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ORIGINAL RESEARCH ARTICLE

AI-based monitoring and management in smart aquaculture for ocean fish farming systems

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ABSTRACT

Background: The growing global demand for seafood and the limitations of conventional aquaculture practices have highlighted the need for sustainable and efficient alternatives. Ocean-based fish farming faces challenges such as inconsistent water quality, delayed disease detection, and inefficient feeding strategies. Artificial Intelligence (AI), integrated with the Internet of Things (IoT), computer vision, and machine learning, offers opportunities to address these issues and advance smart aquaculture systems. **Methods:** This review systematically synthesizes literature, industrial reports, and case studies from leading aquaculture regions including Norway, Japan, India, and Chile. The analysis focuses on AI applications in water quality monitoring, fish health management, feeding optimization, biomass estimation, and decision support. The study also evaluates commercial platforms and identifies technical, economic, and ethical challenges, alongside emerging research directions. **Results:** AI-based monitoring and management systems demonstrated significant improvements in aquaculture practices. Commercial solutions such as eFishery, Aquabyte, and Aquaai reported feed cost reductions of 15–30%, early disease detection leading to

up to 20% lower mortality rates, and more accurate biomass estimation exceeding 90% prediction accuracy. These outcomes resulted in enhanced yield, cost savings, operational efficiency, and compliance with environmental standards. **Conclusion:** AI technologies have shown transformative potential in achieving sustainable, climate-resilient aquaculture. While challenges such as data scarcity, high setup costs, environmental variability, and ethical concerns persist, emerging approaches—including multimodal AI, digital twins, robotics, and explainable AI—can enhance robustness and transparency. Future research should emphasize scalable, adaptive, and standardized AI frameworks to support global seafood security and long-term sustainability in ocean-based fish farming.
Keywords: Artificial intelligence, biomass estimation, disease detection, feed optimization, smart aquaculture, water quality monitoring

1. Introduction

Increasing worldwide demand for seafood combined with the exhaustion of wild fish stocks has made aquaculture an essential contributor to global food security. Of the proposed aquaculture systems, oceanic fish farming—especially offshore or open-water farms—is a promising option for mass cultivation. Nevertheless, these systems present several challenges including maintaining optimal water quality, monitoring fish health status and feeding efficiency as well adapting to environmental changes in temperature or disease outbreaks. Traditional monitoring can be labor-intensive, ad hoc and myopic which are not suited to the dynamic environment of open ocean aquaculture.

Recent developments in the field of artificial intelligence (AI) have led us to new possibilities on how we can improve efficiency, precision and sustainability in our aquaculture practice. By applying AI methods like machine learning, deep learning and computer vision, smart aquaculture systems can automate real- time monitoring predictions analytics or decision making [1]. Such platforms combine data from multi-source sensors, sub-sea camera and remote operated vehicles in order to enable timely interventions; efficient use of resources through resource optimization algorithms together with as minimizing impact on the environment. AI-enabled solutions have the potential to revolutionize aquaculture, aiding in data- driven applications leading to higher productivity levels at lower costs and more responsible environmental practices [2, 3]. Real-time monitoring can avoid diseases and deaths by preventing and specifying the treatment of biomolecules [4]. Combination of AI and IoT (the Internet of Things) is changing industries in terms of sustainability, efficiency, innovation etc [3].

It is a revolution of the traditional fish farming, using IoT and big data analysis technology to remotely operate with robotics control system that enabled by 5G/Cloud/AI technologies [5]. This technology chain is conducive to creating real-time data acquisition, quantitative regulation accuracy of decision-making means, intelligent control mode and refined investment direction as well as personalized service content that have a new way for fish farming [6]. Integration of IoT devices as sensors, cameras and monitoring systems have improved data collection from remote and dynamic aquaculture ecosystems [1]. AI models can be used with machine learning to analyze large amounts of data in order to optimize feeding strategies, monitor fish behavior and forecast environmental impacts [3]. In addition, drones, nano/micro sensors and bionic robots as well as energy-efficient devices contribute towards increased productivity and sustainability of aquaculture [6]. The application of AI technology in smart cities studies Aquaculture and creates the means to in-service such aquaculture management, thus its use with AET to improve aqua farm productivity [7].

In this article, the utilization of AI methods and tools in developing aquaculture to close food supply-demand gap was reviewed [8]. The review evaluates the contribution of AI in improving traceability, feeding optimization, disease detection and growth prediction as well as environmental monitoring and market information. The application of AI to aquaculture can help reduce human intervention in industry and increase output with better sustainability [9]. The targeted introduction of AI applications into various aquaculture processes is essential for delivering large productivity gains, increased operational sustainability and higher efficiencies that will be required to meet growing global demand for seafood, while at the same time complying with increasingly demanding environmental standards.

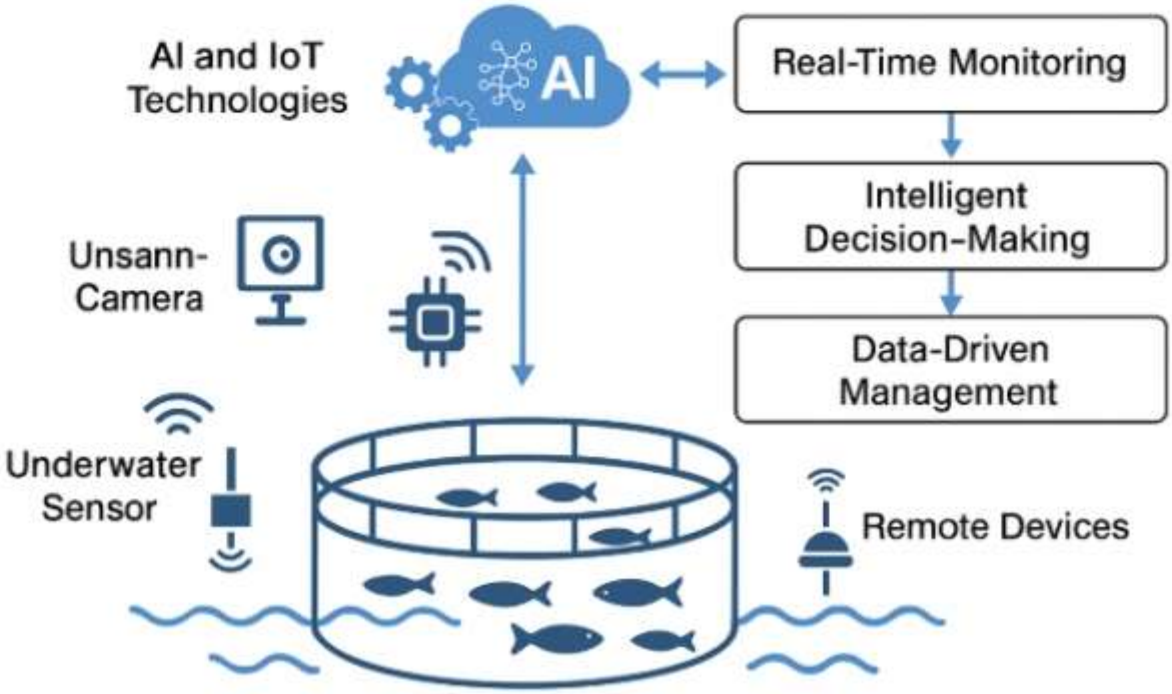

Figure 1. Conceptual Framework of Smart Aquaculture Using AI and IoT Technologies

Figure 1 shows a smart aquaculture system with AI-IoT technologies, where data from underwater sensors/cameras and remote devices are fused to achieve real-time monitoring. This is conducive to the intelligent decision and data-driven management for the oceanic fish farming. Smart aquaculture involves the use of sophisticated digital technologies—such as AI, IoT (Internet of Things), edge computing, big data analytics and automation in combination—to optimize decision making based on real-time information within an agricultural framework [10]. However, such systems aim to overcome the increasing demand for sustainable and scalable solutions of truck farming that have also been developed with favorable growth conditions in ocean-based environments where natural parameter fluctuate much more than inland system due to several constraints[3]. AI in surveillance and management systems achieve functions including real-time environmental monitoring, automation feeding system operation, detection of fish health status prediction models for the growth or disease outbreak [11]. In this context, the application of AI and IoT has proven effective in cage culture facilities where continuous monitoring of fish health, survival rate as well as feed residuals is possible.

Central to smart aquaculture are networked equipment, underwater sensors and actuators, moving robots (AUVs or drones), high-resolution video cameras for filming the aquatic environment and feeders [6]. These are tools that monitor water temperature, dissolved oxygen levels, pH level of the waters, salinity to name a few as well as monitoring fish behavior and feeding activity through sensors; hence providing you with every single information about your livestock (fish), their size and other health indexes. AI-powered algorithms process this data, analyses the resulting information to provide actionable insights and even automate responses while minimizing human intervention in routine monitoring activities [1].

