Research Review

© 2024, Centre for Advanced Research in Agricultural Sciences
Research Journal of Agricultural Sciences
Volume 15; Issue 03 (May–Jun 2024); pp 665–671

ISSN: 0976-1675 (P)
ISSN: 2249-4538 (E)

Application of Digital Technologies in Aquaculture

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Received: 24 Dec 2023; Revised accepted: 20 Apr 2024

Abstract

Aquaculture, as a vital component of global food production, faces pressing challenges in meeting the growing demand for food while ensuring environmental sustainability and resource optimization. To address these challenges, the integration of emerging digital technologies, including the Internet of Things (IoT), Unmanned Aerial Vehicles (UAV), Artificial Intelligence (AI), Machine Learning (ML) and Robotics, has gained considerable momentum in the aquaculture industry. By utilizing the real-time data insights from IoT, the aerial capabilities of UAVs, and the intelligent decision-making of AI and ML, aquaculture farmers can adjust their practices for optimal outcomes. The combined utilization of these technologies empowers aquaculture farmers with data-driven decision-making capabilities, promoting sustainable practices and minimizing environmental impacts. As technology continues to advance, the potential for further innovation in these fields promises to drive significant advancements in aquaculture practices, fostering a resilient and thriving industry for the future.

***Key words*:** Internet of things, Unmanned aerial vehicles, Artificial intelligence, Machine learning, robotics

Aquatic animals are an important source of protein and micronutrients, such as essential vitamins and minerals that are necessary for a healthy diet [1]. Among these, fish is an excellent source of high protein foods and omega 3 fatty acids needed to handle the body's crucial nutritional deficiencies. Aquaculture is more diverse than other agricultural industries in terms of species, production processes, feeds, ailments, products, business structures, and marketing [2]. Aquaculture is the act of breeding, rearing, producing, and harvesting aquatic inhabitants like fish, molluscs and crustaceans in a highly dynamic structure with intricately interrelated physical, biological, and economical settings. Therefore, fish farmers and enterprises must make a number of decisions each day to navigate the complex issues and influencing factors that determine the final fish yield, productivity, and profit margins [3]. As a result, a crucial component of the welfare of aquaculture processes is the monitoring of behavior and growth status of fishes [4]. Fish monitoring at various stages not only boosts productivity and earnings but also lowers the danger of serious failure and spinal deformity caused by illnesses and stressful situations [5]. Conventional aquaculture practices require a lot of human involvement and intelligence, which requires time, adds to labor costs, and creates regulatory concerns [6]. For instance, numerous water quality parameters like dissolved oxygen (DO), temperature, salinity, ammonia, pH and feed input, and diseases must be continuously monitored to foresee and prevent disasters like unexpected fish mortality and slow growth rate [7]. Therefore, for fish monitoring across a range of depths and habitats, standardized, affordable, and highly trustworthy monitoring techniques are absolutely essential [8].

The global agri-food industry is confronted with massive challenges caused by changes in dietary patterns, shifting demographics, climate change adaptations, unstable national and international markets, diverging wages, and emerging technologies across the world [9]. The sector is therefore under more pressure than ever to innovate in order to increase profitability and sustainability, which can be made possible by digitalization [10]. The Smart aquaculture management systems (SAMS) are therefore currently working to reduce the amount of human involvement while successfully controlling all the parameters remotely [11-12]. Smart aquaculture, also known as digital aquaculture, refers to the application of cutting-edge technologies and data-driven strategies to increase the productivity, sustainability, and efficiency of aquaculture operations [13-14]. In order to monitor and run aquaculture systems effectively, smart aquaculture aims to include modern technologies into the system [15]. Currently, a variety of data collection and processing technologies are available to enable fully monitored fisheries and precision aquaculture, including high-resolution satellite imagery, automatic identification systems, big data, *in situ* multiple sensor networks, artificial intelligence, machine learning and the Internet of Things (IoT) [16-17].

