

Review

Artificial Intelligence of Things (AIoT) Advances in Aquaculture: A Review

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Abstract: The integration of artificial intelligence (AI) and the internet of things (IoT), known as artificial intelligence of things (AIoT), is driving significant advancements in the aquaculture industry, offering solutions to longstanding challenges related to operational efficiency, sustainability, and productivity. This review explores the latest research studies in AIoT within the aquaculture industry, focusing on real-time environmental monitoring, data-driven decision-making, and automation. IoT sensors deployed across aquaculture systems continuously track critical parameters such as temperature, pH, dissolved oxygen, salinity, and fish behavior. AI algorithms process these data streams to provide predictive insights into water quality management, disease detection, species identification, biomass estimation, and optimized feeding strategies, among others. Much as AIoT adoption in aquaculture is advantageous on various fronts, there are still numerous challenges, including high implementation costs, data privacy concerns, and the need for scalable and adaptable AI models across diverse aquaculture environments. This review also highlights future directions for AIoT in aquaculture, emphasizing the potential for hybrid AI models, improved scalability for large-scale operations, and sustainable resource management.

Keywords: artificial intelligence of things (AIoT); aquaculture automation; production optimization; machine learning; deep learning



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1. Introduction

Aquaculture, commonly known as fish farming, involves cultivating aquatic organisms in controlled environments [1]. It is crucial for meeting the increasing global demand for seafood while alleviating pressure on wild fish populations [2]. This practice extends beyond fish to include a diverse array of aquatic species cultivated for food, environmental restoration, and ornamental purposes [3,4].

Fish are the most prominent group in aquaculture, with species such as salmon, tilapia, catfish, trout, carp, and seabass commonly farmed due to their commercial value and adaptability to aquaculture environments [4,5]. In addition to fish, crustaceans like shrimp and crabs are significant contributors, especially in regions where their demand is high. Shrimp farming, in particular, has become a cornerstone of global aquaculture exports [6,7]. Mollusks, including scallops, oysters, and mussels, are another essential category. These species are valued for their economic and nutritional contributions and are

often cultivated in marine environments. Pearls, produced by certain species of oysters, are an example of aquaculture's intersection with luxury markets. Coral farming, though niche, is increasingly vital for ornamental trade and ecological restoration, particularly in efforts to rehabilitate damaged coral reefs [8,9]. Other species cultivated in aquaculture include jellyfish, which are farmed for both culinary purposes and ecosystem management, and aquatic macroinvertebrates, which serve as indicators of environmental health and are used in ecological assessments [10,11]. Phytoplankton, integral to the aquatic food chain, are also cultivated for their ecological and nutritional roles [12,13]. Aquatic plants such as seaweeds and algae further diversify aquaculture, with applications ranging from human consumption to cosmetics and biofuel production [1,14]. This broad spectrum of species reflects the adaptability and significance of aquaculture in addressing global challenges, including food security, environmental sustainability, and economic development.

Aquaculture continues to evolve as a vital component of modern agriculture and environmental management through the facilitation of AIoT, which integrates AI and IoT to enhance fish farming practices. For instance, digital twins enable real-time monitoring and decision-making [15], sustainable IoT solutions reduce resource wastage and promote environmental resilience [16], IoT-based systems improve disease detection and health management [17], and AIoT-driven water quality inspection systems enhance operational efficiency and scalability [18,19]. The development of IoT devices, including sensors, cameras, and monitoring systems, has revolutionized data collection from remote and dynamic aquaculture environments [20,21]. These devices provide continuous streams of data on critical parameters such as water quality, fish behavior, feeding patterns, and environmental conditions and AI algorithms analyze these data to generate actionable insights that drive real-time decision-making and autonomous operations, thereby reducing human intervention and enabling smarter, more sustainable practices [22,23].

The foundational IoT infrastructure in aquaculture consists of data-gathering devices, connectivity gateways, and cloud platforms for data storage and processing [20]. This infrastructure supports real-time monitoring and analysis of environmental parameters like temperature, salinity, pH, and dissolved oxygen; factors critical for maintaining optimal aquatic conditions [24]. Cloud computing enables the parallel processing and scalability needed to handle large-scale datasets efficiently, providing a robust platform for integrating AI capabilities into aquaculture systems [24]. AIoT applications in aquaculture span a broad spectrum of innovations, including smart feeding systems, water quality management, disease detection, fish biomass estimation, fish behavior monitoring, organism counting, species segmentation and classification, breeding and growth estimation, individual fish tracking, and automation and robotics. For instance, IoT-enabled smart feeding systems, as demonstrated in [25], utilize data from sensors and underwater cameras to monitor fish behavior and optimize feeding schedules and quantities. The AI models applied in this study analyze the collected data to ensure fish are fed adequately while minimizing waste, improving growth rates, and reducing environmental impact.

In water quality management, IoT sensors monitor variables like temperature, pH, dissolved oxygen, and ammonia levels, while AI-based predictive models use these data to forecast trends and recommend interventions [26,27]. Deep learning techniques such as long short-term memory (LSTM) networks analyze time-series data to predict oxygen depletion [26,28], enabling proactive aeration adjustments. Similarly, reinforcement learning (RL) algorithms dynamically optimize water management strategies to balance energy efficiency with environmental stability. Early disease detection and prevention are critical to reducing losses in aquaculture, and AIoT systems offer significant advancements in this area. IoT-enabled cameras capture high-resolution images of fish, which are analyzed by deep learning models like YOLO and U-Net to detect early signs of disease, such as lesions

or abnormal swimming patterns [21,29–31]. These systems detect fish diseases by analyzing data from biosensors and AI models, as demonstrated in [21], where AIoT technologies were applied to identify early signs of disease such as lesions, enabling farmers to intervene early and mitigate outbreaks.

Applications such as species segmentation, organism counting, and breeding optimization further demonstrate AIoT's versatility. Convolutional neural network-based models like ResNet and VGG facilitate species identification and population monitoring, ensuring compliance with regulations and maintaining biodiversity [32,33]. Selective breeding programs benefit from AI models that analyze genetic and environmental data to predict traits like disease resistance and growth efficiency, enhancing productivity and resilience. Robotics and autonomous systems integrated with AIoT technologies are redefining aquaculture operations. Autonomous underwater vehicles (AUVs) equipped with cameras and sensors perform tasks such as tank cleaning, fish inspections, and feed delivery with precision and minimal human oversight [34]. Reinforcement learning algorithms enhance these systems, enabling them to adapt to complex environments and learn optimal strategies through trial-and-error interactions [35].

These advancements are pivotal for the aquaculture industry, which has seen exponential growth over recent decades. Since the 1950s, aquaculture's share of global fisheries output has risen from 4% to nearly half of total fish production in 2020, with an estimated market value of USD 265 billion as of 2020 [2,36]. By 2030, aquaculture is projected to account for more than half of global fish production. Though the sector still faces some challenges such as environmental fluctuations, disease outbreaks, and feeding deficiencies [37], AIoT-enabled systems are uniquely positioned to address these challenges by integrating predictive analytics, real-time monitoring, and autonomous decision-making. Moreover, emerging technologies such as edge computing, blockchain, and hybrid AI models hold further promise for enhancing AIoT's role in aquaculture [38]. Edge computing enables faster, decentralized data processing, reducing latency in decision-making, while blockchain improves data security and traceability [39].

Scope and Methodology

This review systematically investigates AIoT advances in aquaculture, focusing on applications in real-time environmental monitoring, data-driven decision-making, and automation, providing a comprehensive analysis of the literature published between 2012 and 2024. The methodology employed was designed to ensure scientific rigor, comprehensive coverage, and relevance of the reviewed material.

Database selection: The review utilized well-established academic databases to collect relevant literature. The primary sources included IEEE Xplore for research on AIoT technologies and sensor-based systems; ScienceDirect to access journals focusing on aquaculture practices, environmental monitoring, and automation; SpringerLink for multidisciplinary articles bridging aquaculture and AIoT advancements; Web of Science to ensure inclusion of high-impact, peer-reviewed articles across relevant domains; PubMed for biosensor and disease detection studies targeting aquaculture species; Google Scholar to supplement the search with gray literature, including conference proceedings and preprints.

Search strategy: A structured search strategy was adopted using combinations of predefined keywords. The primary search terms included the following: “artificial intelligence in aquaculture”; “internet of things in aquaculture”; “AIoT for fish farming”; “smart feeding systems AIoT”; “water quality management IoT”; “fish disease detection using AI”; “automation in aquaculture”; and “robotics and AI in aquaculture”. These keywords were expanded to include synonyms and related terms, such as “intelligent aquaculture”,

“machine learning in aquaculture”, and “IoT-enabled monitoring systems in fish farming”. The iterative search process ensured comprehensive coverage of the relevant literature.

Scope and focus of the review: This review comprehensively analyzes advancements in AIoT applications within aquaculture, drawing from 215 research papers published between 2012 and 2024. The papers are systematically categorized into ten core application areas: smart feeding systems, water quality management, disease detection, fish biomass estimation, fish behavior monitoring, organism counting, species segmentation and classification, breeding and growth estimation, individual fish tracking, and automation and robotics. Further, the review explores AIoT advantages, adoption challenges such as high implementation costs, data privacy concerns, and the need for scalable and adaptable AI models across diverse environments. It also highlights future AIoT trends, including the development of hybrid models, scalability solutions, and AIoT’s role in promoting sustainable aquaculture practices. By providing an in-depth analysis of the long-term potential of AIoT, this paper highlights its transformative role in advancing global aquaculture practices and sustainability.

Inclusion and exclusion criteria: To ensure relevance and quality, the following criteria were applied. The inclusion criteria encompassed peer-reviewed journal articles, conference proceedings, and book chapters, studies explicitly addressing AIoT applications in aquaculture, with a focus on real-time monitoring, automation, and decision-making research published between 2012 and 2024. Conversely, the exclusion criteria comprised non-English articles and papers lacking technical depth or failing to directly link AI and IoT to aquaculture systems. The initial pool of 402 papers was refined through title and abstract screening, full-text evaluations, and prioritization based on novelty, technical depth, and scope alignment, resulting in the final selection of 215 studies.

Research contributions: This review paper makes significant contributions to the literature on AIoT integration in aquaculture, setting itself apart through its unparalleled breadth and depth of analysis:

- (1) The paper systematically categorizes 215 research works (2012–present) into ten application areas, offering a holistic perspective on AIoT advancements, challenges, and opportunities in aquaculture. This organization provides a comprehensive understanding unmatched by prior reviews.
- (2) To the best of our knowledge, this work represents the most extensive review of AIoT applications in aquaculture, integrating diverse insights to highlight the transformative potential of these technologies and serving as a foundational resource for multidisciplinary research and innovation.
- (3) The review addresses critical adoption barriers such as high costs, data privacy concerns, and scalability issues. It also explores future directions, including hybrid AI models, blockchain for secure data management, and edge computing for real-time, remote operations.

2. AIoT Components in Aquaculture

The integration of AIoT in aquaculture relies on two core components: IoT sensors for real-time data collection and AI algorithms for data processing and decision-making. IoT sensors continuously monitor key environmental and biological factors, such as water quality (pH, temperature, dissolved oxygen) and fish behavior. The deployment of sensors is supported by advanced communication protocols, such as LoRa, NB-IoT, and 5G, ensuring reliable data transmission from remote farms to central management systems. These components, as illustrated in Figure 1, work together to enhance efficiency, reduce waste, and improve the sustainability of aquaculture operations by enabling automated, data-driven management practices.

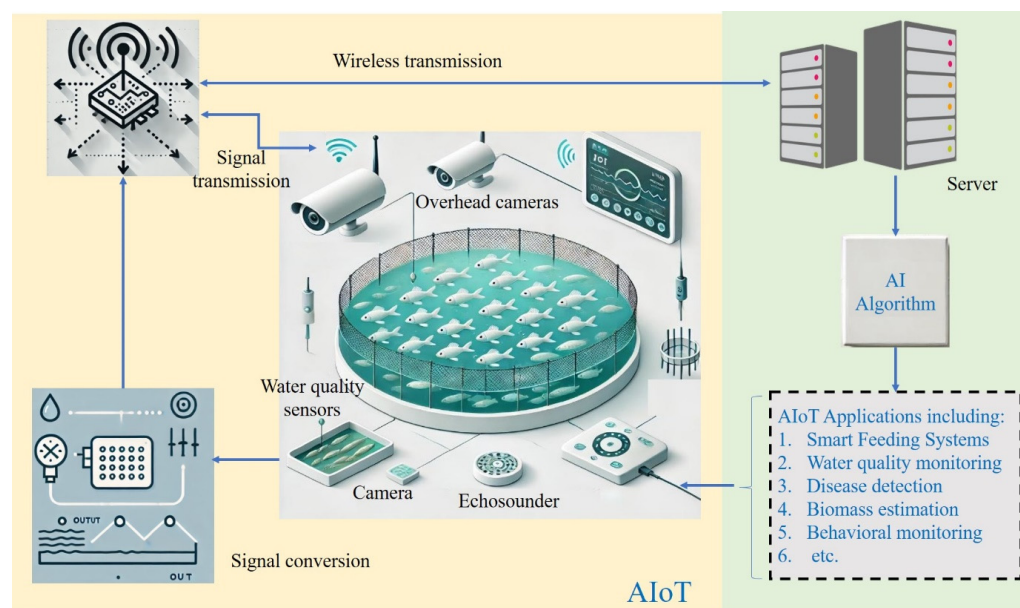


Figure 1. Conceptual framework of AIoT in aquaculture.

2.1. IoT Sensors

IoT sensors are central to transforming aquaculture through real-time data collection and monitoring, enabling precise management of both environmental and biological parameters crucial for maintaining healthy aquatic ecosystems [20]. For example, dissolved oxygen levels, which naturally fluctuate throughout the day, can be monitored in real-time to alert farmers to potentially harmful drops, enabling them to activate aeration systems as needed [40]. Temperature sensors also allow for quick detection of sudden temperature shifts, allowing farmers to maintain optimal conditions to reduce fish stress and prevent thermal shock [41]. Moreover, IoT sensors facilitate early warning systems for issues such as disease outbreaks, feeding inefficiencies, and water pollution [42].

