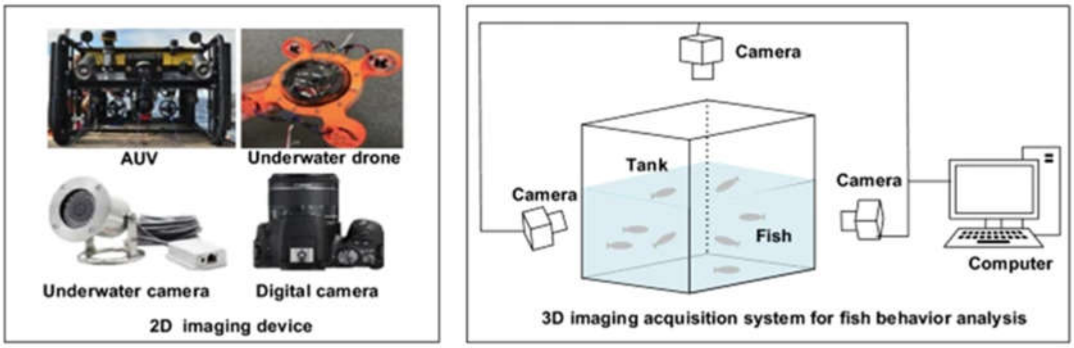

(a) (b)

Figure 4. Fish image experimental acquisition system (a) Equipment involved (b) Concept diagram.

Public databases provide a valuable resource containing fish images from different regions and conditions, enhancing the model's generalization ability. Web collection offers real-time, dynamically updated image data that reflects the latest aquaculture conditions. Controlled experimental setups can provide image data under precise environmental conditions. The fish image experimental acquisition system shown in Figure 4 is crucial for testing and validating the model's performance. To further improve the quality and efficiency of image acquisition and analysis, researchers and practitioners should focus on the latest technologies and methods. For instance, deep learning and machine learning techniques have proven highly effective in image recognition and classification tasks and can be applied to the automatic identification and counting of fish populations. Additionally, image preprocessing techniques, such as image enhancement, noise removal, and background segmentation, are vital for improving the accuracy and efficiency of image analysis[39].

4.2. Sensor Collection

In aquaculture, the application of sensor technology provides an efficient means to monitor environmental parameters and fish behavior, thereby achieving refined management of the breeding environment. As shown in Figure 5, data collected using sensors includes, but is not limited to, key environmental indicators such as water temperature, pH value, and dissolved oxygen content. These indicators are crucial for maintaining the stability of the water environment and fish health. Today, the combination of sensors with communication technologies permits to monitor these crucial parameters in real-time, allowing to take fast management decisions[40]. Sensors not only provide real-time data on environmental conditions but also monitor fish behavioral patterns, such as swimming speed and aggregation tendencies. This information is essential for understanding how fish respond to environmental changes and helps farmers make timely adjustments to ensure optimal growth conditions and avoid potential health problems. Furthermore, the continuous and real-time data stream collected by sensors allows farmers to receive instant updates on the breeding environment and fish condition, enabling quick reactions to solve any arising issues. This real-time monitoring and data analysis help maintain ideal farming conditions, reduce disease incidence, and improve overall farming efficiency.

To achieve these goals, sensor technology must be combined with advanced data processing and analysis techniques. By using data analysis software and intelligent algorithms, valuable information can be extracted from vast amounts of sensor data and transformed into actionable insights to guide the aquaculture decision-making process.

