DOI: https://doi.org/10.70749/ijbr.v4i5.3214

INDUS JOURNAL OF BIOSCIENCE RESEARCH
https://ijbr.com.pk
ISSN: 2960-2793/ 2960-2807

Artificial Intelligence-Driven Smart Aquaculture: Technologies, Applications and Future Directions

Usman Naveed[1], Rimsha Latif[2], Maryam Abbas[3], Gumza Mushtaq[4], Aneeqa Tehreem [5], Amina Ayub [6], Saifullah[7]

[1-7]Department of Zoology, Wildlife and Fisheries, University of Agriculture Faisalabad, Faisalabad, Pakistan

ARTICLE INFO

Keywords: Artificial intelligence, Smart aquaculture, Machine learning, Deep learning, Computer vision, Water quality monitoring, Disease detection, Precision feeding, Biomass estimation, Internet of Things, Sustainable aquaculture

Correspondence to: Usman Naveed, Department of Zoology, Wildlife and Fisheries, University of Agriculture Faisalabad, Faisalabad, Pakistan.
Email: ranausmannaveed26@gmail.com, & 2022ag8958@uaf.edu.pk

Declaration
Authors' Contribution
All authors equally contributed to the study and approved the final manuscript.

Conflict of Interest: No conflict of interest.

Funding: No funding received by the authors.

Article History
Received: 08-03-2026 Revised: 06-05-2026
Accepted: 19-05-2026 Published: 30-05-2026

ABSTRACT

Aquaculture is in a critical state globally, with unprecedented demand for sustainable seafood production and numerous environmental and operational challenges. In the era of modern aquaculture, artificial intelligence (AI) has become a game-changer, providing innovative solutions that include real-time sensing, predictive analytics and autonomous decision making into aquaculture production systems. This comprehensive review explores the state of the art, applications, and future trends of AI-enabled smart aquaculture. We methodically examine five research areas: water quality monitoring and predictive modelling, automated disease detection and diagnosis, precision feeding and nutritional optimization, biomass estimation and growth prediction, integrated risk management frameworks. Also, the intersection of AI with other emerging technologies such as IoT, blockchain, robotics, and cloud computing is discussed. From our analysis, we have found that the machine learning algorithms such as convolutional neural networks (CNNs) and long short term memory (LSTM) networks have been able to attain very high accuracy rates of more than 92% in the disease detection and biomass estimation. Despite this, major barriers still exist in the implementation process, such as high costs, lack of practitioner technical skills, data standardization problems, and the gap between algorithmic predictions and operational decision-making procedures. We pinpoint key research gaps and outline a research agenda for future development that focuses on explainable AI, federated learning and hybrid decision support systems. The review offers valuable insights for researchers, industry professionals, and policymakers to tap into the potential of AI to support sustainable aquaculture practices globally.

INTRODUCTION

The aquaculture industry on a global level has had exceptional growth within the last two decades and is currently the fastest growing food production industry worldwide. According to the FAO estimations, there has been an aquaculture production of 94.4 million tonnes in 2022 with a valuation of USD 296 billion making it the first time that the aquaculture industry becomes more valuable than capture fisheries (FAO, 2024). This trend is projected to continue with the increasing population, reaching 9.6 billion by 2050, thus requiring a doubling of the food production to meet the demands of the growing population (Roy et al., 2025). Even with this impressive development, the aquaculture industry faces numerous challenges threatening its sustainability. Diseases remain a huge concern in the aquaculture industry causing USD 6 billion in annual losses globally (Yue and Shen, 2022). Fish diseases contribute to over 30% production loss in some of the top producers such as China, India and Vietnam (Irshath et al., 2023). Feed cost constitutes one of the largest costs in the operation of an aquaculture facility representing up to 60% of the total cost of operation with sub-optimal feeding resulting in substantial economic losses and environmental issues (Fernandes et al.,2019)

With the current Fourth Industrial Revolution, the growth of smart aquaculture has been fueled through the incorporation of new technology to create intelligent and data-enabled systems for production. The application of artificial intelligence (AI), including machine learning (ML), deep learning (DL), computer vision, and natural language processing (NLP), has been the mainstay in this revolution (Fernandes and D'Mello, 2025). AI, combined with IoT, cloud computing, and robotics, can offer unique real-time surveillance and prediction capabilities in aquaculture operations. Bibliometric studies over the past few years have revealed that AI research in aquaculture has grown exponentially since 2015, and that the USA and China are the top two countries for the numbers of publications (Roy et al., 2025). But, despite the significant advances in technology, there is a major disconnect between the academic world and the commercial world. A limited number of published studies have shown how to integrate with an existing standardization of risk management (e.g. ISO 31000), again pointing to the need for interdisciplinary work that connects innovation in algorithms and operational use (Gkikas et al., 2026).

The objective of this comprehensive review is to present a systematic analysis of AI-based smart aquaculture, covering the key applications such as water quality management, disease detection, precision feeding, and biomass estimation; showcasing how AI is integrated with other technologies like IoT, blockchain, and robotics; highlighting commercial products and real-world case studies; outlining the major challenges and limitations; and suggesting future research directions to enhance the field. Drawing on recent literature, we aim to provide practical advice for research, practice and policy development that will advance sustainable aquaculture with smart technology.

FOUNDATIONS OF AI IN AQUACULTURE

Artificial Intelligence is an umbrella term for every computer science field whose goal is to design systems that can execute tasks usually associated with human intelligence such as perception, reasoning, learning and decision making (Huang and Khabusi, 2025). AI technologies in aquaculture can be categorized by functionality and capability, from simple systems that react to certain stimuli to more complex systems that have learning and adaptive capabilities. Artificial neural networks, optimization algorithms, expert systems, and machine learning models that are capable of analyzing complex datasets and providing insights for action are among the key areas of AI application in aquaculture (Roy et al., 2025).

