ARTIFICIAL INTELLIGENCE DRIVEN TRANSFORMATION OF MODERN AQUACULTURE: REVIEW

By

AFIA, O. Edet
Department of Fisheries and Aquatic Environmental Management,
University of Uyo, Uyo, Nigeria

And

UDO, E. Ndarake
Department of Computer Science,
University of Uyo, Uyo, Nigeria

ABSTRACT

Aquaculture has undergone a rapid transition from traditional, labour intensive practices to more intensive and intelligent production systems, driven by the need to meet rising global demand for aquatic food in a sustainable manner. This transformation has been supported by advances in automation and digital technologies, which aim to address persistent challenges in aquaculture such as inefficient resource use, high labour costs, environmental degradation, and increasing disease risks. As aquaculture systems become more complex, conventional management approaches are often inadequate to ensure optimal performance and sustainability. Recent developments in automation and smart technologies, including the Internet of Things, big data analytics, cloud computing, artificial intelligence, and blockchain, have enabled real time monitoring, data driven decision making, and automated control of aquaculture operations. Artificial intelligence, in particular, has emerged as a core component of smart aquaculture systems by providing predictive and inferential capabilities that support efficient process control and adaptive management. Current AI applications in aquaculture include biomass estimation, size and weight measurement, species identification and classification, feeding optimisation, disease detection, stock counting, and continuous water quality monitoring. These applications have demonstrated potential benefits such as improved production efficiency, reduced energy and water losses, lower labour requirements, enhanced animal welfare, and better operational transparency. The objective of this study is to review the role of automation and artificial intelligence in modern aquaculture systems. Specifically, the study aims to examine key digital technologies driving smart aquaculture, highlight major application areas of artificial intelligence and machine learning, and assess their contributions to productivity, sustainability, and management efficiency. By synthesising recent research and practical developments, this review provides a comprehensive overview of how intelligent technologies are reshaping aquaculture and outlines future prospects for their wider adoption.

KEYWORDS: Smart Aquaculture, Automation, Artificial Intelligence, Precision Fish Farming, Automation, Aquaculture Sustainability and Digital fisheries

Conflict of interest statement:
The research did not receive any specific grant from funding agencies in the public, commercial or non-profit sectors.

INTRODUCTION

Aquaculture and capture fisheries together constitute a multi-billion-dollar global industry that provides food, employment, and income for millions of people worldwide. Global aquatic animal production is projected to increase substantially in the coming decades as the demand for animal protein continues to rise with population growth and urbanization (1). While aquaculture has demonstrated strong capacity to contribute to food security, its rapid expansion has intensified pressures on farm management systems, environmental quality, and production efficiency (2).

Traditionally, aquaculture operations have relied heavily on manual labour and experience-based decision-making. However, such approaches are increasingly inadequate for managing high-density production systems characterized by dynamic environmental conditions and biological variability (3). Technological innovations have therefore become central to improving operational efficiency, minimizing losses, and ensuring long-term sustainability.

In recent years, digital technologies including artificial intelligence, machine learning, IoT, cloud computing, and blockchain have been introduced into aquaculture systems, driving the sector toward intelligent and automated production models (4). AI, in particular, enables the analysis of large and complex datasets to support real-time monitoring, prediction, and optimization of aquaculture processes (5). These capabilities are transforming conventional fish farming into smart aquaculture systems capable of precise control over water quality, feeding, health management, and harvest planning.

Despite these advances, the implementation of fully automated aquaculture systems remains challenging. Aquaculture is inherently biological and dynamic, requiring continuous observation, contextual interpretation, and adaptive decision making. Over-reliance on automation without adequate human oversight may increase operational risks, particularly under variable environmental conditions or during disease outbreaks [6,7]. Against this background, a critical review of artificial intelligence applications in aquaculture is timely and necessary to clarify current capabilities, identify limitations, and guide future research and adoption. Such an assessment is essential for ensuring that AI contributes effectively to productivity gains while supporting sustainability and responsible aquaculture development.

This study aims to critically review the application of artificial intelligence in aquaculture systems; explain the concept and key components of smart aquaculture systems; examine recent technological developments in smart and automated aquaculture; identify and discuss major applications of artificial intelligence in aquaculture production and management; and analyse the key challenges, bottlenecks, and limitations associated with the current development and adoption of AI technologies in aquaculture.

Aquaculture Automation: Concepts, Systems, and Emerging Digital Technologies

Automation is increasingly recognized as the cornerstone of future aquaculture development, offering pathways to enhanced productivity, reduced production costs, and improved environmental sustainability. Through the integration of sensor based monitoring, aerial and underwater platforms, and intelligent decision support systems, aquaculture operations are transitioning from labour intensive practices to data driven and remotely managed production models capable of meeting the growing global demand for nutritious aquatic food [8]. Automation, defined as the shift from manual to automatic control of processes and equipment, has driven aquaculture through successive stages of technological development, from basic mechanisation to fully intelligent systems [9]. These advances have supported the evolution of aquaculture toward intensive, efficient, and environmentally sustainable production systems.