Smart aquaculture farms are generally divided between onshore (land-based recirculating systems) and offshore (open-ocean cages or net pens). Although onshore systems can better implement environmental control, offshore ones can make the most of natural water exchange and be easily scaled up but with stronger requirements to monitoring system because they are away from land where current, tide, storm should have impact. In both environments, AI plays a very important role in supporting predictive management that can help to decrease operational costs and reduce the number of fish destroyed while improving their welfare as well as environmental compliance.

Aquaculture, especially marine fish farming is receiving intense pressure to feed the growing world population and now in need of more sustainable approach [8]. Smart aquaculture with the combination of sophisticated technologies such as AI and IoT is a promising approach to transforming fish farming systems [10]. With this method, the real-time monitoring, data-driven decision making and automated procedures which improve productivity while decreasing environmental impact as well as improving fish welfare is achieved [12]. The anticipated growth in aquaculture production to almost 109 m tonns by 2030 further emphasizes the need for alternative measures [12]. Precision aquaculture systems are necessary to optimize feeding regimes and increase fish farming efficiency [13]. The adoption of a IoT solutions is revolutionizing conventional farming approaches facing problems related to pest control and post-harvest management [14]. Aquaculture, a fast-growing industry and an important contributor to global food security, requires novel strategies for improving its efficiency and sustainability [15]. New friendly intensive breeding will be targeted nontoxic agents and non-destructive products using antibiotics for the pro-biotic nature substances, immunocompetent to adjust with physiological regulation cultured organisms [16]. Fish farming problems can be overcome using AI technologies to achieve accurate, scalable and efficient solutions [10]. Automatic systems could be made used to manage for a success of 70-80% which would also bring about an advantage in profit by 20–30% [17].

Designing and deploying AI systems for aquaculture necessitates a thorough understanding of the unique challenges as well as opportunities in open ocean fish farming settings. For example, AI-based monitoring can help to foster an optimal environment for fish growing which may increase production and profitability quite considerably [5]. Generative AI is a disruptive force for aquaculture, as the industry turns towards a data-driven decision automation and digital integration; GAI models provide new opportunities in environmental monitoring (e.g. detecting contamination or algal blooms), robotized processing plants design optimization metrics development Flood management [18]. It also enables from analysis in situ of the environmental and biological parameters that influence aquaculture system performance. AI capabilities include optimization of fish feeding by real-time monitoring and combining an understanding of the behavior of the fish with environmental conditions to avoid waste for feed while increasing growth rates [19]. Data from such sensors, as well as cameras and others can be analyzed by AI algorithms to identify early signs of disease, predict growth rates, and optimize feeding routines [16]. Additionally, AI can also help with predictive maintenance of aquaculture machinery to prevent down times and reduce operational costs [20]. When deploying AI-based applications in aquaculture, it is necessary to address data privacy and security stakes as well as ethical issues. AI has capacity to turn existing systems into extremely efficient and scalable frameworks [21].

The Precision Fish farming concept applies control-engineering principles to enhance the supervision, regulation and surveillance of biological operations within fish farms [22]. As production is up scaled, however biological as well economic and social issues will more surely start to affect the ethical soundness, productive viability and environmental beings of producing fish [22]. Thus, the promotion of Integrated Farming System technologies will increase yields and income by resource efficiencies and waste minimization [23]. AI-based methods in aquaculture have a wide variety of applications, from monitoring fish behavior and optimizing feeding strategies to forecasting environmental conditions. An analysis of data from sensors and cameras is of importance to achieve early disease detection in aquaculture using AI systems. These systems can detect subtle alterations in fish behavior; for example, lower feeding activity or abnormal swimming patterns that might be indicative of the presence of disease. The early recognition of such changes might give possibility to an efficient intervention and preventing the spread of diseases, with following reduction in mortality rate and economic losses.

AI has also been applied to improve industries such as food quality control and supply chain optimization [24]. Taking inspiration from our terrestrial agriculture, AI algorithms are able to calculate when it is the best time for harvesting aquatic species, predict potential wasted based on growth and environmental conditions or perceiver how healthy their infrastructure waters are as in full rain with a network of sensors mediated by advanced machine learning model.

More concretely, AI programs can crunch real-time data from sensors to calculate the most auspicious time for harvesting and predict potential waste using variables like growth progressions or water quality; ceaselessly monitoring aquaculture conditions. **Figure 2** depicts the main elements of smart-aquaculture, showing how AI and IoT enable oceanic fish farming. It focuses on the monitoring in real time, intelligent decision and data-driven management to improve productivity and sustainability.

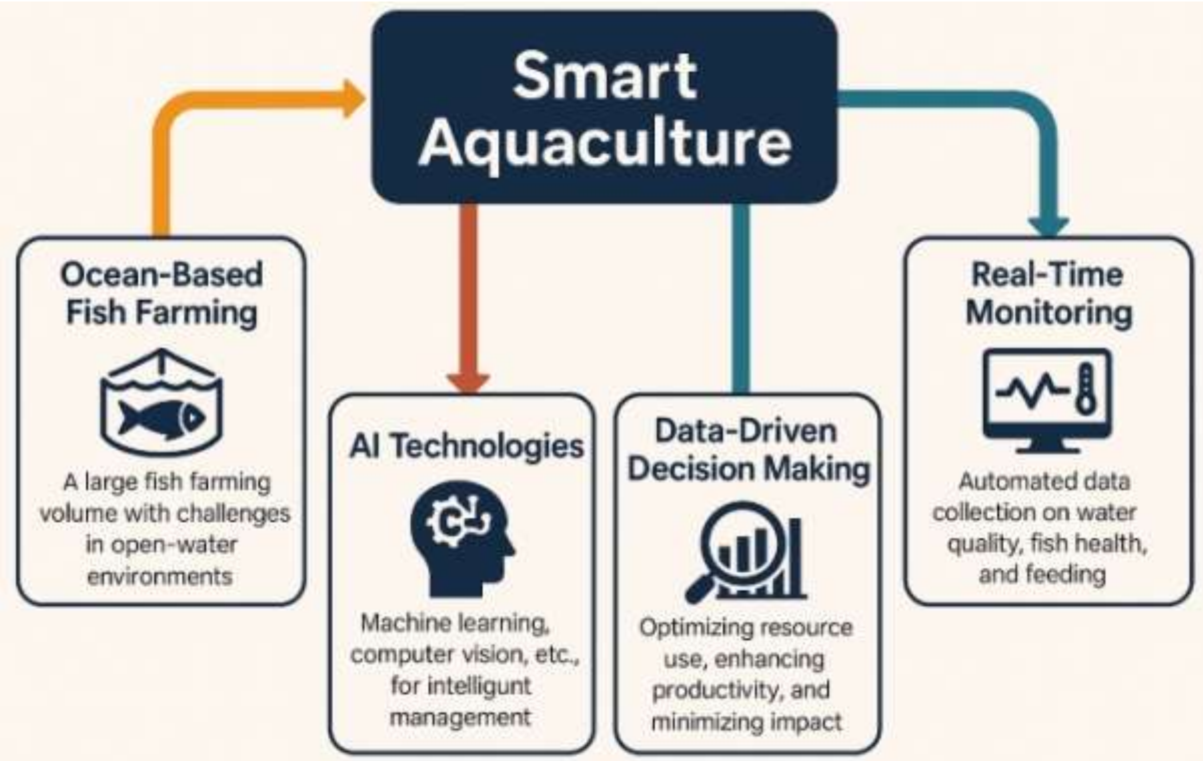

Figure 2. Conceptual framework of smart aquaculture using AI and IoT technologies

The integration of AI and IoT allows automatic, real-time monitoring with intelligent analysis of animal health status to enhance productivity, farm economy and animal welfare by reducing risks through machine learning algorithms (ML) [25]. In combination with artificial intelligence (AI)-based analysis, near real-time data is collected then processed resulting in decision making based on the collection of hyper spectral and multispectral imagery for optimal resource use as well as to combat minimizing environmental damage [26]. This serves to improve even more the sustainability and efficiency of aquaculture farms [28]. AI is currently applied in many areas, such as food quality inspection and supply chain optimization [29]. AI algorithms may also assist in deciding the optimal time for harvesting aquatic organisms, predicting potential waste by combining growth trend with environmental data and monitoring continuously and on a network basis the healthiness of an ecosystem thanks to sensors field-pointed based measurements together with advanced machine learning models [21-31].

Combining such sensors with deep learning and AI algorithms provides the ability to quickly analyze large datasets in real-time, discovering patterns, anomalies or trends [32].

By being able to handle large datasets, the AI models can unearth trends and patterns in water quality that conventional techniques may miss [33]. AI systems, by automatically controlling the levels of crucial water quality parameters such as dissolved oxygen, pH, temperature and salinity to optimize conditions for fish health and growth in an online mode [34].

In this work we review the status of AI technologies for smart ocean fish farming and their perspectives. It concentrates on key applications including water quality monitoring, disease detection estimation of feed and fish biomass. The contribution of the paper is, also, to survey recent advances for AI hardware and software in IoT systems discuss implementations based on real world data – with a not negligible part being focused onto public description of city services implemented both by commercial operators than local government bodies as well limitations achievements and research gaps. The aim is to develop a broader vision of how AI can transform the aquaculture industry, and outline potential future for intelligent and sustainable netwin systems in ocean farming. **Table 1** provides a brief summary of the major challenges encountered in ocean fish farming and associated AI approaches/achievements that contribute to intelligent aquaculture systems.

