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OVERVIEW OF AQUACULTURE ARTIFICIAL INTELLIGENCE (AAI) APPLICATIONS: ENHANCE SUSTAINABILITY AND PRODUCTIVITY, REDUCE LABOR COSTS, AND INCREASE THE QUALITY OF AQUATIC PRODUCTS

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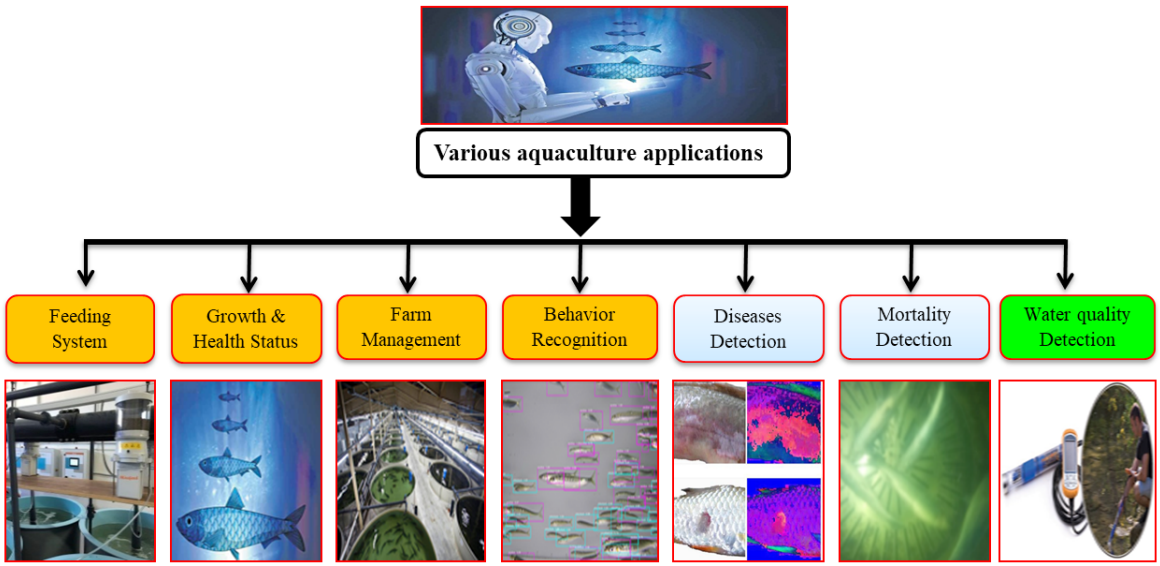
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Abstract

The current work investigates the prospective applications of Artificial Intelligence (AI) in the aquaculture industry. AI depends on collecting, validating, and analyzing data from several aspects using sensor readings, and feeding data sheets. AI is an essential tool that can monitor fish behavior and increase the resilience and quality of seafood products. Furthermore, AI algorithms can early detect potential pathogen infections and disease outbreaks, allowing aquaculture stakeholders to take timely preventive measures and subsequently make the proper decision in an appropriate time. AI algorithms can predict ecological conditions that should help aquaculture farmers adopt strategies and plans to avoid negative impacts on the fish farms and create an easy and safe environment for fish production. In addition, using AI aids to analyze and collect data regarding nutritional requirements, nutrient availability, and price could help the farmers to adjust and modify their diets to optimize feed formulations. Thus, using AI could help farmers to reduce labor costs, monitor aquatic animal's growth, health, optimize feed formulation and reduce waste output and early detection of disease outbreaks. Overall, this review highlights the importance of using AI to achieve aquaculture sustainability and boost the net profits of farmers

Key words: Artificial Intelligence, disease outbreaks, farm management, nutrition, feeding systems and welfare

Graphical Abstract



Fish farming was previously limited to small-scale operations that provided the means of subsistence for a single-family or small community. However, as the global population grows, food security is becoming an urgent concern (Ubina et al., 2023). In addition, climate changes have a negative impact on the fish caught and aquatic animals in the open sea (Essa et al., 2024), aquaculture in protected ponds (Goda et al., 2024), and aquaculture-based fish cages in open waters which widely affects the animal protein supply of fish. Because it is shifting fish and shellfish stocks coming from their native habitats and dynamic ecosystems and biodiversity, climate change threatens the world's ability to produce enough food for humanity (Jie et al., 2019; Mayormente, 2024). Aquaculture can be considered an optimum solution to mitigate these challenges and it is a fast-growing global protein-generating industry, providing 50% of protein for human consumption (Prem and Tewari, 2020; Lotfy et al., 2023; El Basuini et al., 2024). With the expected population increase by 2030, an additional 83 million tonnes of fish will be needed to face the demands in consumption (Goda et al., 2020 a; Emam et al., 2022; Ragab et al., 2024; Mandal and Ghosh, 2024; Ashraf et al., 2024; Lim, 2024; Er-Rousse and Qafas, 2024). The aquaculture sector is considered the major sector and an important contributor to the total global animal protein production (Abbas et al., 2023). Indeed, aquaculture contributed 44.1% in 2018 (FAO, 2022). The aquaculture industry, valued at $281.55 billion in 2020 (FAO, 2022), it is expected to grow 14% by 2030 and double its current capacity by 2050 to facing the global increase in fish consumption (Ansari et al., 2021; Lim, 2024; Sherine et al., 2023; Austin et al., 2022; Hu et al., 2024; Mayormente, 2024; Singh et al., 2024; Olanubi et al., 2024; Aljehani, 2023; Alshater et al., 2023; Glencross et al., 2023; Ubina et al., 2023; Føre et al., 2023). Thus, aquaculture stands up as the main and vital role of involvement of global seafood production to achieve food security. Sustainability and development of the aquaculture sector is an excellent strategy to meet and fulfill the future demand for animal proteins of a world population of 9.6 billion by 2050.

