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Automization in Aquaculture – A Short Review

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ABSTRACT: The increase in population and the challenge of feeding them nutritious food is the main issue facing the world. One of the sectors that produce food that is nutrient-rich is the aquaculture industry. This business is entirely reliant on manual labor, which makes for laborious, time-consuming work that consequently raises the cost of production for farmers and results in them receiving a minimal profit today. The effective approach to managing all situations and enhancing production while lowering production costs is through automation. water quality monitoring by the sensor-based and controlled areal unnamed vehicles to spray using biosensors to monitor water quality and remotely piloted aerial vehicles to spray fertilizer or chemicals. The intelligent aeration system regulates the level of dissolved oxygen. Automatic biomass estimation and feeding management are the second things. To reduce feed loss and lower the FCR, robotics and automatic feeders are used in ponds and cages. These devices rely on the water's quality and the behaviour of the organisms. A farmer receives information on biomass estimation when the crop is harvested to ensure maximum output. The most essential aspect is the automatic monitoring of the organism's health and welfare management to detect any adverse conditions or early signs of abnormalities. A camera-based visual system known as an underwater surveillance system collects data on water quality, organism activity, feeding, cage biofouling, and net cleaning. The future of the aquaculture sector is automation. However, implementing automation technologies on a large scale and ensuring their compatibility with diverse aquaculture systems and practices pose logistical and operational challenges. Aquaculture automation enhances productivity, reduces costs, and improves sustainability. Through sensor-based monitoring, aerial vehicles, and intelligent systems, farmers optimize efficiency and meet the demand for nutritious food. Integrated camera systems monitor water quality, organism health, and welfare, ensuring optimal performance.

Keywords: Automization, Aquaculture, Biomass, Disease, Drowns, Feeding, Parameters.

INTRODUCTION

The need for food is rising to the current human population of 8 billion and is continuous increase. Fish is a great source of vitamins, minerals, protein, nutrients, and micronutrients. It plays a significant role in consumers' diets, particularly in developing and undeveloped nations. To supply the market with nutritious seafood is a difficult task for farmers. The gap between the supply and demand for seafood can be filled by aquaculture (Karim *et al.*, 2021). Rearing aquatic organisms in controlled or semi-controlled environments is known as aquaculture (Stickney, 2022). The production of global fisheries and aquaculture in 2020 is 87.5 million tonnes, slightly more than in 2019. Asia contributes a huge 77.05% of the world's aquaculture production, with China leading the pack by a wide margin with a contribution of 57.93%. India produces more than 8% of the world's aquaculture, putting it as the second-largest producer of farmed fish after China (FAO, 2022).

Compared to other sectors, including agriculture, commercial aquaculture technology is under performing. Numerous challenges, like manual water testing, water rescores, abrupt climatic change, etc., are faced by farmers. It is exceedingly difficult to manually assess thousands of culture organisms on a regular basis for behavior and health in aquaculture (Andrewartha *et al.*, 2015). Other issues include inadequate site selection, poor record keeping, low water quality, and incorrect management techniques. The dynamics of aquaculture water quality monitoring cannot be changed by traditional water quality monitoring, which only allows for fixed-point monitoring (Wei *et al.*, 2020)

Automation is the transition from manual to automatic operation or control of a labor process, technique, or equipment component (Newell & Simon 1956). Aquaculture has gradually progressed toward an intensive and intelligent direction thanks to advancements in automation and intelligent technology. The breeding environment has also gradually changed to a sustainable aquaculture system, which has greatly increased aquaculture's productivity (Avnimelech, 2009). Intelligent aquaculture will be targeted to resolving challenges with fisheries development and enhancing aquaculture productivity as part of the third green revolution (Yang *et al*., 2020). When used in combination with powerful computers, machine learning technology can harvest data for high-dimensional characteristics and depth information, providing a solution for intelligent aquaculture and ushering in a new era for the fishery industry (Zhao *et al.*, 2021).

Aquaculture practitioners have often viewed the field as both an art and a science, with the success of operations relying heavily on the farm manager's intuition rather than a deep understanding of the physiology, ecology, and behavior of the cultivated species. Consequently, farm managers have been reluctant to rely on automated management systems for their crops. However, recent advancements in research and commercial operations have led to the adoption of new technologies, driving the evolution of aquaculture as a scientific discipline. The ability to monitor system parameters in real-time provides managers with unprecedented insights into the physical and biological conditions of their aquaculture facilities. This level of understanding would be unattainable in manually monitored systems due to the labor-intensive process of data collection, entry, graphing, and reporting. While recirculating aquaculture systems have the most obvious requirements for such technology, pond and offshore aquaculture systems can also reap significant benefits (Lee, 2000).