Internet of things (IoT)

IoT refers to the ever-expanding networks of physical objects (sensors and data loggers) connected via IP addresses and communicating with other internet-enabled systems and devices, such as computer/mobile to wireless sensors via software [18]. The IoT technology makes it possible for objects to be sensed and controlled across existing networking infrastructures and opens up opportunities for much greater direct integration between computer-based systems and the real world. This leads to increased efficiency, accuracy, and financial gains in a number of fields, including aquaculture,

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Citation: Pegu M, Singh MK. 2024. Application of digital technologies in aquaculture. *Res. Jr. Agril. Sci.* 15(3): 665-671.

agriculture, environmental management, energy, infrastructure management, and transportation [19]. IoT is a useful tool for tracking various environmental factors in aquaculture ponds and providing on-site guidance for the best remedies to unfavourable environmental conditions [20-21]. The system is composed of numerous components that enable it to carry out several tasks, including sensing, identification, actuation, communication, and management [22]. Thus, it is feasible to connect big data throughout the aquaculture sector [23]. The most basic architecture of IoT is three layered model consisting of perception layer, network layer and application layer [24]. Sensors in the perception layer enable IoT systems to collect quantitative environmental data [25]. It features a variety of sensor devices as the system's input components, including temperature, DO, conductivity, and pH sensors [26]. The Arduino Uno board is connected to each sensor. Arduino is an open-source, programmable microcontroller-based electronic tool frequently used to create low-cost electronic sensors and actuators [27]. IoT devices are linked to a Wireless Sensor Network (WSN), via which all network communication takes place [28]. The application layer is the platform that introduces Application Programming Interfaces to link people with the core of IoT devices [29]. The majority of IoT systems are used for monitoring factors that affect water quality, including dissolved oxygen, temperature, pH, alkalinity, and nitrate levels [30-31].

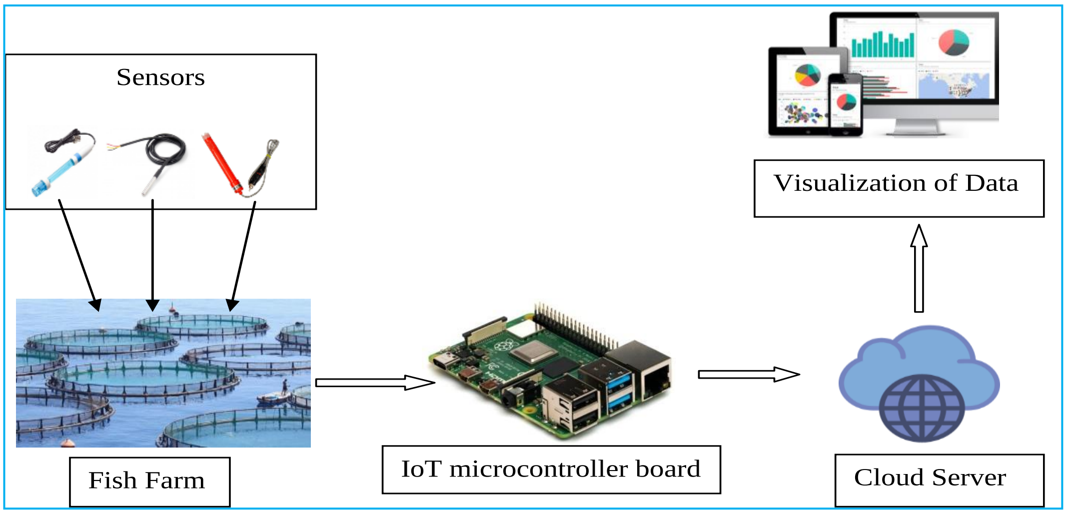

Fig 1 Schematic representation of IoT based aquaculture system

Unmanned aerial vehicles (UAVs)

