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Implementation of Artificial Intelligence in Aquaculture and Fisheries: Deep Learning, Machine Vision, Big Data, Internet of Things, Robots and Beyond

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Abstract: The aquaculture and fishery industry are multi-billion-dollar business across the globe, and the demand for aquatic species produce increases exponentially throughout these years. However, the depletion of aquaculture lands and aquatic pollution are some of the major worrying predicaments challenging the future of this industry. Sustainable growth strategies are the only way out, and they must come hand in hand with the implementation of artificial intelligence to achieve the desired outcome high throughput in short time periods. The intelligent fish farm and smart cage aquaculture management system are some of the fruits of this drive, and the system keeps improving to date. In this review, we provide recent updates over the past half-decade of artificial intelligence implementation in fishery and aquaculture in hope to provide highlights and future directions to push the industry to greater heights.

Keywords: artificial intelligence, aquaculture, machine vision, Internet of Things, big data

1. Introduction

The aquaculture and fishery industry are USD 281.5 billion global business, yielding 122.6 million tons of aquatic produce in 2020 alone (FAO, 2022). Asia remains as the largest aquaculture producer that accounts for almost 91.6% of the world's total (FAO, 2022). The world's aquatic animal production is expected to grow by another 14% by 2030 (FAO, 2022). This industry has great potential to feed the worlds' growing population, but the growth of this industry must be sustainable in the long run (Lau et al., 2021; Lau et al., 2021). Genetic research such as genetic engineering is one of the solutions to cater to this need (Lim, 2023) to make aquatic species grow faster but most research are time-consuming and might not come in time to solve this dire issue. Unfortunately, most of the industry players across the globe are facing these major predicaments, namely the massive reduction of viable aquaculture zones, good varieties scarcity, manual labor shortages, aquatic pollution, germplasm degradation, drug residues in aquatic animals (due to antibiotics, hormones, and chemical drugs usage) as well as technological insufficiency (Wang et al., 2021).

There are several intelligent fish farms established to date that applies artificial intelligence, edge computing, 5G, big data, Internet of Things (IoT), cloud computing, machine vision, deep learning, robots, and more to facilitate the maintenance of an ideal totally unmanned fish farm. This green data-driven efficient technological solution to fish farm will not only solve most of the aforementioned predicaments above but also drive the productivity and harvest volume to soar to greater heights (Rawat, 2022). There are typically four major smart fish culture environments adapted by aquaculture and fishery players globally: cage-type intelligent fish farm, intelligent marine ranch, land-based factory-type intelligent fish farm as well as pond-type intelligent fish farm (Wang et al., 2021). In this review, we highlighted recently emerged intelligent fish farm technologies over the past half-decade period, namely environmental conditions surveillance, smart feeding, smart fish seed screening, harvesting and processing, AI and blockchain technology in shrimp farming, stocks check-up, and shrimp supply chain, as well as aquatic species behavior and disease analysis. We further highlighted some latest examples for intelligent fish farm and cage culture system from the industry as well as one interesting deep learning framework comparison work for precision fish farming. Not to forget that we have included the implementation of artificial intelligence in one of the recently emerged aquaculture subdivisions: cultured meats. Moreover, we have also provided

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some future directions to advance the intelligent fish farm technologies further.

2. Environmental Conditions Monitoring

Unmanned aerial vehicle (UAV) system is one of the most frequently used AI drones in aquaculture to monitor the water quality of fish farm. Koparan et al. (2018) developed an UAV system that works with satellite remote sensing and is capable of gathering georeferenced electrical conductivity, water depth, turbidity, pH, sensor depth, temperature, nitrates, chlorophyll a level as well as dissolved oxygen from a 1.1 ha agricultural pond. One of the major limitations to this system is the flight duration, which can be easily solved with the advancing battery capacity technology (Koparan et al., 2018). Ubina et al. (2021) proposed a cloud-based autonomous drone system incorporated with a myriad of deep learning recognition models and computer vision that is low cost and scalable for aquaculture all-rounder applications. Interestingly, their visual surveillance system can perform detection of suspicious objects like ships and humans employing the captured red, green, and blue (RGB) image (Ubina et al., 2021). They plan to further improve their system to include multiple surveillances at the same time, fish behavior monitoring, ship plate-number detection, as well as big data analytics for more efficient data processing (Ubina et al., 2021).