In order to overcome these challenges, it is necessary to embrace innovative technological approaches. Interestingly, the agricultural industry has made greater strides in adopting advanced practices such as the utilization of IT devices and tools like drones, autonomous tractors, sensors, robotics, and data analysis to improve efficiency and sustainability in farm management compared to the aquaculture sector. Additionally, emerging companies specializing in precision agriculture are dedicated to developing technologies that enable farmers to optimize crop yields by meticulously controlling variables such as moisture levels, pest pressures, soil conditions, and micro-climates (Abdullahi *et al.*, 2015). The significance of technology's rapid advancement in streamlining tasks, eliminating the need for manual labor, and automating routine operations cannot be overstated. Various technological aspects, including Artificial Intelligence (AI), Internet of Things (IoT), and Cloud Computing, offer solutions in this regard. These technologies provide convenient access to a diverse range of IT services without requiring upfront costs (pay-as-you-go model), enabling faster operations and cost-sharing for hardware, facilities, and power expenses. Furthermore, the emergence of web-enabled smart devices allows for the collection and sharing of information regarding their usage and the surrounding environment without human intervention (Mustapha *et al*., 2021).

The advancement of automation and intelligent technologies has progressively propelled the global aquaculture industry towards a more intensive and intelligent approach. This transition has resulted in the development of sustainable aquaculture systems, leading to significantly improved efficiency in the sector. However, the labor-intensive nature of aquaculture, coupled with the complexity of managing farming organisms, aquaculture environments, and various variable factors, has presented challenges. Consequently, the substantial growth in aquaculture has also given rise to numerous issues, including fish feeding, disease management, and water pollution. As a key component of the third green revolution, intelligent aquaculture aims to address these challenges in fisheries development and enhance overall aquaculture productivity (Zhao *et al.*, 2021).

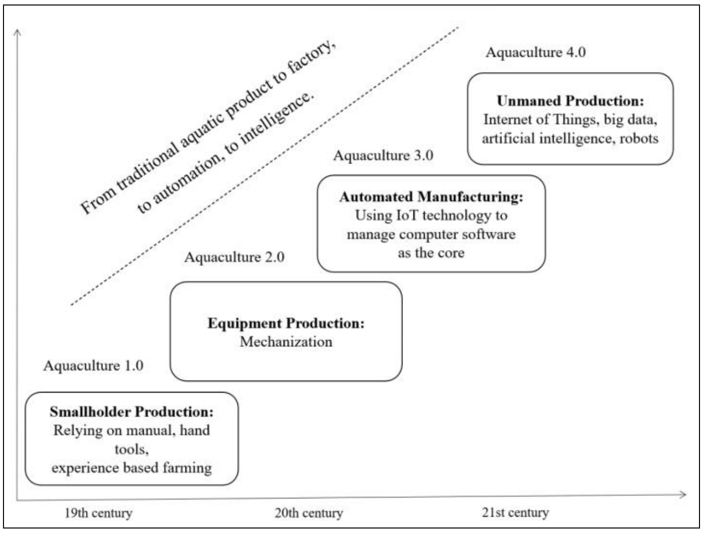

Fig. 1. Aquaculture Developing Generation 1.0 to 4.0 (Daoliang, 2018).

BASIC CONCEPTS OF AUTOMIZATION

Although aquaculture is advancing toward intense, controlled environment production with a large increase in output, it does so at the expense of an increasing risk of catastrophic loss due to equipment or management failures (Simbeye *et al.,* 2014).

For fish or shrimp ponds to monitor the system and react right away to any unexpected changes, effective management is required. Any environmental changes could make it difficult for fish or shrimp to grow. Technology advances in monitoring and automation have enhanced production processes in aquaculture, resulting in increased fish output in huge quantities with better-quality fish farming ponds. One of the many artificial ecosystems created by humans is the fish farming pond. Ponds can be divided into two categories: those that breed tropical fish for use as pets and are more frequently referred to as aquariums than ponds, and those that breed fish for consumption. Fisheries and aquaculture have a key role in ensuring food security and generating employment for a large number of people. Since fisheries and aquaculture are expanding so rapidly, millions of people throughout the world are receiving sources of nutrition, food, and income (Teja *et al.,* 2020).

A. Network Monitoring

Based on virtual instruments, a wireless sensor network for aquaculture monitoring and control is proposed. Additionally, both the software and detailed hardware designs for the coordinator/gateway and smart sensor nodes are described. Finally, a coordinator/gateway, two smart sensor nodes, and a prototype system are constructed and put into operation. The gathered data allows for an accurate examination of the system's successful operation. The monitoring and control of crops, hydrological water conservation, and irrigation of farms are only a few examples of the many applications for this work (Simbeye *et al*., 2014).