Aquaculture is currently faced with several difficulties, including a lack of workers, disease outbreaks, and management problems that have a detrimental effect on output and profitability. Furthermore, traditional fish farming methods raise the cost of production. Artificial intelligence (AI) is one new technological option that has been offered to overcome these issues and meet the growing demand for fish (Chiu et al., 2022; Taleb et al., 2025). Artificial intelligence, which is defined as the application of computer programs to simulate intelligent action with little to no human intervention, is dependent on unprocessed data that improves the ability of these algorithms to recognize and anticipate patterns that are evolving. Artificial intelligence has grown significantly since the early 1990s. Thanks to significant advancements in computing power, algorithms, and data availability, this science is now the foundation for numerous fields, including the military, medical, remediation, education, aquaculture, and agriculture, among many others (Mijwil et al., 2023). These technologies contribute to eliminating human errors, helping farmers and veterinarians preserve fish, and enhancing overall productivity. Additionally, incorporating AI technologies into aquaculture improves fish growth and decreases costs for farmers (Mayormente et al., 2024). Thus, the AI application in the aquaculture industry has improved fish production, profitability, and productivity (Xia et al., 2021; Chen et al., 2023; Mandal and Ghosh, 2023).

In order to screen and monitor fish behavior, optimize feed strategy, detect diseases, estimate size and biomass, count populations, and monitor water quality, Artificial Intelligence (AI) uses data from cameras, sensors, and biosensors (Wang et al., 2021, 2022 a, b; Zhang et al., 2022, 2023; Hu et al., 2023; Chen et al., 2022 a, b; Muñoz-Benavent et al., 2022; Li et al., 2022; Su et al., 2020; Barreto et al., 2022; Føre et al., 2018; Tonachella et al., 2022).

Furthermore, AI is recognized as a promising tool for fish feed formulation programs to face the nutritional needs of different fish species, improve growth performance, minimize waste outputs from aquaculture operations (Kaur et al., 2021), and improve fish reproduction management (Migaud et al., 2013). Thus, using real-time data, predictive analytics, and decision support systems enhances performance and global aquaculture efficiency (FAO, 2018; Mandal and Ghosh, 2023).

The AI applications in data analytics, decision support systems, and operational control, in smart aquaculture have been previously comprehensively studied by several reports (Føre et al., 2018; Saberioon et al., 2017; Antonucci and Costa, 2020; Hu et al., 2020; Li et al., 2020; Gladju et al., 2022). Accordingly, Raj and Jayanthi (2018) and Mayormente et al. (2024) suggest that AI systems could significantly improve production and reduce costs for fish farm owners. The current review broadly explains effective aquaculture management through AI systems by providing an extensive appraisal of up-to-date digital technology solutions for fish health, nutrition, feeding, and growth. The rest of the paper is organized as follows: Section 2 discusses various applications of AI in aquaculture in feeding systems, growth and health status, farm management, behavior recognition, diseases, mortality, and water quality. Section 3 presents the main challenges of AI in aquaculture: advantages and limitations. Finally, the conclusions and future perspectives achieved from the study are reported in Section 4.

Applications of AI in aquaculture systems and practices

Aquaculture enterprises face daily decisions affecting productivity which reduce the profit margins. Therefore, AI applications can provide smart solutions in the fields of water quality, feeding, monitoring, and disease identification.

Feeding system, growth, and health status

Fish feeding is crucial in aquaculture, affecting fish growth performance, flesh quality, water quality, and feed efficiency (Gasco et al., 2020; Zaki et al., 2020; Gladju et al., 2022; Ragab et al., 2024; Ashraf et al., 2024; Lim et al., 2024; Aljehani et al., 2023; Føre et al., 2023; Awad et al., 2024).

In order to maximize fish growth, minimize feeding expenses, and prevent water pollution from uneaten food and wasted elimination, fish feeding management is concentrated on effectively managing fish feed. Therefore, the goal of aquaculture management is to manage fish feed as efficiently as possible because the feed's nutritional qualities affect three things: 1) the growth and final flesh quality; 2) the water quality and the final quantity of N and P in the aquaculture wastewater effluents; and 3) the effectiveness of feed conversion and use (Gladju et al., 2022). However, the expansion of aquaculture has increased feed costs (Goda et al., 2020 a, b, 2019; Li et al., 2020). Feed cost represents up to 75% of aquaculture operational costs (Ansari et al., 2021). About 60% of the delivered feed is in the form of particles from the feed remaining in the water (Adegboye et al., 2020; Mayormente, 2024; Mandal and Ghosh, 2024). Underfeeding increases fish aggression, while overfeeding leads to feed waste, increased feeding costs, and reduced feed efficiency due to inefficient feed management (Føre et al., 2016). Fish nutrition is impacted by several factors (Sun et al., 2016; Zhou et al., 2018), as shown in Figure 1. The feeding technique strategy is determined based on several factors, such as fish size, age, species, biomass in the tank, and water quality. To maintain feed utilization efficiency, it is necessary to develop monitoring tools to provide comment, advice and precisely measure feed intake and feed waste during feeding period. Furthermore, aquaculture industry profits from this predictive model that can provide data on fish feeding behaviors and feeding process which help to provide a proper amount of feed (Chen et al., 2022 a).