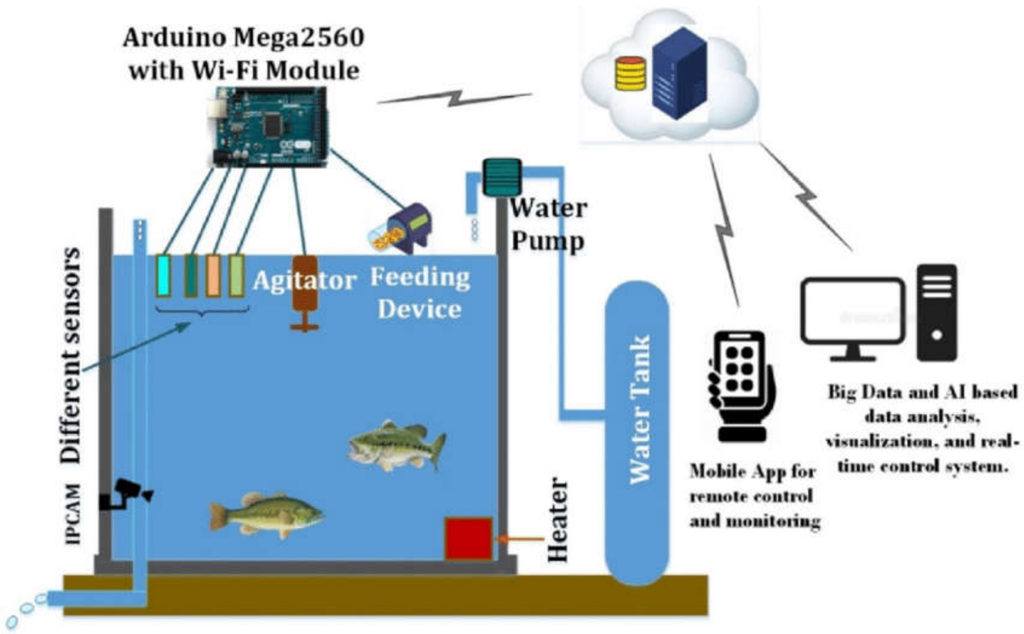

Figure 5. Acoustic acquisition.

4.3. Sensor Collection

Acoustic data collection is an important and rapidly growing area in aquaculture that uses sound waves to obtain information about fish populations, behavior, and habitat. Since the first biological applications of underwater acoustics, four approaches have been used singly or in combination to survey marine and freshwater environments: passive sonar; prior knowledge and direct sampling; echo statistics from high-frequency measures; and matching models to low-frequency measures. Echo amplitudes or targets measured using any sonar equipment are variable signals. Variability in reflected sound is influenced by physical factors associated with the transmission of sound through a compressible fluid, and by biological factors associated with the location, reflective properties, and behaviour of a target. The current trend in acoustic target identification is to increase the amount of information collected through increases in frequency bandwidth or in the number of acoustic beams. Exclusive use of acoustics to identify aquatic organisms reliably will require a set of statistical metrics that discriminate among a wide range of similar body types at any packing density, and incorporation of these algorithms in routine data processing[41]. Compared with other data collection methods, the acoustic technique shown in Figure 6 provides a non-invasive way to assess underwater environments, which is especially valuable for scenes that are difficult to observe directly. By deploying acoustic equipment such as echo sounders and sonar systems, researchers and farmers can collect acoustic data from fish schools and analyze it to infer fish behavior and environmental conditions. This method is particularly useful in deep water and turbid environments where visual monitoring is not feasible or economical. Acoustic technology can reveal the population density, body size distribution, migration patterns, and responses to environmental changes of fish schools, thereby providing a scientific basis for breeding decisions. In recent days, a lot of study has been made in classification and recognition of an image. It becomes a challenging task due to some factors such as segmentation errors, distortion, noise, overlapping of images and the most crucial aspect in fisheries is the recognition of live fish. So, to overcome the above said problem and also to classify whether the fish is a breeding fish or not, an approach has been proposed. Several videos are captured from the fisheries and the videos are converted into 900 frames. A deep learning and machine learning classifiers have been tried for classification of breeding and non-breeding fish. Convolution Neural Network (CNN) which is one of the deep learning techniques has been used for classifying the fish. In machine learning, the frames are first segmented and pre-processed and the features are extracted from the pre-processed and segmented frames. The extracted features are then used for classification. For classifying the fish several machine learning classifiers are used. Several dimensionality

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reduction techniques and ensemble methods have also been tried. Finally, the comparison results prove that CNN gives a better accuracy for classifying the breeding and non-breeding fish[42].

In addition, acoustic collection technology provides a powerful tool for environmental protection. Through continuous monitoring, underwater ecological changes and potential environmental problems, such as pollution or habitat destruction, can be detected in time, allowing for timely protective measures. To use acoustic data effectively, detailed analysis and interpretation of the collected acoustic signals are required. This often involves complex signal processing techniques and pattern recognition methods to ensure data accuracy and reliability.