2.1.1. Water Quality Sensors

Water quality sensors are essential in maintaining the health and productivity of aquaculture systems by continuously monitoring critical parameters like pH, temperature, dissolved oxygen, salinity, and ammonia. Studies such as [16,19,26] have demonstrated that these factors significantly influence aquatic species' physiological well-being and growth. Slight deviations can lead to stress, vulnerability to disease, and, in severe cases, mortality [26]. Recent advancements have aimed to improve sensor precision, durability, and cost-effectiveness, ensuring that water quality monitoring meets the high standards required for aquaculture environments. For pH measurement, glass electrode sensors and ion-sensitive field-effect transistor (ISFET) sensors are commonly utilized due to their reliability in detecting subtle changes in water acidity, a critical aspect of fish health [43]. Glass electrodes, although widely used, require regular calibration and can be affected by biofouling, which limits their long-term applicability in aquaculture [44]. In contrast, ISFET sensors offer better resistance to drift and durability, making them more suitable for harsh aquatic environments as demonstrated in [44], where their performance in long-term aquaculture monitoring was evaluated.

Temperature sensors, such as thermocouples and resistance temperature detectors (RTDs), are crucial for regulating water conditions that directly affect fish metabolism and growth rates. Dissolved oxygen (DO) levels are another critical factor in fish welfare, with levels needing to remain within specific ranges to prevent hypoxia, which can impair fish health [16]. Electrochemical DO sensors, such as the Clark electrode, operate through

amperometric techniques but require regular maintenance to address membrane fouling, a recurring issue in high-organic-content waters [27]. Optical DO sensors, based on fluorescence quenching by molecular oxygen, provide a non-invasive and accurate alternative. A recent review by [42] highlights their effectiveness in aquaculture, particularly in maintaining stable dissolved oxygen levels. However, these sensors are more costly and can degrade over time, particularly when exposed to certain chemicals in water.

Salinity, which influences osmotic balance in fish, is often monitored with conductivity-based sensors, specifically through inductive methods. Inductive sensors have become popular due to their ability to isolate sensing components from direct contact with water, thus minimizing biofouling and corrosion [45]. A study by [46] shows that while conductive sensors are effective for consistent salinity readings, inductive sensors are more durable for long-term deployment in aquaculture, where biofouling is a significant challenge.

Ammonia, a byproduct of metabolic waste, is toxic to fish at high levels, and its monitoring is therefore critical for maintaining safe water conditions. Ion-selective electrodes (ISEs) and colorimetric sensors are the two main approaches to ammonia measurement in aquaculture. ISEs provide accurate, continuous measurements but are prone to sensor drift, particularly under variable water conditions, necessitating frequent recalibration [47]. Colorimetric methods, while effective in detecting ammonia, are limited by slower response times and are generally less suitable for real-time applications in high-density aquaculture systems [48]. Collectively, these sensor technologies support an integrated approach to aquaculture water quality monitoring. However, the literature highlights several challenges, including sensor drift, biofouling, and maintenance requirements, which can impact data reliability and sensor lifespan [49]. Consequently, recent research has focused on enhancing sensor materials, developing anti-biofouling surfaces, and integrating multi-sensor systems to improve data accuracy, minimize maintenance, and facilitate rapid detection of water quality fluctuations.

2.1.2. Optical Sensors

Optical sensors have been widely adopted in water quality monitoring for aquaculture, offering valuable insights into turbidity and water clarity, both essential indicators of environmental health in aquatic systems. Turbidity can arise from sediment particles, organic matter, or plankton, which may compromise fish health by altering oxygen levels, light penetration, and other ecological conditions [42]. Increased turbidity is often linked with the presence of pollutants or phytoplankton blooms, both of which can elevate stress and disease risk among fish [44]. Optical turbidity sensors operate based on light interactions with particles, generally measuring either scattering or absorption.

Cameras, typically combined with computer vision algorithms, are widely used for behavioral analysis, allowing for the real-time monitoring of movement and spatial distribution within tanks. Studies have demonstrated that analyzing fish swimming patterns and spatial dispersion can be effective in identifying early stress signals and detecting disease [50]. For instance, abnormal changes in swimming speed, turning rates, or erratic movement patterns often indicate environmental stress or health issues, prompting timely interventions [51]. Additionally, computer vision-based tracking can optimize feeding routines by correlating feeding response with behavior, thereby reducing feed waste and promoting sustainable practices [8]. Despite their benefits, optical sensors have limitations, such as biofouling, which can obstruct optical pathways and lead to inaccurate measurements over time as discussed in [42]. Given these considerations, optical turbidity sensors remain a practical, cost-effective solution for aquaculture water quality management, particularly when accurate, low-energy measurements are required. Their ability to detect subtle changes in water clarity allows for proactive responses to

environmental shifts, potentially preventing adverse effects on fish health and productivity in aquaculture facilities.

2.1.3. Motion Sensors

Motion sensors, including accelerometers, are crucial in monitoring movement patterns, feeding behavior, and stress indicators. These sensors enable a non-invasive approach to tracking fish activity and well-being, which is essential for maintaining health and productivity. Accelerometers, typically embedded in tags or attached externally, offer high-resolution data on individual fish movements, such as tail-beat frequency, burst swimming, or rest periods. These data provide critical insights into metabolic rates, activity levels, and feeding behavior. Studies have found that accelerometer-based monitoring is effective in detecting subtle changes that may not be apparent through visual observation alone, such as increased activity due to suboptimal water quality or decreased activity due to illness [52]. Integrating accelerometers with telemetry systems has further allowed for remote, real-time behavioral monitoring, improving the ability to respond quickly to changes in fish health.

2.1.4. Deployment Strategies

Effective deployment strategies for IoT sensors in aquaculture are essential to maximize data accuracy and reliability, as well as to meet specific environmental and operational demands. Selecting the appropriate wireless communication protocol is a primary consideration, with Long Range (LoRa), Narrowband IoT (NB-IoT), and 5G emerging as popular options due to their distinct advantages. LoRa, for instance, is widely favored for large-scale, remote aquaculture applications because of its long-range transmission and low power requirements, allowing for effective monitoring in vast or hard-to-reach areas [42]. In contrast, 5G technology is gaining traction in aquaculture settings that require high data throughput and low latency, particularly for high-frequency video feeds used in real-time behavior monitoring [52]. NB-IoT also offers a viable solution in scenarios where power efficiency and long-range capabilities are needed without the bandwidth demands of 5G, proving effective for transmitting data from lower-frequency sensors like dissolved oxygen or pH meters [38]. Sensor placement is another crucial aspect of deployment [38]. Strategic distribution across various depths and locations within ponds, tanks, or cages allows for a comprehensive assessment of environmental variables, from temperature gradients to oxygen levels, which can vary significantly within the same body of water.

2.2. AI Algorithms

AI algorithms are critical in converting extensive data collected by IoT sensors into actionable insights, transforming farm management practices through predictive modeling, automation, and optimizing processes like feeding and water management. The integration of machine learning (ML), deep learning (DL), computer vision and image processing, and fuzzy logic in aquaculture enables efficient handling and analysis of diverse, complex datasets, each bringing unique strengths that address specific challenges within the field.

2.2.1. Machine Learning (ML)

ML offers powerful methods for predictive analytics and pattern recognition, particularly when dealing with structured data collected from IoT sensors. The ML algorithms are categorized into supervised, unsupervised, and reinforcement learning algorithms, which uncover intricate patterns and trends within data, enabling farmers to anticipate changes and make informed decisions to optimize operations.

Supervised learning involves training ML algorithms on labeled data and the various tasks here include classification and regression. In classification tasks, the goal is to catego-

size data into discrete classes. For instance, ML models such as support vector machines (SVMs), decision trees (DTs), random forest (RF), k-nearest neighbors (KNNs), and logistic regression (LR) can classify water quality as “safe” or “unsafe”, enabling farmers to make immediate decisions to mitigate risks. Similarly, classification can be used to detect fish diseases by analyzing image data or behavioral patterns, thereby enabling early diagnosis and reducing disease spread. Classification models are assessed using metrics like accuracy, precision, and recall, which provide insight into their ability to identify safe and unsafe water conditions correctly. Regression, on the other hand, deals with predicting continuous values. For example, linear regression and neural networks can estimate future water temperatures or fish growth rates based on historical data and environmental conditions. These models are evaluated based on metrics such as root mean square error (RMSE) and mean absolute error (MAE), which measure the accuracy of predictions for continuous variables like temperature or oxygen levels.

Unsupervised learning involves training models on unlabeled data and a typical example under this category is clustering, used to group similar data points based on underlying patterns without predefined labels. In aquaculture, clustering techniques like k-means, hierarchical clustering, and DBSCAN can identify patterns in fish behavior, group fish based on feeding activity, or detect anomalies in water quality parameters. For example, clustering can help segment fish populations exhibiting abnormal behavior, which may indicate stress, disease, or environmental changes. Metrics such as Silhouette coefficient, Davies–Bouldin Index (DBI), Jaccard Index, and normalized mutual information (NMI), among others are used to evaluate clustering algorithms.

Conversely, reinforcement learning (RL) is a branch of machine learning where an algorithm (agent) learns to make decisions by interacting with an environment and receiving feedback in the form of rewards or penalties. This trial-and-error framework is particularly suited for dynamic and adaptive processes, making RL an ideal solution for challenges in aquaculture, such as optimizing feeding schedules, water quality management, and disease detection, among others. RL’s strength lies in its ability to model sequential decision-making problems, where actions taken at one time can influence future outcomes, aligning perfectly with the complexities of aquaculture systems. Various approaches and models within RL, such as Q-learning, Deep Q-Networks (DQNs) [51], Policy Gradient methods, and Actor–Critic frameworks, offer flexible solutions tailored to different types of aquaculture challenges. For example, Q-learning, a value-based approach, allows an agent to learn an optimal policy by estimating the expected cumulative reward for each action in a given state. In aquaculture, Q-learning can be applied to determine optimal aeration strategies, where the state is defined by water quality parameters such as oxygen levels and pH, and the actions involve aeration settings. For more complex environments with high-dimensional state spaces, Deep Q-Networks (DQNs) combine Q-learning with deep learning. DQNs use neural networks to approximate the Q-function, making them suitable for tasks where the state space is too large to represent explicitly. For instance, in a fish behavioral detection system, a DQN could process real-time data from sensors and video feeds to model collective behavior in fish schools to understand social behaviors in aquaculture and ecology. Chen et al. [51] demonstrated the effectiveness of RL-based behavioral detection systems, highlighting how DQNs can be used to model fish schooling behavior without relying on pre-defined rule-based models, instead learning behaviors through environmental interactions. Policy Gradient methods represent another critical RL approach, directly optimizing the policy that determines an agent’s actions, rather than estimating value functions like Q-learning. These methods excel in continuous action spaces, making them well-suited for fine-grained adjustments in aquaculture operations. Actor–Critic frameworks, which combine the strengths of Policy Gradient methods

and value-based approaches, are particularly effective for managing trade-offs between exploration and exploitation. In aquaculture, an Actor–Critic model could optimize the allocation of resources like feed and aeration by balancing immediate operational costs against long-term fish growth and health. The actor component selects actions based on the policy, while the critic evaluates the action's value, guiding the actor toward better decisions over time. RL can also extend to multi-agent settings, where multiple RL agents work collaboratively or competitively in shared environments. For instance, in a multi-tank aquaculture system, RL agents could coordinate aeration and feeding across tanks to ensure uniform growth and resource efficiency. Furthermore, advanced RL methods like proximal policy optimization (PPO) and soft actor–critic (SAC) offer robust solutions for real-world applications by addressing stability and efficiency challenges, making them promising tools for future innovations in aquaculture.

2.2.2. Deep Learning (DL)

DL is a subset of machine learning that utilizes neural networks with multiple layers to extract high-level features from data. These models, inspired by the human brain's neural architecture, are exceptionally powerful for processing and learning from large, complex datasets [4]. The versatility of deep learning lies in its diverse architectures, which are tailored to different types of data and tasks, including classification, detection, segmentation, and prediction. At the heart of DL are neural networks, which form the foundation for various architectures. Feedforward neural networks (FNNs) represent the simplest form of neural networks, where information flows in one direction; from the input layer through hidden layers to the output layer. These networks are primarily used for tasks such as regression and classification when dealing with structured numerical data. For instance, in aquaculture, FNNs can predict water quality parameters like temperature or pH based on historical data. When working with unstructured data, particularly images, convolutional neural networks (CNNs) are the go-to architecture. CNNs use convolutional layers to detect spatial hierarchies in image data, making them ideal for image classification, object detection, and segmentation. Baseline models such as VGG and ResNet have demonstrated state-of-the-art performance in image classification tasks. VGG, with its deep but uniform architecture, is often used for recognizing fish species or identifying abnormalities in images. ResNet, with its skip connections, allows for much deeper networks without the vanishing gradient problem and is widely applied in aquaculture for tracking fish movements or assessing physical health.

For more specialized tasks, deep learning models such as U-Net [29] and YOLO (You Only Look Once) [34] are frequently used. U-Net, a fully convolutional network, excels in image segmentation tasks, such as isolating fish outlines from underwater footage for population monitoring. YOLO, a real-time object detection algorithm, is particularly effective for identifying fish behavior patterns or detecting intruders like predator species in aquaculture systems. These models' ability to process high-resolution images and videos efficiently makes them invaluable in environments where real-time analysis is critical. Beyond image-based tasks, deep learning offers architectures tailored to temporal and sequential data. Recurrent neural networks (RNNs) and their advanced variants like Long short-term memory (LSTM) networks are designed for sequential data and excel in time-series analysis. LSTM networks, with their capability to remember long-term dependencies, are particularly effective for predicting water quality parameters or fish feeding patterns based on historical trends. For example, an LSTM model can analyze sensor data to forecast dissolved oxygen levels over the next 24 h, helping farmers proactively manage aeration.