Aquaculture lends itself naturally to automation due to its reliance on measurable environmental and biological parameters. The application of the Internet of Things, big data analytics, artificial intelligence, cloud computing, 5G communication, and robotics enables remote monitoring and control of production systems. Smart aquaculture platforms can be operated by autonomous or semi-autonomous robotic systems capable of managing infrastructure, equipment, and operational processes to ensure optimal performance [10]. In practice, water quality parameters such as temperature, dissolved oxygen, pH, light intensity, and humidity are continuously measured using sensor networks. These data are transmitted through communication nodes to central control units or cloud platforms, where they are analyzed and translated into operational decisions that are automatically executed by actuators and control devices [6].

The widespread adoption of automation and intelligent technologies has progressively reshaped global aquaculture into a more intensive and knowledge driven sector. Modern production systems increasingly rely on computer controlled environments, where key physiological processes of cultured species and system outputs such as growth rate, ammonia concentration, and pH are regulated through precise control of inputs including feed, oxygen supply, temperature, water exchange, and stocking density [8]. This level of control allows producers to maximize biological performance while minimizing waste and environmental impacts.

From an economic perspective, automated and AI supported aquaculture systems offer several advantages. These include increased process efficiency, reduced energy and water losses, lower labour requirements, decreased stress and disease incidence in cultured organisms, improved record keeping, and deeper understanding of system dynamics [8]. Collectively, these benefits enhance profitability and resilience, particularly for large scale commercial operations.

Smart Aquaculture Systems

Smart aquaculture represents one of the most prominent sustainability driven trends in the sector, combining automation and intelligence to optimise production while reducing environmental footprints. Intelligent technologies have demonstrated substantial benefits across agriculture and aquaculture by lowering labour demands, increasing output, and promoting environmentally responsible practices [6].

At the core of smart aquaculture systems is an integrated workflow that includes real time data collection via sensors, data transmission through wired or wireless networks, data storage and analysis on cloud platforms, automated decision making, and feedback control through actuators and machines [10]. These systems are designed to operate continuously and autonomously, enabling adaptive management that responds rapidly to changing environmental and biological conditions.

Advances in artificial intelligence allow smart aquaculture to span the entire production cycle, from broodstock management and nursery operations to grow out, harvesting, and post-harvest handling. Intelligent systems can manage water preparation, feeding regimes, grading and counting of stock, and even cleaning and maintenance operations. The overarching goal of smart aquaculture development is to increase production efficiency to meet global seafood demand while safeguarding environmental integrity [6].

The deployment of AI and IoT technologies has expanded rapidly in recent years as solutions to persistent challenges in traditional aquaculture. Applications now extend across cages, ponds, hatcheries, and breeding facilities, with specific functions including water quality monitoring [11], behavioural observation, feed optimisation, reduction in feed wastage, and labour saving through system automation [12,13].

Conceptual Framework of Smart Aquaculture

Smart aquaculture systems integrate multiple intelligent devices within a digitally structured environment to monitor production conditions in real time and automatically generate management decisions based on collected data [14]. These systems rely on interconnected digital technologies including IoT, artificial intelligence, big data analytics, cloud computing, advanced communication networks, and robotics. In some configurations, robotic platforms are capable of managing facilities, equipment, and machinery autonomously to achieve efficient and consistent production outcomes [10].

Recent reviews have highlighted a wide spectrum of AI applications in aquaculture, including automated feeding systems, aerial and underwater drones, disease prevention and diagnosis, seed screening, stock inspection, shrimp farming optimisation, smartphone based management tools, fish processing automation, open sea fisheries monitoring, blockchain enabled supply chains, and conservation of endangered aquatic species [15]. Conceptual models of smart aquaculture typically illustrate the deployment of distributed sensors and devices, with system data and management functions accessible through mobile and web based interfaces for real time oversight and control [16].

Water Quality Monitoring in Smart Aquaculture

Water quality remains the most critical determinant of aquaculture success. Parameters such as temperature, dissolved oxygen, pH, turbidity, ammonia, nitrite, nitrate, alkalinity, and carbon dioxide directly or indirectly influence survival, growth, and health of cultured organisms. Among these, temperature, dissolved oxygen, and pH are considered the most influential and sensitive indicators of system performance [17].

The application of IoT in aquaculture has introduced a new paradigm for real time water quality monitoring using interconnected sensors and intelligent data processing. IoT based aquaculture systems typically consist of four layers: the physical layer of sensors and devices, a monitoring layer for data acquisition, a virtual layer for data processing and analysis, and a communication protocol layer for data transmission [17]. These architectures support continuous monitoring, early detection of anomalies, and timely interventions, thereby reducing risks and improving farm management efficiency.

Despite increasing automation, aquaculture operations still involve inherent biological and environmental uncertainties. As such, intelligent equipment including robotic systems, data analytics tools, and energy efficient processing devices are increasingly deployed to support human decision making rather than replace it entirely. These technologies enable fish identification, biomass estimation, and behavioural analysis while progressively automating labour intensive stages of production [18].

New Digital Technologies in Marine Aquaculture

Marine aquaculture has gained strategic importance as natural fishery resources decline and demand for seafood continues to rise. To address operational inefficiencies and modernise fisheries, a suite of digital technologies including IoT, big data, cloud computing, artificial intelligence, and blockchain is being widely adopted [4].