3. Smart Feeding

The feed covers around 60% of the sum of investment costs in aquaculture (Chrispin et al., 2020). Overfeeding can cause water quality depletion as well as feed wastage, whereas underfeeding can cause diminishing muscle conversion, and in shrimp particularly, mutual attack and cannibalism (Chrispin et al., 2020). The acoustic signals and vibration-based sensor are capable of distinguishing hungry fish from well-fed ones. Umitron cell is one of the smart feeding systems that utilizes IoT, machine learning, and satellite remote sensing first installed in Ainan City, Ehime, Japan. Interestingly, Umitron cell can be accessed remotely via cloud computing and mobile smartphone devices (Umitron, 2023). An Indonesian-based start-up eFishery has developed similar technology that are capable of monitoring the hunger levels of fishes in captivity via their vibrations (Huzaifah, 2023). The elevation in harvest has leaped by at least 35% and has doubled net profit significantly (Huzaifah, 2023). Currently, this system has been widely used across the globe, especially in China, Egypt, Indonesia, and United Arab Emirates (Huzaifah, 2023).

4. AI and Blockchain Technology in Shrimp Farming, Stocks Check-up, and Shrimp Supply Chain

Some of the most popular AI implementation in shrimp farming are appetite-based smart feeder, swimming pattern monitoring, real-time water quality surveillance, autonomous aerator system, voice call alert as well as injury and size monitoring using machine learning and camera (Chrispin et al., 2020). One of the most prominent technologies is that from XpertSea in which one of their products XperCount is capable of the aforementioned functions that works based on machine learning, computer vision, and other AI technology (Xpertsea, 2023). ShrimpChain has emerged recently to improve the export feasibility of Bangladeshi shrimps via a blockchain-based traceable and transparent framework (Khan et al., 2022). This system is deemed effective in improving engagement of shrimp farmers in the aspects of certification, quality assurance, and safety of shrimp produce and further expose them to enhanced control over incentive and high-value markets (Khan et al., 2022).

5. Smart fish Seed Screening, Harvesting, and Fish Processing

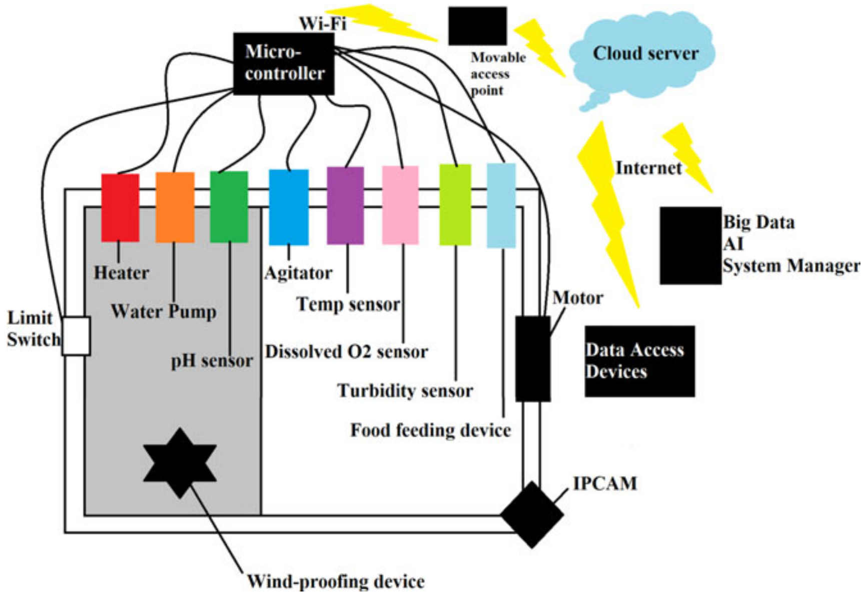
Fish seed screening is essential to ensure the feasibility of fish to grow healthily in their adult stage or during harvest stage. However, the traditional fish seed screening is both laborious and costly. In 2019, Kindai University came out with the smart application of Microsoft Azure Machine Learning Studio in tandem with IoT and other AI technologies to sort fingerlings effectively (Microsoft Asia News Center, 2019). A modular harvesting system introduced by the New Zealand's government allows small and unwanted fish to exit safely from the captive system. Radmantis's equipment from the U.S. can direct sick fish to another holding facility to avoid the spread of infection at early stages (Kidangoor, 2022). Brim had recently introduced an improved salmon deheader equipped with vision technology to achieve automated deheading and fileting with on-screen support (Marel, 2023). The processing speed can reach up to 25 fish per minute (Marel, 2023).