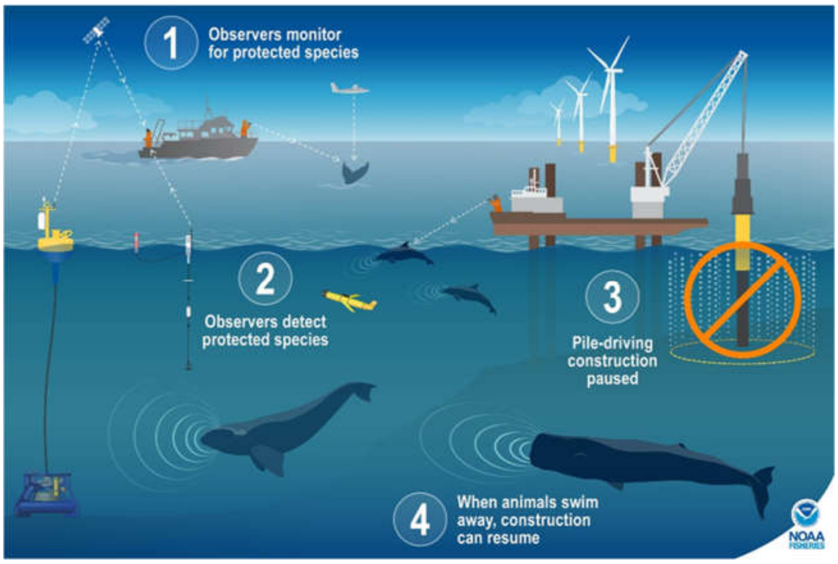

Figure 6. Acquisition system mainly built with sonar.

5. Fish breeding data processing

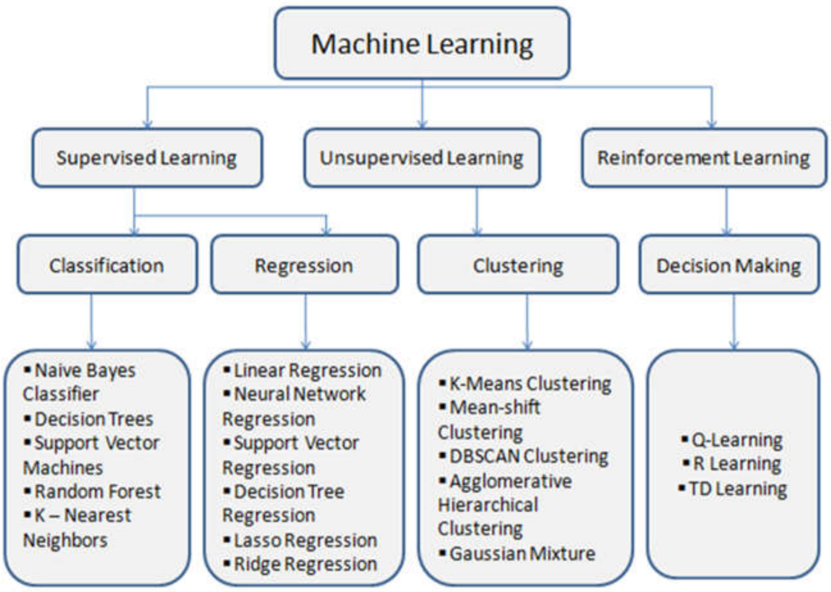

Figure 7. Machine learning and its classificationc.

5.1. Unsupervised Learning

The importance of unsupervised learning in fish farming lies in its ability to automatically discover valuable information and insights from large datasets. This capability is crucial for improving farming efficiency, ensuring fish health, and increasing production returns. By utilizing

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unsupervised learning, fish farming predictive and health management (PHM) systems can better understand and manage the farming environment, thereby promoting sustainable farming practices.

In the field of aquaculture PHM, unsupervised learning plays a key role, particularly in fish farming data processing. As a subset of machine learning, unsupervised learning operates without relying on pre-labeled datasets to identify patterns, associations, and structures within the data. This approach is valuable for understanding and managing complex aquaculture systems because it can reveal hidden information that traditional analytical methods may miss.