Machine Learning Approaches

Machine learning is among the fundamental elements of AI through which the system is made to learn from data and change its behavior without explicit programming. Supervised learning models have been found to work effectively in classification and regression problems in aquaculture, such as fish species recognition, disease diagnostics, and water parameters forecasting (Vo et al., 2021). Algorithms that have been commonly used for different purposes in aquaculture include RF, SVM, k-NN, and ANN. Random Forest algorithm has been seen to have great reliability when used in predicting water quality parameters like salinity, pH, DO and water temperature with an accuracy greater than 88% (Swetha et al., 2023). This technique uses multiple decision trees to minimize errors, thereby improving its generalizability in aquaculture, considering the variability in the industry. The other algorithm that has been employed in fish species recognition and water quality evaluation includes SVM. It has high accuracy in classifying fish species (>99.98% accuracy) and analyzing water parameters like ammonia concentration (>99.98% accuracy) (Ewees et al., 2021).

SVM, which is able to find the optimal hyperplanes in high dimensional feature spaces, has been applied in fish species classification and water quality assessment and obtained high classification accuracy up to 99.98% in ammonia concentration analysis. Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO) have been successfully applied to optimize feeding strategies, aerator design parameters, and operational configurations. Luna et al. (2022) applied (GAs) to optimize feeding strategies, enhancing fish growth performance, while Roy et al. (2022) utilized PSO to optimize geometric and dynamic parameters of aeration systems, achieving maximum standard aeration efficiency (SAE) at optimal parameter configurations.

Deep Learning Architectures

In aquaculture, a powerful and intricate branch of machine learning known as deep learning has become prevalent for handling complex patterns, with neural networks featuring multiple hidden layers. Convolutional Neural Networks (CNNs) have been used to outperform all of the state-of-the-art methods in image classification applications like fish species classification, disease detection, and estimation of biomass. Comparative studies show that the CNN model outperforms the traditional machine learning models with an accuracy margin of 18.5% and precision margin of 41.13% in the fish identification task. For water quality prediction (Wang et al., 2017). Long Short-Term Memory (LSTM) networks have demonstrated their effectiveness in analyzing temporal data, e.g., predicting water quality in aquaculture systems (Alluhaidan et al. (2025). For this purpose, optimized hybrid LSTM models that yielded an accuracy of 92.3% for predicting dissolved oxygen were developed by, while Li et al. (2022) and a combination of LSTM and temporal convolutional networks (TCN) resulted in R-squared values of 0.94 with very low error rates (RMSE 0.34 mg/L) for the prediction of aquaculture parameters like dissolved oxygen and chlorophyll. In aquaculture, environmental conditions often have complex temporal relationships, making LSTM networks well suited for such applications.

Table 1

Comparison of AI Algorithms in Aquaculture Applications

Algorithm	Accuracy	Key Strengths	Primary Applications
CNN	92-95%	Feature extraction	Disease detection, species ID
LSTM	90-94%	Temporal patterns	Water quality prediction
Random Forest	85-89%	Robust, interpretable	Parameter prediction
SVM	84-88%	High-dimensional data	Classification tasks
YOLO	91-94%	Real-time detection	Fish counting, tracking
ANN	84-88%	Nonlinear modeling	Growth prediction

Computer Vision Systems

Computer vision is one of the most important subfields of AI, which is the ability to process visual data in images and videos. In aquaculture, computer vision systems have revolutionized manual observation techniques, offering automated, non-invasive solutions for monitoring fish behavior, assessing their health, and estimating their size. The processing pipeline usually consists of image acquisition, image pre-processing, feature extraction, pattern recognition, and finally, results that can be used for farm management (Matsuzaka and Yashiro, 2023). The field of computer vision has seen remarkable progress in recent years, particularly with the advent of deep learning.In recent years, there have been significant advances in deep learning, which has greatly improved the capabilities of computer vision in aquaculture. CNNs are now able to analyze underwater images with an accuracy of over 95% to detect abnormal swimming behavior, skin lesions and parasitic infection. Real-time processing underwater imaging platforms allow for continuous monitoring of fish populations without stress and potential injury from handling (Liu et al., 2023). In addition, stereo-vision systems and three dimensional reconstruction methods have allowed accurate morphometric measurements which has facilitated automated grading and selective harvesting operations.