6. Aquatic Species Behavior Analysis and Disease Diagnosis

The aquatic species behavior analysis can be done using support vector machine (SVM) and deep convolutional neural networks (DCNNs) to classify fishes' sexes based on caudal fin color and appearance texture of the fish (Hosseini et al., 2019). On another approach, Xia et al. (2018) used computer vision and deep learning to conduct aquatic toxic analysis by monitoring fish behavior. Their model had successfully gathered sufficient detailed behavioral data for toxicity prediction of the fish-enclosed system (Xia et al., 2018). O'Donncha et al. (2021) developed a novel analysis of hydroacoustic datasets employing automated machine learning tools. One major advantage of this approach is that it allows high-quality models that are specific to the data at hand to be trained even in the absence of data science expertise. High-density measurements of fish behavior such as lice count, gill status, and mortalities were enabled via this approach (O'Donncha et al., 2021). They plan to further improve the accuracy of their measurements via the detection of group vertical movement patterns, fish tags to conduct individual fish surveillance, as well as to capture individual fish movement in three dimensions (O'Donncha et al., 2021).

For the detection of fish disease and diagnosis using artificial intelligence, Ahmed et al. (2022) used image-based machine learning approach namely SVM with kernel function on salmon fishes. Their model has achieved 91.42% (with augmentation) and 94.12% (without augmentation) accuracy, respectively. They plan to further improve the accuracy of the system with the coupling of real-life IoT device in the future (Ahmed et al., 2022). Darapaneni et al. (2022) have also developed an AI-based disease detection system that are capable of optical surveillance of the farmed fishes, detection of disease onset, as well as instant alert to stakeholders with minimum time lag. This system allows for all the stakeholders to react immediately to initiate remedial actions to curb the disease spread real time (Darapaneni et al., 2022).

Figure 1
The intelligent fish farm system proposed by Chiu et al. (2022) in Taiwan. The proposed intelligent fish pond encompasses several sensors such as dissolved oxygen sensor, pH sensor, turbidity sensor, and temperature sensor. The heater, water pump, and pH sensor are under the protection of the wind-proofing device throughout the fish pond operation. Other devices that interact directly with the find pond without the protection of wind-proofing device are food-feeding device, turbidity sensor, dissolved oxygen sensor, temperature sensor, and agitator. The heater, water pump, limit switch, all sensors, food-feeding device, IPCAM, motor, and agitator are orchestrated by a micro-controller, namely Arduino Mega2560 with integrated Wi-Fi module for real-time surveillance