For unsupervised learning tasks, autoencoders are a popular deep learning model used for feature extraction and dimensionality reduction. In aquaculture, autoencoders

can process sensor data to detect anomalies, such as unusual water quality readings that could indicate equipment failure or environmental disturbances. Autoencoders learn subtle patterns and deviations by compressing data into a lower-dimensional representation and then reconstructing it, thereby providing insights into system behavior. Multilayer perceptrons (MLPs) are another class of neural networks used for structured data. Characterized by fully connected layers, MLPs are versatile for numerical prediction and classification tasks. For example, in aquaculture, MLPs can classify water quality conditions based on multiple environmental factors, providing actionable insights to improve fish health and productivity.

2.2.3. Computer Vision and Image Processing

Computer vision and image processing are essential components of AI in aquaculture, enabling the interpretation and analysis of visual information from video data. Through computer vision techniques, AI models can assess fish behavior, detect abnormal patterns, and identify signs of stress or disease. Edge detection, image segmentation, and object tracking help to extract actionable insights from footage, such as estimating fish biomass or tracking individual fish movements. Studies like those by Huang et al. [2] highlight how computer vision has enabled a detailed understanding of fish health and behavior, which is essential for developing responsive management strategies.

2.2.4. Fuzzy Logic Control

Fuzzy logic is a computational approach that mimics human reasoning to handle uncertainty and imprecision, making it highly suitable for dynamic environments like aquaculture. For instance, ref. [29] integrates U-Net and a neuro-fuzzy system optimized by particle swarm optimization (PSO) to classify fish diseases in underwater images with high accuracy, enabling timely interventions. Similarly, ref. [53] utilizes fuzzy inference systems with FFAUNet segmentation to optimize fish feeding, reducing waste and enhancing growth rates. Moreover, ref. [54] employs a fuzzy neural network in expert systems for fish disease diagnosis, combining expert knowledge and real-time data to support early detection. These examples underscore the versatility and impact of fuzzy logic in improving efficiency and sustainability in aquaculture.

2.3. AIoT Pipeline

The overall pipeline of AIoT for automation of aquaculture operations is summarized in Figure 2.

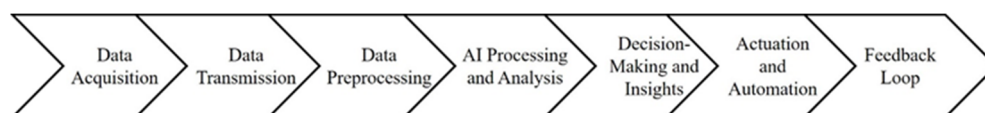


Figure 2. AIoT pipeline in aquaculture.

This pipeline begins with data acquisition. IoT sensors, underwater cameras, and aerial surveillance systems collect real-time data on critical parameters such as water quality, fish behavior, feeding activity, and environmental conditions. This stage ensures continuous and accurate data collection, forming the foundation for all subsequent analyses. Once the data are collected, they are transmitted wirelessly to centralized or cloud-based servers for processing. Wireless communication modules facilitate secure and efficient transmission, ensuring minimal delays and data loss, and enabling seamless integration across devices and systems. Before being processed by AI algorithms, the raw data undergo preprocessing. Techniques such as filtering, augmentation, deblurring, normalization, and data integration are applied to clean and format the data, ensuring their quality and

consistency for reliable analysis. At the pipeline's core is the AI algorithm processing stage, where advanced machine learning and AI models analyze the preprocessed data to extract actionable insights. This step encompasses a wide range of tasks tailored to specific aquaculture needs. For instance, smart feeding systems optimize feeding schedules based on fish behavior and environmental factors, while water quality management algorithms predict and maintain optimal water parameters. AI also facilitates behavior monitoring to detect stressors or abnormal patterns in fish activity, organism counting for accurate stock estimation, and segmentation and classification of aquaculture species to monitor biodiversity and species health [55].

3. AIoT Applications in Aquaculture

Integrating AIoT into aquaculture is revolutionizing farm management by merging real-time IoT sensor data collection with advanced AI-driven analytics. This synergy is enhancing efficiency, sustainability, and productivity in aquaculture operations. We summarize the existing AIoT applications in Figure 3.

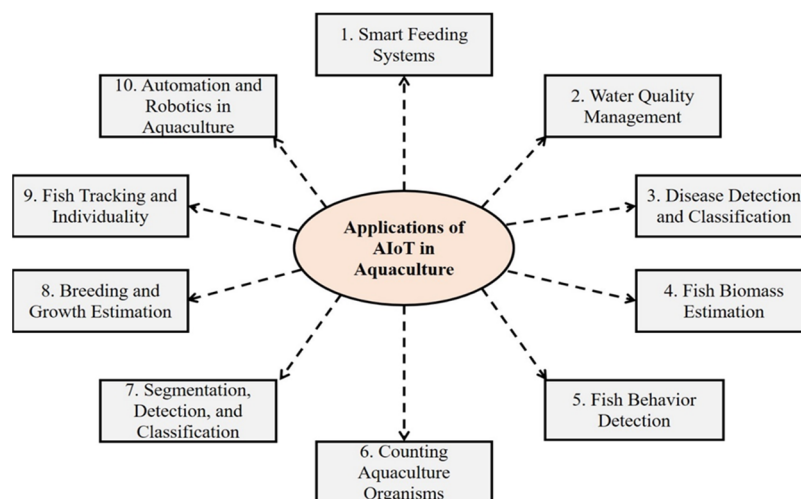


Figure 3. Applications of AIoT in aquaculture.

In Figure 3, *Smart feeding systems* represent a key application area where AI models like ResNet [56] and gradient boosting machines [57] analyze fish behavior and feeding patterns to automate feeding schedules. These systems improve feed conversion ratios (FCRs) and growth rates while minimizing wastage. However, their performance is often influenced by species-specific behavior and environmental conditions. *Water quality management systems* utilize IoT sensors and predictive models such as LSTM [26,28] and Kalman filtering [58] to monitor critical parameters such as dissolved oxygen, pH, and temperature. These systems allow for real-time intervention, ensuring optimal aquatic conditions. Challenges such as sensor biofouling and the need for recalibration in diverse environments remain prominent. In *disease detection and classification*, AI models like YOLO, U-Net, and biosensors [21,29–31] identify early indicators of diseases from visual and physiological data, achieving high detection accuracy. However, the lack of diverse datasets and limited cross-species generalizability hinder widespread application. *Fish biomass estimation* leverages computer vision, sonar imaging, and Structure from Motion (SfM) to provide accurate, real-time assessments of fish size and density [59]. These methods are critical for yield prediction and resource optimization but face challenges related to water turbidity and lighting variability. *Fish behavior detection systems* utilize acoustic monitoring and deep learning models to analyze behavioral patterns that signal stress, disease, or feeding needs. Although these systems achieve high precision, environmental noise and crowding can limit their effectiveness.

Counting aquaculture organisms automates stock assessment using object detection models like YOLOv5 and Faster R-CNN [6,60–66]. These systems streamline population management but encounter issues such as occlusion in high-density environments. *Segmentation, detection, and classification* applications use advanced AI models like Mask R-CNN and transformers to distinguish species and monitor biodiversity [10,11,14]. While these tools provide accurate results, challenges such as small target detection and real-time deployment persist. *Breeding and growth estimation systems* optimize breeding programs by monitoring fish maturity and growth rates using AI models and 3D reconstruction techniques. However, these methods often lack adaptability across species and require continuous data integration for real-world use. *Fish tracking and individuality systems* utilize tracking algorithms like Deep SORT and Gaussian models to monitor individual fish movement and health. These systems enhance behavioral analysis but struggle with ID-switch errors and occlusion in dense environments. Finally, *automation and robotics* in aquaculture employ autonomous underwater vehicles (AUVs) and reinforcement learning algorithms to automate tasks such as tank cleaning, fish inspection, and feed delivery. While robotics improves operational efficiency, limitations like battery life, connectivity, and implementation costs hinder scalability. These diverse applications address a wide range of challenges, from optimizing feeding systems to enabling autonomous operations. To offer a comprehensive overview of recent advances in the ten AIoT applications in aquaculture, Table 1 presents a detailed technical comparison, highlighting the datasets, technologies, key studies, results, limitations, and future directions for each application.

3.1. Smart Feeding Systems

Smart feeding systems represent a transformative application area in aquaculture. These applications monitor fish feeding activity and environmental parameters to automate feeding, ensuring aquatic organisms receive the appropriate amount of food at optimal times. Research to date has provided a solid foundation for smart feeding systems, exploring various methods to enhance feeding strategies and efficiency. These methods, which are detailed in the next subsections, include optimization of feeding frequency and nutrient distribution using models such as GBM and bioenergetic models to refine feeding schedules and improve growth rates [57,67], automated detection of feeding behavior using advanced computer vision techniques (such as R(2+1)D models and enhanced ResNet34) and real-time feed detection systems [23,56,68], acoustic-based monitoring to correlate feeding sound intensity with hunger levels and classify feeding intensity using models such as audio spectrum Swin transformer (ASST) [69,70], AI-enhanced precision feeding systems, including MLPNNs and hybrid models like FFAUNet-ANFIS, for real-time feeding adjustments [25,53], and integration of multimodal data (e.g., ECG, environmental data) to provide a comprehensive understanding of feeding behavior [8,71].

3.1.1. Feeding Frequency and Nutrient Requirements

Efficient smart feeding systems that optimize feed utilization and growth metrics across species are highly essential in aquaculture. Extensive research is being conducted to design systems that refine feeding schedules based on fish activity and improve nutrient distribution. For instance, an investigation of the impact of feeding frequency on fish growth has been conducted in [57]. The authors employ a gradient boosting machine (GBM) model to optimize the feed conversion ratio (FCR) and average daily weight gain (ADG), achieving high predictive accuracy and an R^2 of 93.03% and 72.49%, respectively. It is established that increased feeding frequency generally reduces FCR and feeding to satiation maximizes ADG. Similarly, the authors in [67] use a bioenergetic and protein flux model to optimize feeding in gilthead seabream, achieving a 46.85% improvement in final

fish weight by adjusting feed composition and frequency. These studies emphasize the significance of feeding frequency and nutrient balance in achieving optimal growth and minimizing waste, highlighting a need for tailored feeding schedules across species.

3.1.2. Automated Detection of Feeding Behavior

Automatic fish-feeding behavior detection is critical in determining whether fish are satiated or require more food. Multiple studies have utilized computer vision and acoustic sensing to monitor and dynamically adjust feeding protocols. For instance, in [23], a computer vision system with an R(2+1)D deep learning model is proposed to detect feeding activities by analyzing water surface disturbances (waves) during and after feeding, achieving a classification accuracy of 93.2%. This model shows potential for turbid outdoor environments, although species-specific adaptation remains an area for further validation. An enhancement of ResNet34 with CBAM attention is proposed in [56] for feeding intensity classification in tilapia, achieving a remarkable accuracy of 99.72%. Similarly, ref. [68] advances computer vision techniques for high-density fish tanks, using an SVM classifier with particle filtering to enhance real-time feed detection. These studies demonstrate the versatility and effectiveness of AIoT in diverse aquaculture environments, though they also reveal challenges in adapting to species-specific and environmental variations.

3.1.3. Acoustic-Based Monitoring and Behavioral Analysis

Acoustic-based monitoring has emerged as another effective technique for assessing feeding behavior, especially useful for detecting subtle differences in feeding intensity. In [69], a passive acoustic detection system is introduced to monitor shrimp feeding, using sound pattern analysis. The proposed system correlates feeding sound intensity with hunger levels. Despite challenges from ambient noise, this approach holds potential for real-time feed adjustments. Further, an audio spectrum Swin transformer (ASST) model is proposed in [70] to classify fish feeding intensity based on acoustic signals in aquaculture ponds, achieving a high classification accuracy of 96.16%. These acoustic-based systems offer valuable insights into fish behavior but face limitations in environments with background noise or low-intensity feeding signals, particularly in juvenile or smaller species.

3.1.4. AI-Enhanced Precision Feeding Systems

Precision feeding systems, often enhanced with AI technologies, represent a leading approach in smart feeding systems. The authors in [25] explore this area using a multilayer perceptron neural network (MLPNN) trained on Fourier descriptors to classify fish behaviors, achieving a perfect accuracy of 100% for real-time feeding adjustments. Similarly, ref. [53] combines image segmentation with fuzzy inference through a feature fusion attention U-Net (FFAUNet) and an adaptive neuro-fuzzy inference system (ANFIS) optimized by particle swarm optimization (PSO). This hybrid model reaches a classification accuracy of 98.57%, providing precise feeding based on water waves representing the feeding intensities (heavy, medium, normal).

3.1.5. Integrating Multimodal Data for Enhanced Monitoring

Existing studies have suggested integrating multimodal data can improve feeding system robustness and accuracy. CNN-based grading is combined with fuzzy control in [71] to assess feeding intensity more precisely, while ref. [8] integrates ECG, acceleration, and environmental data to monitor heart rate and feeding in coral reef fish, using Bayesian change-point detection and Kullback–Leibler divergence for reliable detection of feeding events. Such multimodal approaches provide a holistic view of feeding behavior, allowing for comprehensive monitoring, though real-time data fusion and application in field settings present ongoing challenges.

