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Artificial Intelligence in Fisheries and Aquaculture: Enhancing Sustainability and Productivity

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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Review Article

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ABSTRACT

According to its definition, artificial intelligence (AI) is "the future built from fragments of the past." These are applications that acquire novel solutions with practice. Artificial intelligence has been used in various disciplines, from agriculture to full industry automation. Thanks to AI, aquaculture has become a less labor-intensive industry, enabling the fisheries sector to grow quickly and triple production quickly. It can appear as any laborer at work, such as feeders, water quality monitors,

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harvesters, processors, etc. AI can even be employed to protect aquatic life types from extinction. AI monitors fishing activity worldwide and promotes open sea fisheries' sustainability. AI plays a significant role in combating IUU fishing. Artificial intelligence (AI) can be used in aquaculture to limit input waste and cut costs by up to 30%. As a result, AI offers total control over fish production systems at a lower maintenance and input cost. AI's integration into aquaculture has transformed the industry, enabled sustainable growth, increased productivity and cost savings while minimizing environmental impact and labor requirements. Through the application of AI technologies, aquaculture can meet the growing demand for seafood while addressing challenges such as overfishing, environmental degradation, and resource scarcity.

Keywords: Artificial intelligence; application; fisheries; aquaculture.

1. INTRODUCTION

In the modern era, the world grapples with numerous intricate issues, such as hunger, malnutrition, and diseases stemming from dietary deficiencies, all exacerbated by a continually expanding global population in need of ample and nutritious sustenance. In the twenty-first century, aquaculture must be fully acknowledged for its pivotal role in combating poverty, hunger, and malnutrition on a global scale [1]. Nearly 20% of the animal protein consumed by more than three billion people comes from fish and shellfish, which are crucial for food security. Simultaneously, the extensive exploitation has resulted in widespread overfishing, with 90% of fish stocks currently exploited at or near their maximum sustainable levels [2]. Aquaculture water quality deteriorates due to factors such as overfishing, outdated aquaculture practices, human activities, industrial pollution, and other causes. Consequently, aquatic ecosystems suffer damage, leading to a rise in occurrences of diseases among aquatic products [3,4]. Widespread habitat damage and ecological deterioration are results of aquaculture, particularly the production of prawns and salmon. Finding a balance between food production, economic growth, and the proven challenging [5]. The European Union's enduring plan for fostering sustainable growth within the marine and maritime sectors is encapsulated in the concept of "Blue Growth." Presently, these industries sustain more than 5 million jobs and generate a gross added value surpassing 500 billion euros annually, as reported by the EU Commission, underscoring their indispensable role in the economic fabric of each nation [6]. Information extraction from Big Data is crucial to avoid serious effects on sea resource alteration due to overfishing, climate change, invasive species, and other disasters [7]. To ensure long-term sustainability in fisheries and aquaculture and mitigate the effects of prior exploitation of marine and coastal ecosystems, on the other hand, there have been many encouraging examples. Here, we've gathered several heartening examples of best practices, or "blue solutions," that have improved ecosystems, fish populations, and the livelihoods of fishermen and fishing communities. We think that these examples can be applied to other situations and contribute to the long-term sustainability of fisheries and aquaculture. Imagine a world where robots could freely reason and perform tasks based on our needs [8].

Artificial intelligence (AI) and the Internet of Things (IoT) make this possible. Almost 50 billion electronic devices operate today via IOT, with many of them being AI devices [9]. Artificial intelligence is currently being deployed in both the agriculture and fishing sectors. Every aspect of the animal enclosure can be observed, and any necessary actions will be taken without the need for human supervision. The ability of AI to learn from experience is a significant benefit [10]. As the circumstances of the cultural system often vary according to the surroundings, this will aid in the amazing growth of the fishing sector. AI in fisheries assists in open sea fishing as well as farm management by monitoring worldwide fishing activities using a mix of satellite data. Over the past ten years, fish consumption has multiplied four-fold throughout the world. Aquaculture is now a sector with rising demand and declining output. A key to achieving greater productivity with less labour is AI-based technology [11]. The aim of sustainable aquaculture practices is to diminish environmental impacts while concurrently boosting productivity and profitability [12]. Within this framework, the incorporation of artificial intelligence (AI) has demonstrated significant potential in transforming fish growth optimization and health monitoring, thus playing a pivotal role in enhancing the sustainability of aquaculture practices [13]. AI involves the development and deployment of computer systems equipped with the capability to perform tasks traditionally linked with human intelligence, such as learning, problem-solving, and decision-making [14]. Coupled with high-performance computing, machine learning technology has the ability to uncover complex features and delve into detailed information within datasets, offering a route towards intelligent aquaculture and propelling the fisheries industry into a new era, as illustrated in Fig. 1 [15,16].

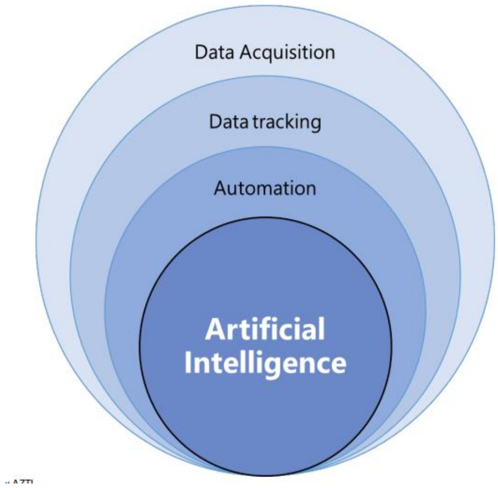

Fig. 1. Illustration depicting the integration of AI within various digitalization endeavors [22]

A nascent scientific discipline, "smart fish farming," strives to optimize resource efficiency and propel sustainable aquaculture progress by closely integrating the Internet of Things (IoT), big data, cloud computing, artificial intelligence, and other modern information technologies. The interconnection and functionality of emerging digital technologies are intertwined, forming a digital virtual network depicted in Fig. 2. [17]. Furthermore, a novel fishery production approach has emerged, facilitated by real-time data collection, quantitative decision-making, intelligent control, precise investment, and personalized service, all made achievable through modern technological advancements [18]. Recent technological advancements have enhanced the spatial and temporal resolution of measurements conducted during traditional scientific surveys, enabling a deeper comprehension of the dynamics and organization of fish populations and their associated habitat in a swiftly evolving environment [19]. Through the utilization of satellite remote sensing technology (SRS), marine ranches can assess the variability of fish stocks across various spatial and temporal scales [20]. Partnerships between governmental organisations, academic institutions, and the commercial sector have enabled the effective deployment of more dependable and affordable sensors, platforms, and processing technologies. In order to advance future technologies and deployment strategies in a cost-effective manner, it is essential to examine emerging sensing technologies for several critical ecological and biological parameters that hold significance in fisheries science [21].