Recently, the AI feeding control has had significant attention due to its potential to adapt to the challenges in growth and behavior by automatically determining the feeding demands of fish. To implement AI in calculating feed intake, some data should be available as follows: First, the total number of fish, average fish weight, and feed rate from above are used to determine the daily requirement for fish food. Second, to check on the fish's location, the robotic feeding system will administer a tiny amount of food. Thirdly, fish location estimation uses the fish's relative position within the cage to estimate the ideal position of the feeder's gun barrel for the best feed dispensing once the fish have shown interest in the food. In order to reduce feed waste, the food dispenser gun is fourthly adjusted such that the food is dispensed directly to the fish. Lastly, the placement of the feeding barrel fish is regularly adjusted by monitoring the feeding behavior of the fish (Ubina et al., 2023).

The intelligent feeding system, as shown in Figure 2, includes an image sensing unit, fish feeder, water quality unit, signal processing module, and server computer (Hu et al., 2022). AI in the aquaculture feeding application has many advantages as i) monitoring fish feeding behavior, ii) measuring feed intake, iii) calculating uneaten feeds, iv) aiding the farmers to adjust their feed supply automatically, and v) observing cultured fish and accurate diet consumption (Foster et al., 1995, Ang and Petrell, 1997; Parsonage and Petrell, 2003; Alshater et al., 2023; Lim et al., 2024; Er-Rousse et al., 2024; Føre et al., 2023; Ubina et al., 2023; Sung et al., 2023; Dellosa, 2023; Yasin et al., 2023). However, this method was challenged with many limitations as i) not widely accepted by farmers, ii) limitations of the software and hardware processing capabilities, iii) this method was too sluggish for a long time of culture season operation, and iv) the video camera positioning target to several factors affecting the accuracy of output data as the number of other substances in the farm location such as environment background as light and wind, thus the method is complicated and easily generates errors. In conclusion, AI could dynamically help to adjust feed intake based on environmental factors and changes in fish growth, ensuring optimal fish growth, enhancing feed conversion ratio, and minimizing waste by adjusting feeding decisions based on the remaining amount of feed (An et al., 2021) and deciding whether feeding regimes must be kept constant, decreased, or increased to meet the optimum feeding requirements of the fish in real time (Li et al., 2020). Therefore, AI is the direction of future development (Verdal et al., 2018). Finally, despite technological development, developing a common feeding technology across all cultural models is challenging or impossible, necessitating continuous improvements in smart feeding systems. Table 1 provides a comprehensive overview of various feeding control methods, their advantages and disadvantages, and their suitable applications, thereby aiding in selecting the most appropriate method for various culture models.

Fish growth is a critical biological process that shapes their life history, and accurately tracking or predicting the growth path is crucial for better control of an aquaculture system (Goda et al., 2019; Flinn and Midway, 2021). Therefore, aquaculture activities face challenges in improving fish growth performance and health to increase and improve profitability and productivity (Austin et al., 2022; Mandal et al., 2023, 2024; Ashraf et al., 2024; Abangan et al., 2023; Li et al., 2023; Shreesha et al., 2023; Dellosa, 2023; Kristmundsson et al., 2023; Føre et al., 2023), because the growth tracking problem faces challenges from various environmental factors such as dissolved oxygen, salinity, light, and temperature (Chahid et al., 2022; Sun et al., 2016; Abangan et al., 2023; Li et al., 2023; Shreesha et al., 2023; Dellosa, 2023; Kristmundsson et al., 2023; Føre et al., 2023). Thus, new aquaculture techniques are needed to enhance fish efficiency by enhancing water quality control policies and feeding, focusing on factors influencing fish growth like feeding rate, temperature, and dissolved oxygen (Chahid et al., 2022).

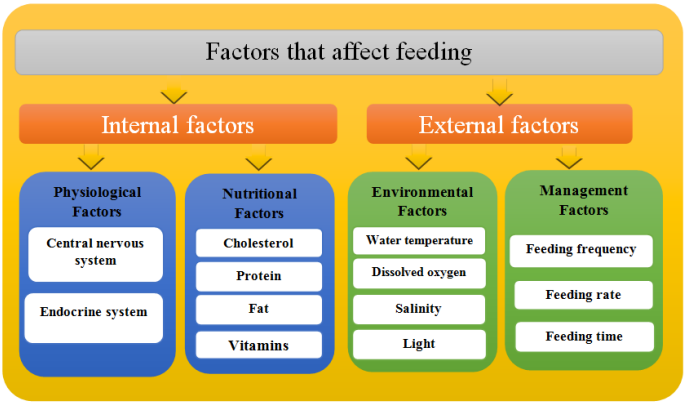


Figure 1. Factors affecting feeding (Zhou et al., 2018)

Table 1. Comparison of various feeding control methods (Zhou et al., 2018)

Feeding methods	Advantage	Disadvantage	Application and acceptance level	Suitable culture model	References
Artificial observation	Intuitive	Expensive, easily affected by subjective experience	Used widely in production site	Small-scale farming	Chen et al. (2022)
Mathematical model	The group level is accurate	Poor flexibility in single-feeding control	Used widely in production site	Intensive cultivation	Li et al. (2022)
Acoustic	Useful in water with low ambient light	High cost, difficult to develop, acoustic label is a contact technology	Rarely used in production site	Large-volume aquaculture model, such as a cage system	Li et al. (2024)
Machine vision	Low cost, simple to develop	Higher visibility requirements, low contrast images	Less used in production site	Good lighting conditions	Saberioon et al. (2017)