B. Intelligent Equipment

Aquaculture is one of the many industries where intelligent and unmanned technology has been used quickly. For the development of intelligent fisheries, intelligent and unmanned technologies present new potential as well as challenges. The four main aspects of intense aquaculture—intelligent feeding, water quality detection, biomass estimation, and underwater inspection also examine how these aspects have advanced from manual labor to mechanization to automation to unmanned, intelligent equipment. Additionally, each intelligent device's practical applications' comfort, effectiveness, and precision are explored. Additionally, the primary barriers to the widespread use of intelligent and unmanned equipment in the aquaculture sector as well as the projected direction of aquaculture robot development are indicated (Wu *et al.,* 2022).

For a smart aquaculture strategy, a number of smart devices are incorporated into a setting that is specifically designed to track cultured environmental parameters in real time and then automatically make decisions based on the data collected (Sharma & Kumar 2021). Aquaculture is a sensible technique of production. By using IoT, big data, artificial intelligence, 5G, cloud computing, and robotics, it may be automated and managed remotely. On the other side, smart aquaculture can be managed by a robot that can operate entire systems to produce effective output by managing facilities, equipment, and machinery (Kassem *et al.,* 2021). In the process of controlling the water quality parameters in an aquaculture system, a variety of temperature, dissolved oxygen, humidity, light, and pH sensors are used. The information is collected, transmitted to the control center by communication nodes, analyzed, and decisions are made using cloud platforms. Each piece of equipment used to carry out the decision is then given feedback (Vo *et al.,* 2021).

C. Unmanned Operation (Robotics)

Unmanned boats (UA) and their uses have recently advanced due to the quick development of new technologies such as automatic control technology, sensor technology, and artificial intelligence (AI). Lightness, flexibility, and low influence from the environment are qualities of UA. The achievement of automatic environmental monitoring has been important (Liu *et al.,* 2022).

Data collection on water quality, water contaminants, water temperature, fish behavior, and current/wave velocity is needed for management and surveillance operations at aquaculture farms, which is labour-intensive and expensive. Technologies for unmanned vehicles make it easier and more accurate to carry out these tasks. When outfitted with sensors and other technologies, they can even detect cages and monitor unlawful fishing. The capacity of unmanned vehicles as a communication gateway to enable offshore cages outfitted with reliable, affordable sensors capable of underwater and in-air wireless communications is also explored in this article to provide a more expansive perspective. To provide a precise aquaculture framework, the capabilities of current commercial systems, the Internet of Things, and artificial intelligence are also discussed (Ubina & Cheng 2022).

ARTIFICIAL INTELLIGENCE(AI)

The introduction of artificial intelligence into the aquaculture sector has improved management and decision-making. The underwater robots used in aquaculture that include a machine vision component make it easier to continuously monitor the fish and their habitat. Then, before they become issues, this information can be employed to lessen growth or production anomalies. The programs are being created to identify individual animal behavior and production. AI is particularly significant because it can understand data far more effectively than humans can, and because it can be used to filter data so that humans only need to get involved when essential (Pathak, 2017).

The term artificial intelligence (AI) refers to "the future built from elements of the past." These are programmes that acquire fresh approaches through practice. AI has been used in a wide range of areas, from full industry automation to agriculture. With the help of AI, the aquaculture industry can become less labor-intensive, allowing production to quickly treble. It can appear as any type of labourer at work, such as feeders, water quality monitors, harvesters, processors, etc. AI can even be employed to protect aquatic life types from extinction. AI assists in monitoring fishing activity throughout the world and promotes open sea fisheries' sustainability.AI improves in monitoring fishing activity throughout the world and promotes open sea industries' sustainability. 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 systems for producing fish with less maintenance and lower input costs (Jothiswaran *et al*., 2020)**.**

The simulation of human intelligence by machines is known as artificial intelligence (AI). Aquaculture becomes a less labor-intensive industry as a result of AI's ability to enable the fisheries sector to grow quickly and double productivity in a short amount of time (Lloyd *et al.,* 2020). Artificial intelligence (AI) is the capacity for thought and learning in a computer program or other system. Aquaculture has rapidly experienced a tremendous surge in innovation. In the last five years, half of the industry's software programmes have been released. The FAO estimates that 53% of all aquaculture aquatic animals were produced as finfish in 2018, with a farmgate value of almost 140 billion USD. However, only 26% of all farmgate value of farmed animals was produced by shrimp, and 35% of aquaculture software is created for finfish farming (Tamm, 2021).