CORE APPLICATIONS OF AI IN SMART AQUACULTURE

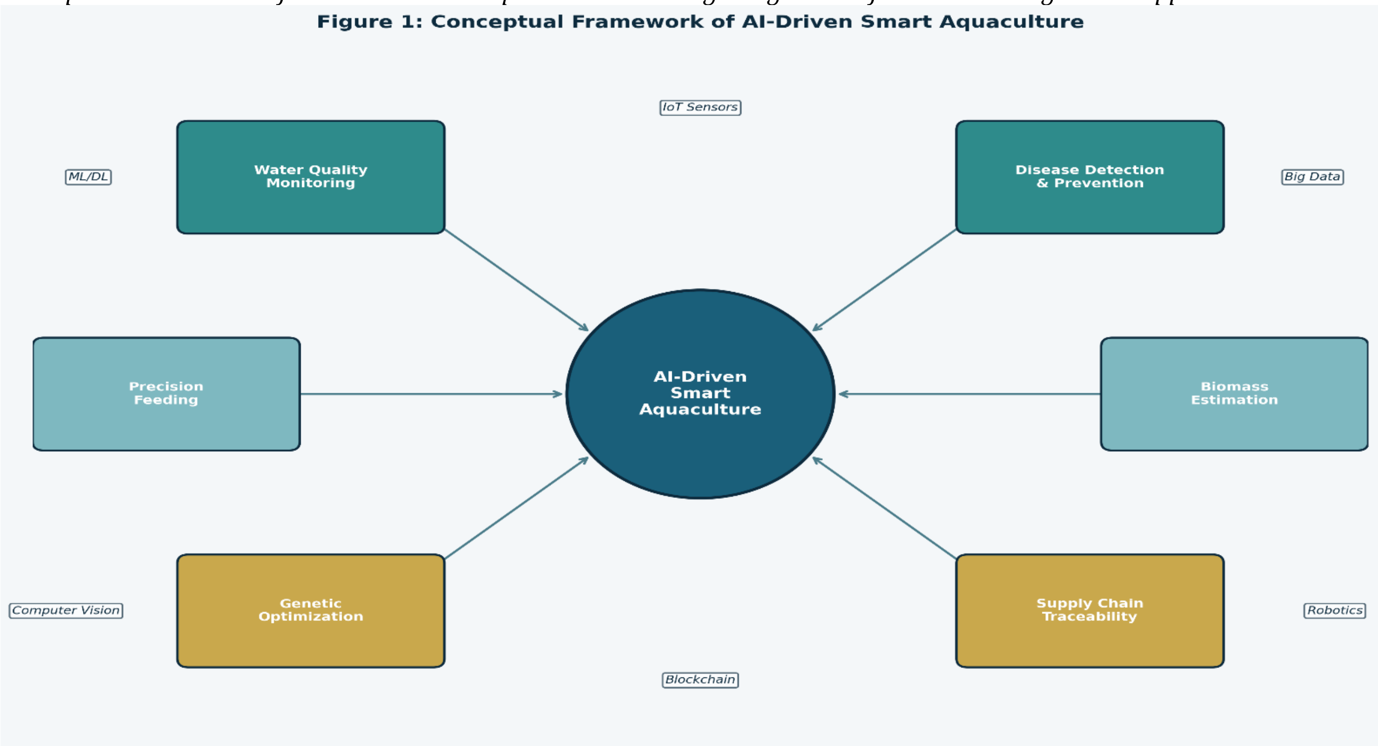
Water Quality Monitoring and Prediction

Water quality is the most important environmental factor affecting aquaculture productivity and fish welfare. The traditional manual monitoring methods, which include twice-daily sampling and lab testing, are time-consuming, labor-intensive and can't detect sudden changes in parameters that could result in catastrophic losses. This is when the AI-based water quality monitoring systems have stepped in with their 24/7 monitoring and predictions to take action beforehand (Vo et al., 2021). In the AI-based water quality monitoring system, the IoT technology and machine learning algorithms are used to measure different water quality parameters like temperature, dissolved oxygen, pH value, ammonia, nitrite, turbidity, and salinity. For recording different water parameters, the different types of sensors are being used which include the traditional electrochemical sensors, optical sensors, and biosensors. All this recorded high-frequency data from these sensors is sent to cloud-based servers (Hemal et al., 2024). Through machine learning algorithms such as ANNs and LSTM networks, analysis of data is done.

Predictive Modeling Perhaps the most significant contribution of AI in managing the water quality environment is predictive modeling. By taking into account past data in addition to certain environmental elements such as weather conditions and feeding cycles, predictive modeling helps AI predict any possible deterioration in water body quality long before it happens. As an illustration, LSTM models using several sets of parameters have successfully predicted low levels of dissolved oxygen up to several days in advance, thereby avoiding the deaths of fish populations by 20-60% due to prevention (Zhang et al., 2023).

Figure 1

Conceptual Framework of AI-Driven Smart Aquaculture Showing Integration of Core Technologies and Application Domains.



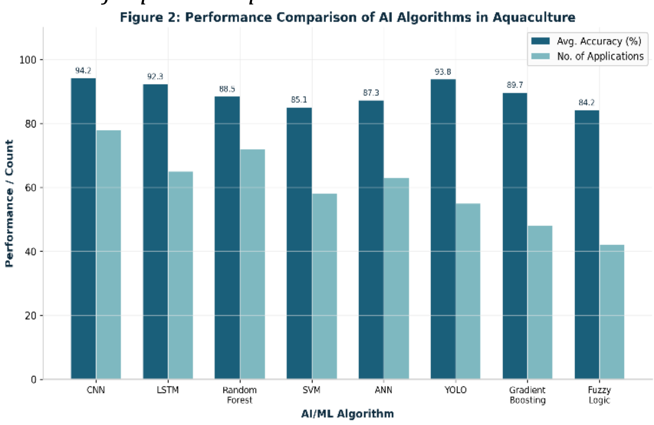
Automated Fish Disease Detection

Diseases constitute the biggest biological threat to aquaculture, leading to annual financial losses amounting to more than USD 6 billion from viral, bacterial, and fungal diseases (Yue and Shen, 2022). High stocking densities associated with intensive farming methods accelerate disease spread, typically resulting in catastrophic die-offs within a few days following infection. Traditional means of monitoring the presence of disease include visual inspection by staff members at the facility. This method is highly prone to errors since infections usually go undetected until they have progressed to a visible stage. AI-powered disease monitoring has brought about major improvements in aquatic health monitoring through early and reliable diagnosis using several techniques. For example, computer vision uses image processing and video analysis to detect visual signs of illness such as skin ulcers, fin degradation, color changes, as well as behavioral symptoms including erratic movement, loss of appetite, and lethargy (Malik et al., 2017). CNN-powered image classification has yielded accuracies greater than 95% when identifying various diseases, including Columnaris (mouth fungus), anchor worms, and infections with Aeromonas bacteria.