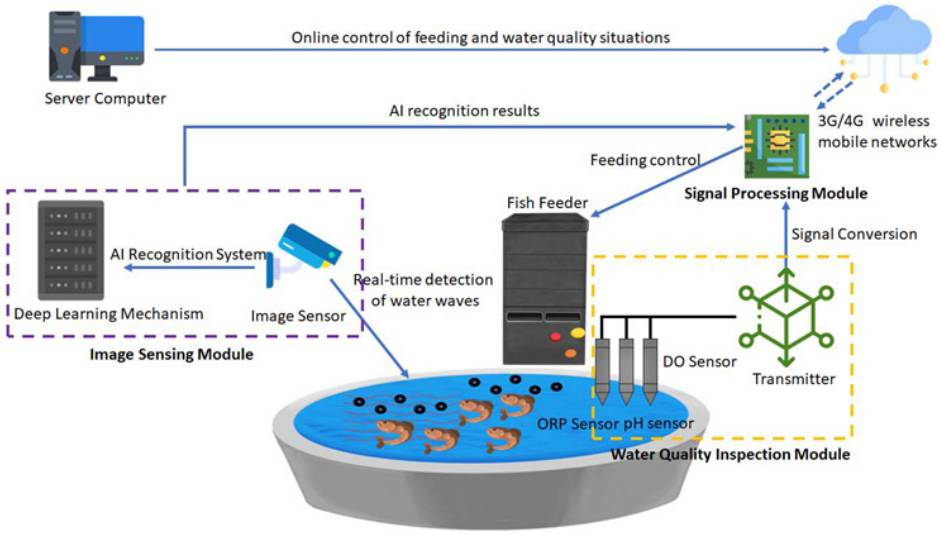


Figure 2. Process of intelligent fish feeding based on Artificial Intelligence (Hu et al., 2022)

Recently, the aquaculture industry has utilized Artificial Intelligence to optimize biomass production, monitor fish growth, and enhance aquaculture sustainability by controlling factors influencing fish growth (Chen et al., 2023), optimizing feeding strategy, and conducting the appropriate quantity of feed at all fish growth stages (Luna et al., 2019; Goda et al., 2019, 2020 a, b; Mandal and Ghosh, 2023; Abangan et al., 2023; Li et al., 2023; Shreesha et al., 2023; Dellosa, 2023; Kristmundsson et al., 2023; Føre et al., 2023; Ashraf et al., 2024).

Farm management

Aquaculture farm management depends on visual observation, which cannot fully monitor fish and wa-

ter quality (Zhou et al., 2023). Aquaculture operations have recently progressively shifted from conventional cultivation to smart industrial operations with the introduction of aquaculture AI (Taleb et al., 2025). AI adopts to manage fish farm which is a comprehensive approach that includes pond and environment condition management (Peng et al., 2022). Data on fish length, body breadth, temperature, and frequency of feeding are used in fish condition management to estimate weight, oxygen consumption, and feeding (Yu et al., 2022; Lin et al., 2022), and environmental condition management include temporal correlation of water quality data (Chen et al., 2022 b; Ahmadzadeh et al., 2022).

AI aquaculture includes several aspects: a) collecting data such as fish growth performance, environmental parameters, operation, resource allocation, water quality parameters (temperature, humidity, CO_2, light, dissolved oxygen), and digital image data acquisition equipment; b) transferring the collected data to the control center through communication nodes; and c) data processing and decision making. Using AI technology, the device gathers images of fish movements and body size parameters in real time and transmits them to laptops, PCs, and mobile applications (Zhan et al., 2022; Peebles et al., 2022). The computer analyses data related to fish morphology and pond conditions including fish final weight, weight gain, length gain, feeding rates, temperature, pH, salinity, DO, TSD, and other data that can gain from the images. Next the data input at the model to predict fish parameters including weight, length, feeding rates, etc. The predicted data is used as an indicator of the normality of fish growth rate (Zhou et al., 2023) to achieve sustainability with efficiency and high quality through intelligent and automatic processes.

AI in aquaculture farms is classified into three stages based on the advanced level of information technology. The first stage is the primary stage, which depends on aquaculture experts for remote operation and control. The second stage is the intermediate stage, called the unattended fish farm, which operates autonomously without human intervention and requires a few people to execute orders and make production decisions. While the third stage is the advanced stage, does not require human involvement, where operations and management decisions are made by cloud management platforms, robots, and intelligent equipment that operate autonomously (Wang et al., 2021). On the other hand, there are several advantages of smart aquaculture, including reduced feed use and better control over water quality, improved output and quality level and comprehensively reduced production costs for fish, increased aquaculture volumes and reduced losses, lower labor costs, and improved production efficiency (Zhou et al., 2023).

Behavior recognition

Recently, observing fish became possible with the breadth of available technology for detailed monitoring of fish, enhancing environmental and fisheries status (Durden et al., 2016; Moustahfid et al., 2020; Essa et al., 2024) by efficiently processing large amounts of image data related to fish behavior, including feeding behavior and abnormal behaviors under all different conditions, paving the way for future advancements (Jahanbakht et al., 2021; Abangan et al., 2023; Li et al., 2020; Ashraf et al., 2024; Li et al., 2023; Shreesha et al., 2023; Dellosa, 2023; Kristmundsson et al., 2023; Føre et al., 2023). Artificial Intelligence methods recognize fish behavior through mathematical and statistical operations. The characteristics of the fish, including shape, size, texture, or color, as well as how they respond to various stimuli, are analyzed in photos and videos of fish swimming and converted into quantitative measurements. Lastly, computer techniques are used to simplify photos and videos and extract the necessary data (Abangan et al., 2023). The human eye can effectively identify swimming movements, fish location, swimming behavior, and interactions with other fish (He, 2010). Recently, as a result of significant developments in underwater cameras by AI (Moustahfid et al., 2020), it is possible to monitor the evolution of fish behavior through a large number of high-resolution images and videos (Logares et al., 2021), as presented in Figure 3.