3.2. Water Quality Management

Maintaining optimal water quality is fundamental for sustainable and productive aquaculture, as aquatic species' health, growth, and welfare are directly influenced by environmental conditions. Deviations in parameters like dissolved oxygen (DO), pH, temperature, and ammonia levels can significantly affect fish health, impacting growth rates and disease susceptibility. Integrating IoT sensors and AI-based predictive analytics has proven essential in modern aquaculture, enabling continuous, real-time monitoring and early intervention to prevent adverse conditions [4,13]. Studies such as [4,16,19,27,28] have demonstrated that proactive monitoring systems can effectively forecast critical events in aquaculture. For instance, ref. [4] reviews the use of deep learning techniques, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), for predicting critical aquaculture events such as oxygen depletion and water quality deterioration. Ref. [16] discusses a sustainable IoT solution for freshwater aquaculture, highlighting its ability to predict algal blooms and maintain environmental stability through AI-driven monitoring. Ref. [19] presents an AIoT-based system that integrates water quality prediction and inspection to detect and mitigate events such as oxygen depletion. Ref. [27] focuses on the use of genetic algorithms combined with ensemble learning to optimize dissolved oxygen predictions, while ref. [28] introduces the TD-LSTM model for accurate marine temperature prediction, which indirectly supports forecasting algal blooms and related events.

3.2.1. Water Temperature

Water temperature directly influences metabolic rates, growth, and health of aquaculture organisms, making its management crucial. IoT-enabled sensors and AI-driven predictive models have enabled continuous temperature monitoring, allowing prompt responses to fluctuations. For example, an improved unscented Kalman filter (UKF) with sequential analysis and optimized extreme learning machine (ELM) is proposed in [58] to enhance temperature monitoring accuracy in aquaculture ponds. This approach reduces data redundancy and interference, providing robust real-time monitoring. The authors in [26] demonstrate the use of a hybrid CNN-LSTM-GRU model to capture time dependencies in temperature data. Moreover, in [28], a temporal dependence-based LSTM (TD-LSTM) model is introduced to capture temporal dependencies in marine temperature prediction, effectively improving accuracy across different ocean depths and regions.

3.2.2. pH

pH levels influence various biochemical processes in aquaculture, affecting nutrient availability, metabolic rates, and fish well-being. Various studies have highlighted the effectiveness of AI models for pH prediction, which helps maintain optimal pH ranges and prevent stress-induced health issues. For example, a random forest (RF) model is proposed in [16], as part of a sustainable IoT-based solution for freshwater aquaculture. This model predicts critical parameters such as dissolved oxygen and pH levels, enabling proactive management of aquaculture environments. In [19], a simple recurrent unit (SRU) model was applied to predict pH changes based on data from outdoor ponds, achieving stable predictions over extended monitoring periods. This approach, supported by moving average smoothing, allows the model to capture both short-term variations and long-term pH trends. Such predictive models contribute to effective pH management, enabling aquaculture operators to make timely interventions and support optimal growth conditions.

3.2.3. Salinity

Salinity is a critical environmental factor that affects osmotic balance and physiological functions in aquatic species. Maintaining stable salinity levels is essential to prevent stress and optimize growth. A low-cost salinity sensor that uses calibration circuits to ensure accuracy in varying conditions is introduced in [46]. Meanwhile, ref. [45] enhances salinity monitoring by integrating a novel transducer design that automatically adjusts sensitivity, achieving minimal linear error in salinity measurements. Similarly, the authors in [72] explore salinity management by developing a durable conductivity meter suitable for real-time monitoring in field conditions. These studies demonstrate the effectiveness of IoT-enabled salinity sensors, providing aquaculture operators with reliable data to maintain optimal salinity conditions and prevent adverse impacts on fish health.

3.2.4. Dissolved Oxygen (DO)

DO is vital for aquatic organisms, directly influencing respiration and overall health. Effective DO management in aquaculture helps prevent hypoxia-related stress and mortality. A predictive model that combines LightGBM, BiSRU, and an attention mechanism to predict DO levels accurately is developed in [73], allowing timely adjustments in high-density tanks. In [74], the ECA-Adam-RBFNN model leverages clustering and optimization techniques to handle non-linear DO fluctuations, demonstrating robust predictive accuracy under varying environmental conditions. In [27], an ensemble model that combines genetic algorithm (GA) for feature selection with XGBoost, CatBoost, and extra trees (XTs) regressors (GA-XGCBXT) for DO predictions is proposed. The study utilizes a dataset from a fish farm in Jeju, South Korea, that includes measurements of DO, pH, temperature, electrical conductivity (EC), and oxidation-reduction potential (ORP), to achieve a prediction RMSE of 0.31. While effective, the model requires recalibration for different environmental conditions. The authors in [75] proposed an enhanced Naive Bayes model that leverages differential sequences and a sliding window method to handle continuous values, combined with Laplacian correction for improved predictive performance on DO values. Similarly, ref. [76] introduces a hybrid PCA-LSTM model, which combines principal component analysis for feature selection with LSTM for time-series prediction, improving DO prediction accuracy. Moreover, ref. [77] uses a sparse auto-encoder (SAE) with LSTM for DO prediction, capturing deep latent features from water quality data for enhanced accuracy.

3.2.5. Turbidity

Turbidity affects water clarity, impacting light penetration, photosynthesis, and fish feeding. High turbidity can affect oxygen distribution in the water and lead to stressful conditions for fish, necessitating effective monitoring. The authors in [78] utilized a multilayer perceptron neural network embedded in IoT-enabled sensor nodes to classify pollutants based on pH, turbidity, and temperature measurements. The proposed approach achieved reliable pollutant detection in controlled environments. Similarly, a fault diagnosis model is proposed in [79] that uses rule-based decision trees (RBDTs) and support vector machines (SVMs) to identify anomalies in turbidity data, thereby enhancing operational reliability. Such IoT-integrated models enable proactive turbidity management, helping maintain optimal water conditions in aquaculture systems.

3.2.6. Chlorophyll

Chlorophyll-a levels serve as indicators of phytoplankton biomass and water quality, but excessive growth can lead to harmful algal blooms, reducing oxygen and threatening aquatic health. The authors in [80,81] explore chlorophyll prediction through SVM and

LSTM models, respectively, supporting early intervention in algal bloom events. Deep learning techniques using CNNs and LSTMs are applied in [82] to analyze chlorophyll data from satellite and IoT sources, demonstrating the potential for real-time chlorophyll monitoring across diverse aquatic environments. Similarly, in [83], LSTM with batch normalization and dropout layers are utilized to improve short- and long-term chlorophyll-a predictions, while ref. [84] uses LSTM for weekly chlorophyll-a concentration predictions to detect algal blooms in South Korean rivers.

3.2.7. Ammonia

Ammonia, a toxic byproduct of fish metabolism, poses significant health risks in aquaculture when present at elevated levels, leading to stress and compromised fish health. Monitoring ammonia levels is essential to prevent harmful accumulations. The concentration of ammonia is highly pH-dependent; when pH levels exceed 9.5, ammonia transforms from NH_4^+ to NH_3 , increasing its toxicity. Other factors, such as temperature, dissolved oxygen, total dissolved solids, and algal growth, influence ammonia levels [13]. In aquaculture ponds, ammonia can build up from organic matter, uneaten feed, algal blooms, wastes of aquatic organisms, decomposing aquatic organisms, and nitrogen-rich compounds [85,86]. Ammonia toxicity is also a significant issue in landfills, where it accumulates and may seep into groundwater [43]. Effective ammonia monitoring in aquaculture ponds is crucial for assessing organism survival rates and overall water pollution levels [87]. The existing studies reflect a trend toward integrating predictive models and bioremediation techniques to improve water quality, which is essential for sustainable aquaculture practices. For example, a general regression neural network (GRNN) and long short-term memory (LSTM) networks are proposed in [47], for real-time prediction of ammonia, nitrogen, and nitrite levels in high-density shrimp aquaculture systems. However, while ammonia predictions were stable, nitrite concentration predictions were less consistent, particularly under high biofilter loads. Building on the use of hybrid AI models, Wang et al. [48] present an advanced approach with a combined XAdaBoost and LSTM model for ammonia nitrogen prediction in aquaculture, which achieves lower RMSE and MAPE values compared to existing methods. Meanwhile, Collos et al. [13] provide a biological perspective by examining ammonium toxicity in unicellular algae. Shifting from prediction to treatment, John et al. [85] explore the application of bioremediation through a bacterial consortium aimed at treating ammonia and nitrite in tilapia aquaculture wastewater. The bacterial treatment achieved an impressive reduction in ammonia, improving the survival rate of tilapia significantly. However, this lab-based experiment prompts questions regarding the efficacy of the consortium on a larger scale, particularly in varied aquaculture environments where external conditions could influence bacterial performance. In another predictive modeling approach, Yu et al. [86] propose a hybrid model that combines empirical mode decomposition (EMD), improved particle swarm optimization (IPSO), and extreme learning machine (ELM) for accurate ammonia prediction. This EMD-IPSO-ELM model demonstrates strong predictive capabilities with enhanced accuracy compared to other methods. Addressing ammonia inhibition in anaerobic digestion, the authors in [43] explore how high ammonia levels affect biogas production during the digestion of municipal solid waste. The study finds that biogas production is inhibited at higher ammonia concentrations, impacting AD efficiency. A review by Karri et al. [87] further investigates ammonia management by comparing conventional and advanced removal methods in wastewater treatment. This critical review identifies the advantages and limitations of techniques such as ion exchange, membrane filtration, and biological treatments. Lastly, Nagaraju et al. [88] revisit predictive modeling with an emphasis on noise reduction in ammonia prediction within shrimp aquaculture. The pelican optimization algorithm (POA)

is combined with discrete wavelet transform (DWT), which outperforms standalone POA in accuracy. Together, these studies provide a multifaceted perspective on ammonia management, from predictive AI models and biological treatments to analytical reviews of conventional methods.

3.3. Disease Detection and Classification

Early disease detection and classification are vital for effective control and management of disease outbreaks in aquaculture farms. This ultimately contributes to the health and productivity of fish and shrimp stocks. Disease outbreaks not only affect the welfare of cultured species but also lead to significant economic losses in fish farming practices.

3.3.1. Computer Vision-Based Disease Detection

Computer vision has been widely applied in aquaculture to detect visual symptoms of fish and shrimp diseases. For instance, in [7], an early detection mechanism of white spot syndrome virus (WSSV) in shrimp through image processing techniques is proposed. The study applies an artificial neural network (ANN), with feature extraction achieved through Canny edge detection and gray-level co-occurrence matrix (GLCM) features. The results indicate a robust performance, with the model achieving 94.71% accuracy, 94.86% sensitivity, and 93.32% specificity, demonstrating its efficacy in distinguishing healthy from infected shrimp, on a primary dataset of shrimp images, featuring both healthy and WSSV-infected specimens. However, limitations include potential image quality issues due to environmental variations and the model's focus on WSSV, which could reduce its applicability to other shrimp diseases. Future directions involve expanding the dataset to cover additional diseases, enhancing feature extraction methods, and developing a real-time monitoring application for practical use in aquaculture. In [89,90] SVM, random forest classifiers with K-means clustering for image segmentation are utilized, achieving classification accuracies of 94.12% and 88.87%, respectively, in classifying both Epizootic Ulcerative Syndrome (EUS) and Tail and Fin Rot diseases.

Attention mechanisms in deep learning models [91] have shown promise for disease classification in aquaculture by allowing networks to focus on disease-specific features. In [92], the convolutional block attention module (CBAM) is integrated with ResNet50, achieving an accuracy of 89.9%. Similarly, ref. [2] proposes a background elimination approach and improves upon traditional CNN models by integrating an online sequential extreme learning machine (OSELN) and CBAM to enhance feature extraction, achieving 94.28% accuracy even in challenging underwater conditions. Similar studies include [93], which classifies epizootic ulcerative syndrome (EUS), Ichthyophthirius (Ich), and Columnaris with AlexNet CNN, and [30], which utilizes InceptionV3 and VGG16, achieving accuracy scores of 93.87% and 91.60%, respectively, on the SB-Fish disease dataset from Kaggle. In [94], multiple machine learning models including decision tree, logistic regression, Naive Bayes, multilayer perceptron, and support vector machine (SVM) with different kernels are reviewed, and SVM with a polynomial kernel achieved the highest accuracy in identifying EUS in fish. In [95], the authors aim to detect EUS in fish using image processing for improved diagnostic accuracy. The proposed model employs FAST and HOG for feature extraction, with PCA for dimensionality reduction and a neural network for classification. The study results show the FAST-PCA-neural network model achieves higher accuracy (86%) compared to HOG-PCA (65.8%), highlighting FAST's effectiveness for EUS detection. Limitations include its focus on EUS, limiting broader application.

3.3.2. Water Quality-Linked Disease Prediction

Predictive models that monitor water parameters can detect deviations associated with disease risk. The authors in [96] employ a gradient boosting model (GBM) to classify

disease risk based on water quality data. The model achieves a 92% accuracy rate in predicting disease likelihood by analyzing parameters such as pH, DO, and nitrate levels. Additionally, ref. [97] integrates water quality monitoring with disease detection through IoT-enabled sensors and the MobileNetV2 CNN model, achieving 91.5% accuracy.

3.3.3. Cross-Modal and Zero-Shot Learning for Disease Identification

In cases where labeled image data for certain diseases are limited, cross-modal and zero-shot learning methods offer innovative solutions. There have been a few studies that have explored this area. They involve applying zero-shot learning by leveraging textual descriptions from the scientific literature and mapping them onto image features to classify diseases in shrimp, achieving effective disease recognition even without direct image data for certain diseases [98]. This cross-modal approach enables knowledge transfer from textual data to visual data, offering a promising solution for identifying diseases beyond the training set. Similarly, ref. [99] further explores transfer learning for fish disease detection, using VGG-16 and AlexNet architectures with data augmentation to achieve a classification accuracy of 91%.

3.3.4. Ensemble and Hybrid Models for Disease Classification

Combining multiple models in ensemble or hybrid architectures has proven effective in enhancing classification accuracy. The authors in [100] introduce the performance metric-infused weighted ensemble (PMIWE) model, combining models such as ResNet-50, DenseNet-121, and EfficientNetB3 to classify freshwater fish diseases with an accuracy of 97.53%. PMIWE achieves high reliability and interpretability by fusing the strengths of various transfer learning models, making it particularly suitable for real-time disease diagnosis. Similarly, ref. [101] employs a CNN with histogram of oriented gradients (HOGs) and thresholding techniques for disease classification. This model exemplifies the utility of combining feature extraction techniques with CNN architectures to improve classification robustness.