In addition to visual observations, AI uses behavioral observation and environmental factors to predict the risk of diseases even before any symptoms become apparent. The machine learning algorithm uses historical information about outbreaks together with the water quality characteristics to establish when certain environmental conditions make the spread of disease likely, thus issuing an early warning. Thermal imaging can detect any temperature anomalies caused by stress in the fish's gills and eyes due to subclinical infections.

Figure 2

Performance comparison of AI algorithms across aquaculture applications, showing average accuracy and number of reported implementations.



Precision Feeding Systems

Feeding alone accounts for about 40-60% of all expenses associated with intensive aquaculture. In addition to reducing the economic profitability of this industry, inefficient feeding causes environmental damage through excessive loading of nutrients, eutrophication, and reduction in water quality. The solution to these problems involves the use of artificial intelligence-based precise feeding systems, which provide optimal feed management according to fish appetites and their behavior and environmental condition evaluation (Zhou et al., 2018). Several sensing techniques allow one to evaluate the need for feeding in the process of fish growth. The computer vision system monitors the surface behavior of fish and fish's feed consumption behavior, while acoustic sensors can detect the sound made by the active feeding. Artificial intelligence algorithms analyze such multimodal data and optimize feeding rates in accordance with fish appetite. It was found that AI-based feeding optimization technology can increase FCR by 15-40%.

Feeding systems with advanced technology use predictive analytics to predict feeding times according to fish growth predictions, environmental predictions, and market situations. The use of reinforcement learning helps improve the process of feeding by constantly analyzing growth results, allowing for an evolving improvement of the feeding method. Some of the current commercial products include the UMITRON CELL (smart feeding system), eFishery (automatic fish feed distribution), and Observe Technologies (artificial intelligence-based video feeding system).

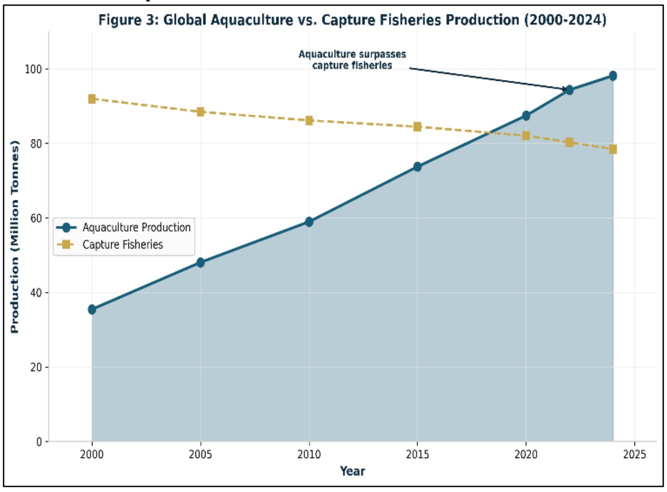
Biomass Estimation and Growth Prediction

Estimation of biomass is crucial to proper aquaculture management, enabling informed decisions regarding stocking density, feed intake, harvesting time, and inventory management. The traditional biomass evaluation techniques such as sampling using nets followed by the weighing of the sample fishes are time-consuming, stressful to the fishes, and pose huge sampling errors. The development of AI has facilitated biomass evaluation without invasive measures and with great accuracy through the use of computer vision technology and sensor-based measures (Li et al., 2020). Biomass estimation using computer vision relies on images from the underwater environment to estimate the size, weight, and population of fish with amazing accuracy. Region-based Convolutional Neural Network (R-CNN) has succeeded in estimating fish length accurately within a deviation percentage of 2.2% in the case of European bass (Nawoya et al., 2024). Biomass estimation systems through machine vision, including those by XpertSea, provide highly accurate biomass estimations based on image analyses that enable the generation of population profiles.

The growth prediction models utilize machine learning algorithms to predict growth rates under certain environmental factors, nutrition, and genetics. With the help of such models, farmers can ensure that they have proper stocking density without overcrowding and stress, thus making sure that their fish grow to market size within the predicted periods. Moreover, the inclusion of genetic information into growth prediction models helps in implementing selective breeding practices to enhance fish growth and resistance to diseases.

Figure 3

Global Aquaculture Production Growth Trend Compared to Capture Fisheries (2000-2024), with Projections for Continued Expansion



ADVANCED TECHNOLOGIES AND INTEGRATION

IoT and Sensor Networks

The IoT provides the required technological backbone that enables the implementation of AI in aquaculture. IoT-based monitoring systems for aquaculture are comprised of four major layers: the physical layer, that includes environment sensors and actuators; the monitoring layer, responsible for data collection and processing; the virtual layer, providing cloud storage and analysis; and the protocol layer, guaranteeing secure information transmission (Vo et al., 2021). The newest monitoring systems for the aquaculture industry measure multiple parameters characterizing the quality of water, such as temperature, the level of oxygen, pH, turbidity, total dissolved solids, ammonia, nitrate, nitrite, salinity, and carbon dioxide. In advanced systems, there are cameras, hydro-acoustic sensors, and meteorological stations that enable monitoring of the environment from three sides. Wi-Fi, Bluetooth, LoRaWAN, and 5G are applied for data transfer between remote facilities and centralized analytic systems (Rastegari et al., 2023).