Cameras may be used in several conditions (Christensen et al., 2018; Jalal et al., 2020), are capable of capturing diverse underwater conditions, including muddy, dark, and light conditions, and may go to higher depths and more extended periods (Torres et al., 2020; Bilodeau et al., 2022; Xia et al., 2022). Furthermore, cameras also can offer 2D or 3D vision to observe fish interactions with fishing gear, enabling observing fish behaviors under various environmental conditions (Robert et al., 2020; Cuende et al., 2022). The equipment selection step is crucial for capturing finer details and determining only targeted species while avoiding unwanted undersized individuals, and catching vulnerable ones (Abangan et al., 2023). Recently, fish vision studies have revealed differences in behavior across species based on spectral sensitivity, prompting the development of visual components to enhance (Carleton et al., 2020; Underwood et al., 2021). Environmental factors significantly influence fish reactions, with movement often varying between individual and group behaviors (Yu et al., 2021; Xu et al., 2022). Thus, changes in water quality parameters, mainly temperature significantly affect fish behavior, health and growth (Ashraf et al., 2024). Thus, fish farmers can advance fish health behaviors by optimizing pond conditions, mainly temperature and dissolved oxygen (Craig et al., 2017). Recently, plenty of research has been conducted to examine different fish species behavior with various weather conditions as responses to temperature changes, for example, bluegills exhibit more aggression in warmer water as a result of food competition (Barber, 2007). Similarly, it has been seen that Atlantic salmon exhibit more aggression in warmer climates, leading to increased stress levels and a higher likelihood of disease

outbreaks (Portz et al., 2006; Svenning et al., 2022). Furthermore, yellow perch, recognized as a cold-water fish species, becomes more aggressive in hot conditions (Stasko et al., 2012). One of the common AI methods used for behavior recognition is Umitron's system introduced by Tokyo-based Umitron Corporation which tracks swimming behavior. This technology provides farmers with data that could aid in determining when, based on real-time observation of swimming behavior, to put food in each fish cage. The fish raised using this AI technique are sold under the name "AI Sumagastsuo" in Tokyo (Ashraf et al., 2024).

Diseases detection

Aquaculture faces significant risks from fish diseases (Yasin et al., 2023; Li et al., 2023; Mandal and Ghosh, 2023). Moreover, fish diseases significantly contribute to 50% of overall production loss, often resulting in large-scale infections and massive deaths due to rapid outbreaks and spreading of pathogens (Abdelrahman et al., 2023). Therefore, early detection and identification of fish diseases are crucial to prevent outbreaks and financial losses, which may negatively impact economic progress (Nayan et al., 2021; Li et al., 2022; Ahmed et al., 2022). Fish diseases are caused by a variety of pathogens, such as fungi, bacteria, parasites, viruses, and some environmental factors (Singh et al., 2021). Traditionally, diagnosis of diseases depends on microscopic examination of fish and symptoms, but this is time-consuming, requires trained labor, and relies on pathologists' expertise (Li et al., 2022, 2023). Modern, rapid, and real-time technologies for predicting and diagnosing fish diseases are crucial to maintaining fish health and preventing disease transmission in aquaculture (Li et al., 2022; MacIntyre et al., 2023). Recently, image-based Artificial Intelligence techniques have been widely used to diagnose fish diseases by detecting changes in hosts, pathogens, and the environment.