7. Latest Example of Intelligent Fish Farm

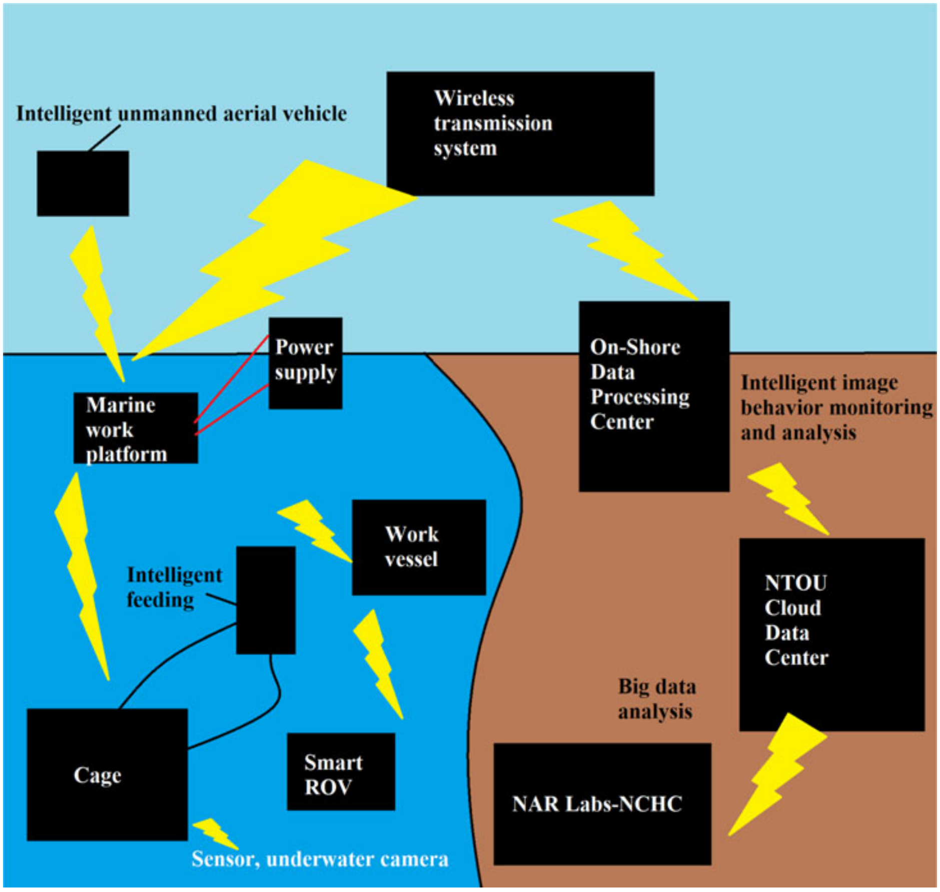
The latest example of intelligent fish farm is the one designed by Chiu et al. (2022) to cater the needs of California Bass fish pond in Taiwan (Figure 1). Their major goal is to condense the manpower for the maintenance of the fish pond with the aid of automated devices and artificial Intelligence of Things (AIoT). The proposed intelligent fish pond encompasses several sensors such as dissolved oxygen sensor, pH sensor, turbidity sensor, and temperature sensor. The heater, water pump, and pH sensor are under the protection of the wind-proofing device throughout the fish pond operation. Other devices that interact directly with the find pond without the protection of wind-proofing device are food-feeding device, turbidity sensor, dissolved oxygen sensor, temperature sensor, and agitator. The heater, water pump, limit switch, all sensors, food-feeding device, IPCAM, motor, and agitator are orchestrated by a micro-controller, namely Arduino Mega2560 with integrated Wi-Fi module for real-time surveillance (Chiu et al., 2022). All data are stored in the cloud server, and they are collected and analyzed at the server system using big data and AI techniques. From there, important and relevant features are employed to generate deductions on the system's productivity via machine learning such as deep learning. Mobile applications are also available for remote surveillance and control (Chiu et al., 2022).

The California Bass fish pond system data were collected over the course of fifty-two weeks. Subsequent to statistical verification and analysis, the optimized prototype was able to yield a high R^2 value of 0.94. The average square value was determined at 0.0015 (Chiu et al., 2022). These values have proven the feasibility of the proposed model to produce the targeted output. They believed that this intelligent fish pond model can be of great value to fish farmers across the globe with the benefits of food residue reduction, fish growth elevation, fish mortality minimization as well as higher feed conversion ratio (Chiu et al., 2022). On the side note, we would like to suggest that this intelligent fish farm to include fish seed screening at early stages as well as fish behavior and disease diagnosis system from seeding stage to harvest stage, in order to significantly reduce fish disease and mortality rate further in the future.

8. Latest Example of Intelligent Cage Aquaculture

The latest example of intelligent cage aquaculture was designed by Chang et al. (2021) based in Taiwan (Figure 2). The ocean fish were cultivated inside an AIoT smart cage immersed under the sea, equipped with underwater camera, integrated sensors as well as a communication system. All data were collected via a remotely operated vehicle (ROV), intelligent UAV, and autogiro integrated into an Omni IoT system (Chang et al., 2021). This system is capable of orchestrating the food delivery intelligent algorithm automatedly. All data were stored inside a cloud system interconnected to the onshore data processing center. The cloud data center utilized belonged to that of National Taiwan Ocean University (NTOU). To detect fish body, deep learning models used in this system are You Only Look Once version 3 (YOLOv3) and Faster Region-based Convolutional Neural Networks (Faster-RCNN). A sum of 2986 augmented and 1204 labeled images were inputted for the training via both the aforementioned machine learning models. Linear regression and ordinary matching algorithm were used to calculate the weight and length of the fish subsequent to machine training. The AI feeding time was determined via the

Figure 2
The intelligent cage aquaculture system proposed by Chang et al. (2021) in Taiwan. The ocean fish were cultivated inside an AIoT smart cage immersed under the sea, equipped with underwater camera, integrated sensors, and a communication system. All data were collected via a remotely operated vehicle (ROV), intelligent unmanned aerial vehicle, and autogiro integrated into an Omni IoT system. This system is capable of orchestrating the food delivery intelligent algorithm automatedly. All data were stored inside a cloud system interconnected to the onshore data processing center. The cloud data center utilized belonged to that of National Taiwan Ocean University