3.3.5. Adaptive Neural Fuzzy Systems

These systems are crucial in enhancing diagnostic precision and management in aquaculture disease detection. For instance, ref. [29] introduces an improved U-Net segmentation model with multi-head attention for accurately identifying disease-affected regions in fish images. Similarly, ref. [54] targets fish health management by developing a fuzzy neural network-based expert system for diagnosing diseases in grass carp. Results show high diagnostic accuracy for common grass carp diseases, though the model currently focuses only on this species. Future improvements aim to extend the system's applicability to other species, increase adaptability, and enable real-time monitoring.

3.3.6. Mobile and IoT-Enabled Disease Monitoring Systems

These solutions offer practical and scalable disease monitoring options for aquaculture. The studies in [21,102] both focus on mobile and IoT-enabled disease detection systems. In [102], the authors utilize a CNN optimized for mobile applications to provide disease alerts and treatment recommendations via a cloud-based interface, making disease detection accessible to small and micro-scale fish farmers. The work in [21] employs the YOLOv5 model for disease detection integrated with water quality monitoring sensors, achieving 97.03% accuracy.

3.3.7. Biosensors for Pathogen Detection

Advancements in biosensor technology contribute to disease prevention by providing precise pathogen detection capabilities. The authors in [103] explore optimizing gold (Au)

electrodes for pathogen detection in aquaculture, utilizing electrochemical impedance spectroscopy (EIS) to measure responses related to electrode surface properties. The study's findings suggest that low roughness levels in Au electrodes enhance the quality of impedance responses, facilitating pathogen detection in aquaculture environments.

3.4. Fish Biomass Estimation

Fish biomass estimation is critical in optimizing aquaculture operations by enabling accurate assessments of fish health, growth, and population density. Reliable biomass estimation facilitates efficient feeding routines, reduces waste accumulation, and promotes sustainable fish farming practices. Modern advancements in machine learning, computer vision, sonar, and smart scale technologies have enabled non-invasive, real-time biomass estimation in aquaculture, overcoming traditional challenges associated with manual measurements and stress-induced inaccuracies.

3.4.1. Computer Vision and Deep Learning for Biomass Estimation

Computer vision and deep learning techniques offer powerful tools for estimating fish biomass in aquaculture environments. Various studies have explored biomass estimation in aquaculture using AI approaches. For example, a custom version of YOLOv5 (DL-YOLO) combined with stereo vision for real-time fish detection is employed in [104], achieving a mean relative error (MRE) of 2.87% and an R^2 of 0.98 in estimating fish length, height, and weight. Similarly, ref. [105] utilizes mask R-CNN with pyramid squeeze attention for instance segmentation and 3D reconstruction, achieving an error rate below 5.6% in biomass estimation. Moreover, in [106], YOLOv7 is applied on the large-scale fish dataset to estimate fish length and biomass, achieving a high mean average precision (mAP) of 0.988, demonstrating the feasibility of using real-time object detection for efficient, automated biomass monitoring. However, the approach can be affected by lighting and visibility in underwater conditions.

3.4.2. Smart Scales for Real-Time Biomass Monitoring

Smart dynamic scales represent a practical and portable solution for biomass estimation in both offshore and in-land aquaculture environments. A Bluetooth-enabled dynamic scale that measures juvenile seabream biomass with a mean relative error of less than 1.4% is introduced in [107]. Designed with portability and cost-effectiveness in mind, this scale provides aquaculture operators with an accessible tool for monitoring fish growth and optimizing feeding practices. The authors in [108] further validate the dynamic scale's accuracy in both offshore and in-land settings, demonstrating stable readings with minimal deviation from laboratory scale results. Moreover, a portable scale optimized for offshore use is presented in [109], achieving a relative error below 2% in oscillating conditions. Future research could enhance these devices by improving mechanical stability and developing dedicated apps to expand usability in commercial settings.

3.4.3. Sonar and Acoustic Methods for Biomass Estimation

These methods have proven effective for biomass estimation in environments where optical imaging is challenging, as evidenced in various existing works. For example, the authors in [110] leverage sonar technology in combination with machine learning models, including a VGG network, to estimate biomass in high-density tanks under varying water conditions. Similarly, in [111], a standalone echosounder device designed for closed aquaculture settings is proposed. The device estimates fish counts and biomass by calculating target strength and backscattering coefficients, achieving an error margin of $\pm 7\%$ in field tests. Moreover, acoustic methods such as those used in [112] rely on ultrasound transducers and cross-correlation processing to detect and monitor biomass in fish migration

channels near hydropower plants. This approach is instrumental in assessing ecological impacts and supporting biodiversity in impacted aquatic environments.

3.4.4. Structure from Motion (SfM) and 3D Modeling for Biomass Estimation

SfM technology enables the reconstruction of 3D models of fish for non-intrusive biomass estimation. In [59], SfM is combined with multi-view stereo (MVS) techniques to generate dense point clouds and 3D meshes from underwater images. The proposed approach achieves a high correlation ($r = 0.98$) between estimated volumes and actual biomass while reducing error margins by over 30% compared to traditional techniques. Further, the method allows for precise volumetric measurements in real-time. However, environmental factors like lighting variability and water turbidity can affect performance, necessitating further refinement to ensure accuracy across diverse aquaculture settings.

3.4.5. Acoustic Signal Processing for Non-Invasive Biomass Estimation

Non-invasive acoustic signal processing techniques have shown promise in biomass estimation for certain fish species. The authors in [113] introduce an acoustic signal processing method that estimates biomass based on chirp signals emitted by damselfish. By using cross-correlation of signals captured by multiple acoustic sensors, this method achieves an error rate within 2% for simulated biomass estimations, providing a reliable non-invasive alternative for biomass monitoring in natural habitats. Although practical deployment remains challenging due to factors like signal propagation and multipath interference, this approach offers a promising direction for monitoring soniferous fish species.

3.5. Fish Behavior Detection

Monitoring fish behavior is critical for maintaining fish health, welfare, and achieving optimal growth in aquaculture systems. Behavioral changes often serve as early indicators of stress, disease, satiety or hunger, and adverse environmental conditions, providing valuable insights for timely interventions. Recent advancements in AI, IoT, acoustic monitoring, and computer vision have revolutionized behavior detection, enabling non-invasive, real-time monitoring even in complex aquaculture environments. These technologies have demonstrated significant improvements in accuracy and reliability, as evidenced by various studies.

3.5.1. Abnormal Behavior Detection

Detecting abnormal fish behaviors, such as erratic swimming or lethargy, is essential for identifying potential health issues in aquaculture. An introduction of a deep learning-based system using a ResNeXt $3 \times 1D$ convolutional network is made in [114], achieving 95.3% accuracy in distinguishing abnormal behaviors. This model improves monitoring efficiency in aquaculture by reducing computational complexity, though further work could expand behavior definitions and refine the model for edge computing. In [50], a combination of faster R-CNN for object detection, directed cycle graphs (DCGs) for posture classification, and dynamic time warping (DTW) for behavior analysis is proposed. The model achieved a 92.8% accuracy in identifying unusual behaviors in fish farms. This multi-model approach allows for accurate real-time behavior detection, but its effectiveness can be influenced by environmental factors like lighting and background noise. Similarly, ref. [115] tackles abnormal behavior recognition in high-density fish swarms, using a dual-flow deep network with a multi-instance learning framework to isolate abnormal behaviors. Moreover, an integration of a modified motion influence map with recurrent neural networks (RNNs) is proposed in [116], providing a robust framework for identifying patterns in sequential data.

3.5.2. Swimming Speed and Locomotion Analysis

Swimming speed and locomotion are important indicators of fish welfare and overall activity levels in aquaculture environments. The authors in [117] present a Doppler-based method that uses acoustic telemetry to measure swimming speed in marine cages, achieving an RMS error of 7.85 cm/s across a range of relevant speeds. This technique, while non-invasive, may be affected by signal reflections and environmental noise, especially in complex, high-density settings. Analysis of swimming behavior using acoustic video and deformable model techniques, which capture fish body deformation to identify species-specific swimming patterns, is undertaken in [118]. Moreover, in the context of cold-water coral ecosystem monitoring, ref. [119] introduces a workflow combining manual annotation, gold-standard creation, and CNNs to estimate coral polyp activity levels. With an accuracy of 96% for polyp activity classification, the study identifies significant temporal patterns linked to environmental events, emphasizing its value in ecological research.

3.5.3. Disease Detection Through Behavior Analysis

Behavioral cues can often signal early disease onset in aquaculture species, allowing for timely interventions. An introduction of EchoBERT, a transformer-based model that analyzes echograms to detect early indicators of pancreas disease in Atlantic salmon, is made in [120], achieving an MCC score of 0.694. The model outperforms traditional LSTM-based approaches, enabling earlier disease detection by over a month. Future work aims to refine this model across varied environments, expanding its applicability for other behavior-linked disease indicators.

3.5.4. Shoaling and Social Behavior Modeling

Shoaling behavior provides valuable insights into group health and social dynamics within aquaculture systems. In [118], a CNN model is proposed to detect different states of fish shoal behavior, such as feeding and stress responses, achieving 82.5% accuracy through spatiotemporal fusion images. This method combines spatial and optical flow information, though its performance may be limited by lighting inconsistencies and other environmental factors. Similarly, ref. [51] explores a simulated environment for schooling behavior, using Deep Q-Networks (DQNs) to model fish interactions without predefined rule-based models. This model successfully reproduces ordered group formations, demonstrating the potential for DQN-based approaches in understanding collective behaviors. Although currently limited to simulations, future work aims to refine this model for real-world schooling scenarios.

3.5.5. Acoustic and Echogram-Based Behavior Detection

Acoustic and echogram-based methods provide non-intrusive options for behavior detection, particularly in turbid or challenging environments. An EchoBERT transformer model that leverages echograms to detect disease-related behaviors is proposed in [120], while ref. [115] applies acoustic imaging to capture behaviors within fish swarms, achieving high recognition accuracy in abnormal behavior detection. These approaches highlight the potential of acoustic monitoring for continuous welfare assessments in aquaculture, though further developments are needed to improve robustness across diverse environmental conditions.

3.6. Counting Aquaculture Organisms

Accurate counting of organisms in aquaculture is vital for managing stock, monitoring health, and optimizing feeding. Traditionally, this task has been labor-intensive, invasive, and prone to inaccuracies, especially in high-density environments. Recent developments in AI, computer vision, and sensor technologies have made automated, accurate counting

feasible for a variety of aquaculture species, including fish, shrimp, and holothurians. Existing studies such as [6,60–66] have reported considerable success in counting aquaculture organisms. For example, ref. [6] introduces Shrimpseed_Net, a smartphone-based deep learning model for counting shrimp seeds, while ref. [60] proposes a density-estimation-based deep learning approach for shrimp larvae. The authors in [61] apply computer vision for behavioral study and fish counting in controlled environments, and ref. [62] uses an echosounder-based algorithm for estimating fish populations in farming nets. In [63], an improved YOLOv5 model for underwater fish counting is developed, and ref. [64] employs multi-scale context-enhanced CNNs for fish density estimation. Moreover, ref. [65] introduces an attention-based fry counting method for high-density cultures, and ref. [66] proposes a non-contact counting framework for Holothurian in situ aquaculture.

3.6.1. Shrimp Larvae and Seed Counting

Shrimp counting is a critical process in hatcheries and farms. The authors in [60] present ShrimpCountNet, a deep learning model using density estimation for automated counting of shrimp larvae, achieving an impressive accuracy of 98.72%. However, its accuracy diminishes with extremely dense populations, indicating the need for further optimization for larger samples. For counting shrimp seeds, ref. [6] introduces Shrimpseed_Net, a lightweight model optimized for smartphone deployment, with an accuracy of 95.53%. This model offers a practical, portable solution for aquaculture workers, though its performance may vary under extreme lighting and high-density conditions. Future work would therefore focus on enhancing accuracy for more challenging scenarios and adapting the model for additional species.

3.6.2. Fish Counting in Controlled and Natural Environments

Fish counting in controlled environments often requires identifying individual fish in crowded ponds, tanks, or nets. YOLOv5 is used for fish detection and counting combined with optical flow to analyze movement for stress detection in [61], achieving an F-measure of 81%. An introduction of a multi-scale context-enhanced CNN to estimate fish density by addressing occlusion and perspective distortions is made in [64]. This approach improves accuracy in crowded environments, with lower mean square and absolute errors compared to previous models, though its accuracy decreases with lower fish densities. Future directions include dataset expansion and semi-supervised labeling for improved low-density performance. A similar study by [65] targets counting young fish (fry) in high-density environments, using a super-resolution GAN density estimate attention network (SGDAN). This model achieved a 97.57% accuracy rate, outperforming existing methods like MCNN and CSRNet, though it is currently limited to still images rather than video streams.

Moreover, refs. [34,121] leverage deep learning to advance automated monitoring and estimation systems for marine ecology and fisheries management. In [34], YOLOv2 and a denoising auto-encoder were used to detect scallops in low-contrast underwater images. Similarly, in [121], autoencoders and GANs were combined to generate synthetic jellyfish images, which were then used to train an FCN for jellyfish swarm density estimation, achieving 83.8% accuracy. Despite their contributions, both models face limitations in adapting to diverse environmental conditions. Future directions focus on enhancing data diversity, expanding applications to other marine species, and integrating additional modalities for robust, scalable monitoring solutions.

3.6.3. Echosounder and Acoustic Counting Methods

Echosounder technology offers a non-intrusive way to estimate fish populations, especially in farming nets where visual counting is difficult. In [62], an acoustic signal processing approach is employed to estimate fish populations in nets with less than 10%

error. The system compensates for reflections from the net, but performance decreases in sparse populations, highlighting the need for enhanced signal processing techniques. Future work should focus on improving accuracy in low-density populations and expanding applications in diverse aquaculture setups.