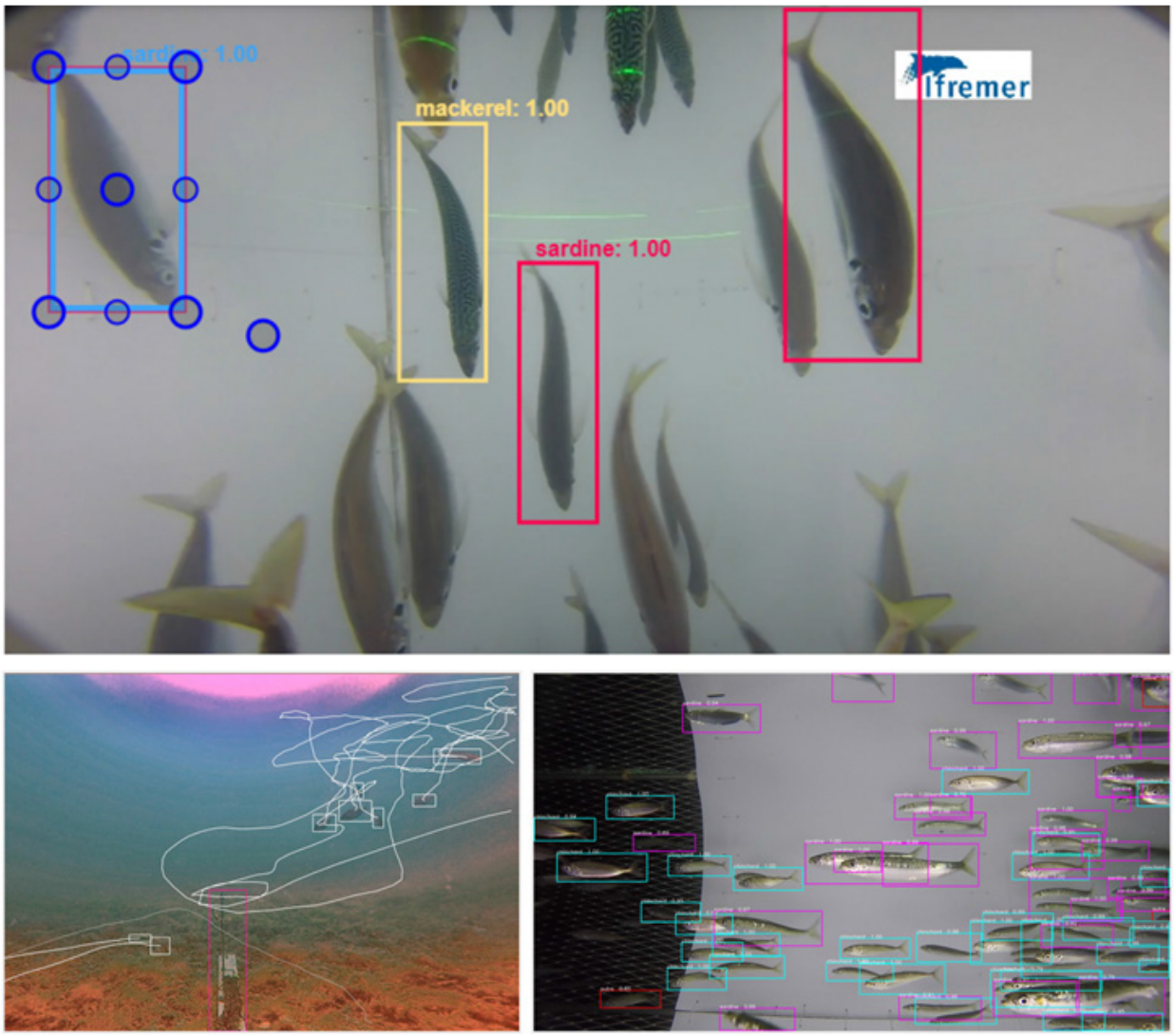


Figure 3. Tracking of fish on the platform for image and video analysis

Enhancing the relationship between the environment and disease recurrence through the analysis of data from multiple sources, such as water parameter quality, fish behaviors, feeding habits, and other factors that may contribute to the spread of disease, may help with early detection of pathogen infections, which in turn may assist farmers and veterinarians in accurately and quickly diagnosing and treating diseases in culture ponds (Machuve et al., 2022) and prevent the spread of disease and improve the effectiveness of treatments (Kumar et al., 2022; Negreiros et al., 2016; Ahmedt-Aristizabal et al., 2021; Zhao et al., 2021). This predicted model is computer software that involves training ML models to recognize patterns in images of fish affected by various diseases. The models were able to identify infected fish with greater than 90% accuracy (Quach et al., 2020). Ahmed et al. (2022) successfully identified the infected fish in aquaculture by using image processing and machine learning (Zhou et al., 2022, 2023). Furthermore, Li et al. (2022) suggest that the process of detecting diseases using images involves two steps: the collection of high-quality photos and the pre-processing of the acquired images. Recently, 2D images have become the primary method for diagnosing fish diseases. Still, they cannot effectively solve some problems, such as the inability to accurately determine the movement speed of fish and the spatial location of fish (Mao et al., 2016). In contrast, 3D images are likely to overcome these problems to some extent (Mao et al., 2017), enabling more accurate detection of changes in fish behavior and providing new methods for timely diagnosis. Park et al. (2007) and López-Cortés et al. (2017) developed a system for diagnosing fish diseases using microscopic image processing by comparing affected tissues to an existing pathogen database through image processing technology combined with spectrometry and machine learning to determine the final diagnosis. Furthermore, Darapaneni et al. (2022) developed an AI-based disease detection system for farmed fish, enabling immediate alerts and remedial actions to curb disease spread. In conclusion, AI is a cutting-edge tool and modern technology that can be used to create new, more effective therapies, vaccines, and preventative measures than conventional ways (Walsh et al., 2019). It analyzes genetic data and identifies patterns in disease progression, but application accuracy remains low and expensive, and the diverse nature and heterogeneity of fish diseases increase diagnosis and image acquisition difficulties in complex water environments.

Mortality detection

The mortality of fish at the bottom of tanks causes blockage of the drainage, causing many problems that ultimately lead to deterioration of water quality and the spread of diseases (Ranjan et al., 2023; Mandal and Ghosh, 2024; Er-Rousse and Qafas, 2024; Aljehani et al., 2023; Kristmundsson et al., 2023). Furthermore, high mortality rates in fish tanks result in significant economic losses, particularly during the grow-out phase before harvest, due to high biomass and feed inputs, and mortality varies based on the types, intensity, and duration of the stress. Therefore, mortality tracking in fish tanks aids in informed decision-making on mortality management by providing instantaneous, daily, and cumulative data, enabling timely and effective action to prevent mass mortality (Ranjan et al., 2023). Mortality data sheets are used as inventory status indicators to develop a plan and strategy for the production of fish at various production stages (Ranjan et al., 2023). These baseline mortality counts are used to anticipate loss in future cycles and recognize unusual patterns of fish mortality. Recently AI techniques had a contribution with the mortality alert, which supplies information about the number of dead fish and the date/time of the death (Bochkovskiy et al., 2020; Glenn, 2020). AI helps to make a proper decisions on fish production, management, and harvest (Sankaran et al., 2015; Jawad et al., 2017; Ranjan et al., 2020; Amogi et al., 2022), via using a camera programmed to get high-resolution images and add comments. Images are manually annotated into live and dead objects and merged to generate datasets for statistical analysis (Ranjan et al., 2023), as presented in Figure 4. Recently (Ranjan et al., 2023; Kristmundsson et al., 2023; Aljehani et al., 2023; Mandal et al., 2024) reported that the use of Artificial Intelligence in culture ponds has made possible continuous monitoring of mortality around the clock and constantly alerts staff to unusual mortality events.