These technologies collectively enable comprehensive data collection, secure data sharing, advanced analytics, prediction, and optimal decision making across the entire production chain. IoT serves as the foundational data source, capturing real world information through sensors and smart devices. Cloud computing provides scalable infrastructure for data storage and processing, facilitating integration and analysis of large datasets [19]. Artificial intelligence transforms processed data into actionable knowledge by identifying patterns and generating rapid, adaptive decisions that can be fed back into IoT controlled systems [20]. Blockchain technologies enhance trust, transparency, and data integrity across digital networks, reinforcing the reliability of integrated aquaculture management systems [21].

The convergence of these digital tools has also accelerated innovation in intelligent fishing vessels, marine information systems, and seafood supply chain supervision, while providing a strong foundation for advanced marine aquaculture operations [22].

Artificial Intelligence Systems in Aquaculture

Artificial intelligence systems are broadly defined as software based systems that generate outputs such as predictions, recommendations, or decisions to achieve specific human defined objectives. AI techniques are commonly classified into three groups: machine learning approaches including deep learning; logic and knowledge based approaches such as expert systems; and statistical or optimisation based approaches including Bayesian methods.

Machine learning approaches enable systems to learn from data through supervised, unsupervised, or reinforcement learning paradigms, making them particularly suitable for complex aquaculture datasets. Knowledge based systems encode expert rules and reasoning processes, while statistical approaches provide the mathematical foundation for uncertainty handling, optimisation, and inference. In practice, many aquaculture applications combine techniques across these groups to improve robustness and adaptability [23].

The expanding application of AI systems in aquaculture reflects their capacity to support automation, enhance understanding of biological processes, and enable intelligent, adaptive management. As technologies continue to mature, AI driven automation is expected to play a central role in shaping the next generation of sustainable and resilient aquaculture systems.

Artificial Intelligence in Aquaculture: Concepts, Applications, and Emerging Frontiers

Artificial intelligence has become a transformative force in aquaculture, reshaping how aquatic systems are monitored, managed, and optimized. Recent advances in sensing technologies, machine vision, robotics, and machine learning have enabled continuous, real time observation of cultured species and their environments. These systems allow early detection of deviations in growth, behavior, and water quality, thereby reducing production risks and improving decision making before minor issues escalate into major losses [8]. Unlike conventional monitoring approaches that rely heavily on manual inspection, AI driven systems can process large volumes of heterogeneous data with greater speed and consistency, involving human operators only when intervention is necessary [24].

Artificial intelligence broadly refers to computer systems designed to mimic aspects of human cognition, including learning, pattern recognition, and adaptive decision making. In aquaculture, AI draws on historical and real time data to improve performance through experience, making it particularly suitable for complex and dynamic biological systems. Its adoption mirrors trends seen in agriculture and industrial automation, where AI has reduced labour requirements while improving efficiency and scalability [25]. In practical terms, AI can function across the production cycle, from automated feeding and water quality control to harvesting, processing, and logistics. Studies suggest that intelligent control systems can reduce feed and energy waste and lower operational costs by up to 30 percent, while maintaining or improving production outputs [26].

The pace of digital innovation in aquaculture has accelerated rapidly over the past decade. A substantial proportion of software tools currently used in aquaculture have been developed within the last five years, reflecting growing investment in data driven production systems. Finfish farming dominates both production volume and digital tool development, accounting for more than half of global aquaculture output and a large share of aquaculture focused software solutions [27]. Beyond farming, AI is increasingly applied in capture fisheries, stock assessment, and conservation, highlighting its broader relevance to aquatic resource management [25]. By enabling precise feeding based on size, weight, and developmental stage, AI supported husbandry systems can enhance feed efficiency and improve the quality and uniformity of farmed aquatic products [28].

Applications of Artificial Intelligence in Aquaculture

- **Conservation and Management of Endangered Aquatic Species**

Declines in aquatic biodiversity driven by pollution, habitat degradation, and overexploitation have intensified the need for effective conservation tools. Traditional monitoring approaches are often labour intensive and spatially limited. AI based solutions, including underwater cameras, autonomous drones, and sensor networks, offer scalable alternatives capable of rapidly assessing habitats and species distributions with high accuracy [25]. The integration of vision systems and telemetry has enabled detailed tracking of large migratory species such as sharks and whales, providing insights into movement patterns and behavioural ecology that support evidence based conservation strategies [15].

The fish value chain encompasses all activities from production to consumption, commonly described as “from sea to fork.” Understanding and managing this chain is critical for improving efficiency, sustainability, and consumer trust. Recent studies highlight that insufficient data quality and availability remain major barriers to effective AI implementation across the value chain [25]. Where robust datasets exist, machine learning models can support traceability, quality control, logistics planning, and market forecasting. By identifying waste and inefficiencies at each stage, AI systems can guide the transition toward low waste, resource efficient production models.

Traceability has become particularly important due to increasing regulatory requirements and consumer demand for transparency regarding food origin, safety, and sustainability. While traditional traceability focuses on recording and tracking basic information, advances in data science and AI extend its scope to include food integrity, environmental performance, processing efficiency, and market dynamics [23,29]. Trustworthy AI driven traceability systems are increasingly viewed as essential for compliance, certification, and competitiveness within global seafood markets [30].