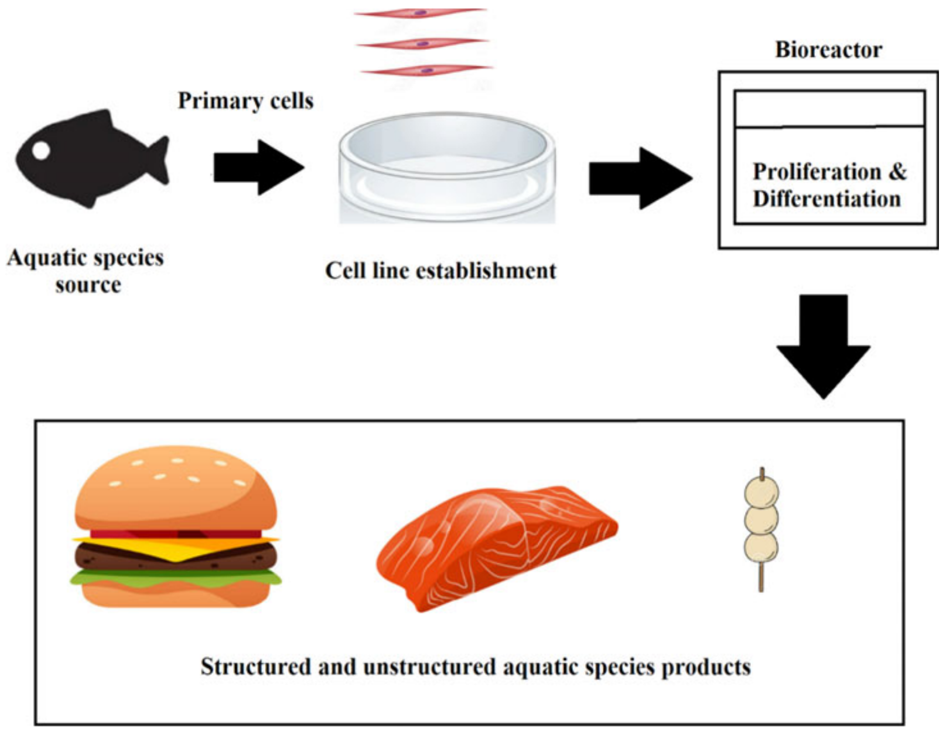
splash intensity produced by fishes competing for feed (Chang et al., 2021).

Chang et al. (2021) suggested that their proposed model for intelligent cage aquaculture system is feasible for aquatic species such as tilapia and all other fishes, cuttlefish, crabs, and shrimps. Interestingly, the fish body weight and length prediction has achieved a high accuracy rate of 90% for tilapia fishes. For cobia fishes, 16 cages with 16 m diameter × 8 m depth were utilized for the offshore cage culture. As a result, the fish survival rate recorded was 55%, which is 5% more than the conservative survival rate estimated for conventional aquaculture (50%). There was a 8.93% improvement in the internal rate of return from 6.47% to 15.4% (without and with the system respectively). On the other hand, for another cage system (16 cages) with dimension 30 m diameter × 15 m depth, the internal rate of return had elevated by 12.06%, from 29.86% to 41.92% after the introduction of this system (Chang et al., 2021). Chang et al. (2021) believed that this system can reduce the barrier to entry into the aquaculture industry as compared to conventional aquaculture system. On the side note, similarly, we propose that this cage culture system can be further improved in terms of initial stage feed seed screening as well as fish disease and behavior diagnosis system to further reduce the mortality, disease rate, behavioral anomalies, and harvest loss rate significantly.

9. AI in a Recently Emerged Aquaculture Field: Cultured Meats

Aquaculture covers a broad range of cultivation involving both marine and freshwater aquatic species in aquaculture lands or in river or ocean. Recently, the aquaculture industry has encompassed a novel way to cultivate aquatic meats and alternative proteins termed the clean meat, lab-grown meat, cultivated meat, or cultured meat (Mateti et al., 2022). Cultured meats do not involve the killing of animals to obtain protein; instead, they can be grown from explants such as skin and muscle from an aquatic species and propagate into clusters of cells and eventually differentiated into muscle tissues and products (Mateti et al., 2022) The overall cultured meat production processes. First, the aquatic species of high-quality, disease-free, injury-free, and good breed stock was chosen. Primary cells or muscle progenitor satellite cells were extracted from the explants of the aquatic species and subsequently cultured inside a culture flask or vessel under strict aseptic conditions with periodic surveillance on parameters such