Unmanned aerial vehicles (UAVs), also referred as drones, are frequently utilized and have attracted much interest recently [32]. UAVs are controlled aerial vehicles that carry out a variety of tasks autonomously through various electronic devices like microprocessors and sensors [33]. UAVs can monitor the environment, access isolated or hazardous locations, and obtain high resolution images [34]. There are various types of UAVs, including fixed-wing, single-rotor, fixed-wing hybrid, and multi-rotor UAVs [35]. Due to its accessibility and affordability, it has recently found widespread use in aquaculture for maintaining and monitoring fish [36]. Drones can now successfully gather environmental data and observe fish behaviour at an aquaculture site [37]. They have sensors like cameras that fly into the sky to keep an eye on the target of interest for surveillance and monitoring [38]. Installed cameras in UAVs can also collect data and send them to a repository system. Combining accelerometers, tilt sensors, and gyroscopes allows UAVs to identify their flight location and orientation [39]. The drones gather data, which are subsequently sent to the cloud for use by computer vision and deep learning applications. Users can learn about the aquaculture farm's conditions from the processed data [40]. The use of UAVs allows researchers to examine a variety of fish behaviours, including schooling [41], swimming [42], tracking [43], stress response [44] and feeding [45-46]. An autonomous drone undertakes visual surveillance in the work of Ubina *et al*. [47-48] to observe fish feeding activities, detect nets and cages, and detect suspicious things (human beings, ships). Drone-collected video from the aquaculture site can be used to calculate fish density, fish count, and fish growth [49-50]. This data can then be sent to the cloud for processing and data analytics to generate predictions or estimations [51]. The detection of illicit fishing activity is now possible with submersible drones and UAVs [52].

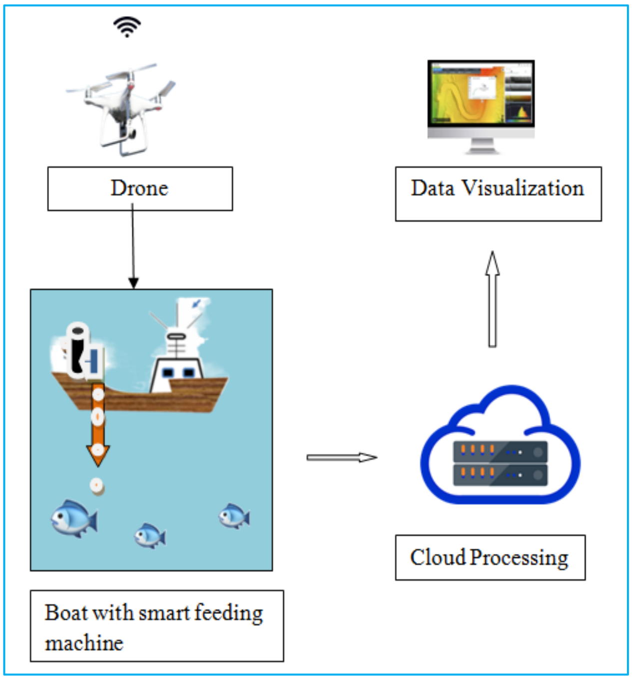

Fig 2 Schematic representation of aquaculture monitoring by drones

Artificial intelligence (AI) and machine learning (ML)

Artificial intelligence (AI) refers to systems that perform cognitive tasks similar to those performed by humans, including recognition of various types of meaning and comprehension of situations [53]. It is a computational, data-driven technology capable of handling activities that typically account for human intelligence [54]. The process to implement AI in aquaculture calls for the acquisition and management of data, processing of data as well as a decision-making system [55]. Aquaculture production may be raised quickly with AI since it reduces the need for manpower and makes the industry less labor-intensive [56]. Several research organizations and aquaculture technology start-ups are currently researching and utilizing AI to make choices that are better and quicker. Fishing activity has a wide range of AI applications, from assessing the economics of commercial fleets [57] to electronic catch and bycatch monitoring [58], from identifying and forecasting fishing grounds [59] to simulating fishing vessel behaviour [60]. Under diverse benthic backdrop and illumination circumstances, fish are reliably detected and counted using AI technology [61]. AI is used to track fish using motion algorithms that are based on successions of images that contain individual or multiple fish [62]. The various parts of artificial intelligence systems that have been trained to recognize fish behavior are all interconnected in branching streams of mathematical and statistical processes [63]. Fish behaviors that can be detected by AI include feeding movements at the individual and school level, feeding intensity [64], abnormal behaviors brought on by low oxygen levels or stress responses [65], and curiosity by displaying inspection behaviors when interacting with bait or objects in an experimental setup [66].