- **Sustainability of the Fish Value Chain**

AI has demonstrated strong potential to enhance environmental, social, and economic sustainability across fisheries and aquaculture systems. Applications include monitoring fishing effort, detecting illegal activities, optimizing spatial planning, and reducing fuel consumption and associated emissions [31,32]. Beyond primary production, processors and distributors also seek AI based solutions to improve resource use efficiency and reduce environmental footprints throughout the chain.

- **Seafood Integrity and Food Safety**

Food fraud, mislabeling, and adulteration remain persistent challenges in global seafood markets. Visual inspection alone is often insufficient for reliable species identification, particularly for processed products. Consequently, AI combined with omics techniques and advanced analytics has gained prominence in seafood authenticity research [33,34]. Machine learning models have also been applied to predict food safety risks, including contaminant bioaccumulation and spoilage dynamics, supporting proactive quality management [35,12].

- **Fish Processing and the Circular Economy**

Fish processing traditionally relies on manual operations, which can result in variable product quality and inefficiencies. AI enabled automation, including vision guided cutting and defect detection, has improved precision and yield while reducing waste [36,37]. Given that processing by products may constitute up to 60 percent of total biomass, AI supported decision tools have also been proposed to valorize waste streams, for example through optimized feed production or by product utilization [38,39]. Within a circular economy framework, machine learning supports product design, demand prediction, maintenance planning, and materials recycling, enhancing overall system resilience [40].

- **Logistics and Supply Chain Management**

The growing volume and complexity of data generated along seafood supply chains necessitate advanced analytical tools. AI methods are well suited to tasks such as transport optimization, risk assessment, and supplier selection, enabling more responsive and efficient logistics systems [41].

- **Monitoring of Environmental Conditions**

Environmental monitoring is a core application of AI in aquaculture. Unmanned aerial vehicles equipped with sensors and computer vision have been used to collect high resolution data on water quality parameters, including temperature, dissolved oxygen, turbidity, nutrients, and chlorophyll concentrations [42]. While limited flight duration remains a technical constraint, advances in battery technology and cloud based analytics are steadily improving system performance. Recent developments integrate deep learning and remote access platforms, enabling scalable, low cost monitoring and surveillance solutions capable of detecting abnormal activities and supporting farm level decision making [43, 44].

- **Smart Feeding Systems**

Feed costs typically account for the largest share of aquaculture operating expenses. AI driven feeding systems address this challenge by aligning feed delivery with actual animal demand. Acoustic, vibration, and vision based sensors can distinguish feeding activity and appetite, reducing overfeeding and minimizing water quality deterioration [15]. Commercial systems combining machine learning, IoT, and remote access have reported substantial improvements in growth performance and profitability, with documented increases in harvest yield and net income across multiple countries [45,46].

- **Behaviour Analysis and Disease Diagnosis**

Fish behaviour provides early indicators of stress, toxicity, and disease. Machine learning techniques, including support vector machines and deep neural networks, have been used to classify sex, detect behavioural anomalies, and assess toxicological responses based on movement patterns and visual cues [47,48]. Automated analysis of hydroacoustic and imaging datasets further enables high resolution monitoring of health indicators such as parasite load and mortality, even in the absence of advanced data science expertise [49]. Image based AI systems have also demonstrated high accuracy in disease detection and early warning, allowing rapid response to emerging outbreaks and reducing economic losses [50].

- **Smart Seed Screening, Harvesting, and Processing**

Seed quality strongly influences survival and growth performance. AI assisted sorting systems reduce the labour and cost associated with traditional screening while improving accuracy. Similar technologies have been applied in harvesting and processing, where vision guided equipment can separate undersized or diseased fish and automate cutting and filleting operations at high throughput rates [51,52].

Artificial Intelligence and Cultured Aquatic Meats

A recently emerging frontier in aquaculture is the production of cultured or cell based aquatic meat. This approach involves growing muscle tissue from selected aquatic species under controlled laboratory conditions, without the need for whole animal farming or harvesting [53]. AI plays a central role in optimizing cell selection, culture conditions, bioreactor control, and product design. Cultured meat systems have been proposed as environmentally sustainable alternatives capable of drastically reducing land, water, and emission footprints compared with conventional aquaculture, although high production costs remain a major limitation due largely to expensive culture media components [44].

Electronic Monitoring of Fishing Catches Based on Artificial Intelligence

The fisheries sector is undergoing a major digital transition driven by the need for transparency, sustainability, and efficiency in catch reporting and resource management. Conventional monitoring approaches, which rely heavily on onboard observers and manual logbooks, are often costly, inconsistent, and limited in spatial and temporal coverage. In response, electronic monitoring systems supported by artificial intelligence have emerged as robust and scalable alternatives for recording fishing activities and catches in real time. These technologies integrate sensors, cameras, and machine learning algorithms to automate species identification, quantify catches, and support compliance with management regulations.

One notable example is the iObserver system developed by Ovalle et al. [54], an onboard electronic device designed for real time, automated identification and quantification of total catch. Installed above conveyor belts prior to the sorting area, the system combines image acquisition with AI based recognition models to continuously document catches as they are processed. Such systems reduce reliance on human observers, minimize reporting bias, and provide high resolution datasets that can support stock assessments and fisheries management decisions.