The applications of unsupervised learning in fish farming are broad and encompass several key areas:

1. Genetic Diversity and Breeding Management: Unsupervised learning helps identify genetic patterns and population structures within fish populations, providing a scientific basis for breeding strategies. Analyzing genetic data enables aquaculture farmers to identify fish with desirable genetic traits, thereby improving the genetic diversity and quality of cultured populations.
2. Environmental and Behavioral Analysis: By analyzing data collected from various sensors, unsupervised learning can detect behavioral patterns of fish under different environmental conditions. This analysis can reveal how fish respond to changes in temperature, light, and water quality, helping aquaculture farmers optimize rearing environments to reduce stress and disease incidence.
3. Disease Surveillance and Prevention: Unsupervised learning can identify abnormal patterns in fish behavioral and physiological data without clear disease labels. These abnormalities may serve as early indicators of health problems. Early detection of such signals allows aquaculturists to take preventive measures, avoiding disease outbreaks and minimizing transmission.

Overall, supervised algorithms allow differences from healthy behaviour of components in an unknown condition to be quantified. The indication of a deviation from a previously defined healthy state however lacks the description of the fault dimension or type. As each individual fault requires a corresponding data set for learning or classification, simultaneously designating the deviation and the fault type is a challenge. Moreover, component behaviour outside of the training or learned cases is challenging to detect and label for supervised approaches. Due to the inherent input–output relationship of supervised models, noise, outliers and inaccurate data have a strong adverse impact. Filling these gaps with simulated data has the disadvantage of inferior performance as pointed out by Sobie et al[43]. Unsupervised algorithms can be applied to detect deviations from a collection of previously observed healthy states, and equally consider a priori known faulty states. The issue of incorrectly labelled data is irrelevant to unsupervised models, and they exhibit a higher robustness to noisy data, as outlined by Zhang et al[44]. They published an unsupervised machining process supervision called AnomDB. It is an outlier detection framework for NC data, in which a PCA is applied to a multivariate time series prior to feature extraction, followed by a density-based spatial clustering of applications with noise (DBSCAN). Zhang et al. showed a superior performance of their proposal compared to other unsupervised approaches. Unsupervised learning's ability to autonomously discover valuable insights and information from massive datasets is critical for improving farming efficiency, ensuring fish health, and increasing production. By leveraging unsupervised learning, aquaculture PHM systems can provide a deeper understanding and better management of farming environments, promoting the development of sustainable aquaculture practices.

5.2. Semi-Supervised Learning

In the field of aquaculture prediction and health management (PHM) systems, semi-supervised learning plays a vital role, especially in processing aquaculture data. Semi-supervised learning combines the advantages of supervised and unsupervised learning by using a large amount of unlabeled data along with a small amount of labeled data for model training. This approach is particularly important in aquaculture, where acquiring extensive labeled data is often expensive and

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time-consuming. Semi-supervised learning provides several key functions in AI-driven PHM systems:

1. Data Efficiency: Given the high cost of obtaining labeled data, semi-supervised learning significantly improves data utilization by leveraging large amounts of unlabeled data, thereby reducing overall costs.
2. Model Performance: With limited labeled data, semi-supervised learning enhances the model's generalization ability by learning from the distribution of unlabeled data, thereby improving the accuracy and reliability of predictions.
3. Adaptation to New Situations: The complexity of aquaculture environments and fish behavior requires data processing methods that can adapt to new changes and unknown scenarios. Semi-supervised learning provides greater flexibility in handling partially unknown datasets.
4. Understanding Fish Behavior and Environmental Interactions: Semi-supervised learning helps reveal the relationship between fish behavior patterns and aquaculture environmental factors, facilitating more refined management decisions.

The importance of semi-supervised learning lies in its ability to leverage both labeled and unlabeled data, providing a powerful tool for improving the efficiency and accuracy of aquaculture PHM systems. This approach is essential for enhancing farming efficiency, ensuring fish health, and promoting sustainable aquaculture practices[45].