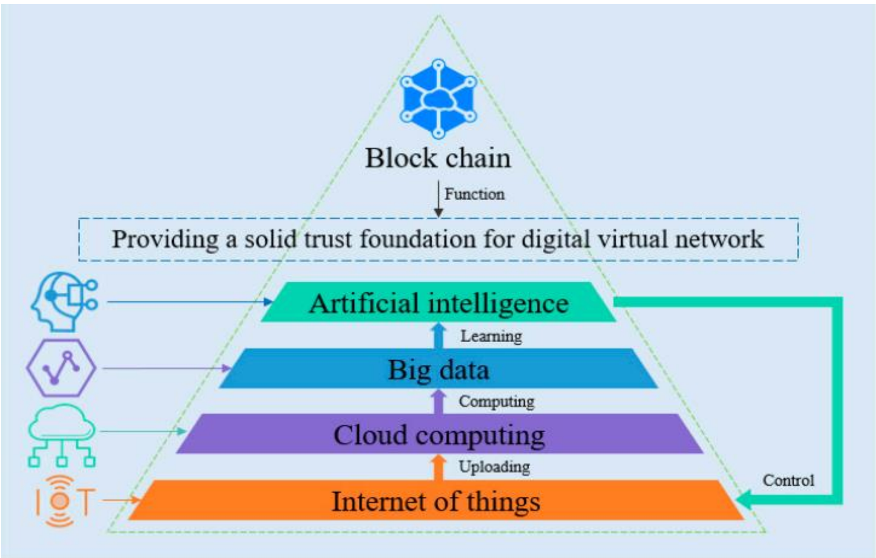

Fig. 2. Diagram of a digital virtual network [17]

2. THE AI REVOLUTION

In the 1940s, the initial strides towards artificial intelligence began. Now, owing to six converging factors, AI has become an integral part of our daily lives, marking a pivotal moment in history: the era of 'Big Data.' Today, computers grant us access to vast quantities of both structured (stored in databases and spreadsheets) and unstructured (such as text, audio, video, and images) data. This wealth of information documents our experiences and deepens our understanding of the world. As trillions of sensors are embedded in everyday items like furniture, packages, clothing, and autonomous vehicles, the volume of "big data" continues to surge. With AI-powered data processing, we can enhance our ability to forecast future trends, discern historical patterns, offer recommendations, and more effectively leverage this wealth of information. Thanks to advancing technologies such as cloud computing and graphics processing units, complex AI systems can now efficiently and affordably handle massive data volumes through parallel processing. Upcoming "deep learning" chips, currently a significant focus of research, will propel parallel computation to new heights. A global network: The way people communicate has fundamentally changed as a result of social media platforms. A "collective intelligence" has emerged as a result of the enhanced connection that has sped up information dissemination and fostered knowledge sharing, including open-source groups creating AI tools and sharing applications. The surge in open-source machine learning standards and platforms like TensorFlow, Caffe2, PyTorch, and Parl.ai underscores the pivotal role of open-source software and data in expediting the democratization and widespread adoption of AI. Less time spent on ordinary coding, industry standardisation, and expanded use of new AI technologies are all possible benefits of an open-source strategy. Algorithm improvements: Researchers have made progress in several AI-related areas, including "deep learning", which uses layers of neural networks that are modeled after how the human brain processes information. "Deep reinforcement" is a new field of study in which an AI agent learns by trial and error that is optimised by a reward function, with little to no initial input data [23].

3. AI FOR BIODIVERSITY

Efforts to combat biodiversity loss encompass various approaches: biodiversity research to establish a foundation for action, direct management of ecosystems and resources by citizens and local communities, formulation of biodiversity protection policies by national and local governments, and the development of biodiversity-aligned market frameworks by businesses and finance institutions [24]. Despite ongoing endeavors in these areas, biodiversity has markedly declined in recent decades, largely due to the historical precedence of natural resource exploitation over sustainable development models focused on long-term benefits [25]. Considering the potential role of AI in biodiversity conservation, it's crucial to recognize that current methods have fallen short and simply integrating AI into conventional conservation practices may not yield significant improvements. Presently, AI applications in biodiversity conservation primarily aim to enhance existing strategies but on a larger scale. Common applications involve AI-driven biodiversity monitoring through the classification of species and landscapes captured by camera traps and satellite imagery. Additionally, AI is utilized to monitor factors driving biodiversity loss, such as tracking fishing trawlers or detecting illegal timber logging activities [26].

4. THE AI OPPORTUNITY FOR OUR ENVIRONMENT

The goal of developing AI that is "human-friendly" and "earth-friendly" is likely the most crucial factor to take into account. The priority action areas for resolving six of the most urgent environmental concerns in the world are highlighted in Fig. 3. At present, most of these applications prioritize automated and assisted intelligence to extract value from extensive, unstructured real-time datasets. However, forthcoming applications are expected to showcase more systems driven by autonomous decision-making, where AI functions independently. This evolution will usher in fresh opportunities along with associated risks. [23].

5. MAIN OBSERVATIONS

The legal examination of AI in fisheries showed that while there are references to digitalization, which may include AI systems, there is no explicit mention of AI systems in the most pertinent EU fisheries legislation. The majority of pertinent fishing laws are written to permit the employment of AI systems [27]. The Artificial Intelligence Act (AIA) proposal's broad scope

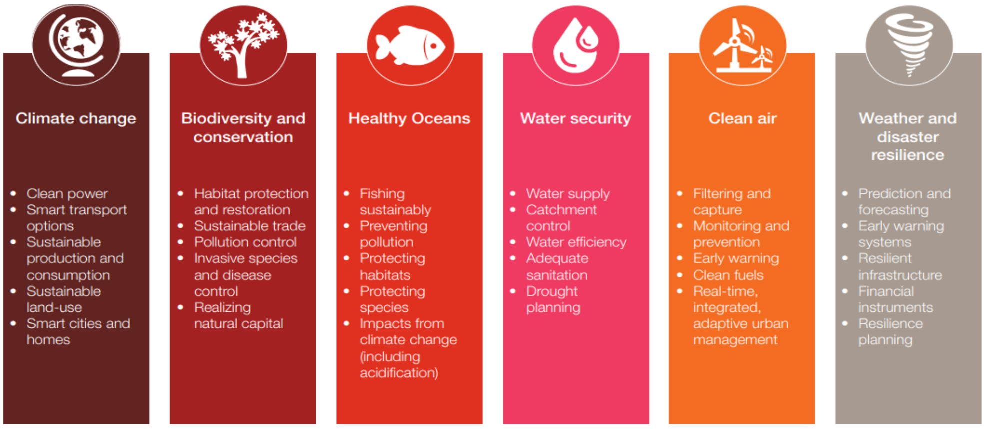

Fig. 3. Priority action areas for addressing Earth challenge areas [23]

makes it easy to apply to the fisheries industry. Many third-world nations are thinking about using AI to automate electronic monitoring systems even more. Machine Learning (ML) techniques have been utilised to automate the processing of biological samples, according to a study of AI techniques in fisheries. ML has been used to count and measure creatures after image analysis and on acoustic data, and research on classifying catches by species and sizes using AI has increased. ML is being used to categorise or ascertain fishers' behavior automatically [28]. Early warning systems and marine spatial planning have both seen the application of knowledge-based and expert systems; classic rule-based expert systems have typically been used when there is a lack of data. Although they are not typically thought of as AI, statistical techniques, Bayesian estimation, search, and optimisation methods can be incorporated into AI systems. Some of the applications for these techniques have been found in species distribution models and stock evaluations. AI technology could help fishing boats become more energy efficient and lower their carbon footprint. AI has promising applications for traceability and seafood product integrity along the whole supply chain [29].