Combining the Internet of Things with AI creates closed-loop systems capable of regulating the surrounding environment on their own. The collected information from the sensors is subjected to analysis through AI-based algorithms, which trigger the automation process if the parameters exceed the optimal values. For example, in the case where there is an automated system measuring the amount of oxygen in water, the system will automatically trigger the use of aeration equipment in cases where the concentration falls below the optimal levels.

Blockchain for Supply Chain Transparency

The combination of blockchain technology alongside AI would provide the required transparency, traceability, and reliability of information throughout the entire life cycle of farmed fish products. While AI focuses on maximizing productivity through optimal decision-making and automation processes, blockchain technology will serve as the underlying layer of security, allowing the collection of trustworthy information regarding the production process. Sensors, farm data, and certifications of farms are all collected on immutable blockchain ledgers, thus creating more reliable and trustworthy data exchange between the parties involved in the aquaculture business. The combination of AI and blockchain technologies will create an intelligent and data-driven aquaculture industry, in which production data will be logged and shared transparently within the ecosystem. Agya et al. (2025) suggested an integrated system based on the interaction between AI and blockchain technologies, which showed great promise for increasing the efficiency of aquaculture and its sustainability.

Autonomous Systems and Robotics

Autonomous systems and robots provide an innovative way of implementing AI in aquaculture by minimizing the need for manual labor while increasing efficiency and safety. ROVs and AUVs perform inspections of cage infrastructure, the condition of the nets and behavior of the fish, while live high-definition video is sent back to the operators on the surface (Ezhilarasi et al., 2021). Robots are also used for various aquaculture purposes, such as net cleaning, biofouling removal, mortality collection, and targeted treatments. One particular robot is a NetCleaner produced by Bluegrove that cleans the nets in aquaculture cages and decreases replacement costs by 30%. AI-based feeding vessels move among cages, dispensing the feed according to the plan generated using artificial intelligence. A drone with a multispectral camera performs surveys in pond and coastal aquaculture facilities to gather information about water conditions, algae bloom, and infrastructure.

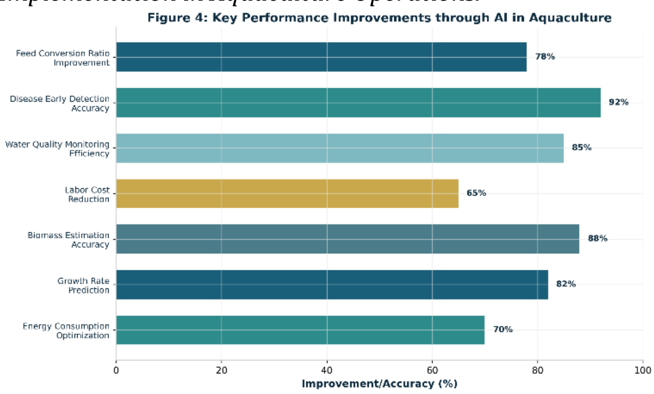
AI IN AQUACULTURE RISK MANAGEMENT

Risk management is another essential but largely unexplored area where AI can be implemented in aquaculture. In their systematic review based on the PRISMA 2020 methodology, Gkikas et al. (2026) reviewed 38 studies where machine learning algorithms were used in aquaculture risk assessment. They found that the correlation between algorithm predictions and decisions taken was low; indeed, only three out of 38 studies showed implementation with standardized risk management systems, such as ISO 31000. The types of aquaculture risks analyzed included biological risks (outbreaks of diseases and parasites), environmental risks (degradation of water quality and extreme weather conditions), operational risks (planning production and feeding strategies), and risks related to the management framework (implementation of decision-making procedures). Deep learning algorithms were used in 37% of the studies analyzed, ensemble learning algorithms in 24%, machine learning algorithms in 21%, and hybrid algorithms in 10%. Biological risk applications were predominant in the literature (17 out of 38 studies focused on disease and mortality prediction).

A critical finding from this systematic analysis is the 'algorithm-to-action void' that characterizes current research. While ML models achieve impressive technical accuracy, their outputs rarely translate into standardized operational responses. The authors proposed a 'Contextualization Layer' framework that converts algorithmic predictions into actionable business recommendations, filtering predictions through economic and ethical criteria to bridge the gap between data science and farm management. This approach emphasizes the need for interdisciplinary collaboration that integrates AI capabilities with established risk management protocols.

Figure 4

Key Performance Improvements Achieved through AI Implementation in Aquaculture Operations.



COMMERCIAL AI PRODUCTS AND CASE STUDIES

The commercial ecosystem of AI-assisted aquaculture technologies has witnessed an impressive increase, with tech companies providing tailored solutions for different types of facilities. As per Crunchbase statistics, the top ten aquaculture technology companies collectively have attracted around USD 282 million in funds, indicating high trust in future growth within this industry (Er-Rousse and Qafas, 2024). Feed optimization technologies make the most advanced commercial group at present. UMITRON CELL features appetite assessment with subsequent automatic adjustment of feed delivery, while eFishery relies on vibrations in water to determine the degree of hunger in fish. Observe leverages AI video analytics to optimize feeding schedule, saving on feed costs between 15% and 25%. AI computer vision solutions include companies like Aquabyte, ReelData's Aqua Eye, and XpertSea, all offering accurate biomass assessment and tracking capabilities.