APPLICATION OF AUTOMIZATION IN AQUACULTURE

Modern aquaculture research and production have started implementing new technologies, such as computer control systems. Aquaculturists are aware that the physiological rates of cultured species and end process outputs (such as ammonia, pH, and growth) can be controlled by managing environmental factors and system inputs (such as water, oxygen, temperature, feed rate, and stocking density). Commercial aquaculture facilities will be able to maximize their efficiency by lowering labor and utility expenses by using these precise types of useful measurements. Artificial intelligence and process control systems for aquaculture are expected to have the following beneficial benefits: (1) increased process efficiency; (2) decreased energy and water losses; (3) reduced labor costs; (4) reduced stress and disease; (5) improved accounting; and (6) improved process understanding. The aquaculturists now have a tested approach for adopting management systems that are both intuitive and inferential thanks to today's artificial intelligence (AI) solutions, such as expert systems and neural networks. Successful commercial applications of AI are numerous (e.g. expert systems in cameras and automobiles). Functionality/intuitiveness, compatibility, adaptability, upgrade path, hardware requirements, and pricing are the main elements to take into account when designing and purchasing process control and artificial intelligence software. The most crucial of these is compatibility and intuitiveness. Users must find the software easy to use for them to use it. To ensure that the chosen software is compatible with other software products, the maker should adhere to open architecture designs (Lee, 2000).

A. Water Quality Online Monitoring

The future of aquaculture involves automated remote monitoring and computer-controlled intense culture. Water quality monitoring is crucial to contemporary aquaculture management. The pace of fish growth can be accelerated, dietary utilization can be affected, and the prevalence of major fish diseases can be decreased with proper regulation of the water quality to maintain the concentration of the water environment parameters in the ideal range (Stigebrandt *et al.,* 2004). It is nearly impossible to carry out the proper water quality control at the proper time in the proper place without the knowledge of the physical and chemical parameters of water quality along with the relevant ecological aspects (Zhu *et al.*, 2010).

(i) Waterproof temperature sensor. The temperature of the water body in which the waterproof temperature sensors are submerged is measured. The majority of waterproof temperature sensors can typically measure between -55°C and +125°C. It includes a temperature limit alarm system, ground wire, power wire, and data transmission wire (Barman *et al.,* 2015).

The following temperature sensing techniques mostly belong to the two groups of electric devices and non-electric devices. The thermocouples are based on the Seebeck phenomenon and require electrical instruments to be near the thing being sensed. Usually constructed of copper, nickel, iron, platinum, rhodium, and their alloys, they are made of two connected metal conductors. Thermocouples are reasonably priced, compact, and very durable (Childs *et al*., 2000; Parra *et al*., 2018).

(ii) pH Sensor. A given water body or solution's alkalinity is determined using the pH sensor. The pH scale has numbers 0 through 14. These sensors are typically used to test the pH level of water and are made of pH glass electrodes with Ag/AgCl reference electrodes (Aakash, 2019).

(iii) Dissolved oxygen sensor. The amount of oxygen present in a water body is measured using a dissolved oxygen sensor, which establishes whether there is enough oxygen for the organisms to survive. A galvanic or polarographic electrochemical DO sensor may be employed for this purpose. The dissolved oxygen from the water body diffuses to the sensor in electrochemical dissolved oxygen sensors through an oxygen-permeable membrane. The sensor reads the electrical signals produced by the chemical reduction reaction taking place inside it with the NaOH solution (Menon & Prabhakar 2021).

The two primary types of water DO monitor sensors at the moment are polarographic and optical. The Clark DO electrode serves as the foundation for most polarographic DO sensors. The rate at which molecular oxygen diffuses through the film affects the DO in water. Simple and less disruptive is this approach. However, the polarographic DO sensor has a limited lifespan and requires frequent upkeep. The fluorescence quenching action of oxygen for fluorescent materials serves as the foundation for the optical DO. Fluorescence intensity or fluorescent lifespan is used to calculate the DO in water. This technique is immediately repeatable and photochemically stable. Additionally, the optical DO sensor offers great accuracy and a prolonged remaining useful (Ma & Ding 2018).

The data gathered by the pH detection sensor and the dissolved oxygen sensor are first converted into a current signal through a conditioning circuit, after which it is converted into a voltage signal by a current/voltage converter and sent to the single-chip microcomputer. The temperature, pH, and dissolved oxygen data gathered by the single-chip microcomputer are used to manage the water quality parameters, as well as data upload and host computer display. The circuit can be used to automatically modify and manage the temperature and, at the same time, the alarm device will send SMS if an abnormality happens and it is determined that the temperature and pH value of the water quality environment exceed the parameter threshold. The system device will automatically turn on the oxygenation pump to provide oxygen promptly when dissolved oxygen levels are abnormal, enabling automatic monitoring and control of the environmental parameters of aquaculture. It will successfully change the environment's water quality (Chunxia & Qiuchan 2020).

(iv) Nitrite ion sensor. Special nitrite ion selective electrodes are used by nitrite ion sensors to measure the concentration of nitrite ions in an aqueous solution or body of water (Pellerin *et al.*, 2013).