The main obstacle is a lack of data generation and collection, but the processing industry is beginning to use AI systems in automation processes, AI proofs-of-concept have been created for the logistics industry, and ML has been used to predict consumer behavior and economic growth [30]. There is a mismatch between the industry's instruments for following rules and the goals of fisheries selectivity improvement management concerning the usage of AI for more selective fishing tactics. AI solutions aiming at automated species forecasting, detection, identification, and sizing of catches could allow for improving fishing decisions and enabling quota tracking. AI can further improve species selectivity. In terms of the application of AI as a motivator for young people to seek employment in the fishing industry, AI, like digitalization, is anticipated to produce new skilled jobs while reducing the demand for low-skilled ones in the fishing industry. Fishing vessel applications for artificial intelligence (AI) systems created for the maritime transport industry include anomaly detection and ship failure prediction. Although a more digitalized and AI-based fishing industry might draw in fresh young talent, it will have to compete with other sectors that are now providing greater incentives [31].

6. THE CLASSIFICATION OF AI TECHNIQUES AND APPROACHES IN THE AIA PROPOSAL EXPANDED WITH FURTHER SUBCATEGORIES USED IN THE STUDY [32]

In the context of a proposal or academic research, the classification of AI techniques and approaches is designed to systematically outline the categorization and application of artificial intelligence. This framework helps in delineating the various methodologies and their uses within the field of AI, offering a clear understanding of its diverse applications and strategies.

7. DEFINITION AND SYSTEM FRAMEWORK OF INTELLIGENT FISH FARM

The latest wave of information technology, encompassing IoT, big data, artificial intelligence

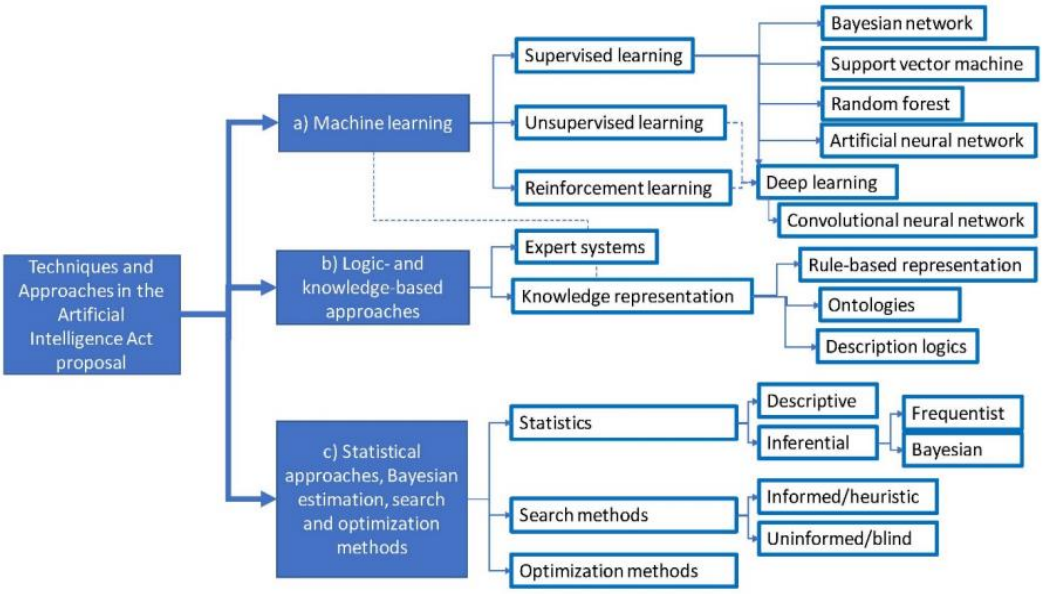

Chart 1. Techniques and approaches in the artificial intelligence act proposal

(AI), 5G, cloud computing, and robotics, is employed for remote monitoring and control of fish farms, or for robot-independent management of fishery facilities, equipment, and machinery to oversee all aspects of production. The authors posit that intelligent fish farming represents a comprehensive, all-weather, end-to-end automated production model. Last but not least, intelligent fish farms use digital and intelligent technologies to address issues including labour scarcity in aquaculture, water contamination, high risk, and low efficiency. The industrialization of fisheries production and the direction of fishery development in the future are represented by intelligent fish farms. According to various cultural contexts, intelligent fish farms may be categorised into four types: pond-type intelligent fish farms, land-based factory-type intelligent fish farms, cage-type intelligent fish farms, and intelligent marine ranches. An intelligent fish farm that resembles a pond uses sensors to gather water quality data in real-time, and unmanned aerial vehicle patrols the area to gather data on fish activity on the water's surface. Bionic fish are designed to monitor fish growth and feeding behavior. Chemicals are sprayed on unmanned boats while fertilisers are applied to control water quality. Unmanned vehicles are used to transport bait. The smart aeration system precisely controls DO.

The primary objective of a land-based, factory-style intelligent fish farm is to implement automated recirculating aquaculture systems (RAS). These systems integrate micro-filters, biological filters, intelligent feeding devices, aquaculture wastewater purification, and recycling devices, alongside advanced modeling and intelligent equipment technologies, to construct a comprehensive model of fish circulation. By extensively collecting production data and leveraging big data analysis technology, scientific decisions are made regarding optimal stocking densities, water quality requirements, and effective management strategies for benthic fish aquaculture within the RAS framework. This process is grounded in a thorough examination of the correlation between the fundamental biological needs of aquaculture and the operational parameters of the RAS system. Through the integration of high-quality seed production and selection technologies, the fish farm establishes supportive methodologies suitable for recirculating aquaculture, enabling seamless management of parent fish mating, egg hatching, fry cultivation, adult fish rearing, sales, and packaging. Fig. 4 illustrates the essential technologies employed in intelligent fish farming. Apart from the particular fishery infrastructure, all four categories of intelligent fish farms incorporate both above and underwater environment monitoring systems, as well as water quality and feeding control systems [33].