Some examples of water quality management technologies include the Eruvaka monitoring kit, HydroNeo smart farm platform, and Aquaconnect iAqua system, all incorporating AI-based predictive analytics to identify early warning signs of stress on the environment. In the disease management arena, IBM offers the AquaCloud platform for largescale disease prediction and biosurveillance in salmon farming operations, whereas Stingray offers an automated delousing solution that uses computer vision and laser technology. A number of relevant case studies show the success achieved by adopting AI technologies. As noted by Yang et al. (2025c), hybrid LSTM-DDPG algorithms cut RAS power requirements by 15–20%, while Alnemari et al. (2025b) showed that transfer learning methods led to a 76% reduction in species adaptation costs. Adoption of IMTA-aquaponic systems guided by AI algorithms has resulted in shorter break-even times and increased profitability (Goda et al., 2025).

Table 2

Representative Commercial AI Products for Aquaculture

Product Name	Developer	Key Functionality
UMITRON CELL	Umitron	Smart feeding with real-time appetite detection
eFishery	eFishery	Acoustic-based automated feed distribution
XpertSea	XpertSea	AI-powered biomass estimation and counting
Aquabyte	Aquabyte	Computer vision for fish health monitoring
Eruvaka	Eruvaka Technologies	IoT-based water quality monitoring
AquaCloud	IBM/Seafood Innovation	Disease forecasting and bio-surveillance
NetCleaner	Bluegrove	Robotic net cleaning and biofouling removal
Stingray	Stingray	Optical delousing with computer vision

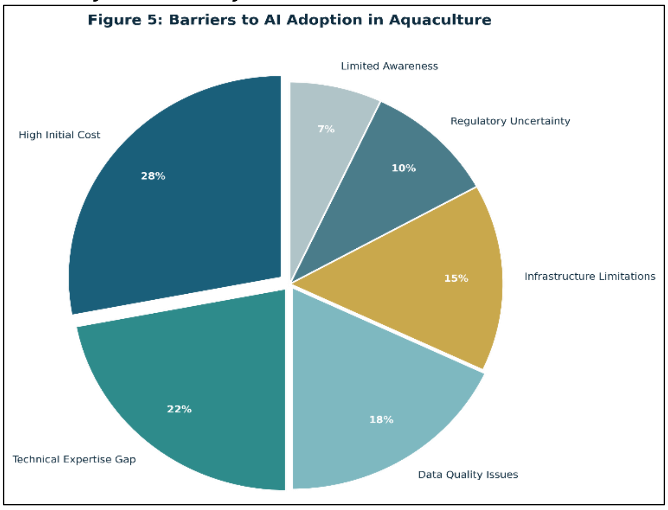
CHALLENGES AND LIMITATIONS

However, although there have been some impressive breakthroughs in AI technologies in aquaculture, several factors prevent the extensive application and proper use of the technologies. Economic, technical, infrastructural, and human capacity constraints stand out as the common impediments. Cost is arguably the most commonly mentioned factor impeding AI adoption. As stated by Georgopoulos et al. (2023), 31.5% of farmers viewed cost as the major limitation towards AI use, which includes cost of hardware, software, system maintenance and upgrading, as well as training cost. Though it is known that cost savings resulting from adoption of AI could be realized within 1-3 years, this poses an initial challenge for most farmers.

The second primary issue lies in technical expertise limitations. The proper deployment of AI technologies calls for interdisciplinary skills involving data science, software engineering, and aquaculture biology. In a survey conducted among 100 farms specializing in pisciculture all around the world, technical knowledge was listed as an impediment in implementing AI technologies by 33% of the respondents (Panda and Baral, 2023). The lack of qualified specialists who can develop, maintain, and analyze AI algorithms acts as a barrier to their application, especially in developing countries that see rapid growth in aquaculture production. There are also some difficulties connected with data availability and quality required for the successful deployment of AI systems. As machine learning algorithms need to be trained and tested on vast amounts of properly structured and annotated data sets, there may appear some problems regarding data availability and inconsistency in formats.

Figure 5

Distribution of Barriers to AI Adoption in Aquaculture Based on Survey Data and Systematic Reviews.



FUTURE PERSPECTIVES AND RESEARCH DIRECTIONS

The future trends associated with AI-enabled intelligent aquaculture include new technological advancements, the development of research agenda, and the necessity to produce seafood sustainably to serve the growing world population. As a result of our systematic review, we propose six key directions of future research that may contribute significantly to further advances in the field and overcome existing limitations. Explainable Artificial Intelligence for Aquaculture. In spite of all its advantages, the black-box feature of complex deep learning algorithms prevents them from being readily accepted by end-users due to the lack of explainability. In the future, researchers will need to develop techniques for explaining AI decisions

(e.g., by using SHAP values, attention mechanisms, and extracting rules). It is important to build trust through providing explanations of particular actions taken in order to encourage the use of AI-enabled systems for aquaculture management. Federated Learning and Collaborative Intelligence. In order to cope with both data shortages and confidentiality issues, federated learning can be used for developing machine learning models using distributed training across many farms. In this case, all facilities train their own models, but share only the parameters of those models, which helps build collaborative intelligence.
Integration with Digital Twins: The merging of artificial intelligence and digital twins will result in the creation of digital twins of the physical aquaculture systems, which can be simulated, optimized, and planned for various scenarios. Digital twins will make use of live sensing data in addition to using mechanistic models for simulating different scenarios without affecting the real-world system. Multimodal Artificial Intelligence: The future AI-based solutions for aquaculture will involve multiple modalities of data, such as visual data, acoustic data, environmental data, genomic data, and financial market data, to aid decision-making. The multimodal fusion of computer vision techniques with environmental data, genomics, and financial data will enable management from multiple perspectives.
Synergy Between AI and Genomics: The synergy between AI and genomics, along with genetic engineering technologies like CRISPR-Cas9, provides an innovative opportunity for improving selective breeding processes. By using algorithms to analyze genomics data, the identification of genes related to desirable traits, prediction of results, and quality improvement of selection programs become possible. Such synergy may result in rapid genetic enhancement, taking into account sustainable aquatic genetics management. Policy and Regulation: With respect to the rising trend toward AI technology, policy formation is essential in facilitating innovation in conjunction with environmental protection, animal welfare, and consumer safety. Knowledge exchange and technology diffusion will be feasible with standardized data sets and networking through ethics.