3.6.4. Counting Holothurians (Sea Cucumbers)

Holothurian populations are increasingly managed using non-contact counting to minimize disturbance. A system utilizing YOLO-V3 and Faster R-CNN for detection, combined with tracking algorithms like SORT and IOU, is presented in [66], achieving robust counting even in turbid water. However, accuracy is affected by underwater visibility and occlusion. The researchers plan to expand the underwater dataset and test more advanced tracking algorithms to handle diverse environmental conditions.

3.6.5. Automated Scale Counting and Phenotypic Feature Detection

Counting lateral line scales is essential for breeding programs and species identification. In [63], the TRH-YOLOv5 model, which uses transformer mechanisms and a small-target detection module to improve precision in counting these scales, is introduced and achieves 98.8% precision. This method supports phenotypic analysis in sustainable fisheries, though underwater lighting and motion blur remain challenges. Future improvements will address these environmental factors and broaden phenotypic feature detection for more species.

3.7. Segmentation, Detection, and Classification of Aquaculture Species

The segmentation, detection, and classification of aquaculture species are critical tasks for effective aquaculture monitoring and biodiversity conservation. Advances in AI and computer vision have introduced robust solutions for these tasks, even in challenging underwater conditions. In this section, we discuss the recent research studies that address the complexity of recognizing aquaculture species and marine structures in a variety of environments.

3.7.1. Fish Species Classification

Identifying fish species is fundamental to ecological monitoring and fisheries management. Numerous works have been performed on fish species identification involving AIoT. In [122], the authors introduced an ANN-based model to classify nine fish species, achieving a perfect score of 100%. This study demonstrates the model's potential but remains limited by its focus on only nine species. An ensemble model (Ens_MobV3+NasNet) is proposed in [33] for species classification in aquaculture, achieving 98.6% accuracy. Despite the model's robustness, misclassifications occur with occluded or poorly oriented images. Similarly, ref. [123] developed WildFishNet, a neural network utilizing a fusion activation mechanism combining softmax and openmax functions, with a structure inspired by EfficientNetV2 to enhance feature extraction for fine-grained recognition. The model achieved an 86.3% accuracy in distinguishing known and unknown fish species. In [124], an unsupervised learning framework for underwater fish recognition is presented and evaluated on Fish4Knowledge and NOAA Fisheries datasets. Conversely, a modified U-Net CNN is proposed in [125] to classify herring, salmon, and bubbles in multi-frequency echograms, achieving high F1 scores (93.0% for herring, 87.3% for salmon, 86.5% for bubbles). However, the proposed method is limited in its ability to handle class imbalance and a small test set; thereby, it is proposed to expand annotated data and incorporate additional environmental factors for improved classification in future work. Moreover, ref. [126] introduces a compact CNN model with under 20,000 parameters for classifying six pelagic fish species in underwater images, achieving ~49% accuracy. Similarly, the authors in [127] utilize

a vision transformer (ViT) model for classifying estuarine fish species, achieving 99.04% accuracy (and 100% with augmentation) on a 12-species dataset, outperforming traditional models like VGG16 and ResNet50. Similar studies include [128,129], which develop a customized CNN based on AlexNet (termed Deep-ShripNet) and a deep learning model using stacked auto-encoders for feature extraction combined with logistic regression for classification (SAEs–LR) for distinguishing soft-shell (defective) shrimp from sound shrimp using image-based classification and evaluating shrimp freshness during cold storage, respectively. Moreover, in [10,14,130–132], the overarching aim is to develop advanced deep learning-based systems for automated classification in diverse domains, leveraging the strengths of convolutional neural networks (CNNs) and related architectures. These studies focus on specific applications such as pearl quality assessment [130], coral species classification [131], jellyfish monitoring [10], aquatic macroinvertebrate classification [132], and diatom identification for water quality assessment [14].

3.7.2. Underwater Species Detection in Complex Environments

Low-quality underwater images pose unique challenges in species detection. Though there have been numerous research efforts aimed at handling species detection in complex environments, real-time species detection remains a challenge. The study by [32] developed composited FishNet, a two-stage cascade R-CNN model for fish detection and classification in low-resolution, complex underwater environments. This model showed high robustness with an AP of 75.2% and AP50 of 92.8%, although challenges remain with small fish targets and occlusions. In [133], YOLOv5-Fish, an enhanced YOLOv5 model that incorporates advanced feature extraction layers, is proposed to improve detection in blurred, low-contrast scenes. Similarly, ref. [11] develops an improved faster R-CNN model for real-time jellyfish detection in marine environments, achieving over 93% mAP and enhanced training speed (1.85 bit/s to 7.35 bit/s). In autonomous underwater robotic applications, ref. [134] introduced YOLO8-FASG, a YOLOv8-based model enhanced for small fish detection. Moreover, the authors in [31] develop an enhanced YOLOv5-nano model (YOLOv5n-GAM-CoordConv) for real-time jellyfish detection in underwater images, achieving a high mAP@0.5 of 89.1%.

3.7.3. Segmentation in Underwater and SAR Images

Precise segmentation is essential in aquaculture monitoring and resource management by enabling accurate analysis of underwater and SAR images. Several research initiatives have focused on addressing the challenges associated with these tasks. Among these is [135], which used the STFF model, a self-supervised transformer model with feature fusion, to enhance semantic segmentation in SAR images. The model achieved superior accuracy and continuity in segmenting marine aquaculture zones but struggled with small targets and adverse sea conditions. Future directions will involve improving the detection of small targets and adapting the model for a wider range of marine environments. For segmenting aquaculture rafts, ref. [136] introduced MDOAU-Net, a lightweight U-Net model tailored for noisy SAR images. Similarly, the authors in [137] developed an optimized segmentation model for offshore farms using SAR images, achieving a FWIoU of 0.9876 with a fast inference time. This model's speed and accuracy make it suitable for large-scale applications, though sensitivity to SAR image noise is a limitation. Expanding the model to different aquaculture structures is a promising future direction. An introduction of the IDUDL model is completed in [138] for semantic segmentation of SAR images in marine aquaculture, and achieves high accuracy in OA, MIoU, and Kappa scores.

For underwater segmentation, ref. [139] utilized a combination of manual bounding boxes and automated mask generation for training Mask R-CNN models, incorporating

U-Net++ and DeepLabv3+ for mask creation. Finally, ref. [140] introduced U_EFF_NET, a U-Net-based model with EfficientNet-b0 and CBAM for segmenting offshore aquaculture farms in SAR images. The model achieved an FWIoU of 98.12% and demonstrated fast inference speeds, ranking highly in the 2021 Gaofen Challenge. Despite its impressive performance, it remains sensitive to extreme SAR image noise.

3.7.4. Detection and Classification of Aquaculture Structures

The detection of aquaculture structures, such as floating rafts, is crucial for environmental and resource management. Fan et al. [141] introduced a novel clustering algorithm, CMKFCM, for detecting aquaculture rafts in SAR images. The model integrates neurodynamic optimization with particle swarm optimization for enhanced clustering accuracy. Despite its robustness, detection performance is affected by sea surface roughness and noise. Future improvements will focus on adapting the model to varied marine environments. Similarly, an RSC-APMN model for SAR image segmentation in marine aquaculture is developed in [142], incorporating modules to handle fluctuating sea conditions.

3.7.5. Image Processing for Fish Quality Assessment

For fish quality and freshness assessment, ref. [143] developed an adaptive thresholding method to segment fish gills, achieving a high correlation with expert annotations. This method provides a reliable approach for real-time quality validation. However, careful handling is needed to avoid interference from blood spills. Future work will explore enhancing segmentation precision for broader applications in quality assessment. The authors in [144] focused on fish segmentation in retail environments, achieving an 88.69% segmentation accuracy with SegNet. This model is promising for automated seafood quality assessment but faces challenges with noisy backgrounds and species variability. Future directions include expanding the dataset to include more species and refining segmentation techniques for realistic retail settings.

3.8. Breeding and Growth Estimation

Breeding and growth estimation in aquaculture is essential for optimizing fish feeding, fish health evaluation, reproductive success, and environmental safety. Recent studies have focused on developing automated and accurate techniques to estimate growth parameters and monitor breeding maturity, utilizing advanced AI models, computer vision, and stereo vision technology.

3.8.1. Automated Breeding and Spawning Detection

Automating breeding and spawning detection in aquaculture can significantly improve reproductive success and breeding schedules. In this direction, ref. [145] introduced a YOLOR-based system for assessing cobia maturity, achieving an accuracy of 74.3% on test datasets. Although promising, the system's performance is limited by environmental factors such as water clarity. For oyster farming, ref. [146] developed a fault detection-based algorithm for automatic spawning detection using valve movement data, achieving high accuracy with no false alarms. However, parameter tuning by trial-and-error limits its adaptability.

3.8.2. Fish Population Estimation Using Echosounders and Digital Twins

Accurate estimation of fish populations is essential in determining feed quantities and stocking densities. Advances in technologies such as echosounders and digital twins (DTs) have opened new possibilities for monitoring and decision-making in aquaculture, though significant challenges remain in their development and deployment. Existing studies that have explored this area include [62], which employed echosounder technology to

estimate fish populations within farming nets, achieving an error margin of less than 10% in densely populated areas. Despite its success, the algorithm encounters challenges in sparse populations and with interference from net signals. Future work aims to enhance net signal removal techniques and explore advanced echosounders to further improve estimation accuracy. In parallel, ref. [147] reviewed the potential of DTs in aquaculture, emphasizing their promise for real-time monitoring and informed decision-making. DT applications in aquaculture are still in their early stages and face obstacles such as interoperability issues and data security concerns.

3.8.3. Growth Estimation

Accurately estimating fish growth parameters, including body size, weight, length, and growth trajectories, is crucial for optimizing feed management, health monitoring, and ensuring sustainable aquaculture practices. Several studies have explored innovative approaches for measuring fish growth metrics. For body size estimation, ref. [148] developed an underwater stereo vision system capable of measuring fish length and height, achieving a low error rate of 0.85% for length estimation. Similarly, ref. [149] introduced YOLO-FL, a YOLO-based model that integrates segmentation and key point detection to measure fish body length with an MAPE of 3.7%. A possible future research direction is to pilot the model under practical aquaculture settings and refine image processing techniques for broader applicability.

For weight prediction and growth trajectory estimation, ref. [150] compared empirical methods with LSTM-based models, identifying a combined weighted-sum approach that reduced errors by 61.3% compared to empirical models alone. Although effective, the model's generalizability across species and environments is limited, prompting future exploration of environmental data integration and testing in diverse conditions. Non-invasive techniques for fish length estimation reduce stress on fish and optimize labor in aquaculture. For example, ref. [151] presented a CNN-based system using stereo vision to estimate fish length, with relative errors of 3.15% for seabream and 7.4% for seabass. Environmental factors like fish movement and turbidity affect accuracy. Real-time fish size measurement optimizes feeding practices by allowing precise size tracking. In [152], the authors developed a stereo vision-based size measurement system, achieving an accuracy with an error margin of 4%. However, fish rotation and distance from the cameras can impact measurements.

3.8.4. Environmental Monitoring for Growth and Health

Environmental monitoring is essential for sustainable aquaculture practices, particularly in detecting and mitigating risks from natural phenomena. A related study in [153] addressed jellyfish bloom detection using sonar images enhanced with GAN-generated data, achieving improved classification accuracy and reduced false positives. The study by [12] leverages high-throughput imaging flow cytometry and a fine-tuned ResNetv2 CNN for automated phytoplankton species and life-cycle stage classification, achieving 97% overall accuracy.

3.9. Fish Tracking and Individuality

This is critical for monitoring fish behavior, health, feeding patterns, breeding, and population dynamics in both controlled and natural environments. Recent advancements in AIoT have enabled more accurate and scalable solutions for individual and group tracking and behavior analysis in complex aquatic environments.

3.9.1. Individual Fish Identification

Biometric approaches, such as iris recognition, have emerged as promising solutions for achieving reliable and non-invasive identification. These methods leverage unique physical traits, enabling accurate distinction between individuals without needing external tagging or invasive procedures. A study by [154] utilized iris patterns as biometric identifiers for Atlantic salmon, achieving over 95% accuracy in short-term identification. The approach combined convolutional neural networks (CNNs) with Log-Gabor filters to extract iris features. However, the reliability of this method decreases over the long term due to changes in iris patterns as the fish grow. Future research directions include exploring near-infrared imaging to improve robustness and adapting the system for underwater environments to enhance practicality.

3.9.2. Multi-Fish Tracking in Controlled and Unconstrained Environments

Various studies have explored innovative approaches to tackle challenges like high density, occlusions, and behavioral variability, highlighting the progress in multi-fish tracking technologies while addressing key limitations. A study by [155] developed a 3D video tracking system for monitoring fish behavior in controlled water tank environments, achieving over 95% precision. In unconstrained marine settings, ref. [156] introduced DFTNet, a tracking framework combining a Siamese network for appearance similarity with an attention-based LSTM for motion analysis. This approach significantly reduced ID switches by 60.9%, improving tracking accuracy. However, challenges persist in differentiating highly similar species and handling complex behaviors in crowded scenes. Moreover, ref. [157] applied a tracking-by-detection approach to monitoring Sillago sihama fish in aquaculture, using Gaussian mixture models (GMMs) to identify behavioral patterns.

3.9.3. Activity Segmentation and Tracking in Sonar and Echogram Data

Using sonar and echogram data to track fish activity is essential for behavior monitoring in turbid or low-visibility aquatic environments. A study by [158] developed a sonar-based tracking method incorporating Kalman filtering and Gaussian modeling, achieving improved multi-object tracking accuracy and reducing false detections. While effective, further research would integrate deep learning to enhance segmentation precision and adaptability. In echogram analysis, ref. [159] introduced U-MSAA-Net for identifying and segmenting finfish and krill, demonstrating superior accuracy despite challenges with noisy data. Similarly, ref. [160] addressed fish detection and tracking in fishways using YOLO-CTS and Deep-SORT, achieving high precision even in complex environments. However, the system struggles in high-density scenarios, prompting future efforts to integrate sonar data and refine tracking algorithms for greater scalability and accuracy.