- **Tracking Fine Scale Fish Movements Using Autonomous Maritime Robotics**

Understanding fish migration patterns and movement dynamics is fundamental to fisheries ecology, conservation planning, and sustainable exploitation. Fine scale tracking of fish movements allows researchers to link behavioural responses to environmental drivers such as temperature, currents, and habitat structure, and to predict how fish populations may respond to ecosystem change [55]. This knowledge is particularly critical in the context of overfishing, which remains one of the most significant threats to marine ecosystems and food security worldwide [56].

Recent reviews highlight the growing role of autonomous maritime robotics in dynamic fish tracking. Nash et al. [55] employed a systematic PRISMA based review approach to synthesize developments in autonomous tracking technologies, ensuring methodological rigour and relevance in a rapidly expanding field. These tools enable continuous observation of fish movements across spatial scales that are impractical for traditional survey methods.

- **Digital Tools for Fish Tracking and Underwater Monitoring**

A range of autonomous and semi- autonomous platforms are now used for fish tracking and underwater monitoring, including autonomous underwater vehicles, unmanned surface vehicles, aerial drones, and multi vehicle systems. These platforms are increasingly favoured due to advances in robotics, sensor miniaturisation, and onboard intelligence.

Autonomous underwater vehicles are among the most widely used tools for collecting biological, physical, and chemical data in marine environments. Typically designed with streamlined, torpedo like structures, AUVs are capable of operating at depth while carrying imaging systems and environmental sensors. However, mission duration remains constrained by battery capacity and power demands. Studies have shown that while AUVs perform well in short missions, extended deployments require careful optimisation of energy use and sensor configurations to minimise drag and power consumption [57].

Communication underwater presents additional challenges due to signal attenuation. Acoustic communication remains the most common solution, enabling limited data transfer through water using defined frequencies. Alternatively, some platforms rely on periodic surfacing to establish GPS, satellite, or wireless connections, allowing higher bandwidth communication and command updates. These strategies have supported successful applications such as tracking the movements of leopard sharks and other mobile species.

Unmanned surface vehicles complement underwater platforms by providing extended range and endurance, often powered by renewable energy sources such as solar and wind. Long duration deployments exceeding several months have been demonstrated, making USVs suitable for large scale monitoring and as communication relays for AUV missions [58]. By maintaining acoustic contact with underwater vehicles, USVs help overcome communication barriers and improve mission reliability.

More recently, multi vehicle deployments have gained prominence. By integrating multiple platforms such as AUVs, USVs, and UAVs, researchers can expand spatial coverage, improve tracking accuracy, and reduce data gaps. For example, combined deployments have enabled long distance tracking of highly migratory species such as ocean sunfish, where simultaneous monitoring of fish position and surrounding environmental conditions would not be feasible using a single platform.

- **Artificial Intelligence in Water Quality Monitoring**

Artificial intelligence has a long history in industrial process control, where it has been used to improve stability, efficiency, and decision making. These advantages have motivated its application in aquaculture, particularly for real time water quality monitoring. Early expert systems demonstrated the feasibility of AI driven control in intensive systems. For instance, the recirculating intensive aquaculture expert system developed by Padala and Zilber [59] integrated sensors, programmable logic controllers, and rule based decision support to manage feeding, temperature, oxygen, and water flow in tilapia culture. Such systems illustrated how expert knowledge could be embedded into automated platforms to optimise production while reducing labour demands.

Modern AI systems extend these concepts by incorporating machine learning models capable of adapting to changing conditions. Continuous monitoring of parameters such as dissolved oxygen, temperature, pH, ammonia, and nutrient concentrations enables early detection of anomalies, disease risks, and system failures, thereby enhancing biosecurity and operational resilience.

- **Convergence of Aquaculture Genetics and Machine Learning**

Artificial intelligence is a key driver of the fourth industrial revolution and is increasingly intersecting with aquaculture genetics. Machine learning, a subset of AI, enables the extraction of meaningful patterns from large biological datasets without explicit programming [60]. In aquaculture, these approaches have been applied to biomass estimation, behavioural analysis, species recognition, and water quality prediction.

The integration of computer vision and machine learning has significantly improved the estimation of fish size, weight, and abundance, supporting more precise stock management [61]. Behavioural analysis further contributes to welfare assessment and ecosystem monitoring by identifying deviations associated with stress or disease.

In genetics and selective breeding, machine learning has been used to predict disease resistance and improve genomic selection strategies. Models such as decision trees, support vector machines, random forests, and boosting algorithms have been applied to identify resistance traits against viral and bacterial diseases in species such as carp, gilthead seabream, and whiteleg shrimp [62]. Similar approaches have been used to develop molecular markers for parasite population differentiation and to analyse microbiomes relevant to aquaculture performance and environmental interactions [63].

- **Artificial Intelligence in Benthic Organism Monitoring**

Benthic monitoring is essential for assessing the environmental impacts of aquaculture and determining appropriate fallowing periods. Traditional monitoring methods, including drop cameras and sediment grab sampling, provide valuable but spatially limited information and may fail to capture far field effects of organic enrichment. Moreover, hard bottom substrates and complex oceanographic conditions can limit the effectiveness of sediment based assessments [64].