8. THE APPLICATION OF NEW DIGITAL TECHNOLOGIES IN MARINE AQUACULTURE

8.1 Big Data Applications

The data that is acquired during the application of big data in marine aquaculture should be managed and kept by specific standards, and it should be analysed using the proper information fusion and mining technologies. Scientific visualisation is then used to convey this reconfigured multidimensional data to consumers along with useful knowledge. This would aid in the comprehension, use, and decision-making of the procedures involved in producing marine fisheries [34]. Table 1 highlights the characteristics of the main sources of big data on marine fishing. The IoT, the internet, specialised databases, and marine fishery management systems are just a few of the places where big data on marine fisheries can be found. Professional databases can be acquired quickly and with great authority, but they can be a little challenging. Aquaculture water quality analysis, a thorough examination of the benefits of aquaculture, and data visualisation are some of its applications [17]. A high-quality aquaculture environment is the primary factor to assure yield and quality in the area of aquaculture water quality analysis. Marine fish in particular have high standards for water quality, and negative changes in water factors like pH and dissolved oxygen will directly impact fish growth. To detect biological abnormalities in aquaculture, prevent infections, and lower associated risks, real-time analysis and prediction of water quality indicators in aquacultural environments are of major importance. To assess a culture pond's viability for fish farming, it is crucial in inland marine aquaculture to analyse a variety of environmental parameters. Through the use of sensors, farmers may keep tabs on a pond's salinity, temperature, oxygen concentration, pH, and oxidation-reduction potential (ORP) [17].

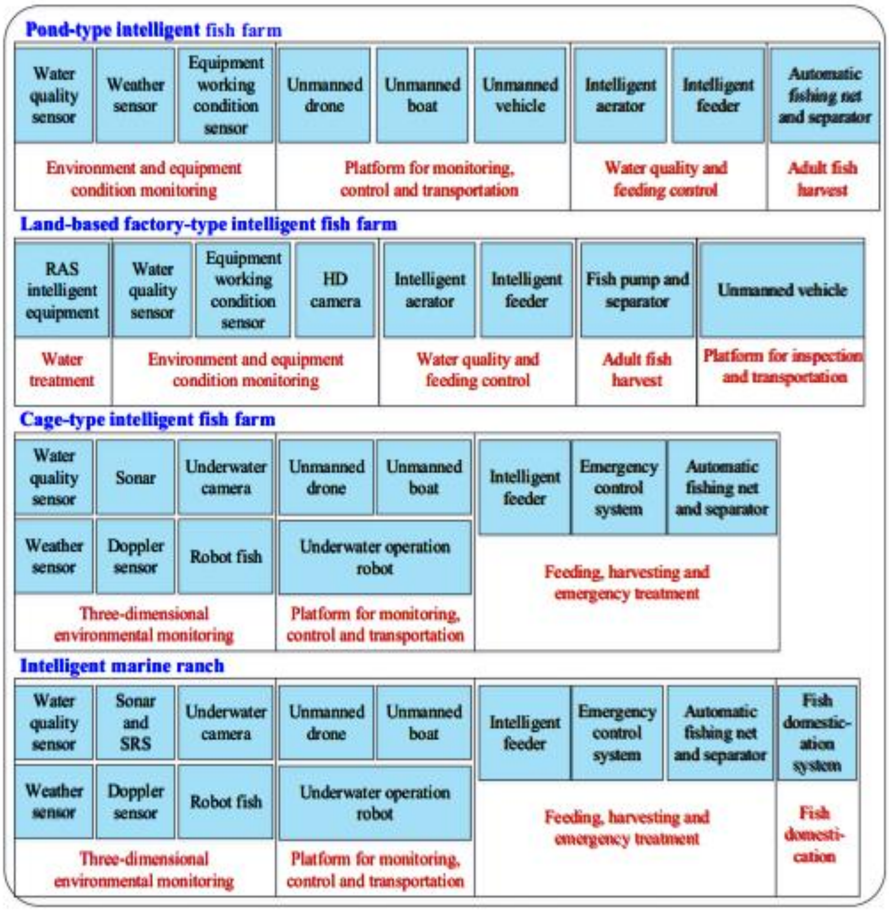

Fig. 4. The involved key technologies in intelligent fish farms [33]

Table 1. Comparison of big data acquisition sources for marine fisheries [17]

Sources	Method	Speed	Difficulty Level	Reliability
IoT	Sensor	Quick	Easy	Moderate
Internet	Crawler	Quick	Easy	Moderate
Professional databases	Application programming interface (API)	Quick	Moderate	High
Marine fisheries management systems	Crawler/API	Moderate	Moderate	High
Traditional data sources	Inquiry/Consultation	Low	Difficulty	High

8.2 Intelligent Equipment and Robots in Intelligent Fish Farm

The conventional aquaculture Internet of Things (IoT) system entails a significant integration of both cloud technology and IoT technology [35]. Traditional aquaculture primarily relies on first-hand knowledge of its ineffectiveness, expense, and lack of automation. Currently, multiple workers on board service vessels handle daily activities on fish farm facilities, such as fish welfare monitoring, facility inspections, management of feed rationing, and lice counts [33]. Given that the working conditions in aquaculture are extremely intricate and change frequently and severely, especially in marine cage culture, autonomous and remotely operated systems may play a significant role in the future in carrying out various activities at fish farm facilities. Advanced sensors, big data, and AI will be integrated by intelligent machinery and robotics to enable the independent operation of intelligent fish farms and effective adaptation to the challenging operating environment. They can also significantly lower labour costs and labour intensity while increasing the productivity of the fisheries. As a data source for big data analysis, intelligent machinery, and robots can also independently recognise and communicate the vast amounts of data generated by intelligent fish farms [27]. Fig. 5 depicts conceptual design of IoT ecosystem in intelligent fish farm.