Figure 3
The overall cultured meat production processes. First, the aquatic species of high-quality, disease-free, injury-free, and good breed stock was chosen. Primary cells or muscle progenitor satellite cells were extracted from the explants of the aquatic species and subsequently cultured inside a culture flask or vessel under strict aseptic conditions with periodic surveillance on parameters such as temperature, pH, and culture media waste and nutrient contents from time to time. When there are enough cell line cells established or the cell line established is deemed stable genetically after several passages, they were then transferred to scaled-up bioreactor for suspension culture, which allow them to proliferate and differentiate in larger volume of culture media. The harvested muscle cells and tissues were then packaged into unstructured product like burger patty. Besides, structured products such as steak, nugget, and meat ball can be manufactured via bioprinting or edible scaffolding



as temperature, pH as well as culture media waste and nutrient contents from time to time. When there are enough cell line cells established or the cell line established is deemed stable genetically after several passages, they were then transferred to scaled-up bioreactor for suspension culture, which allow them to proliferate and differentiate in larger volume of culture media. The harvested muscle cells and tissues were then packaged into unstructured product like burger patty. Besides, structured products like steak, nugget, and meat ball can be manufactured via bioprinting or edible scaffolding (Figure 3).

This is one green alternative protein production plan that solves all global impacts and concerns posed by traditional aquaculture such as seasonality, natural calamities, depletion of feasible aquaculture lands, habitat pollution, overfishing, species extinction as well as incapability of some species for artificial fertilization (Mateti et al., 2022). Cultured meats are believed to have the capacity to produce a million kilograms of meat per annum at the price of traditional aquaculture in a 2000-liter bioreactor, at only 5% expenditure of the emissions release, land use, and water use (Coldewey, 2021). The only downside of the industry to date is the high production costs which leads to highly priced cultured meat products. Majority of the expenditure comes from the animal-based supplements such as the fetal bovine serum included in the culture media. Interestingly, researchers have found some other alternatives to these animal-based supplements, namely plant-based and serum-free products, which could drive the production costs low. To date, these alternatives might not be able to achieve the high growth rate of muscle cells as seen in animal-based supplemented cultures, but there are many new and novel formulations being developed from time to time with hope to achieve better growth rates as compared to animal-based supplemented cultures in the near future. When the production costs can be successfully brought down, the selling price of cultured meat products can be as competitive as conventional meat products. Even better, the cultured meat products might contain more proteins and nutrients as compared to conventional meat products.

Artificial intelligence in the cultured meats industry is gaining its importance as the process involves a lot of monitoring and maintenance of a specific condition in order to produce the desired products to meet the safety food standards (Mateti et al., 2022). Parameters such as temperature, pH, serum replacement, nutraceutical addition, sterility, carbon dioxide supply, bioreactor maintenance, confluency, seeding density, culture media formulation, microfluidics, and bioelectronic surveillance are deemed very laborious and technical consuming (Mateti et al., 2022). In these aspects, AI-driven software, models, and frameworks can play their parts in automation of most of the production and surveillance processes in real time, especially when scaling up to commercial scale. This innovation is postulated to significantly improve the efficiency as well as diminish the costs and energy of production by over 92% (Coldewey, 2021).

10. Future Directions

The ideal intelligent fish farm and fishery facility should contain most, if not all, of the abovementioned properties to achieve an all-rounder, fully unmanned, all-weather, full-process, and full-space automated facility. One most important yet vastly neglected feature is the equipment faulty diagnosis as this acts as the heart of all systems mentioned above. One example is the system developed by Liu et al. (2020) to detect anomalies in aerators automatedly using Kanade-Lucas-Tomasi (RF-KLT) algorithm. With that in mind, other challenges such as service life of equipment, equipment and maintenance costs, as well as battery life can be easily solved with the unprecedented exponential advancement of technology in this era. On the side note, the introduction of another alternative protein source such as cultured meat in the recent aquaculture industry will not only help significantly in promoting green protein sources for the earth but also present consumers with more choices to create a healthy competition in the food manufacturing industry of aquaculture. The implementation of artificial intelligence in the cultured meat aquaculture industry will drive the production costs down and elevate the production speed further in the future with the reduction in reliance on manual labor force and animal-based supplements.

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

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