Table 1. Summary of AI-Based smart aquaculture systems—Challenges, technologies, and expected outcomes

Focus Area	Key Challenges	AI-Based Solutions	Technologies Involved	Expected Outcomes
Global Seafood Demand	Depletion of wild fish stocks; inefficiency of traditional farming	Predictive analytics for resource planning and management	Machine Learning, Big Data, IoT	Increased production; better food security
Monitoring & Health Management	Manual, delayed fish health monitoring; disease outbreaks	Real-time fish behavior and disease detection using vision and sensors	AI + Computer Vision + Underwater Sensors	Early intervention; reduced mortality; improved fish welfare
Feeding Optimization	Feed wastage and cost inefficiency	Automated, adaptive feeding schedules based on fish behavior and environment	ML algorithms; Smart Sensors; Automated Feeders	Cost savings; enhanced growth rates
Environmental Control	Variability in open-ocean conditions	Continuous monitoring and predictive adjustment of water parameters	IoT, Edge AI, Drones, Autonomous Vehicles	Better environmental compliance and sustainability
System Integration & Automation	Limited scalability of traditional systems	AI-integrated control systems for autonomous and remote aquaculture operations	Cloud computing, Robotics, 5G, Edge Computing	Labor reduction; efficient large-scale operations
Market Intelligence & Sustainability	Lack of traceability, harvest planning, and ethical considerations	Smart decision systems for market data, traceability, harvesting time, and ethical resource management	Generative AI, Digital Twins, AIoT, Cyber-Physical Systems	Sustainable practices; enhanced profitability; minimized environmental impact

2. Role of artificial intelligence in aquaculture

Artificial Intelligence (AI) significantly transforms contemporary aquaculture systems through intelligent surveillance, prediction and automation over a range of fish farming procedures. In conventional culture the tasks are carried out basically by manual labor and decisions in many cases take place reactively, causing lack of efficiency action delays on critical issues or high costs. AI tackles some of these weaknesses by providing tools that are data-driven and able to learn about patterns, identify anomalies and help optimize management decisions as they're made. **Figure 3** depicts AI -Machine Learning (ML), Deep Learning (DL) and Computer Vision (CV)-inclusion in aquaculture systems with data derived from camera, sensors, fish behavior. Moreover, it also summarizes the stages in an AI lifecycle to data acquisition and pre-processing till model training for smart fish farm management.

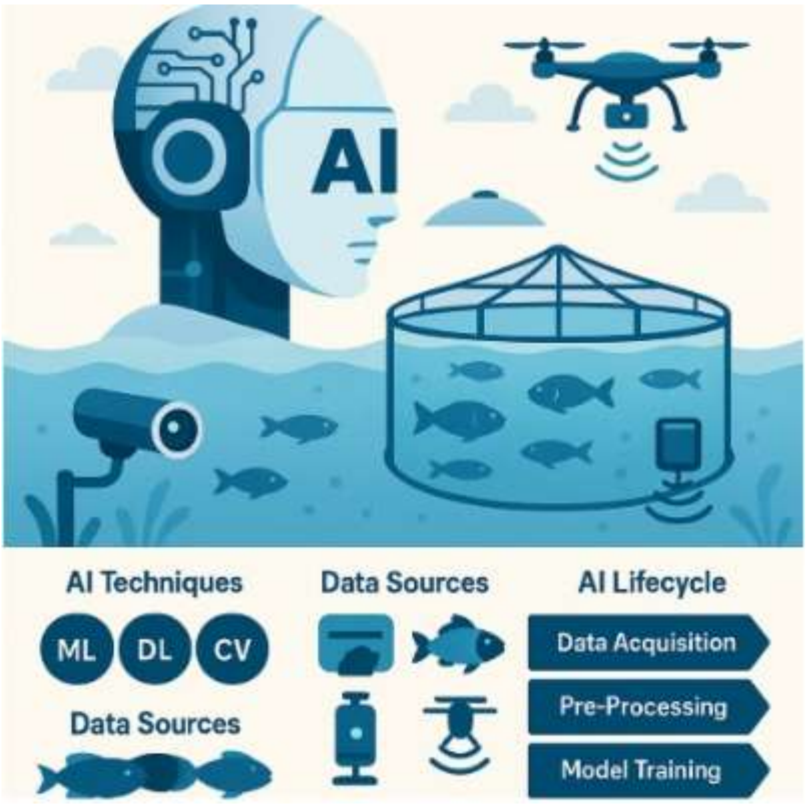

Figure 3. AI-Driven smart aquaculture: techniques, data sources, and lifecycle

2.1. Types of AI techniques used

There are many AI methods already used in aquaculture systems. Machine Learning (ML) can be applied for water quality prediction [10, 11], feed optimization [12] and disease classification by training with record historical data [1]. Deep Learning (DL) which is a subfield of ML technology has gain significant popularity in the recent years for analyzing complex image and video data, e.g., fish detection [2], behavior analysis [6,8], biomass estimation with CNNs [35]. Underwater cameras are combined with Computer Vision to observe fish activity, detect stress behavior and measure the abundance of automatically counted individuals [36]. Moreover, fuzzy logic controller are also adopted to deal with uncertain aquaculture environments and enables the rule-based reasoning technique for regulating factors such as aeration or feeding in an imprecise conditions [37]. Such AI techniques contribute to the less need of human effort for CSPTS and its efficiency.

2.1.1. Comparative discussion of AI approaches in aquaculture

Machine Learning (ML) techniques such as support vector machines, random forests, and regression models have been widely applied for predicting water quality trends, classifying disease symptoms from tabular datasets, and optimizing feeding schedules. Their strengths lie in relatively low computational demand and interpretability, which makes them suitable for small- to medium-scale farms. Yet, ML models often struggle when handling high-dimensional or unstructured inputs such as video and sonar imaging.

Deep Learning (DL), especially Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), offers clear advantages for processing complex image and temporal data. In aquaculture, CNN-based models have achieved high accuracy in lesion detection, abnormal behavior recognition, and biomass estimation from underwater video streams. RNNs, by capturing temporal dependencies, are particularly effective for predicting fish appetite and feeding demand based on behavioral sequences. The challenge, though, lies in their need for large annotated datasets and substantial computational resources, which may limit adoption in resource-constrained farms.

Computer Vision (CV) serves as the practical interface for DL and ML models, translating underwater images and video into analyzable features. CV-based disease detection enables real-time diagnosis from fish skin discoloration or abnormal swimming patterns, while CV-guided feeding optimization adjusts feed supply based on observed appetite and pellet wastage. While CV approaches are highly scalable in offshore cages with dense populations, they are vulnerable to issues such as turbidity, lighting variability, and biofouling on camera lenses.

Overall, ML provides accessible baseline models, DL drives accuracy in complex data environments, and CV ensures real-time field applicability. A hybrid approach—leveraging ML for structured environmental data, DL for unstructured imaging and CV for operational monitoring—appears most promising for robust, multimodal aquaculture systems. This integration aligns with the identified research gap on multimodal AI frameworks for sustainable and adaptive fish farming.

2.2. Data sources for AI models

The application of AI in aquaculture: Success and challenges although the value of using a AI-based system is well-recognized, its success will be highly reliant on achievement in data input. Today's fish farms use a variety of data sources including underwater sensors that measure the temperature, pH value and salinity among other parameters, or even dissolved oxygen [1]. Imaging systems (e.g., HD cameras and sonar) collect visual and acoustic information to track fish health, census populations, count dead biomass for commercial landings in real time [2], detect when the fish are feeding etc. [38]. For the open-ocean, drones and Autonomous Underwater Vehicles (AUVs) are becoming commonly used for remote monitoring, inspection of structures and habitats [39]. These devices run constantly, wirelessly feeding data to onshore or cloud systems and underpinning the real-time AI that is used for farm management.

2.3. AI lifecycle in aquaculture systems

The application of AI technologies in aquaculture generally embodies the life cycle and can be divided into several stages. The first part, Data Collection is the step where raw data from sensors or cameras and even actuators are gathered [6]. Then, the data is pre-processed (cleaning, normalization and feature extraction) integrating it into an adequate format for modelling [40]. The processed dataset is utilized in the training phase of model building where various patterns, relationships are learnt by algorithm under supervised and unsupervised learning [41]. Finally, during the decision support stage, that same trained model informs predictions and automates responses (e.g. modifying feeding rates or aeration) in addition to offering suggestions/insights/alerts for operators [42]. Such a lifecycle supports the closed-loop nature of how AI systems learn over time based on new data and improved system performance. **Table 2** presents six main ingredients of AI-driven smart aquaculture systems with the associated technologies, their primary roles and real-time benefits. It highlights how AI supports sustainable and effective monitoring, feeding, health diagnosis of fish populations and their local conditions in marine based aquaculture.