The biosensing approach is a straightforward way to find nitrates in water. To quantify the concentration of the desired ions in a sampling solution, biological materials are combined with a detection system and a signal-conditioning circuit in biosensing systems. To determine the concentration of the sample, the biosensor and sensing material is immediately exposed to the sampling or analyte solution. The biological substance interacts with the target ions to exchange information. To measure from the sensor system, the interaction process must be turned into an electrical signal, such as voltage, current, or impedance. The biosensing technique determines how the sensing signal is converted (Alahi & Mukhopadhyay 2018).

(v) Ammonium ion sensor. To determine the ammonium ion concentration in a given solution or body of water, an ammonium ion sensor is utilized. Ammonium ion sensors typically use Ag/AgCl electrodes with a customized filling solution (often bromide in oxidised form) to interact only with ammonium ions (Menon & Prabhakar 2021).

To measure the ammonia content of water, an ammonia electrode was chosen. The ammonia electrode is a composite electrode with a silver-silver chloride electrode serving as the reference electrode and a pH glass electrode as the indication electrode. Place the electrodes inside a plastic sleeve that has a gas-sensitive film and is filled with 0.1mol/L ammonium chloride liquid. If you add ionic strength to the aqueous sample solution, the pH may be raised to 11 or higher, converting ammonium salts to ammonia, which will then diffuse across the membrane. Ammonia causes the balancing equation to shift to the right, and as a result, the pH value increased. The pH glass electrode finally recorded value variations. The ammonia concentration and electromotive force recorded in water samples satisfy the Nernst equation at constant ionic strength, temperature, nature, and electrode parameters. Finally, to determine the concentrations of the unknown samples, create a standard curve using the voltage signal that was measured (Huang *et al*., 2018; Zhang *et al*., 2013).

B. Intelligent Aeration System

Aerators are devices used in the aquaculture sector. When the aerator is running, the water is stirred through the impeller to incorporate more oxygen from the air into the water (Deng *et al.*, 2019). Equipment that can precisely measure and regulate the DO in water is referred to as an intelligent aeration system (Huan *et al*., 2020). The intelligent aerator can keep an eye on the DO, air pressure, humidity, and temperature of the water. At the same time, it may capture scene data through video surveillance and transfer it to a cloud platform so that the aerator can be precisely controlled (Wang *et al.*, 2021).

The aerator will monitor and show on LCDs placed outside the pond the pond's temperature, salinity, and oxygen levels. The device has a DO sensor fitted underneath it to gauge the water's oxygen content. attached to the microcontroller is a DO sensor. The sensor will send a signal to the microcontroller to turn on the aerator when the DO state gets close to the tolerance limit. To measure the temperature of the water, a temperature sensor is also placed under the device. The aerator will automatically turn on when the temperature falls below the ideal level. When the measured port of the sensor is in perfect condition, the aerator will automatically shut off. The aerator's motor is a 1/2 HP AC motor. Installed outside of the pond, the sensor measurement, including salinity level, was also relayed to the pond guard by SMS and LCD (Rahayani & Gunawan 2018).

Designing an autonomous controlled aeration device system with solar panel technology as an energy source is the goal of this project. This system makes use of a DO sensor to monitor the controlled oxygen levels, and the findings are subsequently shown on the LCD. To decide whether to turn on or off the aerator engine, the data will be processed. A gadget coupled to a sensor continuously regulates the aerator engine's activity. Dissolved oxygen levels will be continuously measured by the sensor and shown on the LCD. The automation response system test and a power resistance test based on the load of the electronic circuit are the tests performed on this tool. In the automatic system setup, the aerator engine will shut off when the DO value exceeds 6.86 mg/L and restart when the DO level is below 5.20 mg/L. Electronic circuit loads can be powered by solar panel electrical devices with a capacity of 10 WP, 10 A controllers, and a 12 V, 7 Ah battery. System evaluation demonstrates that the system is operating as intended (Kusumah *et al*., 2020).

C. Automatic Feeding System

Up to 80% of the overall cost of aquaculture is made up of the cost of the bait. The secret to maximizing the profit from aquaculture is to figure out how to lower feed costs. Currently, the method for delivering bait is primarily reliant on the fish's growing conditions and breeding history, which makes it difficult to produce proper bait feeding and makes it very simple to cause fish underfeeding, bait waste, and water pollution. The current bait-casting devices don't provide input on the fish's feeding status. Real-time feeding amount adjustments can be made by providing the control system with the evaluation findings of the bait-feeding impact. A regression fitting analysis approach is used to build a mathematical equation connected to the nutrient requirements of fish growth and the amount of feed. The artificial experience model is typically based on a significant amount of observation experience in aquaculture. The ratio of the fish's body mass or length determines how much feed is needed (Sun *et al.*, 2016).