Alternative approaches incorporating hydroacoustics, microbial indicators, and environmental DNA have been explored to address these limitations. Hydroacoustic systems, which analyse reflected acoustic signals to characterise seafloor properties, offer continuous spatial coverage and have shown potential for detecting organic matter deposition around aquaculture sites. While promising, further validation is needed in diverse substrate types to support broader regulatory adoption.

Challenges, Bottlenecks, and Ethical Considerations

Despite rapid technological progress, the adoption of AI based monitoring in aquaculture faces several challenges. High initial costs, data intensive infrastructure requirements, and the need for technical skills can limit uptake, particularly among small scale operators[65]. AI models are also highly dependent on the quality and representativeness of training data, and biases in data collection or interpretation may be transferred into automated systems.

There is also a dual use concern associated with AI technologies. While AI can support conservation goals by reducing bycatch and improving monitoring, it may also enhance fishing efficiency in ways that increase pressure on already stressed stocks if not properly regulated [66].

CONCLUSION AND RECOMMENDATIONS

Although aquaculture has been practiced for several millennia, its modern form remains a relatively young and rapidly expanding sector. Contemporary aquaculture production is still largely characterized by manual operations, high feed costs, significant labour requirements, and persistent disease risks, all of which contribute to elevated production costs. In this context, the integration of modern internet based technologies and artificial intelligence offers a clear pathway to improving efficiency, reducing operational costs, and minimizing environmental impacts. When effectively implemented, these technologies have the potential to enhance farm profitability while supporting the long term sustainability of the aquaculture industry.

Rapid advances in digital technologies have fundamentally changed how complex production systems can be managed. Artificial intelligence, the Internet of Things, and cloud computing collectively enable automation of routine tasks, reduction of manual labour, and real time decision support. The pay as you go nature of many cloud based services lowers entry barriers by reducing upfront investment costs and allowing shared use of computing infrastructure, energy, and hardware resources. In addition, smart and web enabled devices can continuously collect, transmit, and analyze data on system performance and environmental conditions with minimal human intervention, thereby improving responsiveness and management precision.

The progressive adoption of automation and intelligent systems has already begun to shift global aquaculture toward more intensive and data driven production models. These developments have contributed to improved resource use efficiency, enhanced monitoring, and more sustainable production practices. Nevertheless, aquaculture remains inherently complex due to the biological nature of cultured organisms and the dynamic environments in which they are raised. As the sector continues to expand, challenges related to feeding efficiency, disease control, and environmental pollution persist and, in some cases, intensify.

In capture fisheries, AI enabled electronic monitoring and intelligent fishing technologies are still at an early stage of adoption. Practical applications aimed at improving gear selectivity and reducing ecological impacts are therefore not yet widely observed. A major limitation remains the availability and quality of training data, particularly high resolution underwater imagery, which constrains the performance and generalizability of AI models. Compared with terrestrial and aerial studies, underwater behavioural analysis faces additional technical challenges due to the size, weight, and operational constraints of submerged sensing systems.

Finally, while intelligent technologies hold promise for improving sustainability and management outcomes, their adoption should proceed with caution. The environmental costs associated with manufacturing, deploying, and maintaining advanced technological systems must be carefully evaluated. The integration of artificial intelligence into aquaculture and fisheries should be accompanied by rigorous environmental impact assessments and continued exploration of alternative, environmentally responsible materials and system designs. A balanced approach that aligns technological innovation with ecological responsibility will be essential to ensure that the benefits of AI are realized without creating new environmental burdens.

REFERENCES

1. FAO. The state of world fisheries and aquaculture: towards blue transformation. Food and Agriculture Organization of the United Nations; 2022. Available from: https://www.fao.org/3/cc0461en/cc0461en.pdf

2. Rather MA, Ahmad I, Shah A, et al. Exploring opportunities of artificial intelligence in aquaculture to meet increasing food demand: techniques, productivity, and automation. Aquac Rep. 2024;27:101309.

3. Lau ML, Lim LWK, Ishak SD, et al. Emerging challenges and sustainability pathways in intensive aquaculture systems. Rev Aquac. 2021;13:2076–2091. doi:10.1111/raq.12544

4. Zhang Y, Gui Z. Digital transformation of fisheries and aquaculture: integration of IoT, artificial intelligence, and big data. Aquaculture. 2023;560:738543. doi:10.1016/j.aquaculture.2022.738543

5. Lim LWK. Implementation of artificial intelligence in aquaculture and fisheries: deep learning, machine vision, big data and IoT applications. J Comput Cogn Eng. 2023;2:1–15. doi:10.47852/bonviewJCCE32021563

6. Vo TTE, Ko H, Huh JH, et al. Overview of smart aquaculture system. Electronics. 2021;10:2882. doi:10.3390/electronics10222882

7. Ahmed MS, Aurpa TT, Azad MAK. Fish disease detection using image-based machine learning technique in aquaculture. J King Saud Univ Comput Inf Sci. 2022;34:5170–5182. doi:10.1016/j.jksuci.2021.02.014

8. Rajesh VC, Tandel JM, Zala NA, et al. Automization in aquaculture: a short review. Biol Forum. 2023;15:688–698.

9. Li D. Unmanned fish farming: the fourth generation of aquaculture. International Telecommunication Union; 2018.

10. Kassem T, Shahrour I, El Khattabi J, et al. Smart and sustainable aquaculture farms. Sustainability. 2021;13:10685. doi:10.3390/su131910685

11. Hamid MS, Wahab MAA, Abdullah R, et al. Development of water quality monitoring for smart aquaculture system. J Eng Appl Sci. 2019;14:2840–2847.