Table 2. Key components and functions of AI-Based smart aquaculture systems

Component	Technology Used	Primary Function	Benefit in Aquaculture	Real-Time Capability
Water Quality Monitoring	IoT Sensors + ML	Detect pH, DO, temperature	Ensures healthy aquatic habitat	Yes
Fish Health Assessment	Computer Vision + CNN	Analyze fish behavior and lesions	Early disease detection	Yes
Feeding Optimization	AI Algorithms + Cameras	Auto-feed based on fish appetite	Reduces feed waste	Yes

Component	Technology Used	Primary Function	Benefit in Aquaculture	Real-Time Capability
Environmental Prediction	Deep Learning Models	Forecast weather and water trends	Prepares farm for disturbances	Yes
Waste and Contaminant Detection	Image Processing + Sensors	Identify pollutants and debris	Maintains water cleanliness	Yes
Central Decision System	AI Dashboard	Integrates all data and alerts	Smart control and alerts	Yes

Table 2. (*Continued*)

3. AI applications in monitoring systems

Utilization of AI in the aquaculture monitoring system makes it much more accurate and time saving especially for an unfriendly marine environment. AI allows round the clock, real-time tracking of living conditions (e.g. water quality and fish health/condition), feeding regime used or biomass by using machine learning-based solutions combined with deep leaning and computer vision. These applications support anticipatory decisions and autonomous operations, thus supporting greater productivity and sustainability. **Figure 4** provides a summary of the AI contribution in aquaculture monitoring by performing real time data analysis for four main aspects, i.e., water quality management, fish health tracking and feed control together with biomass estimation.

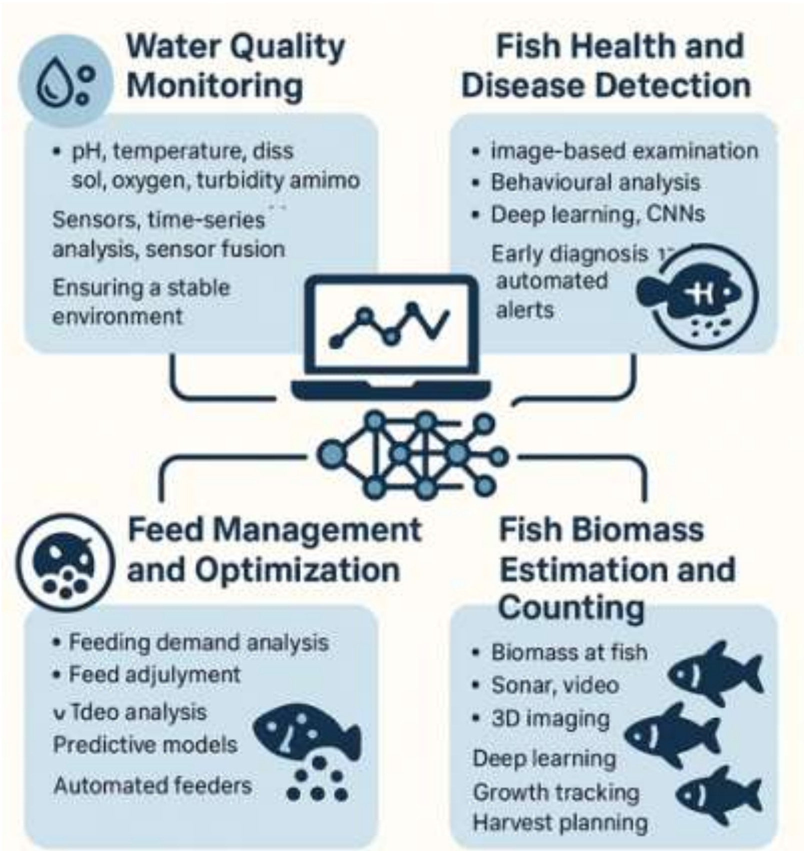

Figure 4. AI applications in aquaculture monitoring systems

3.1. Water quality monitoring

Good water quality is critical for fish survival, growth and system stability in aquaculture. Sensed parameters such as pH, temperature, DO (dissolved oxygen), turbidity and ammonia concentration are measured by a distributed sensor network in the AI-based monitoring systems [43]. These quantities can change rapidly in ocean, such as tides and rain fall etc. Time series data from multiple sensors are processed using machine learning algorithms to recognize patterns, trends and anomalies. Sensor fusion methods integrate measurements of multiple sensors to enhance reliability and robustness [44]. The AI model is able to generate alarms or drive controlling devices, e.g., aerators and water exchange pumps for environmental conditions that are not desired in the aquatic environment.

3.2. Fish health and disease detection

Monitoring the health of fish plays a crucial role in smart aquaculture, especially for large-scale systems that cannot be easily inspected manually. AI allows for imaging-based diagnosis through deep learning, particularly CNNs that recognize physical symptoms of a disease such as lesions or discoloration from underwater camera feeds [45]. Apart from visual observation, behavior pattern algorithms that analyses the movement data can be used to detect early signals of stress or disease (such as low activity levels, and non-habitual very rapid motions) [46]. When these models are linked to real-time monitoring systems predictive diagnostics and automated alerts can be produced, which could allow farmers to isolate affected fish or alter environmental conditions before a disease becomes established.

3.3. Feed management and optimization

Feeding is one of the most important tasks in aquaculture and misfeeding can cause not only poor economic profit but also water pollution. AI-based systems analyses live video feeds in real time and predictive models—such as CNNs or RNNs—are used to predict feeding demand using fish behavior, among other measurements [1]. These models enable to dynamically adapt the feeding schedule and ration according to the actual appetite of fish [47]. AI contributes to time-based and dose-controlled feeding, which also affects the feed conversion ratio of those farmed animals. These systems save money, because the best water is just never wasted by overfeeding.

3.4. Fish biomass estimation and counting

Accurate biomass and counting of fish is an important step in determining growth, harvest scheduling, or stocking density. Conventional approaches are invasive and laborious, yet AI can provide non-invasive methods through sonar data camera footage as well as computer visions models [48]. Using deep learning algorithms it is possible to process high resolution video feeds and count the number of fish, in a clustered environment. More recently, AI has been employed with 3D imaging technology (stereo vision and structured light scanning) to enhance the precision of biomass estimation by calculating fish volume/shape as it swims through in real time [36]. These methods allow prediction of growth rate and automatic harvesting schedule, making it possible to control the farming more efficiently. Key AI applications in aquaculture: monitoring of water quality, fish health, feed management and biomass estimation are summarized on the **table 3**. It indicates artificial intelligence methods, data sources and end-users advantages that are key to encourage real-time decision-making, operational efficiency and sustainability in marine aquaculture.

Table 3. AI Applications in Aquaculture Monitoring Systems

Monitoring Area	AI Techniques Used	Data Sources	Functionality	Key Benefits
Water Quality Monitoring	Machine Learning, Sensor Fusion	pH, DO, Temp, Ammonia Sensors	Detect anomalies, trigger control actions	Stable environment, reduced manual checks
Fish Health & Disease Detection	Deep Learning (CNN), Behavior Recognition	Underwater Cameras, Movement Data	Identify diseases, predict outbreaks	Early intervention, lower mortality
Feed Management	CNN, RNN, Video Analytics	Feeding Videos, Historical Feed Data	Optimize feed quantity & timing	Cost savings, minimal waste
Fish Biomass Estimation	Computer Vision, 3D Imaging, Deep	Sonar, 3D Cameras, Video	Estimate weight, count fish	Non-intrusive, harvest planning

4. AI in decision support and farm management

Artificial intelligence in smart aquaculture Artificial Intelligence is also not restricted to surveillance and detection in Smart Aquaculture systems; it further involves supporting decisions as well as managing operations. Using AI tools has the potential to make decisions quickly and based on up-to-date information by synthesizing enormous amounts of environmental, biological, and operational data. These systems enable farm operators to better manage resources, automate tasks and facilitate a proactive approach to dynamic ocean processes. Using AI within management systems Adds transparency, traceability and sustains the process of production.

4.1. Smart dashboards and visualization tools

Some of today's AI-driven aquaculture systems come equipped with intelligent dashboards that display data in an easy to understand and user-friendly manner. The sensors data (censoring tension, spray factor and weight) is processed through a server database architecture which compresses it to still graphical views of the system states [50]. Charts and heat maps are used to report KPIs such as water quality, fish growth, feed consumption etc., while simple trend analyses demonstrate changes over time [51]. Through these dashboards, farm managers can view ongoing operations in real-time, compare historical trends across time periods and make informed decisions without actively possessing background knowledge of data analysis.

4.2. Real-Time farm control using AI-integrated platforms

By incorporating AI in the management of farms, farmers can control farms automatically and respond to changes occurring about it or system errors immediately. For instance, if AI notices a sudden decrease in dissolved oxygen levels it can instantly switch on the aerators or start water changes [52-54]. Such systems allow remote monitoring and control which are particularly useful in offshore (and large scale) aquaculture farms where only limited manual access is possible [55]. Through the use of feedback loops, a system adjusts various parameters (e.g., feeding rate lighting or circulation) according to AI-based recommendations and thereby infinite conditions with minimal human intervention.