5.3. Supervised Learning

In the field of aquaculture prediction and health management (PHM) systems, supervised learning plays a central role, particularly in processing fish farming data. Supervised learning models predict outcomes on unknown data based on labeled training data. This approach is crucial in aquaculture because it uses historical data and experience to forecast or classify future culture conditions and fish health. Supervised learning provides several key functions in AI-driven PHM systems:

1. Disease Diagnosis and Prediction: Supervised learning algorithms can predict the likelihood of disease occurrence based on historical fish health data and environmental parameters, enabling preventive measures to be taken.
2. Growth and Yield Prediction: Supervised learning can predict fish growth rates and final yields, helping aquaculture farmers optimize feeding strategies and resource allocation.
3. Water Quality Management: By analyzing the relationship between water quality parameters and fish health and growth, supervised learning models assist aquaculture farmers in monitoring and maintaining optimal water conditions in real time.
4. Behavioral Analysis: Supervised learning can analyze fish behavioral data to identify correlations between various behavioral patterns and health conditions or environmental factors.

The importance of supervised learning lies in its ability to provide accurate and reliable predictions based on labeled data, making it a valuable tool for enhancing the efficiency and effectiveness of aquaculture PHM systems. This approach is critical for increasing productivity, ensuring fish health, and supporting sustainable aquaculture practices. A lot of works face the fault detection problem as a binary classification task. The normal status and the faulty status were first labeled. Although the normal and abnormal samples are provided in the artificially constructed dataset, the abnormal samples are usually absent, or in an extreme imbalance ratio by comparing with the normal samples in the real production process. Since the normal samples are generally obtained from the industrial processing, the fault detection problem meets the class-imbalance situation. Faced with seriously class-imbalance samples, this paper studies the feature extraction method based on KPCA (Kernel Principal Component Analysis), a self-supervised learning method, to achieve the rapid detection of the faulty or abnormal situation[46].

In AI-driven predictive and health management (PHM) systems for aquaculture, three key machine learning methods—unsupervised, semi-supervised, and supervised learning—play vital roles. Unsupervised learning autonomously identifies patterns and structures in large datasets, aiding in genetic diversity management, environmental and behavioral analysis, and disease

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surveillance, thereby enhancing farming efficiency and sustainability. Semi-supervised learning, by leveraging both labeled and vast amounts of unlabeled data, improves data utilization, model performance, and adaptability to new conditions, while deepening the understanding of fish behavior and environmental interactions. Supervised learning relies on labeled data to provide accurate predictions for disease diagnosis, growth and yield forecasting, water quality management, and behavioral analysis, thereby optimizing resource allocation and ensuring fish health. Together, these methods significantly enhance the efficiency, accuracy, and sustainability of aquaculture PHM systems.

6. Construction of Overall Fish Health Index (HI)

In the rapidly advancing field of aquaculture, establishing comprehensive, high-quality health indicators is pivotal for ensuring the sustainability and efficiency of farming practices. Leveraging the latest scientific research and cutting-edge artificial intelligence (AI) technologies, researchers are developing multidimensional models that integrate physiological, behavioral, and environmental data to comprehensively assess fish welfare. Both unsupervised and supervised learning methods are instrumental in analyzing complex datasets and identifying subtle patterns and anomalies that traditional methods might overlook.

Supervised learning algorithms, for instance, have shown significant promise in constructing predictive health models capable of identifying disease or stress states before fish exhibit overt symptoms. This is exemplified by the work of Jónsson et al. (2023), who demonstrated the effectiveness of convolutional neural networks (CNNs) in processing video and sensor data to detect behavioral changes indicative of health problems.

However, constructing reliable health indicators involves several challenges. One primary concern is the need for large and diverse datasets to train robust models, as frequently highlighted in the literature. Moreover, ensuring that these models can adapt to various aquaculture environments remains a critical research focus. Over time, the deeper integration of AI technology into aquaculture practices is expected to revolutionize fish health monitoring, making it more predictive, responsive, and tailored to the specific needs of different aquatic species.

Developing a comprehensive health indicator (HI) framework is crucial for maintaining productivity and ensuring the well-being of fish populations in aquaculture. Overall health indices are key components of predictive health management (PHM) systems, designed to predict, identify, and mitigate potential health problems in fish farming.