CONCLUSION

This comprehensive analysis of smart aquaculture has provided an overview of current applications, limitations, and future prospects in using AI technology. As demonstrated by the conducted research, artificial intelligence technology has moved from being experimental to becoming vital for efficient aquaculture management. Indeed, this study has demonstrated the ability of AI technologies to produce significant results in such areas as water quality monitoring, disease identification, precision feeding, biomass assessment, and risk management. To be more specific, according to the reviewed literature, AI technologies have proven their efficiency by providing the accuracy of over 92% in dissolved oxygen estimation, over 95% in disease diagnosis, and over 88% in biomass evaluation. The economic benefits of implementing AI technologies into commercial production processes involve better efficiency in terms of feed (15-40%), lower mortality rate (20-60%), and decreased labor expenses (25-50%). Such achievements prove the effectiveness of AI technologies in solving major problems of aquaculture management when scaling up the process. However, a range of barriers to implementing AI technologies should be mentioned. These include algorithm-to-action gaps in risk management, economic problems of small aquafarms, lack of technical expertise, and poor data quality.
In the future, AI integration with innovative technological frameworks like digital twin technologies, federated learning, genomics, and blockchain traceability can be leveraged to build an overall smart aquaculture ecosystem. The proposed research areas relate to global sustainability efforts including UN Sustainable Development Goals related to food security, sustainable production practices, and protection of marine resources. As the development and use of AI in smart aquaculture becomes more mature, with fewer barriers to adoption, the relevance of smart aquaculture for the purpose of ensuring a sustainable seafood supply becomes even more relevant. It is advised for academia, technology developers, and aquaculture professionals to investigate the proposed research fields focusing on areas of explainability and collaborative intelligence in particular.

REFERENCES

1. Agya, B.A., Agyemang, P., Anokye, K., 2025. Beyond silos: an integrated AI-blockchain framework for sustainable aquaculture in Ghana. Smart Agricultural Technology, 12, 101576. https://doi.org/10.1016/j.atech.2025.101576
2. Ahmed, N., Turchini, G.M., 2021. Recirculating aquaculture systems (RAS): Environmental solution and climate change adaptation. Journal of Cleaner Production, 297, 126604. https://doi.org/10.1016/j.jclepro.2021.126604
3. Ahmed, S.F., et al., 2023. Deep learning modelling techniques: Current progress, applications, advantages, and challenges. Artificial Intelligence Review, 56(11), 13521-13517. https://doi.org/10.1007/s10462-023-10466-8
4. Alluhaidan, A.S., et al., 2025. Enhanced LSTM-based AI model for accurate dissolved oxygen prediction in aquaculture systems. Smart Agricultural Technology, 12, 101140. https://doi.org/10.1016/j.atech.2025.101140
5. Alnemari, A.M., et al., 2025a. Energy optimization in large-scale recirculating aquaculture systems: Implementation and performance analysis of a hybrid deep learning approach. Aquacultural Engineering, 111, 102561. https://doi.org/10.1016/j.aquaeng.2025.102561
6. Alnemari, A.M., et al., 2025b. Enhanced transfer learning and federated intelligence for cross-species adaptability in intelligent recirculating aquaculture systems. Aquaculture International, 33, 564. https://doi.org/10.1007/s10499-025-02212-4
7. Chandran, S.P., et al., 2025. Review on IoT-AI-blockchain integrated aquaculture for efficiency, traceability, automation. Aquaculture International, 33, 661.
8. Erh-Rousse, O., Qafas, A., 2024. Artificial intelligence for the optimization of marine aquaculture. E3S Web of Conferences, 477, 00102. https://doi.org/10.1051/e3sconf/202447700102
9. Ewees, A.A., et al., 2021. Optimized support vector machines