4.3. Risk analysis and forecasting

AI can improve resilience in aquaculture by providing predictive risk analytics [8]. With the utilization of historical along real-time data, ML models can predict on event-based cases like algal blooms and outbursts of diseases or groups die-offs etc. [53]. These are predictions based on observed relationships between environmental cues and biological responses through time. High biosecurity standards and early warning mechanisms enable to take step decisions, for example with adjusting stocking rate, transferring cages or using preventive treatments as such, AI enables great financial loss and fish welfare saving [56-62].

4.4. Supply chain integration and yield optimization

Outside the farm gates, AI also has a place in optimizing the wider aquaculture supply chain, from planning production to delivering produce to market. Predictive models aid to predict harvest date, match transportation scheduling and production in accordance with the market's requirements [63-66]. AI solutions can be connected to inventory systems, traceability platforms and QA protocols in order to guarantee compliance as well as transparency [67-70]. Additionally, yield optimization algorithms help to optimize stocking density and feeding rates as well as harvesting policies in a way that maximizes output while reducing environmental pollution or waste of resources. **Table 4** presents a summary of how AI facilitates the management in an aquaculture farm via smart dashboards, real-time control, risk forecast and supply chain integration by improving automation and decision making as well as operational efficiency.

Table 4. AI applications in decision support and farm management in aquaculture

Application Area	AI Techniques	Function	Data Sources	Automation/Control	Key Benefits
Smart Dashboards & Visualization	Data Aggregation, Visualization Algorithms	Display KPIs and trends	Sensors, Cameras, Feeding Logs	Manual Interpretation	Informed decisions, user-friendly interface
Real-Time Farm Control	Rule-Based AI, Control Systems	Adjust aerators, lights, feeders	Environmental & Sensor Data	Automated Actions	Timely response, reduced manual work
Risk Analysis & Forecasting	Machine Learning, Predictive Analytics	Forecast algal blooms, diseases	Historical + Real-Time Data	Alerts & Recommendations	Early mitigation, improved resilience
Supply Chain Integration	Optimization Algorithms, Predictive Models	Align harvest & logistics	Inventory, Market Trends, Yield Data	Integrated Systems	Market alignment, reduced waste

5. Case studies and commercial implementations

The real-world adoption of AI in aquaculture is growing steadily, with several countries and companies demonstrating measurable improvements in productivity, sustainability, and operational efficiency. This section presents selected international case studies, reviews of industry-driven AI solutions, and comparative insights into the outcomes before and after AI integration in fish farming systems.

5.1. Global examples from Norway, Japan, India, and Chile

Countries like **Norway** and **Japan** are at the forefront of smart aquaculture. Norway, a global leader in salmon farming, has implemented AI-driven systems in open-sea cages to monitor water quality, detect sea lice outbreaks, and optimize feeding using underwater cameras and predictive models. Companies collaborate with research institutions to implement digital twins and automate farm operations under extreme weather conditions.

In **Japan**, AI technologies are being used to maintain the high quality of yellowtail and tuna farming. Systems apply deep learning for visual monitoring and utilize sonar to estimate biomass. These developments have supported sustainable production with reduced feed wastage and better stock control.

In **India**, several start-ups and research initiatives are applying AI and IoT in shrimp farming and inland fisheries. Projects in coastal regions of Andhra Pradesh and Tamil Nadu use AI to predict pond water quality and automate feed management, leading to improved yields and reduced disease risk.

Chile, another major player in salmon aquaculture, has deployed AI-based platforms to monitor fish behavior and optimize environmental conditions in fjord-based farms. Machine learning models are applied to forecast algal blooms and avoid mass mortalities, which have historically affected the region's aquaculture operations.

5.2. Review of industry solutions: eFishery, Aquabyte, Aquaai

Several companies have emerged as pioneers in the commercial deployment of AI for aquaculture:

- **E-Fishery** (Indonesia) provides AI-powered smart feeders that adapt to fish behavior and feeding patterns. Their systems collect real-time data to optimize feeding schedules, reduce costs, and prevent overfeeding, particularly in catfish and tilapia farms.

- **Aquabyte** (Norway/USA) uses underwater cameras and deep learning to track individual fish health, detect lice, and estimate biomass. Their platform helps salmon farmers reduce manual inspections and adopt precision farming techniques.
- **Aquaai** (USA) has developed robotic fish equipped with sensors and cameras that swim inside cages to monitor water parameters and fish welfare. These autonomous units mimic natural fish behaviour and collect data with minimal disturbance.

Such solutions are designed for plug-and-play deployment and offer cloud-based analytics, mobile dashboards, and integration with existing farm infrastructure.

5.3. Comparative analysis of outcomes before and after AI adoption

Multiple studies and farm-level reports have shown that the adoption of AI leads to significant improvements in aquaculture efficiency and sustainability. Before AI integration, fish farms commonly faced issues such as inconsistent feeding, delayed detection of health problems, and optimized harvesting schedules. After implementing AI-based systems, farms reported:

- **Feed cost reduction by 15–30%** due to precise feeding predictions
- **Early disease detection**, reducing mortality rates by up to 20%
- **Improved biomass estimation**, resulting in better planning and higher yield accuracy
- **Increased traceability** and compliance with environmental standards

These comparisons demonstrate that AI not only improves operational performance but also reduces ecological impact and enhances data transparency, making it a critical enabler of next-generation aquaculture practices.

Across documented implementations, AI adoption has yielded measurable technical benefits. For example, feed efficiency improvements of 15–30% have been reported when adaptive feeding algorithms replace manual schedules. Early disease detection using computer vision and deep learning has led to mortality rate reductions of 10–20%, depending on species and farm conditions. Biomass estimation tools based on CNNs and sonar integration have achieved prediction accuracies above 90%, enabling optimized harvest planning and reducing waste. From an economic perspective, farms adopting AI-powered platforms such as eFishery and Aqua byte have reported operational cost savings between 12–25% due to reduced labor, optimized feed use, and lower loss from disease. These quantitative outcomes highlight the tangible technical and economic impact of AI solutions, reinforcing their role in advancing sustainable aquaculture practices.

6. Challenges and limitations

Despite the promising advancements in AI-based smart aquaculture, several challenges and limitations hinder its widespread adoption, particularly in open-ocean environments. These issues span technical, economic, environmental, and ethical domains, and need to be carefully addressed to ensure the long-term success and scalability of intelligent aquaculture systems.

6.1. Data scarcity and inconsistency in offshore environments

A crucial obstacle in the application of AI to ocean fish farming is a lack of reliable, high-quality data. AI models depend on a large amount of data in order to train and validate, but offshore sites are often subject to frequent gaps due sensor failures, transmission breakdowns and power limitations. Challenging environmental conditions in the marine environment are not conducive to continuous and accurate quantitative data on variables of interest, such as fish activity, water chemistry and system performance. This lack of data results in low relationship or generalization power for AI models, which may not adapt between different farms and species. There are numerous examples where models, trained on inshore or laboratory datasets do not generalize well for offshore conditions. To mitigate these limitations, several technical strategies can be employed. Redundancy in sensor networks ensures continuous monitoring by deploying multiple sensors for the same parameter, thereby reducing data gaps caused by failures or transmission errors. Sensor fusion techniques combine data from heterogeneous sources—such as sonar, optical cameras, and chemical probes—to enhance reliability and compensate for individual sensor noise or drift. Moreover, synthetic data generation methods, including physics-based simulations and generative adversarial networks (GANs), can augment scarce offshore datasets by creating realistic training samples for AI models. Together, these approaches improve model robustness, reduce overfitting to limited data, and enable more reliable deployment of AI systems in challenging offshore aquaculture environments.

6.2. High setup costs and maintenance issues

Operation of AI-based systems in marine aquaculture requires significant investment at the outset for hardware, infrastructure and software integration. High-resolution cameras, underwater sensors and autonomous vehicles are expensive to purchase or install in many cases) and technical know-how is needed. In addition, the operation load is increased by keeping these systems in corrosive saline and remote sites. Sensors calibration, battery changing, biofouling control and data transfer systems require maintenance which may not be possible in the cases of small or medium fish farming production. Adoption of these technologies is expensive and acts as a barrier, particularly for regions where aquaculture activities are fledgling.

6.3. Environmental factors: Tides, storms, and salinity variability

Cage systems in open sea are typically exposed to environmental factors like tide and surge, wave action as well variable salinities. (These also have negative effects on fish as well, but they can distort sensor measurements and AIs performance too.) Inclement weather can throw equipment out of place, knock communications offline and stop data collection and system control in its tracks. Additionally, salinity and temperature are not homogeneous in the deeper water layers for calibration of sensors impacting AV predictions by AI. Approaches that do not accommodate this variability can result in either false positive alarms or the failure to detect important events and, thus, may have limited practical utility.