Regarding the framework definition, technologies such as Cyber-Physical Systems (CPS), IIoT, edge computing, and cloud computing are receiving more and more attention for PHM systems in industries [47]. Indeed, machine producers could take advantage of these technologies for collecting the data they need, when they need them, from the machines they want [48]. In literature, there are several examples of PHM frameworks based on these technologies. The basic idea is to exploit edge computing to perform the PHM tasks that have to provide real-time feedback while leaving in the cloud the data storage and batch analysis for more complex and accurate results. In [49,50], a cloud architecture for PHM is described. It consists of at least two clouds: the first one is the service provider and includes several PHM units; the second cloud offers expert service. In this way, the provider offers shared software for PHM, and the client can create its maintenance applications and methods with the tools provided by the provider; finally, storage and networking resources are available for implementing the maintenance solutions. In [51], a framework for Edge Computing-based fault diagnosis of rotating machinery is proposed, where edge computing is preferred to global or offline approaches performed in a centralized cloud server because of the following reasons: first, it reduces the storage and computing resources in the cloud, since it realizes the data computing on the edge node; second, it avoids unnecessary data transmission, resulting in low latency fault diagnosis; third, it also allows the simultaneous dynamic control of the machinery. In [52], a framework including both edge and cloud computing for equipment failure prediction is proposed. According to this framework, a machine learning prediction model is built based on historical data in the cloud, which has theoretically unlimited resources; then, the model is applied to new incoming data streams at the

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edge, which has fewer computation resources, to identify possible failures with increased responsiveness. A similar approach was adopted in , where a multi-sensor edge computing architecture was proposed for wind turbine generators. To the best of our knowledge, no edge-cloud PHM framework has been designed for facilitating the data exchange and analysis between a machine producer and a machine user. In this context, the edge-cloud-based framework should allow reducing the amount of data to transmit and store.

Reliable health indices enable aquaculture operators to effectively monitor and assess the overall health of fish populations. Accurate HIs can detect potential health problems early, allowing for preemptive actions that significantly reduce mortality and increase yields. By integrating expert knowledge, mathematical models, and advanced analytical techniques, HIs provide a multidimensional view of fish health, encompassing physiological, behavioral, and environmental factors.

7. Challenges and Solutions

Addressing challenges in aquaculture from the perspectives of data, models, and applications is critical for advancing breeding practices and increasing productivity. Each perspective presents unique challenges and opportunities for innovative solutions. Implementing a predictive and health management (PHM) system in aquaculture is essential for enhancing efficiency and productivity, representing a significant step forward in modern farming practices. However, overcoming the challenges in this process requires innovative and systematic solutions. The following sections provide a detailed discussion of these challenges and their solutions from the perspectives of data, models, and applications.

7.1. Data Perspective

The quality, completeness, and diversity of data are major challenges in aquaculture, significantly impacting the effectiveness of analysis and decision-making processes. Addressing these issues from a data perspective is crucial for the successful implementation of AI-driven fishery prediction and health management (PHM) systems.

Challenges：

1. Data Quality and Collection: Aquaculture often contends with incomplete, inaccurate, or noisy data, which complicates analysis and decision-making. The variability in data quality can stem from inconsistent sensor performance, environmental factors, and manual data entry errors.
2. Integration of Multiple Data Types: Combining data from various sources, such as environmental sensors, genetic information, and behavioral observations, poses substantial challenges due to differences in data formats, sampling rates, and data structures.

Solutions：

1. Improving Data Quality: Deploying high-quality and high-precision sensors and adopting IoT technology can enhance the quality and granularity of data through real-time, continuous data collection. High-fidelity sensors reduce noise and inaccuracies, providing more reliable datasets for analysis.
2. Advanced Data Collection Methods: Utilizing advanced sensors and IoT devices allows for the collection of comprehensive datasets that capture various aspects of the aquaculture environment, such as water quality parameters, fish health indicators, and behavioral data. This holistic approach ensures a more robust dataset.
3. Data Preprocessing: Implementing advanced data preprocessing techniques, including data cleaning, outlier handling, and data interpolation, is essential to ensure the accuracy and reliability of analyses. Techniques such as machine learning-based anomaly detection can be employed to identify and correct data errors automatically.
4. Data Integration Techniques: Leveraging sophisticated data integration platforms and adopting standardized data formats can facilitate the merging of disparate datasets, enhancing analytical capabilities. Utilizing middleware and APIs to harmonize data formats ensures seamless integration and interoperability between different data sources.