3.9.4. Fish Group Activity and Behavior Recognition

The existing related studies emphasize the potential of advanced computational models for recognizing fish group activities while highlighting the need for improved efficiency and deeper integration with environmental data to enhance real-world applicability. The study by [161] utilized a graph convolution network (GCN) with feature calibration for group activity recognition, achieving an impressive accuracy of 93.33%. A similar study in [162], focused on tracking fish behavior to assess water quality, combining an Otsu adaptive segmentation algorithm with a Kalman filter to achieve over 98% detection accuracy across various water conditions.

3.9.5. Tracking Fish Around Marine Structures and Moving Cameras

This is critical for understanding interactions with man-made installations and improving environmental monitoring. These tasks present unique challenges due to turbulence, occlusion, and dynamic environments. To monitor fish and seabird behavior around tidal turbines, ref. [163] employed a modified nearest neighbor algorithm, effectively tracking in turbulent conditions. For tracking with moving cameras, ref. [164] introduced the deformable multiple kernel (DMK) tracking algorithm, achieving high accuracy under variable camera motions. While effective, the method faces challenges in tracking larger schools and maintaining performance over longer durations.

3.9.6. Individuality and Behavior Tracking for Aquaculture Monitoring

Understanding tracking individual fish and their behaviors is vital in optimizing feeding practices, monitoring health, and reducing stress. A study by [157] developed a system combining fish tracking with behavior clustering for *Sillago sihama* fish, enabling detailed behavior analysis to support aquaculture management. While effective, future research will enhance the robustness of this system to adapt to diverse aquaculture conditions and environments. Similarly, ref. [165] introduced an online survival prediction system for monitoring stress during waterless transport, achieving high accuracy in predicting survival rates.

3.10. Automation and Robotics in Aquaculture

These advancements are critical for addressing the challenges of sustainable fish farming, resource management, and environmental conservation. Below, contributions from notable studies are categorized under various thematic areas.

3.10.1. Remote Sensing and Monitoring Systems

Remote sensing and monitoring systems are essential for efficient aquaculture management. A smart aquaculture assistant system [166] integrated IoT and big data for real-time pond monitoring and decision-making, showing effective environmental analysis and expert advice capabilities. Similarly, a segmentation model [167] mapped cage and raft aquaculture (CRA) structures with high accuracy using Sentinel-2 imagery, but future research aims to expand datasets and validate with multi-source imagery. A low-cost conductivity meter [72] accurately measures water quality but will benefit from IoT integration for remote sensing and improved calibration for diverse environments. An SRUNet model is developed in [168] to monitor offshore raft aquaculture in coastal areas, achieving high accuracy in aquaculture area delineation using SAR and MSI satellite imagery. A video-based system for real-time monitoring of Arctic Char in indoor tanks is introduced in [169]. The system tracks swim trajectories as health indicators, but it faces challenges in water turbidity and multilayer tracking. Future improvements include integrating multi-camera setups and real-time machine learning capabilities. The authors in [170] focus on coastal aquaculture monitoring, aiming to accurately delineate aquaculture areas for environmental management using high-resolution GF-2 satellite images. The authors in [171] address offshore aquaculture resilience by developing an autonomous submersible fish cage system designed to descend during adverse weather and resurface in calm conditions, protecting fish stocks and infrastructure. Moreover, ref. [172] implemented an IoT-based smart aquarium system using decision tree regression to predict and regulate water conditions autonomously, achieving high-temperature prediction accuracy.

3.10.2. Robotic and Autonomous Systems for Underwater Monitoring

Robotics and autonomous systems have advanced underwater aquaculture operations. An ROV-based system [173] inspected fish nets using monocular odometry, with plans to incorporate SLAM systems for better robustness. A hybrid energy system [174] powered shrimp pond aeration using wind, solar, and electrolyzers, reducing CO₂ emissions but requiring strategies to lower initial investment costs. Additionally, a robotic crayfish monitoring system [175] automated feeding and water quality management but faces challenges with connectivity and scalability. For eel larvae tracking, a vision-based system [176] employed kernel density estimation but requires stable environmental conditions for improved accuracy.

3.10.3. UAV- and AUV-Based Aquaculture Inspections

UAVs and AUVs play a pivotal role in aquaculture inspections. A UAV-based system [177] assessed post-typhoon damage to oyster racks using edge detection but struggled with weather-related image quality issues, prompting research into UAV swarms for faster assessments. For underwater obstacle avoidance, an AUV system [178] utilized a custom CNN for transmission map estimation, demonstrating effective navigation but requiring real-time deployment and testing in varied underwater conditions. A trajectory tracking system [179] for UUV inspections achieved high precision but needs stability improvements under diverse environmental conditions. A motion planning framework for AUV navigation in aquaculture termed ResiVis is proposed in [180]. The proposed framework demonstrated robust navigation but faces limitations in highly dynamic settings, prompting future work on advanced object detection and state estimation modules for safe, autonomous underwater navigation.

3.10.4. Hybrid and Smart Monitoring Systems

Hybrid systems combine diverse technologies for aquaculture monitoring. An IoT-enabled robotic system to automate crayfish pond management is proposed in [175]. The HAUCS system in [181] achieved high accuracy in dissolved oxygen prediction and aims to enhance reliability for broader applications. A hybrid ultrasonic imaging system [182] for shrimp counting and positioning demonstrated accuracy but requires integration with underwater drones for expanded functionality. In aquaponics, a digital twin framework [183] enhanced real-time monitoring and factory management, though challenges in data integration and real-time interaction remain. Moreover, ref. [184] focuses on developing an automated system for identifying blood defects in cod fillets and enabling precise robotic processing in aquaculture. Using a multimodal RGB-D imaging approach, the study combines SVM for pixel-wise segmentation and CNN for defect detection, achieving 99% and 100% accuracy, respectively. Despite its high performance, challenges include spectral similarity between blood spots and normal tissue and environmental variations like lighting and texture. Moreover, ref. [185] focuses on marine aquaculture zone (MAZ) extraction for environmental management using dual-polarimetric Sentinel-1 SAR imagery. The study introduced MAZ-Net, a modified U-Net architecture enhanced with GLCM-based texture maps and hybrid-scale convolution blocks, achieving a high F1-score of 94.77%, outperforming other models in identifying aquaculture areas across varying tidal and structural conditions.

3.10.5. Advanced Imaging and Sensor Technologies

Advanced imaging and sensor technologies support precision aquaculture monitoring. BI²Net [186] achieved high accuracy in extracting aquaculture areas despite sediment challenges, with plans to expand the dataset. A rule-based method [187] identified oyster

aquaculture areas in turbid waters but requires refinement to address seasonal changes. A jellyfish monitoring system [10] using CNNs demonstrated high detection accuracy. Similarly, a fish catch forecasting system [188] achieved accurate predictions using hybrid models, with plans to integrate additional environmental features. A precision monitoring system [189] applied YOLO to multibeam echosounder images, aiming to improve object differentiation with 3D representations.

3.10.6. Digital Twin and Predictive Modeling

Digital twin frameworks and predictive modeling optimize aquaculture operations. A DT system [15] combined AIoT for feeding and environmental management but requires improvements in connectivity and energy availability. Federated learning [190] on an edge-cloud platform supported privacy-preserving data processing for prawn farming, though scalability challenges persist. A smart Biofloc system [191] achieved high mortality prediction accuracy, with future work focusing on expanding species support. Additionally, a dynamic mapping system [192] for inland aquaculture utilized U-Net and recursive feature elimination, achieving high accuracy but requiring better segmentation for complex regions.

3.10.7. Biologically Inspired Robotics

Biologically inspired designs bring innovation to aquaculture robotics. A biomimetic AUV [193] inspired by Atlantic Salmon demonstrated efficient propulsion but requires real-world testing. MARL-based robotic fish [35] enhanced stability and reduced oscillations but need calibration for dynamic environments. A VR-based robotic grasping system [194] achieved high success rates in simulated environments, with future work focusing on real-world adaptation. Additionally, a cost-effective tracking strategy [195] for robotic fish demonstrated accuracy in trials, with plans to improve adaptability using ultrasonic sensors.

3.10.8. Specialized Aquaculture Applications

Specialized applications expand the scope of robotics in aquaculture. A hybrid energy system [174] optimized shrimp pond aeration using renewable resources, while a robust submersible cage system [196] maintained integrity under extreme sea conditions. A numerical model [197] analyzed mooring failures in net cages, prompting plans for experimental validation. Additionally, a sonar-based tracking system [198] achieved high accuracy in underwater target recognition, with future work focusing on lightweight models for real-time application.

Table 1. Technical comparison of AIoT applications in aquaculture.

Application	Dataset	Technology	Study	Results	Limitations	Future Directions
Smart Feeding Systems	Fish activity data, water quality parameters, and environmental factors from various sources	IoT sensors, AI algorithms: CNN, ResNet, OSELM, SVM, RNN, Gradient Boosting, Naive Bayes	[8,23,25,53,56,57,67–71,184,199–201]	Improved feeding efficiency, reduced waste, enhanced fish growth rates	Specificity to controlled environments and limited species diversity	Integrating more species, real-time IoT-enabled feeding systems, edge computing
Water quality management	Water quality metrics (DO, pH, temperature, turbidity), historical data, environmental sensors, and WSNs collected across various aquaculture and reservoir environments	IoT sensors, AI algorithms: LSTM, ANN, SVM, CNN, LightGBM, PSO, Gradient Boosting, PCA-LSTM, SAE-LSTM,	[13,16,18,26–28,40,41,43,45–48,58,72–83,85–88,172,202–204]	High accuracy in water quality prediction, improved sustainability measures	Variability in generalizability across aquaculture environments	Real-time monitoring, scaling for larger environments, incorporating additional water quality factors
Disease detection, classification, and prevention	Fish images, histological images, water quality data, and environmental factors were collected across aquaculture sites.	IoT sensors, AI algorithms: CNN, ResNet, SVM, AlexNet, Random Forest, Transfer Learning, Decision Trees	[2,7,21,29,30,54,89,90,92–103,205]	High classification accuracy, effective early disease intervention	Limited disease types covered in studies and reliance on controlled images	Expanding datasets for varied diseases, development of mobile applications for real-time diagnosis
Fish Biomass Estimation	High-resolution images, stereo vision, sonar imaging, and underwater acoustic signals collected in various fish farming environments	IoT sensors, AI algorithms: YOLOv5, Mask R-CNN, DL-YOLO, 3D reconstruction, LAR, SfM	[59,104–113,206]	High biomass estimation accuracy, aiding in resource management and sustainable production	Susceptible to environmental variables (e.g., water clarity, lighting)	Real-time monitoring, broader species adaptability, integrating IoT for continuous tracking

Table 1. Cont.

Application	Dataset	Technology	Study	Results	Limitations	Future Directions
Fish Behavior Detection	Video data, echogram data, and telemetry data from controlled and natural aquaculture environments	IoT sensors, AI algorithms: ResNeXt3×1D, LeNet-5, EchoBERT, FR-CNN, deformable models, DQN, CNN, RNN	[50,51,114–120,207]	Effective identification of abnormal behaviors and collective behavior patterns	Dependent on environmental conditions like lighting and noise	Real-time monitoring, expanding behavior categories, edge computing deployment
Counting Aquaculture Organisms	Images, videos, and acoustics for various fish, shrimp larvae, fry, and holothurian populations collected across aquaculture sites	IoT sensors, AI algorithms: YOLOv2, v5, Faster R-CNN, Multi-Scale CNN, MCNN, SGDAN, ShrimpCountNet, GAN	[6,34,60–66,121]	High counting accuracy, fast execution time, practical for commercial applications	Limited accuracy in extremely high-density populations and dependence on specific environmental conditions	Optimizing for diverse aquaculture species, reducing hardware requirements for mobile deployment
Segmentation, detection and classification of aquaculture species	SAR images, echograms, underwater images and videos, from secondary sources like GaoFen-3, NOAA, and Fish4Knowledge, as well as primary datasets.	IoT sensors, AI algorithms: YOLOv5, ANN, Mask R-CNN, Cascade R-CNN, SegNet, SVM, EfficientNet, U-Net, CNN, Transformer-based models, SAEs–LR	[10,11,14,31–33,122–143,208,209]	High segmentation and classification accuracy, effective monitoring and species recognition	Limited generalization to broader species and varied underwater conditions	Expanding datasets and models for new species and environmental settings, optimizing models for mobile use
Breeding and Growth Estimation	Diverse datasets including cobia images, oyster valve activity, fish length and weight data, and simulated growth data	IoT sensors, AI algorithms: YOLOv8, OpenPose, FHRCNN, CNN, LSTM, stereo vision, ResNetv2	[12,32,33,62,125,133,135,138,143–153]	High accuracy in growth and breeding stage predictions, non-invasive measurement approaches	Limited adaptability to varying environmental conditions, accuracy affected by underwater factors	Expanding to broader species, integrating real-time sensors, and refining models for environmental robustness

Table 1. Cont.