Emerging AI approaches offer new ways to manage such environmental variability. Physics-informed neural networks (PINNs) integrate governing equations of fluid dynamics and environmental processes into the learning framework, allowing predictions that remain robust even under sparse or noisy sensor data. Similarly, hybrid AI–physics models combine machine learning with established hydrodynamic and ecological models, improving the accuracy of forecasts for tides, salinity gradients, and storm impacts on cage stability. These methods enable more reliable predictions in dynamic offshore conditions, where purely data-driven models may fail. By embedding physical constraints into the learning process, such models can enhance resilience, reduce false alarms, and support proactive management decisions in ocean-based aquaculture systems.

6.4. Ethical concerns and dependency on automation

As AI systems become more autonomous in making decisions, questions about over-reliance on fully-automated decisions naturally follow. While critical judgments such as feeding, medicating or harvesting can be delegated to algorithms without appropriate human supervision could produce unintended outcomes. For example, an algorithm that is not functioning properly might underfeed fish or miss the early onset of a disease. Moreover, the emerging automation would reduce jobs available for workers with traditional aquaculture tasks which may create social issues in rural areas. The transparency and explainability of AI decisions, as well, continues to be an issue however when trying to parse complex deep learning outputs that seem unmoored from clear explanation.

To address this, Explainable AI (XAI) methods are increasingly being explored in aquaculture applications. Techniques such as saliency mapping and Grad-CAM can visually highlight which parts of an image influenced a CNN's decision, making disease detection in fish more transparent to farmers. Similarly, SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) can identify how environmental parameters like dissolved oxygen or salinity contribute to predictive outcomes in feed optimization or mortality risk assessment. By embedding such interpretability tools into aquaculture dashboards, operators can better understand model reasoning, validate predictions against their domain knowledge, and maintain human oversight. Incorporating XAI thus reduces blind reliance on opaque algorithms and supports more ethical, trustworthy, and accountable deployment of deep learning systems in aquaculture. **Table 5** gives Summary of main challenges that prevent A.I. from being widely adopted in offshore aquaculture classified into technical, economic, environmental and ethical issues. It details the reasons for each problem, its effects and potential ways to address it.

Table 5. Challenges and Limitations in AI-Based Smart Aquaculture

Challenge Area	Subsection	Description	Underlying Cause	Affected Domain	Impact	Remarks
Data Issues	Data Scarcity and Inconsistency	Offshore systems lack consistent, high-quality datasets for training AI models.	Sensor failures, power issues, dynamic marine conditions	Technical	Poor model generalization; reduced accuracy	Requires robust data strategies and redundancy
Economic Barriers	High Setup Costs and Maintenance	High cost of equipment and maintenance limits scalability, especially for small farmers.	Expensive hardware, harsh environment maintenance needs	Economic	Low adoption in developing regions	Subsidies or cost-effective models needed
Environmental Challenges	Tides, Storms, and Salinity Variability	Weather events and ocean variability interfere with AI system reliability.	Natural ocean disturbances and sensor calibration issues	Environmental	Inaccurate readings; equipment damage	Design systems for extreme environments
Ethical and Social Issues	Dependency on Automation	Automated systems may make flawed decisions or reduce human employment.	Lack of human oversight, opaque AI decision-making	Ethical/Social	Risk of error, job displacement	Ensure explainability and hybrid control models

7. Research gaps and future scope

While the integration of AI in smart aquaculture has shown considerable promise, several research gaps still exist that limit the full realization of its potential. Addressing these gaps is essential to move from isolated applications toward holistic, adaptive, and intelligent aquaculture systems that are scalable, resilient, and environmentally sustainable. The following sub-sections outline the key areas where further research and innovation are required.

7.1. Need for multimodal AI systems

Most AI applications in aquacultureally employ individual data sources, such as visual or time-series sensor data. Fal1: However, ocean farming is a complex environment where physical dynamics influence biological and environmental processes all at the same time. Multimodal AI systems that can read and correlate different kinds of data, (e.g. images with sonar readings, chemical sensor outputs with weather forecasts), are increasingly demanded in practice. Such systems would enable stronger and more context aware predictions, increasing the robustness of decision-making in uncertain and varying marine conditions. Investigating multimodal fusion methods, cross-domain learning based on hybrid mounting and AI models is the cornerstone to get this method working properly.

Deploying multimodal AI in offshore aquaculture also presents several practical challenges. Data synchronization across heterogeneous sources—such as cameras, sonar, and water-quality sensors—requires precise temporal alignment, as delays or mismatches can degrade model accuracy. Bandwidth limitations in remote marine environments constrain the real-time transfer of high-resolution video or sensor data to cloud servers, often necessitating compression or selective transmission strategies. Moreover, computational load at the edge is a critical factor, since running deep learning inference directly on offshore devices requires energy-efficient hardware and optimized algorithms. Without addressing these constraints, multimodal frameworks risk becoming impractical for continuous farm monitoring. Research on lightweight AI architectures, edge–cloud hybrid models, and adaptive sampling strategies will be essential to overcome these technical hurdles and unlock the full potential of multimodal systems in real-world aquaculture.

7.2. Integration of AI with digital twins and robotics

Another significant research frontier lies in the integration of AI with digital twin models and autonomous robotics. A digital twin is a virtual replica of a physical aquaculture system that enables simulation, forecasting, and real-time optimization. When combined with AI, digital twins can model fish behavior, environmental changes, and equipment performance with high precision. Similarly, incorporating AI into robotic systems—such as autonomous underwater vehicles (AUVs), robotic feeders, and cleaning drones—can support dynamic adaptation and autonomous decision-making in complex underwater environments. Current research is limited in this area, and developing coordinated frameworks that combine sensing, actuation, and virtual modelling remains an open challenge.

In practical deployment, digital twins rely on continuous synchronization between physical systems and their virtual replicas. AI models play a central role in this loop by processing incoming sensor data, calibrating the digital twin against observed states, and updating simulation parameters in real time. For instance, predictive models can adjust hydrodynamic simulations of cage environments based on live current and temperature data, ensuring the twin reflects evolving conditions. Model calibration and validation are performed by comparing simulated outputs (e.g., fish growth curves, water quality predictions) with actual farm measurements, thereby refining both the AI model and the twin's fidelity. Real-time synchronization allows proactive decision-making, such as adjusting feeding regimes or triggering maintenance alerts, before deviations in the physical farm escalate. This iterative interplay between AI and digital replicas demonstrates the potential of digital twins not only for forecasting but also for adaptive, closed-loop farm management in offshore aquaculture.

7.3. Standardization of protocols and data formats

The lack of standardized protocols for data collection, labelling, storage, and sharing poses a barrier to large-scale AI adoption in aquaculture. Presently, most farms operate in silos, using proprietary systems and non-uniform sensor configurations. This fragmentation restricts the development of scalable AI models and impedes collaboration across research and industry. There is a pressing need to define universal data formats, benchmarking datasets, and interoperability standards for AI tools in aquaculture. Such standardization will facilitate model validation, reproducibility of results, and cross-farm integration, thereby accelerating innovation and regulatory acceptance.

Some preliminary steps toward standardization are already emerging. For example, the International Organization for Standardization (ISO) has developed guidelines related to aquaculture operations and data handling, such as ISO 12878 for traceability of finfish products, which could be extended to AI-driven monitoring systems. In parallel, open-source benchmarking datasets are being curated by research groups in Norway, Japan, and China, focusing on fish disease images, underwater behavior videos, and water quality sensor streams. These resources enable reproducibility of AI models and provide a foundation for comparative evaluation across research studies. Collaborative frameworks, such as the Global Aquaculture Alliance's data-sharing initiatives, also highlight the push toward interoperability. Incorporating these early standardization efforts into future frameworks will help bridge the gap between experimental AI applications and industry-wide deployment.

7.4. AI for sustainable and climate-resilient aquaculture

As climate change continues to impact ocean ecosystems, AI can serve as a key enabler of climate-resilient and sustainable aquaculture. Predictive analytics can forecast temperature anomalies, disease outbreaks, or harmful algal blooms, helping farms prepare for environmental stress. AI can also optimize resource use—such as feed, water, and energy—thus reducing environmental footprint. However, research is still limited in exploring how AI can be designed with sustainability goals in mind. Future studies should focus on energy-efficient AI models, low-power hardware, and decision systems that promote biodiversity, reduce waste, and support circular aquaculture economies.

8. Conclusion

This review highlights the transformative role of artificial intelligence in modern ocean-based aquaculture. AI technologies—including machine learning, computer vision, and deep learning—are instrumental in real-time water quality monitoring, disease detection, feeding optimization, and biomass estimation. Commercial implementations like eFishery, Aquabyte, and Aquaai demonstrate measurable benefits in yield, cost-efficiency, and sustainability. However, key challenges persist, such as data scarcity in offshore environments, high setup and maintenance costs, environmental variability, and ethical concerns over automation. Notably, research gaps remain in developing multimodal AI models, integrating AI with digital twins and robotics, and establishing standardized data protocols. The review emphasizes the potential of AI not only to improve productivity and reduce manual intervention but also to contribute to environmentally resilient and ethically sound aquaculture systems. Moving forward, emphasis must be placed on developing scalable, adaptive, and sustainable AI solutions tailored for dynamic marine conditions to support global seafood security.