Water quality detection

Water quality control in real time is essential for fish growth, survival, disease prevention, and reducing risks (Zounemat-Kermani et al., 2019; Al-Mutairi and Al-Aubidy, 2022; Arepalli et al., 2022; Lotfy et al., 2023; Ashraf et al., 2024; Hu et al., 2024; Olanubi et al., 2024; Yang et al., 2023 a; Yamuna et al., 2023; Helal et al., 2024). Furthermore, poor water quality leads to high mortality rates, but monitoring physico-chemical parameters can reduce losses by 20% to 40% (Vo et al., 2021). Therefore, aquaculture requires continuous monitoring of water quality parameters due to changes over time and space, which are influenced by multiple environmental parameters such as fish density, feed availability, environmental impacts (industrial discharges, enthronization, etc.), and meteorological conditions such as lack of wind and intense heat, which can result in poor oxygen regeneration due to a lack of mixing in the water (Vo et al., 2021), causing difficulties in predicting their characteristics (Zhao et al., 2021). Water quality straightly affects the bottom line of aquaculture operations. High mortality rates slowed growth rate, and increased healthcare costs can result from inadequate water quality, posing financial challenges to the industry. The management of water quality in aquaculture is mandatory since it is a multifaceted task, requiring continuous care and inventory (Yamuna et al., 2023).

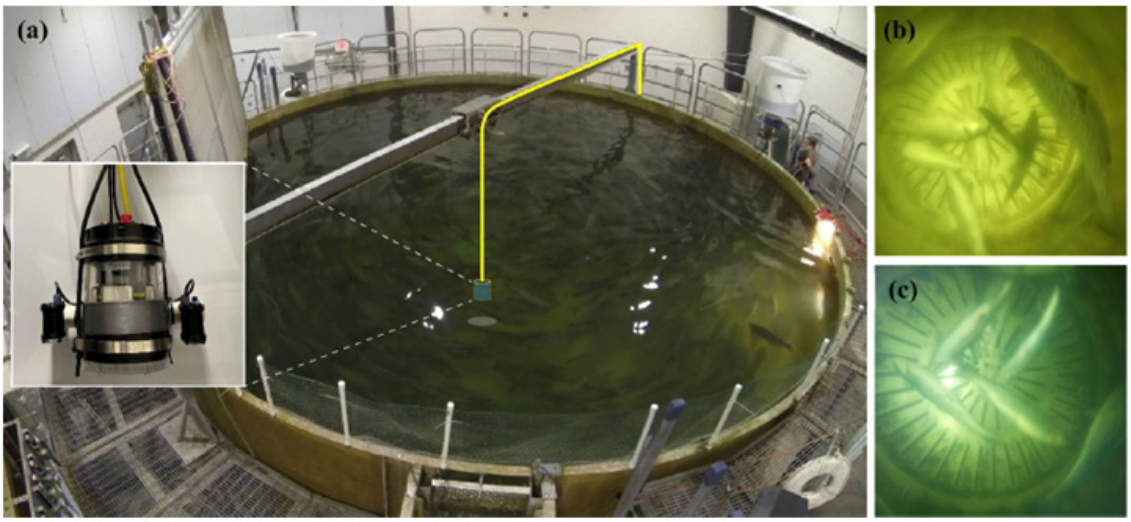


Figure 4. AI-aided fish mortality detection deployed in the (a) growout tank to acquire mortality data above the drain plate in (b) ambient light and (c) supplemented light conditions (Ranjan et al., 2023)

Traditionally, water quality can be judged by visual inspection, but this method is ineffective and inaccurate (Vo et al., 2021; Hassan et al., 2024). Recently, scientists have conducted many studies on using AI (Rajaee et al., 2020) to solve the water quality problem and improve prediction accuracy in aquaculture (Yang et al., 2023 b); by adopting and implementing a mixture of a network of sensors and automated control mechanisms, this technology allows for continuous, real-time monitoring of critical water quality (Jie et al., 2019; Mayormente, 2024). Implementation of AI is a promising technique to minimize pollution and control pathogens infections within ecosystems, in parallel with sustainability goals and regulations. Furthermore, AI plays a vital role to avoid mortality, increase survivability and enhance performance. It can reduce waste outputs from aquaculture operation costs associated with monitoring and physical intrusions, which consequently improve economic sustainability of aquaculture (Yamuna et al., 2023). Nowadays, many aquaculture and fisheries scientists are using AI to predict the status of water quality to improve prediction accuracy (Rajaee et al., 2020; Tiyasha et al., 2021; Yang et al., 2023 a; Ashraf et al., 2024; Olanubi et al., 2024; Hu et al., 2024; Singh et al., 2024). Likewise, Agossou and Toshiro (2021) implemented AI technique to measure water quality parameters. In addition, Duangwongsa et al. (2021) used AI to store water quality data including T, pH, turbidity, and DO. Also, Olanubi et al. (2024) stated that implementing and adopting AI in aquaculture enhanced water quality and aquaculture production efficiency.