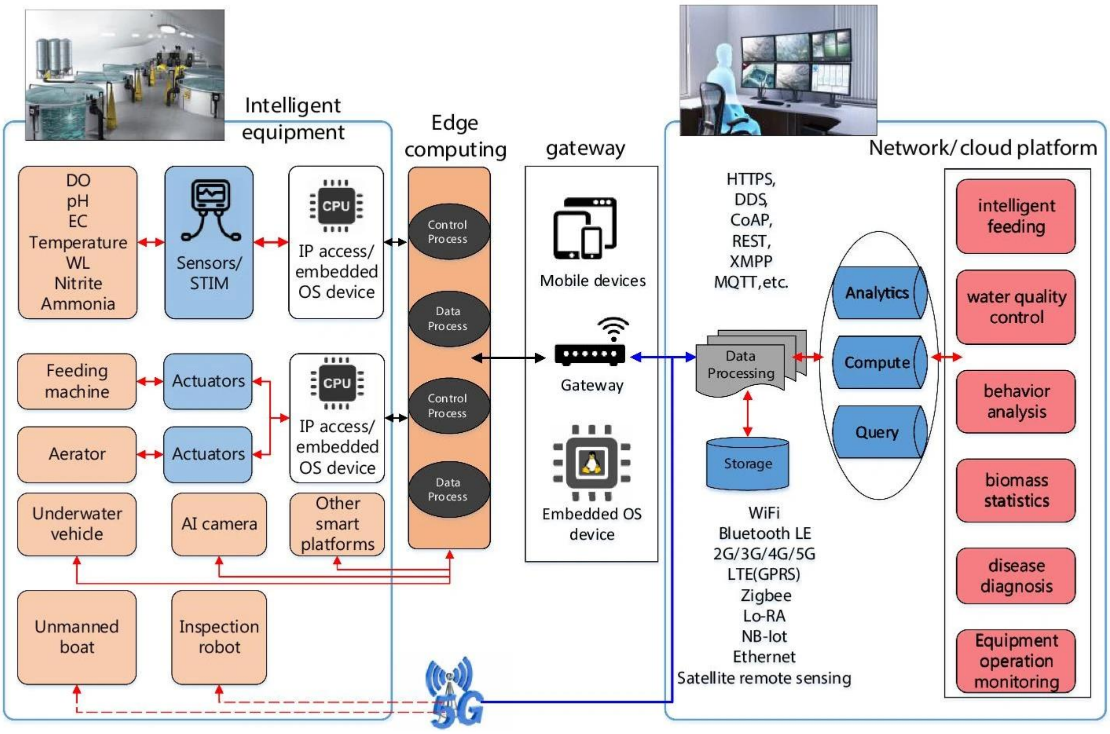

Fig. 5. Conceptual design of IoT ecosystem in intelligent fish farm [33]

AI helps intelligent machines and robots and gives them "intelligent brains" that can learn, judge, and make decisions on their own in the production of fisheries. Information, machine, and automation technologies are effectively combined in robot technology. It can make it possible for any type of machine to take part in the entire fishing production process just like a human [36]. In order to fulfill the requirements of machines replacing humans, intelligent machinery and robots also rely on edge computing, machine vision, navigation, and precision control technologies for assistance. To perform precise operations in an intelligent fish farm, intelligent equipment built on traditional fisheries equipment uses contemporary information technology and clever manufacturing technology as shown in Fig. 6 [37]. Mobile equipment and fixed equipment are the two categories under which intelligent farm equipment and robots fall. Unmanned ground vehicles (UGV), unmanned aerial vehicles (UAV), unmanned ships or unmanned surface vessels (USV), and unoccupied underwater robots (ROV) are the most common examples of mobile equipment. Fixed equipment includes tools for feeding, oxygen, and water quality monitoring and management, as well as harvesting tools including fish suction pumps and categorization tools [33].

8.3 Intelligent Hardware for Precision Self-Feeding

Industrial recirculating aquaculture has made extensive use of automatic feeding systems, including automatic feeding robot systems and automatic feeding systems with multi-monomer centralized control. In certain developed countries such as Norway, Japan, and the United States, automatic feeding systems have advanced to the application stage, facilitating precise control over feed distribution, storage, and transportation chains. The net cage automatic feeding system, developed by a Norwegian fishery equipment company, consists of a management system, online monitoring system, and feeding module. The management system directly regulates the fan and feeder, continuously adjusting the feeding process. Simultaneously, the online monitoring system can track multiple aquaculture water parameters in real-time, including pH, dissolved oxygen (DO), and temperature. The feedback data is then transmitted to the management system, enabling automatic feeding adjustments [39].The

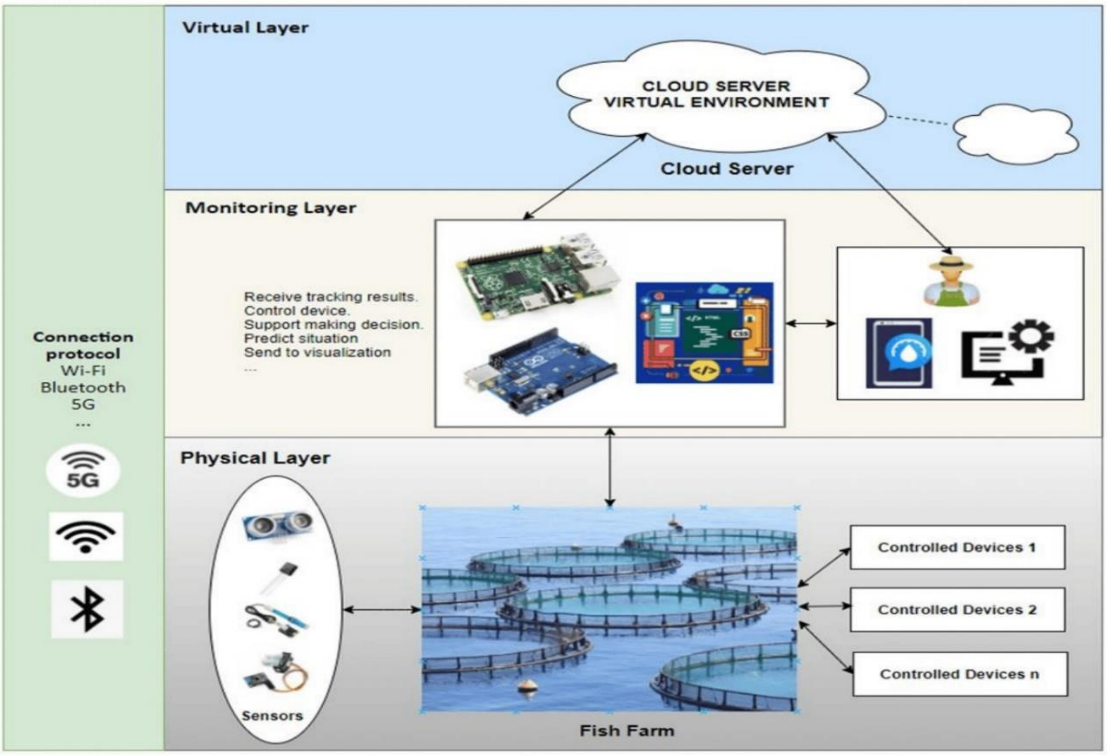

Fig. 6. Internet of things (IoT) aquaculture system [38]

Finnish company Arvo-Tec has pioneered a robot feeding control system, allowing for remote feeding management, water quality improvement, and precise feeding via a web interface. The Arvo-Tec command module, known as WOLF, encompasses feeding, measurement, light control (photoperiod), and alarm functionalities, all fully integrated. Utilizing an energy demand model based on initial data such as water temperature, oxygen content, biomass, and other environmental parameters, the system executes feeding control with precision [33]. Additionally, the system calculates fish growth using the feed conversion ratio. Intelligent bait-dropping equipment is intended to be deployed on unmanned boats or UAVs within pond-type intelligent fish farms. The UAV will be responsible for autonomously transporting and loading bait [40].

8.4 Fish Disease and Health Management

Disease outbreaks pose the biggest hazard to aquaculture. By comparing programmed data with the data gathered from the site, AI programs can predict disease outbreaks. They are even able to take preventative action [41]. When a disease outbreak occurs, it can result in incalculable losses. The rapid processing technique for images of sick fish, employing machine vision, replaces human observation with computer-based automatic and intelligent recognition of sick fish images [42]. In April 2017, Norway's seafood innovation centre introduced "Aquacloud," a cloud-based program that helped farmers stop the growth of sea lice in cages. As a result, there was less fish mortality and less need for more expensive treatments [41].