A subset of AI, machine learning (ML) involves the usage and creation of computer systems that learn and adapt without being given explicit instructions. This is done by analyzing data patterns using statistical models and algorithms [67]. The primary goal of machine learning is to develop mathematical models that improve system performance in computers by solving problems that are based on algorithms and learning data [68]. The four forms of machine learning structures are supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning, with supervised learning being one of the most frequently used [69]. Machine learning is used in a variety of aquaculture applications, including fish recognition [70], Fish count [71] sex identification [72], fish species classification [73], fish biomass detection [74], size estimates [75], weight estimates [76], age detection [77], feeding behavior [78].

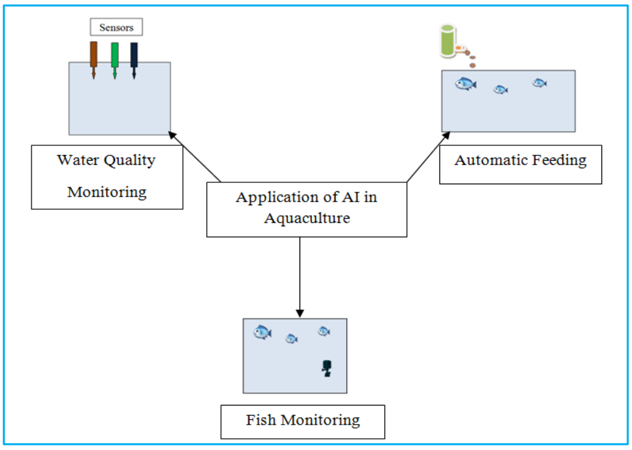

Fig 3 Schematic representation of application of AI in aquaculture

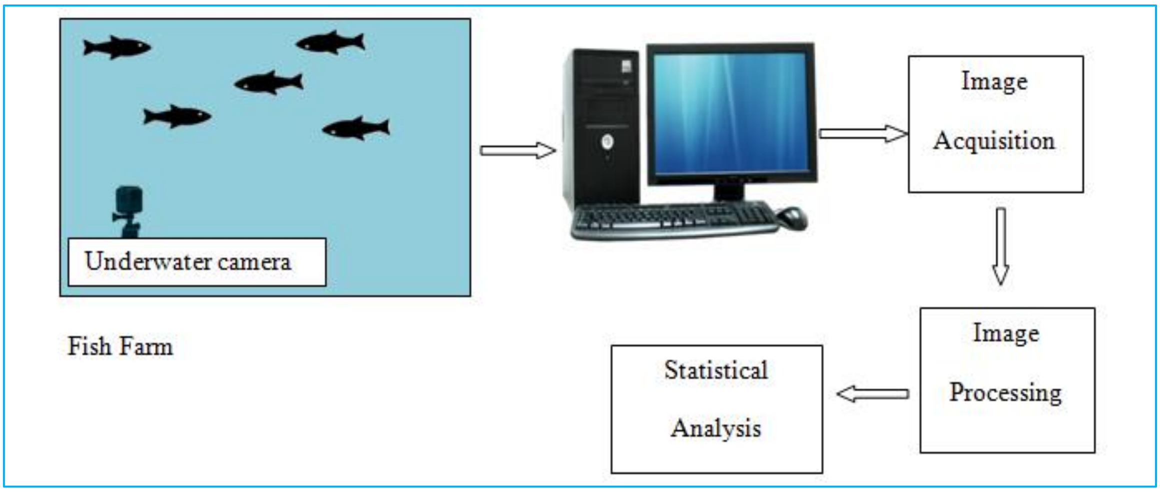

Fig 4 Schematic representation of machine learning in aquaculture

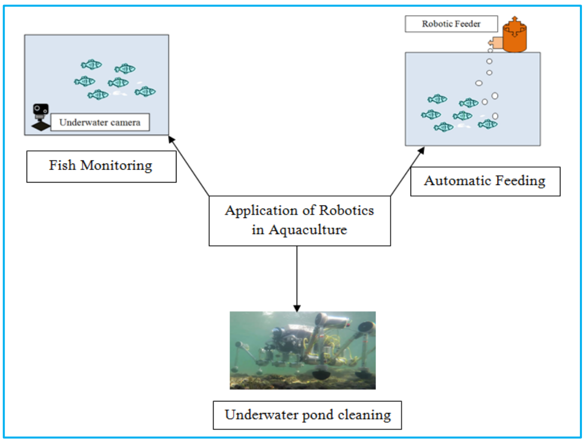

Fig 5 Schematic representation of application of robotics in aquaculture

Robotics

The field of robotics is concerned with the creation, maintenance, and use of robots [79]. Due to their ability to work continuously without disruptions in challenging environments and without the need for human support, robots can increase the profitability of aquaculture [80]. Robots can be used in aquaculture for various tasks, including feeding, cleaning ponds and nets [81], injecting vaccines [82], and removing diseased fish [83]. The computer vision techniques employed in the estimation of fish could be implemented using robotic devices for fish feeding and underwater pond cleaning [84]. Ogunlela [85] built a low-cost automatic fish feeder composed of a hopper (stainless steel), a feed platform, a bi-directional motor, and an electrical control box. Automated underwater robots have already been utilized in the salmon industry to inspect and clean the condition of nets, reducing the need for human operations [86]. Robots have also been employed to monitor, survey, and prevent the escape of farmed fish [87]. Robots can be used to monitor fish behaviour in real time [88].

CONCLUSION

Aquaculture is under increasing pressure to meet its essential role of providing high-quality protein to fulfill the continuously expanding world population. Even though aquaculture is more varied than other agricultural sectors, the industry nevertheless faces substantial obstacles that can be overcome with the use of digital technologies. The use of new digital technology in fisheries has gradually led to the intensification and intelligence of fishery farming worldwide, and the aquacultural environment has gradually changed to a sustainable fishery farming system, which has greatly increased aquaculture's efficiency. It is a challenging process to