12. Wang C, Li Z, Wang T, et al. Intelligent fish farms: the future of aquaculture. Aquac Int. 2021;29:2681–2711. doi:10.1007/s10499-021-00773-y

13. Huang YP, Lin CY, Khabbusi S. Artificial intelligence of things advances in aquaculture management: real-time monitoring, data-driven decision-making, and automation. Processes. 2025;13:73. doi:10.3390/pr13010073

14. Sharma D, Kumar R. Smart aquaculture: integration of sensors, biosensors and artificial intelligence. In: Pudake RN, Jain U, Kole C, editors. Biosensors in agriculture. Springer; 2021. p. 417–438. doi:10.1007/978-3-030-66165-6_21

15. Chrispin L, Jothiswaran VV, Velumani T, et al. Application of artificial intelligence in fisheries and aquaculture. Biotica Res Today. 2020;2:499–502.

16. Imai T, Arai K, Kobayashi T. Smart aquaculture system: a remote feeding system with smartphones. In: Proc IEEE Int Symp Consum Technol; 2019. p. 93–96. doi:10.1109/ISCT.2019.8901029

17. Rahman M, Bapery C, Hossain MJ, et al. Internet of Things-based water quality monitoring systems for aquaculture. Int J Multidiscip Curr Educ Res. 2020;2:168–180.

18. Divinely SJ, Sivakami K, Jayaraj V. Fish disease identification and classification using machine learning. Int J Adv Res Basic Eng Sci Technol. 2019;5:46–51.

19. Qi Q, Tao F. Digital twin and big data towards smart manufacturing and industry 4.0. IEEE Access. 2018;6:3585–3593. doi:10.1109/ACCESS.2018.2793265

20. Shabbir J, Anwer T. Artificial intelligence and its role in the near future. arXiv. 2018:1804.01396.

21. Dhar Dwivedi A, Singh R, Kaushik K, et al. Blockchain and artificial intelligence for 5G-enabled nternet of Things. Trans Emerg Telecommun Technol. 2018:e4329. doi:10.1002/ett.4329

22. Han H, Liu Z, Wang X, et al. Research on cloud computing, IoT, big data, artificial intelligence and blockchain in maritime applications. J Phys Conf Ser. 2021;1927:012026.

23. Fernandes-Salvador JA, Oanta GA, Olivert-Amado A, et al. Artificial intelligence and the fisheries sector. European Parliament; 2022.

24. Pathak AK. Role and applications of disruptive technologies in aquaculture. Vindhya Bharti. 2017:66–69.

25. Abedin J, Jamwal A, Brahmchari RK, et al. Applications of artificial intelligence and machine learning in fisheries. Vigyan Varta. 2022;3:127–130.

26. Jothiswaran VV, Velumani T, Jayaraman R. Application of artificial intelligence in fisheries and aquaculture. Biotica Res Today. 2020;2:499–502.

27. Tamm EE. AI guide: tracking AI's explosive growth in aquaculture. This Fish Inc.; 2021. Available from: https://this.fish/blog/ai-guide-tracking-ais-explosive-growth-in-aquaculture/

28. Yongqiang C, Shaofang L, Hongmei L, et al. Application of intelligent technology in animal husbandry and aquaculture. In: Proc Int Conf Comput Sci Educ; 2019. p. 335–339. doi:10.1109/ICCSE.2019.8845468

29. Oliveira J, Lima JE, da Silva D, et al. Traceability system for quality monitoring in the fishery and aquaculture value chain. J Agric Food Res. 2021;5:100169.

30. Mora-Cantallops M, Sánchez-Alonso S, García-Barriocanal E, et al. Traceability for trustworthy AI. Big Data Cogn Comput. 2021;5:20. doi:10.3390/bdcc5020020

31. Vinuesa R, Azizpour H, Leite I, et al. The role of artificial intelligence in achieving the Sustainable Development Goals. Nat Commun. 2020;11:233. doi:10.1038/s41467-019-14108-y

32. Tzachor A. Artificial intelligence for agricultural supply chain risk management. CGIAR; 2020.

33. Ghidini S, Varra MO, Zanardi E. Authenticity issues in fish and seafood products. Molecules. 2019;24:1812. doi:10.3390/molecules24091812

34. Monteiro RS, Ribeiro M, Viana C, et al. Fish recognition model for fraud prevention using convolutional neural networks. Adv Comput Intell. 2022. doi:10.1007/s43674-022-00048-6

35. Petrea ŞM, Costache M, Cristea D, et al. Machine learning analysis of heavy metal bioaccumulation in fish tissues. Molecules. 2020;25:4696. doi:10.3390/molecules25204696

36. Elíasson EI. Convolutional neural network benchmarking for fish fillet segmentation. MSc thesis. Reykjavík University; 2019.