for unveiling mortality incidence in tilapia fish. Ain Shams Engineering Journal, 12(3), 3081-3090. https://doi.org/10.1016/j.asej.2021.01.014
10. Ezhilarasi, V., et al., 2021. ROV (remotely operated vehicle) - A splash in aquaculture. Biotica Research Today, 3(7), 553-555.
11. FAO, 2024. The State of World Fisheries and Aquaculture 2024: Blue Transformation in Action. FAO, Rome.
12. Fernandes, S., D'Mello, A., 2025. Artificial intelligence in the aquaculture industry: Current state, challenges and future directions. Aquaculture, 598, 742048. https://doi.org/10.1016/j.aquaculture.2024.742048
13. Fernandes, S., et al., 2019. Probiotic role of salt pan bacteria in enhancing the growth of Whiteleg shrimp. Probiotics and Antimicrobial Proteins, 11(4), 1309-1323. https://doi.org/10.1007/s12602-018-9503-y
14. Georgopoulos, V.P., et al., 2023. Factors influencing the adoption of artificial intelligence technologies in agriculture, livestock farming and aquaculture. Sustainability, 15(23), 16385. https://doi.org/10.3390/su152316385
15. Ghosh, M., et al., 2025. Robotics and autonomous systems in aquaculture: A comprehensive review. Reviews in Aquaculture, 17(2), 489-512.
16. Gkikas, M.C., et al., 2026. Artificial intelligence in aquaculture risk management: A systematic review by PRISMA. Applied Sciences, 16(4), 2032. https://doi.org/10.3390/app16042032
17. Goda, A.M., et al., 2025. Small-scale solar-powered IMTA-aquaponics with smart monitoring: Economic and LCA assessment. Aquaculture, 612, 743502.
18. Hasan, M.M., et al., 2024. Blockchain integration in aquaculture supply chain management. Aquaculture International, 32(4), 1567-1589.
19. Hemal, M.M., et al., 2024. An integrated smart pond water quality monitoring and fish farming recommendation aquabot system. Sensors, 24(11), 3682. https://doi.org/10.3390/s24113682
20. Huang, W., Khabusi, Z., 2025. Artificial intelligence applications in aquaculture: A systematic review. Reviews in Aquaculture, 17(1), 1-28.
21. Irshath, A.A., et al., 2023. Bacterial pathogenesis in various fish diseases: Recent advances and specific challenges in vaccine development. Vaccines, 11(2), 470. https://doi.org/10.3390/vaccines11020470
22. Li, D., et al., 2020. Nonintrusive methods for biomass estimation in aquaculture with emphasis on fish: A review. Reviews in Aquaculture, 12(3), 1390-1411. https://doi.org/10.1111/raq.12388
23. Li, T., et al., 2022. Predicting aquaculture water quality using machine learning approaches. Water, 14(18), 2836. https://doi.org/10.3390/w14182836
24. Li, X., et al., 2024. Thermal imaging and AI for early fish disease detection. Aquacultural Engineering, 85, 102389.
25. Liu, H., et al., 2023. Application of deep learning-based object detection techniques in fish aquaculture: A review. Journal of Marine Science and Engineering, 11(4), 867. https://doi.org/10.3390/jmse11040867
26. Luna, M., et al., 2022. Determination of feeding strategies in aquaculture farms using genetic algorithms. Annals of Operations Research, 314(2), 551-576. https://doi.org/10.1007/s10479-019-03227-w
27. Malik, S., et al., 2017. A novel approach to fish disease diagnostic system based on machine learning. Advanced Image and Video Processing, 5, 49-57. https://doi.org/10.14738/aivp.51.2809
28. Matsuzaka, Y., Yashiro, R., 2023. AI-based computer vision techniques and expert systems. AI, 4(1), 289-302. https://doi.org/10.3390/ai4010013
29. Nawoya, S., et al., 2024. Computer vision and deep learning for fish size estimation. Computers and Electronics in Agriculture, 216, 108503. https://doi.org/10.1016/j.compag.2023.108503
30. Panda, R.K., Baral, D., 2023. Adoption of AI/ML in aquaculture: A study on pisciculture. Journal of Survey in Fisheries Sciences, 10(1), 228-233.
31. Rastegari, H., et al., 2023. Internet of Things in aquaculture: A review of the challenges and potential solutions. Smart Agricultural Technology, 4, 100187. https://doi.org/10.1016/j.atech.2023.100187
32. Roy, S.M., et al., 2025. Application of artificial intelligence in aquaculture: Recent developments and prospects. Aquacultural Engineering, 111, 102570. https://doi.org/10.1016/j.aquaeng.2025.102570
33. Roy, S.M., et al., 2022. Optimizing aeration performance using hybrid ANN-PSO technique. Information Processing in Agriculture, 9(4), 533-546. https://doi.org/10.1016/j.inpa.2021.09.002
34. Sen, K., et al., 2026. Artificial intelligence in aquaculture: Advancing sustainable fish farming through AI-driven monitoring, optimization, and disease management. Aquaculture, 614, 743602. https://doi.org/10.1016/j.aquaculture.2025.743602
35. Swetha, P., et al., 2023. Random Forest regression based water quality prediction for smart aquaculture. Proceedings of the 4th International Conference on Computing and Communication Systems (I3CS), IEEE, 1-5. https://doi.org/10.1109/i3cs58314.2023.10127488
36. Vo, T.T.E., et al., 2021. Overview of smart aquaculture system: Focusing on applications of machine learning and computer vision. Electronics, 10(22), 2882. https://doi.org/10.3390/electronics10222882
37. Wang, X., et al., 2017. Automatic multiple zebrafish larvae tracking in unconstrained microscopic video conditions. Scientific Reports, 7(1), 1-8. https://doi.org/10.1038/s41598-017-17894-x
38. Yang, X., et al., 2025c. Machine learning models for predicting feed conversion ratio using short-term feeding data. Aquaculture, 608, 742891. https://doi.org/10.3390/ani15121773
39. Yang, Z., et al., 2023. Prediction and control of water quality in RAS based on hybrid neural network. Engineering Applications of Artificial Intelligence, 121, 106002. https://doi.org/10.1016/j.engappai.2023.106002
40. Yue, K., Shen, Y., 2022. An overview of disruptive technologies for aquaculture. Aquaculture and Fisheries, 7(2), 111-120. https://doi.org/10.1016/j.aaf.2021.04.009
41. Zhang, H., et al., 2023. AI in aquaculture water quality prediction: A comprehensive review. Aquaculture International, 31(5), 2231-2256.
42. Zhou, C., et al., 2018. Intelligent feeding control methods in aquaculture with emphasis on fish: A review. Reviews in Aquaculture, 10(4), 975-993. https://doi.org/10.1111/raq.12218