In certain developed nations, like Norway, Japan, and the United States, automatic feeding systems have reached the application stage and have enabled precise control over the feed distribution, storage, and transportation chains. The management system, online monitoring system, and feeding module make up the net cage automatic feeding system created by the Norwegian fishery equipment firm. The online monitoring system can simultaneously track the number of aquaculture water parameters, including pH, DO, and temperature, and communicate feedback data to the management system to enable automatic bait feeding (Wang *et al.*, 2021). The Arvo-Tec firm in Finland created a robot feeding control system that uses a web interface to enable remote feeding control, water quality enhancement, and precision feeding (Arvotec, 2021).

(i) Automatic Feeder. An automated feeding device known as an automatic feeder allows shrimp farmers to programme feed time and quantity using digital control. This machine is equipped with a microcontroller that controls the gadget. The feeding mechanism used in shrimp farming is operational both day and night. It is possible to pre-set different feeding rates for different hours of the day and night. It aids in avoiding the use of labor at night. It also includes a control panel that may be conveniently positioned indoors. This system adjusts the amount of feed delivered to the shrimp by moving the feed bowl lid to open or close in accordance with the quantity and time settings. The feed bowl is fitted with a sensor as well, and if the stock feed height is less than one-fourth of the height of the bowl, the microcontroller will tell the user through SMS that the feed is available (Rahayani & Gunawan 2018).

(ii) Acoustic Feeding System. Current applications of acoustic automatic feeders, which use passive acoustic principles to distribute feed in ponds, can be found in Ecuador and Southeast Asia, two regions with significant penaeid shrimp production. Such systems offer a number of advantages over conventional feeding regimens that rely on the use of feeding trays. By ensuring feed is given when shrimp are most likely to ingest it, acoustic feeders assist in reducing feed waste (Ullman *et al.*, 2019).

The hydrophone transmits signals to the controller, which is either on the feeder or the shore, and records the pond's ambient sounds. In the following step, the controller evaluates the relative feeding activity and automatically modifies the feeding ratio. Regularly, acoustic and feeding data are transmitted to a computer in the farm's office (Tailly *et al.*, 2021).

(iii) Computer Vision Feeding. Traditional fish feeding decisions are primarily based on knowledge and straightforward time management. The majority of earlier research has been on the image-based analysis of the residual feed at the bottom of the pond to decide whether to keep feeding or quit. However, there is little chance that such a technique would work in a real outdoor aquaculture pond. The primary causes of this include the muddy water quality, small feed targets, interference from high fish activity, overlapping images of fish and feed, etc. that are present in actual outdoor aquaculture ponds. Therefore, it is difficult to use image-based recognition in practical outdoor aquaculture. The suggested system employs deep learning technology to recognize the size of the waves produced by fish eating feed to decide whether to continue or stop feeding, in contrast to conventional computer-vision-based methods for identifying fish feed underwater. Additionally, a number of water quality monitors are used to aid with feeding choices. In order to determine whether to continue casting feed or to stop feeding, the suggested system makes use of deep learning technology to recognize the magnitude of the water waves created by fish eating feed (Hu *et al.*, 2022).

D. Biomass Estimation

One of the most frequent and significant techniques in aquaculture is the estimation of fish biomass. To optimize daily feeding, manage stocking densities, and eventually choose the best time for harvesting, managers urgently need to regularly collect information on fish biomass. However, because fish are sensitive and move freely in an environment where visibility, lighting, and stability are uncontrollable, it is challenging to estimate fish biomass without human involvement. Fish biomass assessment has traditionally relied heavily on invasive, time-consuming, and labor-intensive manual sampling. Therefore, the creation of a non-intrusive, quick, and economical method is essential and highly desirable. Environmental DNA, acoustics, machine vision, and resistivity counters have the potential to create non-intrusive, quicker, and less expensive techniques for in situ assessment of fish biomass (Li *et al*., 2020).

(i) The Visible Counter System. The pixel-level visual information provided by a monocular camera or stereovision system using visible light can then be used to extract and analyze quantitative data for object recognition, which has the potential to enhance human vision by electrically perceiving and comprehending an image. Image acquisition, image processing, and statistical analysis processes are frequently included in a conventional machine vision system. It has been widely utilized in aquaculture for the past 20 years as a non-invasive and economical technology, with three of its main uses being fish mass measurement, counting, and direct fish biomass estimation (Serna & Ollero 2001; Martinez-de Dios *et al*., 2003).

A crucial factor during various growth phases is fish size, which includes length, area, width, and perimeter. It is feasible to estimate fish mass by size due to machine vision, which provides an automated and precise method for evaluating size. As of today, weighting has been the most often used method of estimating fish mass, which is time-consuming, expensive, difficult, invasive, and results in poor consistency. The fish farming sector is therefore very interested in autonomous and non-intrusive mass measurement techniques (Viazzi *et al.,* 2015).