37. Xu JL, Sun DW. Computer vision detection of salmon muscle gaping. Food Anal Methods. 2018;11:34–47. doi:10.1007/s12161-017-0984-6

38. Islam MJ, Peñarubia OR. Seafood waste management and silage production potential. Sustainability. 2021;13:2372. doi:10.3390/su13042372

39. Cooney R, Wan AH, O'Donncha F, et al. Environmentally efficient aquafeeds using decision support tools. Curr Opin Environ Sci Health. 2021;23:100276. doi:10.1016/j.coesh.2021.100276

40. Uribe-Toril J, Ruiz-Real JL, Galindo-Durán AC, et al. Circular economy and retail using deep learning. Environ Sci Eur. 2022;34:1–10.

41. Tirkolaee EB, Sadeghi S, Mooseloo FM, et al. Machine learning in supply chain management. Math Probl Eng. 2021;2021:1476043. doi:10.1155/2021/1476043

42. Koparan C, Koc AB, Privette CV, et al. UAV-based water quality measurements. Water. 2018;10:264. doi:10.3390/w10030264

43. Ubina NA, Cheng SC, Chen HY, et al. Visual aquaculture system using cloud-based drones. Drones. 2021;5:109. doi:10.3390/drones5040109

44. Lim LWK. Implementation of artificial intelligence in aquaculture and fisheries. J Comput Cogn Eng. 2023.

45. Huzaifah G. Creating the future of aquaculture with IoT smart feeding. Unreasonable Group; 2023. Available from: https://unreasonablegroup.com/ventures/efishery

46. Mia MJ, Mahmud RB, Sadad MS, et al. Automated approach for fish disease recognition. J King Saud Univ Comput Inf Sci. 2022;34:7174–7183. doi:10.1016/j.jksuci.2021.12.007

47. Hosseini S, Simianer H, Tetens J, et al. Phenotypic sex classification of zebrafish using machine learning. Ecol Evol. 2019;9:13332–13343. doi:10.1002/ece3.5793

48. Xia C, Fu L, Liu Z, et al. Aquatic toxic analysis via computer vision. J Toxicol. 2018:2591924.

49. O'Donncha F, Stockwell CL, Planellas SR, et al. Data-driven insights into fish behaviour. Front Anim Sci. 2021;2:695054.

50. Darapaneni N, Sreekanth S, Paduri AR, et al. AI-based fish disease detection for small-scale farmers. Proc Interdiscip Res Technol Manag. 2022:1–5.

51. Kidangoor A. Tech companies making fishing and aquaculture more sustainable. Mongabay; 2022.

52. Kao CY, Chen IC. AI-driven fry sorting and identification model. Appl Sci. 2024;14:8803. doi:10.3390/app14198803

53. Mateti T, Laha A, Shenoy P. Artificial meat industry: production and challenges. JOM. 2022;74:3428–3444. doi:10.1007/s11837-022-05335-7

54. Ovalle A, et al. Automated catch identification using electronic monitoring systems. Fish Res. 2020;230:105678.

55. Nash KL, et al. Autonomous tracking of marine organisms. Methods Ecol Evol. 2021;12:1450–1465. doi:10.1111/2041-210X.13635

56. Morgan G. Overfishing and global marine sustainability. World Wide Fund for Nature; 2020.

57. Mora-Cantallops M, Sánchez-Alonso S, García-Barriocanal E, et al. Traceability for trustworthy AI. Big Data Cogn Comput. 2021;5:20.

58. Mousazadeh H, Jafarbiglu H, Abdolmaleki H, et al. Solar-powered unmanned surface vehicle. Ocean Eng. 2017;133:282–295. doi:10.1016/j.oceaneng.2017.01.014

59. Padala S, Zilber R. Expert system for intensive recirculating aquaculture. Aquac Eng. 1991;10:1–17. doi:10.1016/0144-8609(91)90014-Y

60. Ongsulee P. Artificial intelligence, machine learning and deep learning. Int J Adv Comput Sci Appl. 2017;8:1–6.

61. Fernandes JA, Valente A, Martins MS, et al. Fish weight estimation using computer vision. Comput Electron Agric. 2020;173:105386. doi:10.1016/j.compag.2020.105386

62. Palaiokostas C. Predicting disease resistance using machine learning and genomics. Front Genet. 2021;12:620732. doi:10.3389/fgene.2021.620732

63. Jacobs A, Han Y, Kube M, et al. Population differentiation of Lepeophtheirus salmonis. Mol Ecol. 2018;27:3504–3518. doi:10.1111/mec.14789

64. Keeley NB, Forrest BM, Macleod CK. Benthic recovery after salmon farm enrichment. Aquaculture. 2015;435:412–423. doi:10.1016/j.aquaculture.2014.10.007

65. Jham L, Devati. Artificial intelligence and its use in aquaculture. Sci Agric Allied Sect. 2022;4.

66. Clark CM, Forney CR, Manii E, et al. Tracking leopard sharks with autonomous underwater vehicles. J Field Robot. 2013;30:904–922. doi:10.1002/rob.21481