incorporate numerous technologies into different aquaculture systems, necessitating the use of a variety of different types and amounts of aquaculture equipment, such as oxygen enrichment facilities, feeding equipment, various types of sensors, and water treatment equipment. The IoT platform can assist researchers in developing various decision support systems for precise scheduling and monitoring of changing aquaculture pond characteristics that affect the output yield. One of the most often employed AI drones in aquaculture to check the water quality of fish farms is the UAV system. By monitoring the movements of fishing vessels, the use of fishing gear, and fish stocks, machine learning systems can forecast and quantify fishing activities with unprecedented spatial and temporal precision. Robotics can help to boost efficiency and productivity while also improving accuracy and effort. Even though robots, drones, and sensors enable rapid and real-time data collection, it is still highly difficult to use the collected data to make the right decisions due to the vast amount of data, this problem can be tackled by AI to make better and faster decisions. Aquaculture is experiencing a transformation through the integration of cutting-edge technologies such as the IoT, UAVs, AI, ML and robotics. IoT devices equipped with sensors are deployed throughout aquaculture facilities to monitor crucial parameters like water quality, temperature, dissolved oxygen levels, and feeding patterns. This real-time data is fed into AI and ML algorithms, enabling predictive analytics and data-driven decision-making. AI-driven automated feeding systems precisely dispense feed based on fish behavior and growth patterns, optimizing nutrition while minimizing waste. Robotics plays a vital role in aquaculture by automating various tasks, such as cleaning tanks, monitoring fish health, and conducting underwater inspections. Additionally, UAVs equipped with cameras and sensors are employed for aerial surveys, providing valuable insights into large-scale fish farms and environmental conditions. Machine learning algorithms process the data gathered by UAVs, enabling the identification of potential problem areas and enhancing disease detection. The synergy of these technologies leads to significant advancements in aquaculture management and sustainability. By leveraging these technologies, fish farmers can optimize production systems, improve disease prevention and early detection, and enhance supply chain traceability. Ultimately, these technological innovations are reshaping the aquaculture industry, fostering higher yields, reducing environmental impacts, and meeting the growing global demand for sustainable food.

Conflict of interest

Conflict of interest declared none by the authors.

Acknowledgement

Authors are thankful to Department of Life Sciences, Dibrugarh University for providing necessary facilities to carry out this review work.

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