(ii) The Infrared Counter System. The wavelength of infrared light also referred to as nonvisible light, ranges from 760 nanometers to one millimetre. Machine vision based on infrared light has rapidly improved thanks to advancements in computer technology, and it has been used to count fish in aquaculture. It offers a very straightforward, non-intrusive way of counting fish and analyzing behavior that is crucial in the development of an accurate method for estimating fish biomass. Fish counters and near-infrared (NIR) cameras are part of infrared-based machine vision systems that estimate fish biomass (Shardlow *et al*., 2004).

(iii) Acoustics Based System. Since acoustic waves can travel farther through water than light waves can (Martignac *et al.,* 2015), they are the most effective form of remote item detection and identification. The use of acoustics as a distant sensing technique has grown quickly with the advancement of acoustics technologies, especially in protection zones. Recently, acoustics has been widely used in species detection, fish stock assessment, spatiotemporal distribution behaviors, and species detection without stressing fish (Zare *et al.,* 2017).

E. Health and Welfare Monitoring

The main factor contributing to an increase in mortality in fish farms is fish diseases. To stop the disease from spreading, unhealthy fish must be automatically identified in the early stages. Several problems with fish disease diagnosis require a high level of skill to be fixed. Early diagnosis of fish diseases is made possible by recognizing aberrant behavior in fish. Fish trajectory analysis in movies is used to assess fish activity. Environmental changes may be the cause of anomalies (Waleed *et al.,* 2019).

In recent decades, expert systems have been used to identify fish diseases, allowing for a limited diagnosis of specific aquaculture. However, this approach requires aquaculture experts and professionals. The effectiveness and speed of diagnosis are also constrained. Therefore, it is imperative to create a novel rapid, automatic, and real-time diagnosing approach. The accurate detection of fish diseases is made possible by the intelligent integration of image processing and computer vision technology. Although there are numerous methods for identifying pathogens and diagnosing diseases, there is still room for improvement in terms of speed and accuracy. The accuracy and speed of fish disease diagnosis will be improved by creating 3D images of fish diseases, using common and shared datasets, deep learning, and data fusion techniques (Li *et al*., 2022).

(i) Image-Processing Technology. Aquaculture has used image processing technology for a variety of purposes, including weighing and measuring fish, counting fish, classifying fish, and identifying fish diseases. However, due to the complexity of fish survival conditions, the variety of fish diseases, and the heterogeneity of symptoms, fish disease diagnosis could be difficult. To enable the computer to precisely diagnose and identify fish ailments, image-processing technology tries to produce images of greater quality and clarity or to remove undesirable fuzzy data. Image acquisition, picture pre-processing, image segmentation, feature extraction, target detection and recognition, and classification are the primary processes covered by image-processing technology (Awalludin *et al.,* 2020).

(ii) Intelligent Diagnosis Method of Fish Diseases Based on Images. Fish disorders can also be caused by various common physical phenomena and chemical agents, in addition to common pathogens such as parasites, fungi, bacteria, and viruses. Fish health could be stressed by changes to the aquatic environment. By spotting changes in hosts, infections, and the environment, images can be utilized in aquaculture to identify fish diseases. Most studies to date have demonstrated that identifying hosts relies primarily on changes to the fish's surface while identifying infections relies primarily on changes to the fish's interior tissues, such as deformation, necrosis, decay, and bleeding. However, pathogen detection techniques can only detect them in broad strokes. Fish pathogens come in a wide variety of kinds, and biochemical pathogen-detection techniques are typically required for pathogen identification. High-quality photos are required for the accurate diagnosis of illnesses. The quality of fish photographs is first enhanced using image-processing technologies, and then high-quality images are used for segmentation, detection, and identification. Lastly, fish categorization is used to diagnose fish illnesses (Li *et al.,* 2022).

F. Future Interventions – Underwater Surveillance System

Data collection on water quality, water impurities, water temperature, fish behavior, and current/wave velocity is needed for management and surveillance operations at aquaculture farms, which is labor-intensive and expensive. Technologies for unmanned vehicles make it easier and more accurate to carry out these tasks. When fitted with sensors and other technologies, they can even detect cages and monitor illegal fishing (Ubina & Cheng 2022).

Drones work well for surveys and frequently have used both above and below the surface of the water. These devices are used both above and below the sea to manage and monitor the water and its quality, to keep an eye on offshore farms, and to inspect cages by gathering data on cage damage and holes. They can gather data for environmental tracking and fish stock research, which might be utilized to track production. Drones allow for analyzing data for monitoring and decision-making when combined with robotics and sensor devices. Drones employ sensors to gather information on the physical and chemical characteristics of water, including its pH, salinity, turbidity, dissolved oxygen content, and other sorts of contaminants. Algorithms that advance the technology or applications used in the production of aquaculture and offshore fish farms can be developed using drones. This underwater drone can be used to collect and analyze data by connecting to a producer's tablet, smartphone, or computer. Additionally, fish growers can utilize these tools to spray chemicals, maintain water and nutrient flow, and make judgments using aerial photos (Pathak, 2017).