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Discussion:

In aquaculture, the integration of diverse data types—ranging from environmental sensor data to genetic information and behavioral observations—is crucial for developing a comprehensive understanding of fish health and environmental interactions. However, achieving effective data integration requires overcoming challenges related to data heterogeneity and interoperability. Advanced data integration platforms that support standardized data formats can bridge these gaps, enabling more effective data merging and analysis. Furthermore, improving data quality through high-precision sensors and IoT technology not only enhances the granularity of collected data but also facilitates real-time monitoring and adaptive management practices. These technologies provide aquaculturists with the tools needed to make informed decisions based on accurate and timely data. The role of advanced data preprocessing cannot be overstated, as it ensures that the datasets used for analysis are accurate and reliable. Techniques such as data cleaning, outlier detection, and interpolation play a critical role in maintaining data integrity and improving the robustness of predictive models.

By addressing these data-related challenges through the deployment of advanced technologies and methodologies, the aquaculture industry can significantly enhance the predictive capabilities and overall effectiveness of AI-driven PHM systems. This approach not only improves productivity and fish health management but also promotes sustainable aquaculture practices.

7.2. Model Angle

Developing accurate and generalizable models for predictive health management (PHM) systems in aquaculture is particularly challenging due to the inherent variability of species, environments, and practices. Additionally, accounting for the complexity of biological systems within these models adds another layer of difficulty. Addressing these challenges requires leveraging advanced machine learning techniques and fostering interdisciplinary research.

Challenges：

1. Model Accuracy and Generalizability: The variability in species, environmental conditions, and aquaculture practices complicates the development of models that can consistently and accurately predict outcomes across different settings. Models must be robust enough to handle this diversity while maintaining high predictive performance.
2. Complexity of Biological Systems: Aquaculture models must account for intricate interactions within biological systems, including physiological, behavioral, and environmental factors. Quantifying and predicting these interactions is complex due to the dynamic and non-linear nature of biological processes.

Solutions：

1. Adopting Advanced Machine Learning and Artificial Intelligence Techniques: Leveraging state-of-the-art machine learning and AI techniques, such as deep learning, ensemble methods, and reinforcement learning, can significantly improve the ability of models to understand and predict complex systems. These techniques can enhance model accuracy and adaptability, allowing for more precise predictions in diverse aquaculture environments.
2. Incorporating Interdisciplinary Research: Combining expertise from aquaculture, data science, and environmental science is essential for developing comprehensive and robust models. Interdisciplinary collaboration enables the integration of diverse knowledge and methodologies, leading to models that better capture the complexity of aquaculture environments and biological responses.

Discussion:

To enhance model accuracy and generalizability, it is crucial to utilize cutting-edge machine learning and AI techniques. For instance, deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), can process large volumes of complex data and identify intricate patterns that simpler models might miss. Ensemble methods, which combine the predictions of multiple models, can further improve robustness and reduce the risk of overfitting, particularly in heterogeneous datasets. Reinforcement learning can be used to optimize decision-

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making processes in real-time, adapting to dynamic changes in the aquaculture environment. Interdisciplinary research plays a pivotal role in overcoming the challenges of model development. By integrating insights from aquaculture, data science, and environmental science, researchers can develop models that are both scientifically rigorous and practically applicable. This collaborative approach ensures that models are grounded in biological reality while leveraging the latest advancements in data analytics and computational modeling. Moreover, continuous model validation and adaptation are necessary to maintain accuracy and relevance in changing environments. Implementing adaptive learning frameworks, where models are periodically retrained with new data, can help maintain high performance and generalizability. This approach ensures that the models evolve alongside the aquaculture systems they are designed to manage.

In summary, addressing the challenges of model accuracy and generalizability in AI-based fishery prediction and health management systems requires a multifaceted approach. By adopting advanced machine learning techniques and fostering interdisciplinary collaboration, researchers can develop robust models capable of accurately predicting outcomes in diverse and complex aquaculture environments. These advancements will ultimately lead to more efficient and sustainable aquaculture.

7.3. Application Angle

Implementing artificial intelligence (AI)-based fishery prediction and health management systems involves multiple challenges that need to be systematically addressed to ensure successful implementation and widespread adoption. These challenges include technology implementation, scalability, flexibility, and the development of user-friendly technologies.