Disease presents a considerable obstacle to the quality and output of aquaculture. In this context, disease arises from an imbalance among multiple factors stemming from the host, the pathogen, and the environment. Diseases can generally be categorized into two types: infectious (which includes parasitic, fungal, bacterial, and viral infections) and non-infectious (covering environmental, nutritional, and genetic factors) [43]. The inability of farmers to accurately diagnose and treat sudden fish diseases makes it difficult to implement effective and timely treatment measures. Consequently, fish diseases can spread rapidly, leading to massive fish deaths and significant losses for farmers [44]. Machine learning offers a solution to this problem by enabling the early detection and alerting of fish diseases [38].

Epizootic ulcerative syndrome (EUS) is a widespread disease that has resulted in significant mortality rates among fish populations in numerous countries, such as Australia, India, the United Kingdom, Japan, Thailand, and Pakistan. The primary cause of this disease is a fungal infection attributed to *Aphanomyces invadans*. An approach has been investigated for detecting fish diseases by merging two methodologies: Principal Component Analysis (PCA) and classification employing a Neural Network Algorithm (ANN) [45].

The methodology depicted in Fig. 7 begins with the collection of input images, which are images of fish diseases. These images then undergo morphological operations, which include conversion to grayscale, noise removal, and segmentation [38,45]. The results indicate that the FAST-PCA-ANN method outperforms the existing combined technique of HOG-PCA-ANN in terms of classification accuracy and efficiency. Certain methodologies have employed the Raspberry Pi kit to oversee the camera and capture video data of fish within the culture pond [46].

8.5 Intelligent Harvesting System

The final component of the fish farm's breeding cycle is the intelligent harvesting mechanism. With the help of this method, breeding items will be transported with or without water into the market. Trawling is currently the most effective method of fishing. Sonar, an underwater camera, and a net placement device are all used by the system in intelligent fish farms to produce precise fish. The efficiency of fishery output will be significantly increased by the use of autonomous ships and vehicles in the delivery of aquatic items. By doing so, the objectives of high efficiency and energy conservation will be achieved while reducing the labour intensity of fishers. A robot that automatically picks sea cucumbers does so using Doppler-GPS integrated navigation, computer vision, and mechanical servo-drive technologies. The sea cucumber-catching robot's navigation system is in charge of gathering position data from the underwater robot, planning the navigational path, and managing the movement of the robot. The sea cucumber image collection, preprocessing, identification, and determination of the sea cucumber's relative coordinates are all done by the machine vision system [47]. The pressure pump and manipulator used to harvest sea

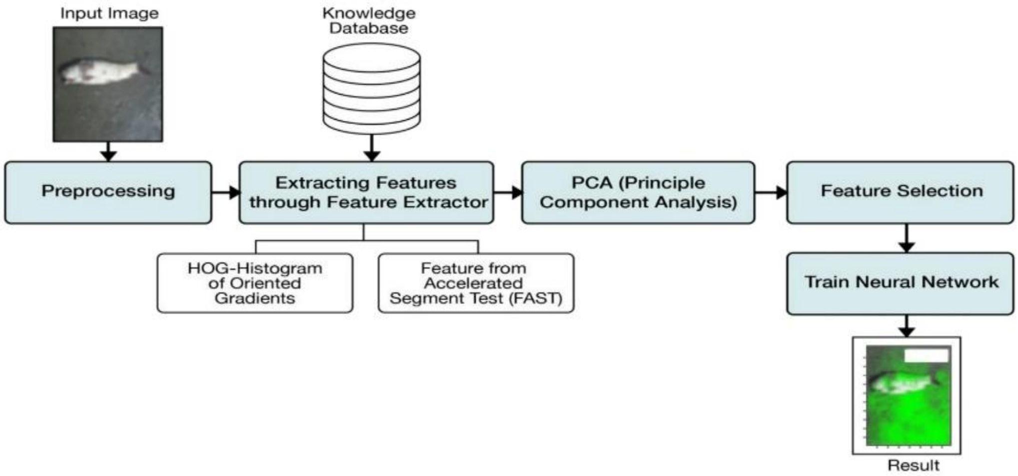

Fig. 7. Proposed methodology [38]

cucumbers can be controlled by the actuator. Automation in aquaculture production will be achieved through the use of intelligent machinery and robots. In achieving unmanned production, environmental monitoring, optimization control, and precise operations, contemporary information technology plays a crucial role, leveraging comprehensive perception, intelligent processing, intelligent navigation, and automatic control technologies. Within an intelligent fish farm, robots, unmanned vehicles, unmanned boats, and robotic fish will each play significant roles [33].

8.6 Water Quality Soft Measurement and Control Method

The pace of growth, state of health, and efficiency of feed intake of fish are all significantly impacted by aquaculture water quality [48]. One water quality parameter in aquaculture can be affected by various factors, complicating detection with a single method and suggesting the use of soft measurement techniques [49]. Currently, aquaculture predominantly relies on traditional methods, primarily involving manual data collection and detection, along with fixed water quality sensor monitoring [50]. This approach is characterized by labor intensiveness, low efficiency, and inadequate coverage of water areas, leading to unsatisfactory outcomes. Presently, mobile internet, big data, cloud computing, artificial intelligence, among other technologies, have been implemented within the aquaculture sector [51]. Using a wireless sensor network for monitoring water quality is crucial for effectively managing aquaculture water quality [52]. Among the parameters monitored, dissolved oxygen plays a critical role, with its prediction offering decision-making support for aquaculture production, thus mitigating associated risks [53]. In order to advance the informatization of aquaculture and enable more precise and convenient monitoring of aquaculture ponds, [54] devised a water quality monitoring system based on narrowband internet of things (NB-IoT) technology.

The fundamental concept behind soft measurement technology is to estimate or infer significant factors that are challenging to see using a few simple variables. The soft measurement model and feature extraction are crucial for soft measurement technologies. Grey box models, machine learning models based on statistical analysis, and process mechanism models make up the majority of the currently used soft sensor modelling techniques [33]. Traditional approaches for predicting water quality are inaccurate and have a slow convergence rate. They are not appropriate for high-dimensional modeling, limited sample data sets, or parameter optimisation influenced by arbitrary variables. propose two nonlinear ACO-LSSVR and IPSO LSSVR-based algorithms for predicting DO in aquaculture [55,56].

Using a local fine search based on the concepts of "detection" and "dynamic update of pheromone," the ACO-LSSVR method enhances the ant colony optimisation algorithm, realises the automatic acquisition of the best LSSVR model parameters, and creates a DO nonlinear prediction model based on ACO and LSSVR [33,56]. They applied the PCA method to identify the primary factors influencing the variation of ammonia nitrogen content, utilized the wavelet threshold method for noise reduction, and introduced a predictive model for ammonia nitrogen based on the particle swarm optimization (PSO) algorithm and a multi-variable deep belief network (MDBN) [57]. Fig. 8 shows IoT monitoring water quality system block diagram.