(i) Unmanned Vehicle System Platforms. Unmanned vehicles can lower operational costs while increasing mission safety and repeatability. The duties carried out by unmanned vehicles are frequently too risky or expensive for people to complete. They are also given tasks that are straightforward yet repetitious and less expensive to perform without people. There are now more affordable off-the-shelf systems available, but many still need to be customized to satisfy the unique monitoring and management needs of aquaculture (Nichols *et al.*, 2020).

(ii) Unmanned Aircraft Systems (UAS). An alternate platform that addresses the drawbacks of manned-aerial surveys is provided by unmanned aircraft systems (UAS) or unmanned aerial vehicles (UAVs). To avoid data loss or deterioration during transmission, UAS should be compact, powered by an electric motor, simple to use, and reasonably priced. They should also record and store data onboard. UAS should communicate data using its wireless capability for real-time monitoring. Since they are pilotless aircraft, they can fly in hazardous areas that are inhospitable to people. They have sensors, like cameras that fly into the sky to observe the target interests, for surveillance and monitoring. UAVs with cameras fitted can also collect data and transfer it to a repository system. Recent advancements in UAS technology also offer safer missions and longer flying times. Although UAS have a lot of potential for monitoring aquaculture, their effectiveness still depends on a number of different elements, including the aircraft's flight capability, the type of sensor they use, their intended use, and any applicable regulatory constraints (Nichols *et al*., 2020).

(iii) Remotely Operated Vehicles (ROVs). Underwater drones of the twenty-first century resemble tiny submarines without any humans inside. They are capable of operating independently thanks to the onboard sensors. Deep undersea exploration has started to change thanks to remotely controlled and autonomous vehicles, which frequently return data for additional analysis. These drones can be improved and tailored to specific needs. Fiber-optic cables buried deep beneath ocean water transmit a significant amount of data, and this needs to be monitored constantly. We have created an underwater surveillance drone that can do water quality tests to gather information about the water quality from various water bodies. To determine the ideal environment for aquaculture and drinking water supply, they comprise pH tests, turbidity tests, and temperature measurements (Choudhari *et al.*, 2021).

Finfish farming is difficult because biofouling can affect the integrity of the cages and the health of the fish. Current anti-biofouling solutions, among others, mainly rely on removing biofouling via in-situ pressure cleaning of nets. The cleaning waste is discharged into the water, where it may hurt the welfare of the farmed fish. Tethered underwater robots are currently being used to investigate grooming, and the routine cleaning of nets to prevent the emergence of biofouling populations. Additionally, stationary sensors at the farm barge are used to extrapolate on environmental conditions in the net pens while remotely operated vehicles (ROVs) are used to inspect the net to maintain its integrity and prevent fish escapes (Ohrem *et al.*, 2020).

CONCLUSIONS

Even though aquaculture has been practiced for 4,000 years, the sector is still new and expanding. This industry is majorly dependent on manual operation, high feed cost, disease risk, and labor requirement which has resulted in higher production cost per capita. However, modern internet-based technology and the use of autonomous machinery cannot only decrease the cost of production for farmers but also has less of an impact on the environment which will lead to economic gains for the farmers. Modern internet-based technology and autonomous machinery will also contribute to the long-term sustainability of the aquaculture industry.

FUTURE SCOPE

- Disease Detection and Management: AI algorithms can analyze large datasets, including water quality parameters, environmental conditions, and fish behavior, to detect early signs of diseases in aquaculture systems. This early detection can help farmers take preventive measures, reducing the impact of diseases on fish health and overall production (Bautista *et al.*, 2019).
- Feed Optimization: AI can optimize feed formulation and feeding practices by analyzing factors such as fish growth rates, nutrient requirements, and environmental

conditions. Machine learning algorithms can learn from historical data and adjust feed formulations in real-time, leading to improved feed efficiency and reduced environmental impact (Sarker *et al*., 2020).

- Water Quality Management: AI-based systems can monitor and control water quality parameters such as temperature, dissolved oxygen, pH levels, and nutrient concentrations. Machine learning algorithms can analyze the data collected from sensors and provide recommendations for adjusting water quality parameters, optimizing conditions for fish growth and minimizing the risk of environmental stress (Bautista *et al*., 2019),
- Autonomous Aquaculture Systems: AI-powered robotics and automation can be utilized for tasks such as fish feeding, monitoring, and cleaning. Autonomous underwater vehicles and drones equipped with AI algorithms can collect data from aquaculture systems and perform tasks efficiently, reducing labor requirements and increasing operational efficiency (Lane *et al*., 2018).
- Decision Support Systems: AI can assist farm managers in making informed decisions by integrating data from various sources, including environmental data, fish health records, and market trends. AI models can provide real-time insights and recommendations for optimizing farm operations, improving productivity, and reducing risks (Sarker *et al*., 2020).

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