Author Contributions

Pramod Dhamdhere contributed to conceptualization, methodology, and the preparation of the initial draft. Swati Dixit provided expertise in electronics and telecommunication aspects, data interpretation, and critical review of the manuscript. Manjusha Tatiya was responsible for formal analysis, visualization, and refining the technical discussion on AI and data science applications. Babaso A. Shinde contributed to the design of AI-based frameworks, data collection, and validation. Anant Kaulage supported software development, data curation, and assisted in editing. Yogendra Patil participated in literature survey, technical validation, and manuscript proofreading. Rupesh Gangadhar Mahajan provided resources, critical revisions, and technical insights into computer engineering applications. Shital Yashwant Waware refined the methodology, supervised the technical content, and contributed to reviewing and editing. Anant Sidhappa

Kurhade led the overall project administration, conceptualization, supervision, and manuscript review, and served as the corresponding author.

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Conflict of interest

The authors declare no conflict of interest

References

1. Huang Y, Khabusi SP. Artificial Intelligence of Things (AIoT) Advances in Aquaculture: A Review. Processes. 2025;13(1):73. https://doi.org/10.3390/pr13010073
2. Channa AA, Munir K, Hansen M, Tariq MF. Optimisation of Small-Scale Aquaponics Systems Using Artificial Intelligence and the IoT: Current Status, Challenges, and Opportunities. Encyclopedia. 2024;4(1):313. https://doi.org/10.3390/encyclopedia4010023
3. Tina FW, Afsarimanesh N, Nag A, Alahi MEE. Integrating AIoT Technologies in Aquaculture: A Systematic Review. Future Internet. 2025;17(5):199. https://doi.org/10.3390/fi17050199
4. Capetillo-Contreras O, Pérez-Reynoso FD, Zamora-Antuñano MA, Álvarez-Alvarado JM, Rodríguez-Reséndiz J. Artificial Intelligence-Based Aquaculture System for Optimizing the Quality of Water: A Systematic Analysis. Journal of Marine Science and Engineering. 2024;12(1):161. https://doi.org/10.3390/jmse12010161
5. Vo TTE, Ko H, Huh J, Kim Y. Overview of Smart Aquaculture System: Focusing on Applications of Machine Learning and Computer Vision. Electronics. 2021;10(22):2882. https://doi.org/10.3390/electronics10222882
6. Ubina NA, Lan HY, Cheng S, et al. Digital twin-based intelligent fish farming with Artificial Intelligence Internet of Things (AIoT). Smart Agricultural Technology. 2023;5:100285. https://doi.org/10.1016/j.atech.2023.100285
7. Kao CY, Chen IC. Smart City Aquaculture: AI-Driven Fry Sorting and Identification Model. Applied Sciences. 2024;14(19):8803. https://doi.org/10.3390/app14198803
8. Rather MA, Ahmad I, Shah A, et al. Exploring opportunities of Artificial Intelligence in aquaculture to meet increasing food demand. Food Chemistry X. 2024;22:101309. https://doi.org/10.1016/j.fochx.2024.101309
9. Mustapha UF, Alhassan A, Jiang D, Li G. Sustainable aquaculture development: a review on the roles of cloud computing, internet of things and artificial intelligence (CIA). Reviews in Aquaculture. 2021;13(4):2076. https://doi.org/10.1111/raq.12559
10. Danvirutai P, Charoenwattanasak S, Tola S, et al. An integrating RAG-LLM and deep Q-network framework for intelligent fish control systems. Scientific Reports. 2025;15(1). https://doi.org/10.1038/s41598-025-05892-3
11. Chang C, Wang JH, Wu J, et al. Applying Artificial Intelligence (AI) Techniques to Implement a Practical Smart Cage Aquaculture Management System. Journal of Medical and Biological Engineering. 2021.
12. Kassem T, Shahrour I, Khattabi JE, Raslan A. Smart and Sustainable Aquaculture Farms. Sustainability. 2021;13(19):10685. https://doi.org/10.3390/su131910685
13. Chahid A, N'Doye I, Majoris JE, Berumen ML, Laleg-Kirati T. Model Predictive Control Paradigms for Fish Growth Reference Tracking in Precision Aquaculture. arXiv (Cornell University). 2021. https://arxiv.org/abs/2102.00004
14. Zukeram ESJ, Provensi LL, Oliveira M, et al. In Situ IoT Development and Application for Continuous Water Monitoring in a Lentic Ecosystem in South Brazil. Water. 2023;15(13):2310. https://doi.org/10.3390/w15132310
15. Gillani SA, Abbasi R, Martínez P, Ahmad R. Review on Energy Efficient Artificial Illumination in Aquaponics. Cleaner and Circular Bioeconomy. 2022;2:100015. https://doi.org/10.1016/j.clcb.2022.100015
16. Lu C, Chen S, Hung S. Application of Novel Technology in Aquaculture. In: IntechOpen eBooks. IntechOpen. 2019. https://doi.org/10.5772/intechopen.90142
17. Gorbunova A, Kostin VE, Pashkevich IL, et al. Prospects and opportunities for the introduction of digital technologies into aquaculture governance system. IOP Conference Series Earth and Environmental Science. 2020;422(1):12125. https://doi.org/10.1088/1755-1315/422/1/012125
18. Akram W, Din MU, Soud LS, Hussain I. A Review of Generative AI in Aquaculture: Foundations, Applications, and Future Directions for Smart and Sustainable Farming. 2025. https://arxiv.org/abs/2507.11974
19. Small BC, Hardy RW, Tucker CS. Enhancing fish performance in aquaculture. Animal Frontiers. 2016;6(4):42. https://doi.org/10.2527/af.2016-0043

20. Melak A, Aseged T, Shitaw T. The Influence of Artificial Intelligence Technology on the Management of Livestock Farms. International Journal of Distributed Sensor Networks. 2024. https://doi.org/10.1155/2024/8929748
21. Agrawal K, Goktas P, Holtkemper M, et al. AI-driven transformation in food manufacturing: a pathway to sustainable efficiency and quality assurance. Frontiers in Nutrition. 2025;12. https://doi.org/10.3389/fnut.2025.1553942
22. Føre M, Frank K, Norton T, et al. Precision fish farming: A new framework to improve production in aquaculture. Biosystems Engineering. 2017;173:176. https://doi.org/10.1016/j.biosystemseng.2017.10.014
23. Ek A, BT F, OA O. Comparative analysis of production performance in integrated aquaculture system and single system of production of fish, rice, poultry and pig. International Journal of Aquaculture and Fishery Sciences. 2020;74. https://doi.org/10.17352/2455-8400.000060
24. Almoselhy RIM, Usmani A. AI in Food Science: Exploring Core Elements, Challenges, and Future Directions. Open Access Journal of Microbiology & Biotechnology. 2024;9(4):1. https://doi.org/10.23880/oajmb-16000313
25. Neethirajan S. AI in Sustainable Pig Farming: IoT Insights into Stress and Gait. Agriculture. 2023;13(9):1706. https://doi.org/10.3390/agriculture13091706
26. Mana AA, Allouhi A, Hamrani A, et al. Sustainable AI-based production agriculture: Exploring AI applications and implications in agricultural practices. Smart Agricultural Technology. 2024;7:100416. https://doi.org/10.1016/j.atech.2024.100416
27. Sidhu KS, Gill AS, Arora A, et al. Advancements in farming and related activities with the help of artificial intelligence: a review. Environment Conservation Journal. 2021;22:55. https://doi.org/10.36953/ecj.2021.se.2206
28. Alkhafaji MA, Ramadan GM, Jaffer Z, Jasim L. Revolutionizing Agriculture: The Impact of AI and IoT. E3S Web of Conferences. 2024;491:1010. https://doi.org/10.1051/e3sconf/202449101010
29. Zatsu V, Shine AE, Tharakan JM, et al. Revolutionizing the food industry: The transformative power of artificial intelligence-a review. Food Chemistry X. 2024;24:101867. https://doi.org/10.1016/j.fochx.2024.101867
30. Chen T, Lv L, Wang D, et al. Revolutionizing Agrifood Systems with Artificial Intelligence: A Survey. arXiv (Cornell University). 2023. https://arxiv.org/abs/2305.01899
31. Hassoun A, Cropotova J, Trollman H, et al. Use of industry 4.0 technologies to reduce and valorize seafood waste and by-products: A narrative review on current knowledge. Current Research in Food Science. 2023;6:100505. https://doi.org/10.1016/j.crfs.2023.100505
32. Artificial Intelligence and Deep Learning in Sensors and Applications. MDPI eBooks. 2024. https://doi.org/10.3390/books978-3-7258-1452-7
33. Rana R, Kalia A, Boora A, et al. Artificial Intelligence for Surface Water Quality Evaluation, Monitoring and Assessment. Water. 2023;15(22):3919. https://doi.org/10.3390/w15223919
34. Yang H, Liu S. A prediction model of aquaculture water quality based on multiscale decomposition. Mathematical Biosciences & Engineering. 2021;18(6):7561. https://doi.org/10.3934/mbe.2021374
35. Ali A, Ali H, Saeed A, et al. Blockchain-Powered Healthcare Systems: Enhancing Scalability and Security with Hybrid Deep Learning. Sensors. 2023;23(18):7740. https://doi.org/10.3390/s23187740
36. Li Y, Wu Z, Yu Y, Liu CH. An Improved YOLOv8 and OC-SORT Framework for Fish Counting. Journal of Marine Science and Engineering. 2025;13(6):1016. https://doi.org/10.3390/jmse13061016
37. Alim SA, Sumaila M, Ritkangnga IY. Design of a Fuzzy Logic Controller for Optimal African Catfish Water Production. Mekatronika. 2021;3(2):42. https://doi.org/10.15282/mekatronika.v3i2.7352
38. Lin J, Tsai HL, Lyu WH. An Integrated Wireless Multi-Sensor System for Monitoring the Water Quality of Aquaculture. Sensors. 2021;21(24):8179. https://doi.org/10.3390/s21248179
39. Ubina NA, Cheng S. A Review of Unmanned System Technologies with Its Application to Aquaculture Farm Monitoring and Management. Drones. 2022;6(1):12. https://doi.org/10.3390/drones6010012
40. Samatas GG, Moumgiakmas SS, Papakostas GA. Predictive Maintenance -- Bridging Artificial Intelligence and IoT. arXiv (Cornell University). 2021. https://arxiv.org/abs/2103.11148
41. Lu X, Zhang H. Sentiment Analysis Method of Network Text Based on Improved AT-BiGRU Model. Scientific Programming. 2021;2021:1. https://doi.org/10.1155/2021/6669664
42. Naqa IE, Murphy MJ. What Is Machine Learning? In: Springer eBooks. Springer Nature. 2015:3. https://doi.org/10.1007/978-3-319-18305-3_1
43. Sivakumar S, Ramya V. An Intuitive Remote Monitoring Framework for Water Quality in Fish Pond using Cloud Computing. In: IOP Conference Series Materials Science and Engineering. 2021;12037. https://doi.org/10.1088/1757-899x/1085/1/012037
44. Duro N. Sensor Data Fusion Analysis for Broad Applications. Sensors. 2024;24(12):3725. https://doi.org/10.3390/s24123725
45. Sarker S, Biswas A, Nasim MAA, et al. Case Studies on X-Ray Imaging, MRI and Nuclear Imaging. arXiv (Cornell University). 2023. https://arxiv.org/abs/2306.02055
46. Yu X, Wang Y, An D, Wei Y. Identification methodology of special behaviors for fish school based on spatial behavior characteristics. Computers and Electronics in Agriculture. 2021;185:106169. https://doi.org/10.1016/j.compag.2021.106169