8.7 AI and Monitoring Fish Stock

The studies that directly address the role of AI in counting fish species are those that fall under the category of fisheries resources. The use of AI to count fish species has several benefits. The marine ecosystems' segmentation, detection, and classification of fish populations enables researchers to collect data on fish abundance. Automation of classification is a major topic in many articles. Fish classification processes are automated using AI technologies. Some papers concentrate on fish detection technologies. Built on deep network architectures, these systems can detect and count fish items across diverse benthic backgrounds and lighting conditions. Although the classification, detection, and identification of fish stocks have certain commonalities, in actuality these automation topics are fundamentally the same. For assessing the condition and well-being of fish assemblages, data on the species composition and abundance distribution of fish species are crucial. The idea of automation includes smart fisheries, which classify, identify, and detect resources to estimate fish quantity. One of the most unsustainable causes of the world and national fisheries, as noted in one of the papers we studied, is the availability of fish. Fish stock monitoring is simply one aspect of the AI-inspired smart fishery for sustainability that is mentioned in the publications under study. The overlap of publications locating the scope of smart fishery in "epidemic of plastics entering the sea warrants urgent action if humanity is to stave off a collapse in fish stocks" reflects the connection between sustainable fishing and environmental monitoring. They show that pollution is a crucial and serious issue when it comes to fish abundance. A further negative impact on aquatic and wildlife is caused by oil spills on seas and oceans, a significant source of maritime and ocean pollution brought on by human activities, the expanding demand for oil, and the capacity of maritime transport [58]. The categorization is thus completed under three research themes: fish/fisheries, fishers/fishing fleets, and policy, as illustrated in Fig. 9.

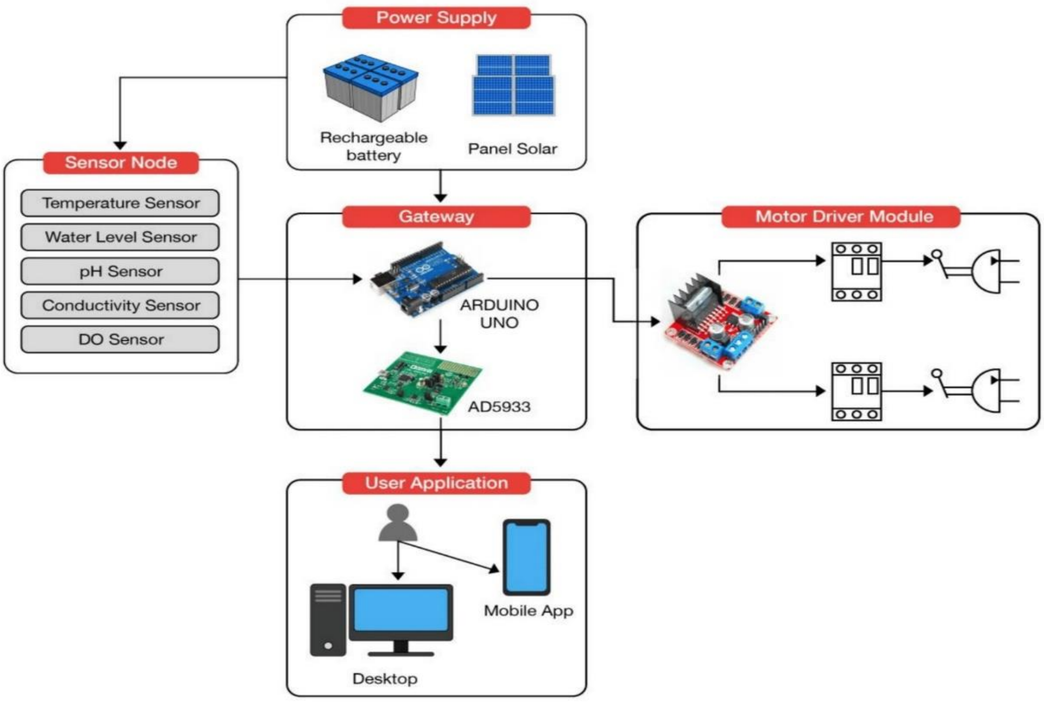

Fig. 8. IoT monitoring water quality system block diagram [38]

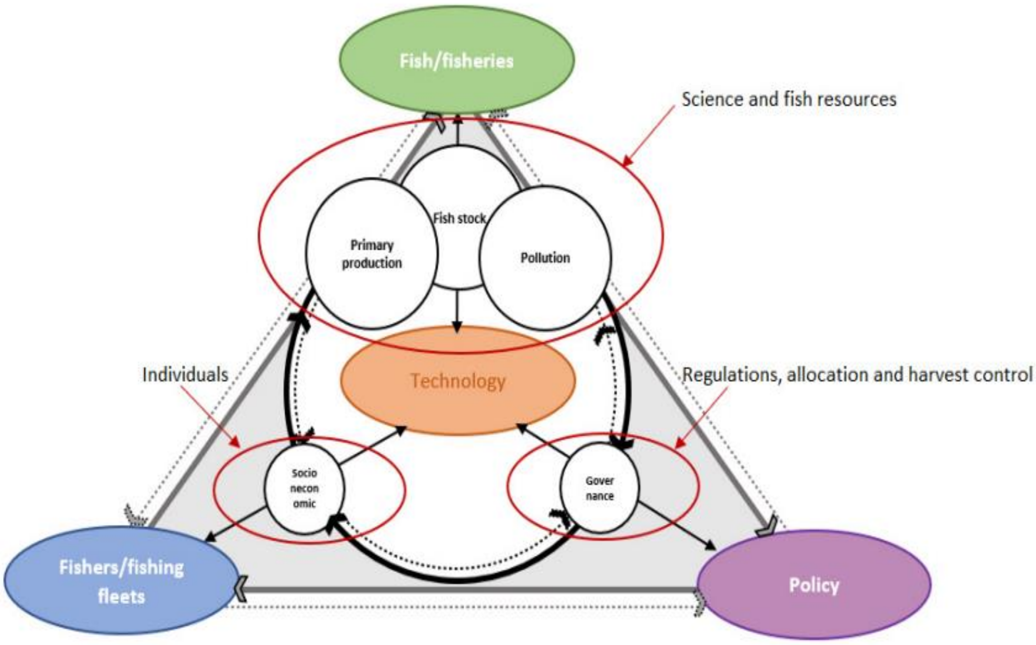

Fig. 9. AI for sustainability in the context of fishery systems adopted from [59]