Ullah and Kim (2018) and Romli et al. (2018) developed an optimization scheme using the Kalman filter algorithm by AI to reduce energy consumption in fish-rearing tanks, enabling remote monitoring and control of water circulation and retention levels. In addition, AI-based aquaculture systems provide 24-hour water quality monitoring, microclimate sensing, and warning functions, extending early response times and controlling equipment such as water wheels and pump motors (Hu et al., 2022). Likewise, Hu et al., (2022) and Zhou et al. (2023) created an AI model to predict water quality in aquaculture through a DLM, where the water quality is automatically processed using appropriate filtration equipment to monitor the cultivation environment and warn of abnormalities in real time. Finally, future research aims to develop more robust water sensors and more accurate prediction models to make the system more accurate and affordable.

AI in aquaculture: advantages and limitations

Artificial Intelligence offers many advantages in aquaculture, but it also has some limitations:

Advantages

– Artificial Intelligence technology enhances aquaculture operations by monitoring water quality, feeding regimes, disease detection, and many other applications. This improves operational efficiency by reducing the need for manual labor and thus helping farmers manage larger-scale operations while fewer resources and in a shorter period (Panda and Baral, 2023; Mandal et al., 2024; Ashraf et al., 2024; Er-Rousse and Qafas, 2024).
– Artificial Intelligence can improve fish health, performance, and feed utilization by optimizing feeding regime, fish growth, water quality, and other related factors (Gladju et al., 2022; Chiu et al., 2022; Georgopoulos et al., 2023; Aljehani et al., 2023).
– Artificial Intelligence has the ability to identify fish infections at an early stage by examining data on physiology, environmental factors, and behavioral patterns, enabling timely intervention and reducing economic losses (Barreto et al., 2022; Glencross et al., 2023; Ubina et al., 2023; Dellosa, 2023; Georgopoulos et al., 2023).

– Artificial Intelligence has the potential to enhance sustainable aquaculture practices by decreasing environmental impacts and optimizing resource utilization, resulting in more informed and efficient decisions made in aquaculture operations (Alshater et al., 2023; Jung and Shin, 2023; Sailaja et al., 2023; Jie et al., 2019).
– The AI in RAS system minimizes the negative impacts of environmental conditions on aquaculture systems.
– AI improves water quality through giving early alarm of water pollution and the ecological footprint of fish aquaculture by maximizing resource consumption (Mayormente et al., 2024).
– AI provides flexibility in the face of unexpected footraces in aquaculture systems that provide adjusting to the change of environmental conditions (Zhao et al., 2021).

Limitations

– The effectiveness of AI in aquaculture systems is strongly correlated and associated to availability and quality of data that could be difficult in some regions as remote or offshore operations (Aryai et al., 2021).
– Aquaculture datasheets are imperfect which limit the efficiency of AI and control development of robust and accurate models (Daniels et al., 2023).
– AI models are limited to interpret in some areas of aquaculture (Tsolakis et al., 2022). However, adoption of AI in aquaculture is limited to be adopted in large-scale fish farmers due to high initial costs, required high skilled expertise and infrastructure requirements (Mustapha et al., 2021; Glencross et al., 2023; Ubina et al., 2023; Dellosa, 2023; Georgopoulos et al., 2023).
– Financial resources, supports and supplies must be achieved for this technology to be widely adopted (O'Donncha and Grant, 2019; Tsai et al., 2022; Yamuna et al., 2023).
– AI in aquaculture raises ethical concerns, such as privacy of the source of the data, farming practices, or market information (Dey and Shekhawat, 2021).
– Several future works are needed on the ability of AI to optimize the aquaculture resources.
– Studies to identify the link between the several barriers to implementing AI in aquaculture industry are required (Yamuna et al., 2023; Ashraf et al., 2024).
– Security concerns related to interconnected systems and networks stand out as a major factor that controls the expansion of adoption of AI in aquaculture (Mustapha et al., 2021).
– One major obstacle to data sharing between various aquaculture operations and research institutions that restricts the effectiveness of AI in aquaculture is the absence of standard data formats and protocols (Georgopoulos et al., 2023; Ashraf et al., 2024).
– Accuracy, quality and quantity of data are needed to guarantee the data fits for the developing of model predictions (Jung et al., 2023).
– Finally, robotization must be balanced with human expertise to achieve maximum benefits.

Conclusions and future perspective

In conclusion, the potential application of Artificial Intelligence in aquaculture industry has witnessed to be an essential strategy to boost the performance of aquatic animals. Utilizing the AI and ML could help to recognize fish diseases early, give the farmers opportunity to make a proper decision for prompt hygiene practices, control disease outbreaks and pathogen infections. Using AI permissible for monitoring water quality, guarantees required conditions for growth and development. In addition, AI increases the efficiency of aquatic animal culture by enhancing the efficiency of resources, productivity, decreasing labor costs, and increases the quality of aquatic products in various aspects; moreover, AI has an extra impact in aquafeeds through adjusting feed supply via monitoring fish feeding behavior and interactions. Still, it is necessary for continued R&D activity of the application of AI in aquaculture industry to solve challenges regarding cost and implementation of these technologies to wider effect.

Conflict of interest

All authors declare no conflicts of interest that could inappropriately influence this manuscript.

Author contribution

All authors contributed equally to writing this review article. All authors read and approved the final version of this manuscript.

Data availability statement

No data is available.

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