47. Zhao H, Wu J, Liu L, et al. A real-time feeding decision method based on density estimation of farmed fish. Frontiers in Marine Science. 2024;11. https://doi.org/10.3389/fmars.2024.1358209
48. Zhang S, Yang X, Wang Y, et al. Automatic Fish Population Counting by Machine Vision and a Hybrid Deep Neural Network Model. Animals. 2020;10(2):364. https://doi.org/10.3390/ani10020364
49. Kandimalla V, Richard M, Smith FH, et al. Automated Detection, Classification and Counting of Fish in Fish Passages With Deep Learning. Frontiers in Marine Science. 2022;8. https://doi.org/10.3389/fmars.2021.823173
50. Lee PG. Process control and artificial intelligence software for aquaculture. Aquacultural Engineering. 2000;23:13. https://doi.org/10.1016/s0144-8609(00)00044-3
51. Aljehani F, N'Doye I, Laleg-Kirati T. Feeding control and water quality monitoring in aquaculture systems: Opportunities and challenges. arXiv (Cornell University). 2023. https://arxiv.org/abs/2306.09920
52. Chen X, Li D, Mo D, et al. Three-Dimensional Printed Biomimetic Robotic Fish for Dynamic Monitoring of Water Quality in Aquaculture. Micromachines. 2023;14(8):1578. https://doi.org/10.3390/mi14081578
53. Kalogiannidis S, Kalfas D, Papaevangelou O, et al. The Role of Artificial Intelligence Technology in Predictive Risk Assessment for Business Continuity: A Case Study of Greece. Risks. 2024;12(2):19. https://doi.org/10.3390/risks12020019
54. Mann K, Good N, Fatehi F, et al. Predicting Patient Deterioration: A Review of Tools in the Digital Hospital Setting. Journal of Medical Internet Research. 2021;23(9). https://doi.org/10.2196/28209
55. Amosu OR, Kumar P, Ogunsuji YM, et al. AI-driven demand forecasting: Enhancing inventory management and customer satisfaction. World Journal of Advanced Research and Reviews. 2024;23(2):708. https://doi.org/10.30574/wjarr.2024.23.2.2394
56. Ramani, P., Reji, V., Sathish Kumar, V., et al., 2025. Deep learning-based detection and classification of moss and crack damage in rock structures for geo-mechanical preservation. Journal of Mines, Metals & Fuels. 73(3), 345–352.
57. Chippalkatti, S., Chekuri, R.B., Ohol, S.S., et al., 2025. Enhancing heat transfer in micro-channel heat sinks through geometrical optimization. Journal of Mines, Metals & Fuels. 73(3), 353–361.
58. Kurhade, A.S., Siraskar, G.D., Chekuri, R.B., et al., 2025. Biodiesel blends: A sustainable solution for diesel engine performance improvement. Journal of Mines, Metals & Fuels. 73(3), 362–370.
59. Kurhade, A.S., Bhavani, P., Patil, S.A., et al., 2025. Mitigating environmental impact: A study on the performance and emissions of a diesel engine fueled with biodiesel blend. Journal of Mines, Metals & Fuels. 73(4), 981–989.
60. Wakchaure, G.N., Vijayarao, P., Jadhav, T.A., et al., 2025. Performance evaluation of trapezoidal ducts with delta wing vortex generators: An experimental investigation. Journal of Mines, Metals & Fuels. 73(4), 991–1003.
61. Wakchaure, G.N., Jagtap, S.V., Gandhi, P., et al., 2025. Heat transfer characteristics of trapezoidal duct using delta wing vortex generators. Journal of Mines, Metals & Fuels. 73(4), 1053–1056.
62. Chougule, S.M., Murali, G., Kurhade, A.S., 2025. Failure investigation of the driving shaft in an industrial paddle mixer. Journal of Mines, Metals & Fuels. 73(5), 1247–1256.
63. Kurhade, A.S., Sugumaran, S., Kolhalkar, N.R., et al., 2025. Thermal management of mobile devices via PCM. Journal of Mines, Metals & Fuels. 73(5), 1313–1320.
64. Chougule, S.M., Murali, G., Kurhade, A.S., 2025. Finite element analysis and design optimization of a paddle mixer shaft. Journal of Mines, Metals & Fuels. 73(5), 1343–1354.
65. Waware, S.Y., Ahire, P.P., Napate, K., et al., 2025. Advancements in heat transfer enhancement using perforated twisted tapes: A comprehensive review. Journal of Mines, Metals & Fuels. 73(5), 1355–1363.
66. Patil, Y., Tatiya, M., Dharmadhikari, D.D., et al., 2025. The role of AI in reducing environmental impact in the mining sector. Journal of Mines, Metals & Fuels, 73(5), 1365–1378.
67. Napte, K., E. Kondhalkar, G., Vishal Patil, S., Vishnu Kharat, P., Snehal Mayur Banarase, Sidhappa Kurhade, A., & Shital Yashwant Waware. (2025). Recent Advances in Sustainable Concrete and Steel Alternatives for Marine Infrastructure. Sustainable Marine Structures, 7(2), 107–131. https://doi.org/10.36956/sms.v7i2.2072
68. Sarode, G. C., Gholap, P., Pathak, K. R., Vali, P. S. N. M., Saharkar, U., Murali, G., & Kurhade, A. S. (2025). Edge AI and Explainable Models for Real-Time Decision-Making in Ocean Renewable Energy Systems. Sustainable Marine Structures, 7(3), 17–42. https://doi.org/10.36956/sms.v7i3.2239
69. Kurhade AS, Kharat PV, Chougule SM, Darade MM, Karad MM, Murali G, Charwad GA, Waware SY, Yadav RS. Harnessing the Power of Plastic Waste: A Sustainable Approach to Fuel Production. Journal of Mines, Metals & Fuels. 2025 Feb 1;73(2).
70. Raut PN, Dolas AS, Chougule SM, Darade MM, Murali G, Waware SY, Kurhade AS. Green Adsorbents for Heavy Metal Removal: A Study on Zinc Ion Uptake by Tinospora cordifolia Biocarbon. Journal of Mines, Metals & Fuels. 2025 Jan 1;73(1).