8.8 AI for Improving Timely Observation and Catch-Monitoring

Several fisheries are implementing in-trawl camera systems. However, without the deployment of operational AI systems, these systems have only been utilised for scientific monitoring purposes. The developed catch monitoring techniques include considerable human processing and archiving of video data. Automated data processing is necessary for these systems to function effectively as decision-support tools. The use of automated processing has increased recently across many industries, and fishing is no exception. In numerous works, automated fish detection and classification using DL model applications are described. These investigations show that the object identification and classification DL models are effective processing methods for underwater and onboard catch recordings. Poor visibility circumstances frequently present a difficulty for underwater video recordings, particularly in demersal trawls, for which technology advancements supporting AI growth will still be necessary. In this area, 3D camera systems utilising techniques like stereo imaging or 'time of flight' (the amount of time it takes for a light pulse to travel to an object and return) developed in the Utofia H 2020 project 83 may soon make it possible to capture fish position and size even in murky environments. Integrated on-board systems comprising cameras, gear sensors, video storage, and Global Positioning System (GPS) units are considered electronic monitoring for this study. These systems record in-depth videos of fishing activity along with related sensor and positional data. An onshore analyst can study the video record, which is normally recorded on a hard drive that is collected after fishing trips, to gather information such as catch volume, bycatch, discards, and fishing location. Some new EM vendors are implementing systems that employ Wi-Fi, satellite, or cellular networks to send data, some of it in near real-time, in place of physically moving hard drives. These systems flag vessel activity that is of interest based on automated analysis of video footage in place of gear sensors [22]. Fig. 10 shows schematic of a trawl with an EM system.

8.9 Live Fish Identification

Accurate and automatic identification of live fish is essential for the development of intelligent breeding management tools or systems, as it provides data support for subsequent production management. Machine vision offers the advantage of enabling long-term, nondestructive, noncontact observation at a low cost. However, there are many difficulties with image and video analysis when dealing with scenarios found in

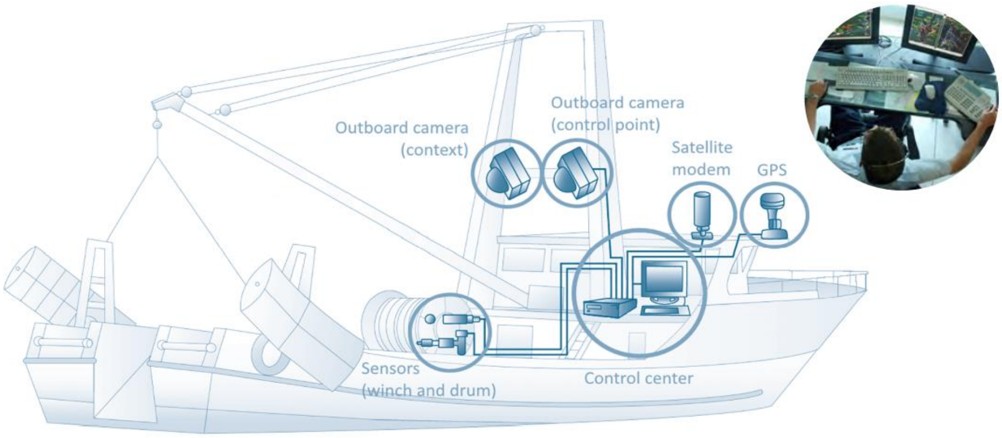

Fig. 10. Stylized schematic of a trawl vessel outfitted with an EM system [60]

aquaculture. First, light, noise, and water turbidity can all harm the image's quality, resulting in a low-resolution and low-contrast image. Second, because fish swim at will and are unrestrained targets, their actions may result in undesirable phenomena such as distortions, deformations, occlusion, overlapping, and others. These challenges harm the majority of modern image analysis techniques. Even though there have been numerous studies done to look at the aforementioned problems, most of them focused on the extraction of conventional low-level features, which are typically tiny elements in an image like feature points, colours, textures, contours, and shapes of interest. The results of approaches based on such features are frequently disappointing in actual applications. Deep learning (DL) employs various data representations, ranging from low to high levels, to recognize and detect targets or objects in an image. High-level features are built upon low-level features, thereby containing rich semantic information [18].

9. ADVANTAGES OF AI IN FISHERIES

It supports more effective aquaculture management and upholds high accuracy in disaster prediction (disease breakout or decline in water quality). All facets of fisheries science, from hatcheries to packing in processing units, can benefit from the use of AI. Input waste is decreased and productivity is improved as a result. Through experience, the AI system can offer a variety of solutions [61]. [61]Artificial Intelligence (AI) technologies streamline a variety of processes in aquaculture, including the surveillance of water conditions, the administration of feeding schedules, and the identification of diseases. This automation minimizes the reliance on human labor and enhances the efficiency of operations, thus allowing farmers to oversee larger-scale enterprises with fewer resources [62]. AI technologies facilitate precision aquaculture by fine-tuning production procedures using real-time data. Through surveillance and evaluation, AI can modify aspects such as feeding, oxygenation, and other factors to cater to the specific requirements of fish populations. This leads to enhanced growth rates, better feed conversion efficiency, and more effective use of resources [63]. AI can significantly promote sustainable practices in aquaculture by enhancing resource efficiency and reducing environmental effects. By scrutinizing data related to water quality, energy use, and waste handling, AI algorithms can fine-tune operations to decrease the environmental impact of aquaculture establishments [64].

10. DISADVANTAGES OF AI IN FISHERIES

AI has various drawbacks despite becoming more advantageous. Many people need help to afford the significantly greater investments required for AI. The maintenance costs of an AI system can be substantial. Moreover, a significant downside of AI is its potential to displace workers from their jobs. While farmers may reap the benefits, individuals whose livelihoods rely on the fishing industry could experience adverse effects [65]. AI models necessitate data specific to their domain for effective training. However, in certain instances, the availability of datasets specific to aquaculture may be scarce, posing challenges in the development of robust and precise AI models [66]. In the field of aquaculture, the acquisition of extensive and superior-quality data can pose difficulties, particularly in remote or offshore operations. The presence of limited or inconsistent data can impact the precision and dependability of AI models [67]. The deployment of AI technologies in aquaculture might entail initial expenses for items such as sensors, data-gathering systems, computational resources, and trained staff. Fish farmers operating on a small scale or those with restricted resources might find the adoption of AI daunting due to the costs and infrastructure prerequisites involved [27].

11. CONCLUSION

While AI continues to advance, achieving full automation remains elusive. Scientists are actively developing technology capable of functioning without human intervention. The progression of AI in aquaculture is dependent on the amalgamation of various data sources, system compatibility and the creation of platforms for decision-making support. By consolidating data from environmental surveillance, genetic information, and market fluctuations, AI can offer extensive understanding and aid in making well-informed decisions. These improvements will encourage sustainable aquaculture methods by enhancing resource efficiency, reducing environmental consequences and advocating for the health and wellbeing of fish. Aquaculture farms utilizing AI can be maintained and managed with remarkable ease, achieving over 95% operational accuracy. Moreover, AI's ability to mimic human labor and monitor global fishing activity has contributed to the conservation of aquatic life and the promotion of open sea fisheries' sustainability. Effective application of AI can lead to rapid increases in aquaculture product production. Consequently, unlike in other industries, AI seems indispensable for the continued growth and enhancement of fisheries and aquaculture.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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