Application	Dataset	Technology	Study	Results	Limitations	Future Directions
Fish Tracking and Individuality	Diverse datasets including Atlantic salmon irises, sonar recordings, Fish4Knowledge, and in situ videos from tidal and aquaculture environments	IoT sensors, AI algorithms: CNN, Kalman Filter, YOLO-CTS, Deep-SORT, DFTNet, GMM, GCVC, DMK, ARIMA	[154–165,210,211]	High tracking and identification accuracy, effective behavior analysis in complex environments	Limited long-term identification stability for iris-based systems, impacted by environmental noise	Enhancing biometric stability, integrating sensory inputs (e.g., sonar), refining detection for complex scenes
Automation and Robotics	Datasets from primary and secondary sources, including satellite images (Sentinel, GF-1, GF-2), underwater video, sensor data from aquaculture sites, simulation data for autonomous systems	IoT sensors, AI algorithms: YOLOv5, Mask R-CNN, LSTM, digital twins, RNN, CNN, Transformer-based models, multi-agent RL, image processing, federated learning, genetic optimization, 3DCNN	[10,15,35,72,166–183,185–198]	Improved monitoring, management, and operational efficiency in aquaculture through autonomous systems and robotic solutions	Limited robustness in complex or variable environmental conditions, reliance on robust connectivity and energy	Enhancing environmental adaptability, expanding capabilities to new species and settings, integrating multi-sourced data and IoT

4. Advantages of AIoT in Aquaculture

Compared to traditional approaches, AIoT brings about transformational advantages. Combining features that provide real-time data collection with intelligent analysis, AIoT can easily reduce the manual efforts of environmental monitoring, feeding, and disease detection. The traditional methods rely on a lot of manpower and periodic sampling. Moreover, these methods are inefficient and prone to errors. AIoT automatically performs these tasks with more accuracy, uniformity, and timeliness, enhancing the productivity and sustainability of responses.

Among the most important benefits of AIoT is the automatic and continuous monitoring of the environment. IoT sensors installed in aquaculture systems monitor critical parameters, thus allowing pro-active adjustment. This is especially critical in sensitive aquaculture environments, where minute changes can have huge implications on the health of organisms. Secondly, predictive analytics for effective resource management too stands out as one of the key benefits of AIoT in aquaculture. Advanced algorithms, such as LSTM networks, can predict oxygen depletion in advance and thus enable farmers to take precautionary measures of aeration or feeding. Thirdly, AIoT automates feeding and behavioral analysis. By applying AI algorithms on real-time video image analysis of fish behavior, the feeding schedules are corrected dynamically. This helps minimize feed waste and enables a healthier growth rate. Fourthly, AIoT systems create unparalleled conveniences for aquaculture operators to manage and monitor conditions from a distance. AI has also developed digital twin technologies, virtual representations of the aquaculture environment, where farmers can obtain a chance to observe, simulate, and operate parameters from afar. This would shut down labor demands, allowing farmers to operate several facilities with efficiency, improving the quality of decisions with quicker response times. Lastly, the ecosystem of AIoT gives way to sustainability and less environmental impact. Powering IoT sensors and devices with integrated renewable energy sources, solar or wind power, the system reduces greenhouse gas emissions due to the AIoT and cuts costs. In hybrid energy systems around shrimp ponds, aquaculture has been able to record a significant reduction in carbon footprint while maintaining optimal aeration, hence proving dual benefits toward environmental and economic sustainability.

5. Challenges and Limitations of AIoT in Aquaculture

While integration with AIoT is revolutionizing aquaculture, its continuous adoption and scalability are still plagued by many challenges and innate limitations, such as high cost and infrastructure requirements, data privacy concerns, environmental variability issues on the natural resources involved, and scaling.

5.1. High Initial Costs and Infrastructure Requirements

Implementing an AIoT system is costly. Sensor networks, data infrastructures, and computational resources for holistic integration of AIoT sometimes involve high upfront costs that may discourage investment by the smaller- and medium-scale aquaculture farms. For such large-scale operations, the cost issues that remain include sensor maintenance, updating software, and storing the data, adding to the complexity and requiring both capital investment and technical expertise.

5.2. Environmental Variability and Model Adaptability

Aquaculture operates in environments subject to considerable variability, such as changes in water quality, temperature, and salinity. This dynamic setting is a major effect culprit of an AI model that often underperforms in generalizing across aquatic

environments or even across species. This may involve frequent retraining and adaptations that are resource-intensive and time-consuming, particularly for smaller operations.

5.3. Data Privacy and Security Concerns

The interconnected nature of AIoT systems also exposes aquaculture operations to some level of risk regarding data privacy and security. There will be constant gathering of data through IoT devices on sensitive operational practices, fish health, and environmental conditions, creating a potential for hacking and unauthorized access. These are risks that call for stringent cybersecurity measures: encryption, secure network architecture, and access controls.

5.4. Scalability Challenges

AIoT scaling in such diversity may prove to be singularly problematic among aquaculture operators who have neither the infrastructure nor the resources to deploy devices by the thousands. Indeed, small-scale farms may find the attendant costs of such extensive networks of sensors and their attached data management systems prohibitively high and outside their investment budgets.

5.5. Complexity and Technical Expertise Requirements

The deployment and operation of the AIoT system is specialized, involving data science and machine learning skillsets besides taking up IoT devices. Most aquaculture operators, especially small- and medium-sized enterprises, may lack the technical expertise needed to effectively implement such technologies and sustain them.

5.6. Limitations in Model Generalization Across Species and Applications

Most AI models in aquaculture have been developed either for particular species or for particular environments, further limiting their general application to diverse aquaculture operations. For example, an AI system tuned for Atlantic salmon will most likely perform poorly if applied directly to shrimp or tilapia owing to differences in behavioral traits and/or environmental requirements. It lacks adaptability and requires frequent retraining or model customization for each species or condition; this decreases the wide applicability of an AIoT solution across a broader range of aquaculture premises.

5.7. Environmental and Ecological Impact

Energy-intensive data processing and monitoring equipment make AIoT systems, especially those employed for this purpose, contribute to environmental degradation that is contrary to the goals of aquaculture sustainability. The energy demand for large-scale deployment of AIoT devices and utilization of electronics within aquatic environments raises concerns over their sustainability and possible disturbance of the ecosystem.

6. Future Directions of AIoT in Aquaculture

From the state-of-the-art AIoT applications for smart feeding systems, water quality management, disease detection, fish behavior monitoring, biomass estimation, and automation, several areas of work are still pending. Future directions in AIoT for aquaculture relate to real-time adaptability, resilience to environmental factors, extendibility, and cost-effectiveness across diverse aquaculture environments.

6.1. Real-Time Adaptability and Decision-Making

An important direction for future studies is how AIoT could improve real-time adaptability in general for aquaculture; that is, enabling such facilities to respond immediately to dynamic environmental changes [23,59]. This would be able to allow systems operating

continuously, even in the most remote environments, to provide optimized parameters, such as feeding intensity and water quality, for fish health and environmental sustainability.

6.2. Species-Specific and Environmental Adaptability

It is an endless challenge to make the AIoT systems of aquaculture adaptable to a wide range of variability in species and environmental conditions. A good number of the models that perform well on a given condition would, perhaps, see a decrease in generalization due to variables such as lighting, water turbidity, or behavior when other species or environments are included. Future work needs to be guided toward adaptive algorithms and multimodal systems for the handling of variability in several species and ecological contexts [53,115]. It can be accomplished either by training the dataset on a wide variety of species and environments or by architecting transfer learning so that models generalize well across aquaculture sites.

6.3. Scalability and Cost-Effectiveness for Broader Adoption

Scalability remains a great concern for adopting AIoT, primarily among small aquaculture operators who may not have the resources to invest in high-end solutions. The potential for innovation and integration of sensors with mobile-compatible systems in a cost-effective way will provide ways for making AIoT solutions accessible to small- and medium-sized farms. Also, it suggests that cloud platforms with data processing will minimize hardware requirements for smart feeding and water quality management, for instance, in the studies reviewed.

6.4. Integrated Multimodal Systems for Comprehensive Monitoring

In future AIoT systems, a set of data sources should be integrated—visual, acoustic, and environmental—into a single monitoring platform that can enhance general fish welfare. The research works carried out on the estimation of fish biomass and behavior have shown clear evidence of a multimodal approach using both visible and acoustic data in capturing comprehensive fish health and population dynamics. With the development of integrated and multimodal systems, aquaculture operators are presented with a complete holistic view of conditions of their culture environments. A system such as this would foster resilience by not being dependent on any one data source that could be influenced by environmental noise or species-specific behaviors related to feeding, water quality, and welfare of fishes.

6.5. Enhanced Disease Detection and Prevention Through Real-Time Biosensing

AIoT systems are yet to become efficient in the early detection and prevention of disease outbreaks, which indeed is a big area for future development. Current disease detection approaches employ AI algorithms over IoT biosensors, monitoring health indicators; however, these approaches have some limitations about dataset constraints and the requirement for generalizability across species. Future research should be directed towards embedding real-time biosensors that can monitor the levels of the pathogen to allow operators to take early recognition and intervention against the emergence of the disease. In addition, through the creation of mobile and offline compatible solutions, AIoT-enabled detection of diseases can achieve even the most remote and resource-poor aquaculture facilities.

6.6. Advanced Automation and Robotics for Efficient Operations

Aquaculture robotics is a developing field, with recent research demonstrating systems capable of performing underwater tasks of increasing complexity related to the inspection of fish nets, structural monitoring, and counting of organisms. Future robotics development should therefore emphasize enhancing adaptability and efficiency for operating in varied

and demanding environments with reliability. Continuous real-time data collection and processing shall be facilitated through enhancement in sensor and algorithm robustness while enabling longer times for deployment by improved means of achieving longer battery life and energy efficiency. Multi-sensor fusion combined with AI could also result in much more autonomous, precision-based robotic systems capable of serving routine operations, saving labor, and improving operational efficiency.

6.7. Sustainable Energy Solutions for Remote Aquaculture

Having aquaculture farms in remote or offshore areas, the requirement for energy independence is, in fact, vital. The hybrid energy platforms on renewable solar and wind energy, together with AIoT-enabled energy optimization, can reduce dependence on conventional sources of power. Aquaculture-specific development of sustainable energy solutions can surely cut operational expenditure by a large extent while addressing the environmental concern of the aquaculture industry as a whole. Future research in this field should focus on bringing these together with traditional AIoT infrastructure that might provide a regular power supply to these systems for continuous monitoring and automated operations, particularly in offshore conditions.

6.8. Digital Twins and Predictive Analytics for Proactive Management

Digital twin technology involves the development of a virtual model of an operating aquaculture system. It has promising potential for real-time simulation and optimization of operations [15]. This will enable predictive analytics, enabling operators to model potentially occurring scenarios and allow them to take proactive steps to mitigate risks, optimize feeding, and boost overall system performance. Increased development of digital twins in aquaculture should enable data integration with higher levels of integration from IoT sensors, enhance real-time monitoring, and ensure predictive decision-making. In turn, future studies should be directed to the better handling of data and a higher level of interoperability in digital twin frameworks while developing flexible models that can simulate different aquaculture ecosystems.

7. Conclusions and Future Work

This review systematically explores and analyzes the extent to which AIoT technologies are advancing the aquaculture industry. Integrating AI and IoT has contributed to the advancement of aquaculture by effectively addressing critical challenges such as operational inefficiencies, environmental sustainability, disease management, and resource optimization. This study categorizes AIoT applications into ten core areas: smart feeding systems, water quality management, disease detection, fish biomass estimation, fish behavior detection, counting aquaculture organisms, species segmentation and classification, breeding and growth estimation, fish tracking and individuality, and automation and robotics. Each area highlights unique methodologies, key achievements, and potential for future advancements. Among these, smart feeding systems exemplify how AIoT optimizes feeding schedules, minimizes waste, and enhances feed efficiency, significantly improving growth rates. Future research in this area is expected to develop adaptive systems and leverage cloud-based monitoring to ensure scalability and robustness. Similarly, water quality management has progressed with real-time monitoring and predictive adjustments enabled by AIoT, helping to maintain optimal conditions for fish welfare. However, challenges such as scaling across diverse environments and incorporating edge computing solutions for real-time processing remain priorities for future development.

In disease detection and prevention, AI-driven biosensors and IoT tools enable early detection of health issues, reducing mortality rates and improving overall fish health.

Nonetheless, the lack of robust datasets and generalized models limits cross-species applicability, requiring further research. Fish biomass estimation, a critical component for yield forecasting, has been improved through computer vision and acoustic analysis techniques. Advancing this area will require refining multimodal systems for varied environments and enhancing real-time capabilities. AIoT also plays a vital role in fish behavior detection, where models analyze patterns indicative of stress, disease, or social dynamics. Despite notable progress, challenges such as environmental variability, noise interference, and species-specific behaviors necessitate the development of more adaptable and species-diverse models. Similarly, automated counting methods for aquaculture organisms streamline management but face issues such as occlusion and environmental variability. These methods need further refinement to ensure broad applicability and versatility. Species segmentation and classification showcase the potential of advanced AI techniques in distinguishing species under complex conditions. Yet, ensuring adaptability to diverse environments and integrating low-power, real-time deployment solutions remains a challenge. In the context of breeding and growth estimation, models assessing fish maturity and growth rates are advancing breeding efficiency. Expanding these models to accommodate various species and integrating continuous real-time data are critical steps for more robust monitoring systems. Fish tracking and individuality monitoring provide valuable insights into behavior and the effects of water quality, but challenges persist in high-density and diverse aquaculture environments. Integrating multiple data sources could improve comprehensiveness and precision. Finally, automation and robotics are revolutionizing labor-intensive tasks, especially in offshore or remote locations, by enabling real-time monitoring and execution. Future advancements should focus on multimodal sensors, enhanced connectivity, and efficient power management to improve resilience and operational efficiency.

While the potential of AIoT in aquaculture is transformative, several limitations remain. High initial investment costs, the complexity of data infrastructure, and the demand for technical expertise create barriers, particularly for smaller operators. Concerns about data privacy and cybersecurity in interconnected systems pose significant challenges. Many AI models trained for specific species or environments lack the flexibility for broader applications, underscoring the need for adaptive AI solutions. Observations from this review suggest that AIoT adoption thrives in environments that prioritize real-time monitoring, adaptive response mechanisms, and scalable infrastructure. Large-scale operations benefit from economies of scale, while smaller operators often face financial and technical hurdles. Bridging this gap will require cost-effective solutions, robust edge computing systems, and accessible training resources for personnel.

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