Challenges：

1. Technology Implementation: Integrating new technologies and models into existing aquaculture practices can be challenging due to high costs, operational complexity, and lack of technical skills among practitioners. Transitioning from traditional approaches to AI-driven systems requires significant changes to workflows and infrastructure, which can be daunting.
2. Scalability and Flexibility: Solutions that work well at a small scale or in a controlled environment may not easily scale to larger operations or adapt to different environmental conditions. Ensuring that AI systems maintain performance and reliability across various scales and environments is a significant barrier.
3. User-Friendly Technologies: Developing technologies that are cost-effective, easy to use, and require minimal technical expertise is critical for increasing adoption among aquaculture practitioners. Complex systems that require extensive training or expertise can be a barrier to widespread use.

Solutions：

1. Developing User-Friendly Technologies: Designing system solutions that are both cost-effective and easy to operate can significantly reduce reliance on user technical skills. This includes creating intuitive interfaces, providing comprehensive user guides, and ensuring strong customer service. User-friendly technologies can facilitate a smoother transition and higher adoption rates.
2. Modular and Scalable Solutions: Developing modular systems that can be customized and expanded to meet the specific needs of different aquaculture operations can provide the necessary flexibility and adaptability. Modular solutions allow for a step-by-step implementation, enabling users to start with basic modules and expand as needed. This approach can meet the needs of farms of different sizes and types, thereby enhancing the applicability of AI systems.

Discussion:

Addressing these challenges is critical to the successful implementation of AI-based fishery prediction and health management systems. The high initial costs of AI technologies can be reduced by demonstrating long-term benefits, such as increased efficiency, reduced mortality, and increased productivity, thus justifying the investment. Simplifying the technology to make it more accessible can also help overcome resistance due to operational complexity and skills shortages. Scalability and flexibility are particularly important in the diverse and changing environment typical of aquaculture. Developing solutions that work at different scales, from small family farms to large industrial operations, ensures that AI technologies can be widely adopted across the industry. Customizable modules that meet specific needs—whether it's monitoring water quality, predicting disease outbreaks, or optimizing feeding schedules—can provide practical and effective solutions. Furthermore, interdisciplinary collaboration between technologists, aquaculturists, and environmental scientists is essential to developing robust and applicable AI systems. Such collaboration can ensure that the technology is rooted in practical aquaculture realities while leveraging the latest advances in AI.

In conclusion, by focusing on the applied perspective and addressing challenges related to technology implementation, scalability, and user-friendliness, the aquaculture industry can move toward more sustainable, efficient, and productive practices. The integration of advanced technologies and interdisciplinary collaboration will be key to overcoming these barriers and unlocking the full potential of AI-driven fishery prediction and health management systems.

8. Summary

This paper comprehensively reviews the application of artificial intelligence (AI) in smart fish farming, particularly in predictive health management (PHM) systems for aquaculture. It outlines the main factors affecting fish farming and introduces the process of smart fish farming enabled by machine learning techniques. This involves an in-depth exploration and analysis of key technologies, including image acquisition, image processing and analysis, and the actual mechanisms of smart fish farming. The discussion highlights the advantages of AI-based fishery prediction and health management systems over traditional methods, noting their automated, efficient, and non-destructive nature. The design of these systems can significantly improve the productivity and profitability of aquaculture operations. However, the paper also acknowledges the significant challenges and obstacles faced by AI in the application of smart fish farming. It elaborates on issues such as the complexity and incompleteness of multi-source data acquisition, uneven data quality, complex backgrounds, and difficulty in identifying target individuals due to different fish sizes. Additionally, the paper addresses the large data requirements of deep learning methods and the need for further research to balance model accuracy with running speed. It recommends exploring multi-angle fish information mining to enhance understanding and application. The paper also discusses the practical challenges of applying these systems and the need to improve model practicality based on identified shortcomings. Looking to the future, it emphasizes the importance of overcoming current challenges, achieving automated farming based on fish needs, and integrating research models into actual production. This will aid in precision feeding in aquaculture and improve overall efficiency. Advances in technologies such as the Internet of Things, big data, and artificial intelligence are expected to bring revolutionary changes to smart fish farming, heralding a bright future for this field. In summary, while the use of artificial intelligence and PHM systems provides innovative solutions for aquaculture, addressing challenges related to data, models, and applications is critical. The paper concludes that interdisciplinary collaboration and technology integration are key to overcoming these obstacles and unlocking the full potential of smart fish farming in aquaculture.

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