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Review Article

Smart approaches to Aquaponics 4.0 with focus on water quality – Comprehensive review

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ABSTRACT

The fast growth of the world population associated with the ever-increasing need for food and the significant contribution of agriculture to anthropogenic global warming is driving the changes from conventional farming approaches to innovative and sustainable agriculture ones. One of these approaches is aquaculture which is founded on the principle of circular economy combining aquaculture and hydroponics in symbiose with aquaculture waste serving as nutrients for plant growth. Conventional Aquaponics has evolved to Aquaponics 4.0 with a fully automated and remote-controlled system for producing foods at an industrial scale. The implementation of the Internet of Things (IoT) and Artificial Intelligence (AI) could simplify farmers' tasks with remote operations while allowing them to achieve automatic and precise control of inputs and outputs as well as to improve the overall efficiency of the system. This review focuses on the use of these smart technologies to analyze, monitor, and maintain good water quality and appropriate replenishment in Aquaponics systems. The identified research gap and future possible contributions in this area are also discussed.

1. Introduction

Producing food for the growing population with the limited available resources is one of the key global challenges. Aquaponics is an innovative and sustainable agricultural approach that combines fish and soilless plant production in a recirculating ecosystem where natural bacteria convert fish waste into plant nutrients (Delaide et al., 2017). The plants take up the nutrients from the water to grow whilst purifying the water which returns to the fish tanks. Fig. 1 shows a coupled aquaponic system with (1) aquatic organisms, (2) bacteria, and (3) plants that benefit from each other in a closed recirculated water body (Goddek et al., 2019). This symbiotic water and nutrients recirculating system contributes to reducing food production inputs such as water, and fertilizer and eliminating the use of pesticides. Based on the World Bank, (2022) estimation of 70 % agricultural expansion by 2050, even more resources and water will be required since agriculture currently uses an average of 70 % of global freshwater with up to 90 % available water consumption in some regions, such as North Africa and the Middle East zone (El-Beltagi et al., 2022). Recirculating aquaculture systems were developed for intensive fish farming where up to 99 % could be recycled and thus less than 10 % water replacement per day (Lunda et al., 2019). However, as highlighted in Fig. 1, the water containing waste products of the fish serve as nutrients for the plant which in combination with the nitrifying bacteria constitute a biological water filtration unit where toxic materials such as ammonia, nitrates, and nitrites are stripped off before the freshly cleansed water is recirculated back into the fish tank (Diver and Lee, 2010, Suhl et al., 2016, Goddek et al., 2019). Therefore, water plays a vital role in maintaining the equilibrium between fish life, plant life, and living microorganisms in an Aquaponics system (Goddek et al., 2019). Water quality parameters such as temperature, dissolved oxygen, carbon dioxide, ammonia, nitrate, nitrite, and pH should be constantly monitored since any accumulation above their critical values will be detrimental to fish and vegetable growth. Indeed, although the biofilter system converts toxic ammonia to nitrite and less toxic nitrate it has been reported that high concentrations of nitrate can also harm fish (Freitag et al., 2015). An appropriate design and water replenishment could allow plants to take up most of the nitrates or reduce their concentration to maintain the balance of the system.

Industry 4.0 in Aquaponics has been growing at a rapid pace. Aquaponic industries use smart technology mainly in aquaponic plant

Abbreviations: APS, Aquaponic System(s); IoT, Internet of Things; DO, Dissolved Oxygen; ML, Machine Learning; DL, Deep Learning; PPM, Parts Per Million; pH, Potential Hydrogen; TAN, Total Ammonia and Nitrogen.

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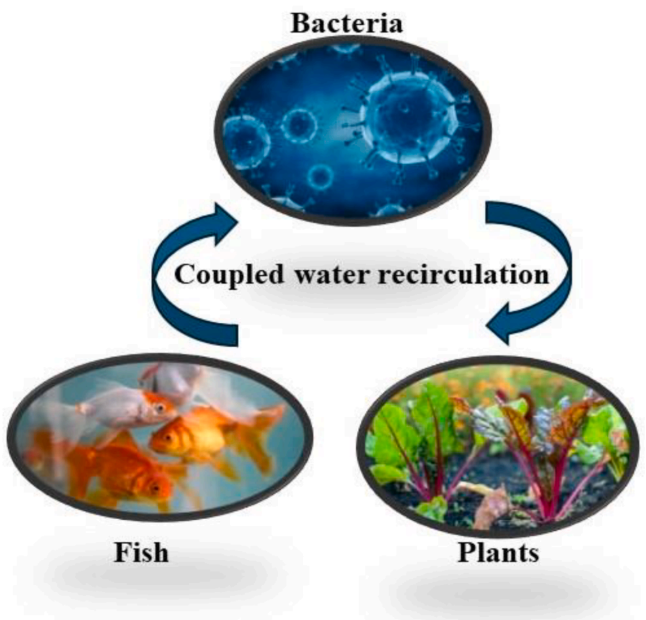

Fig. 1. Principle of coupled Aquaponics system with fish, bacteria, and plants in a fully closed water recirculation, adapted from Goddek et al., (2019). Pictures of the plants and fish are from the Aquaponics University of Wolverhampton system. (Color image preferred).

and vegetable monitoring, fish monitoring, plant nutrient detection, fish counting, and disease detection, water pump malfunction detection, aquaponic environment monitoring, plant growth stage classification, crop harvest prediction, and so on. Industrial level Aquaponics applications and data processing that mainly focus on intelligent farming, remote monitoring, and decision support systems collectively termed Aquaponics 4.0.

In Aquaponics 1.0, farmers used manual tools and domestic methods for fish, plants, and water management. From that base point, Aquaponics has grown to the innovative Aquaponics 4.0 era.(Abbasi et al., 2021) IoT and machine learning have been applied to crop disease diagnostics management (Abbasi et al., 2023). Studies have been done on water nutrition monitoring and real-time monitoring of the environmental parameters using IoT and cloud data management.(Isabella Wibowo et al., 2019) (Manju et al., 2017). Research studies on fish and plant health predictions, water management, plant growth stage classification, disease control, and harvest time predictions have been performed, which are discussed in the later sections.

Conventional Aquaponics systems focus on water conservation and maintain minimal water replenishment or exchange. Nevertheless, a low rate of water replenishment may result in a high nutrient loss in the water (Delaide et al., 2017). The literature reveals that most of the Aquaponics systems have either no daily water replenishment or water replenishment values ranging from as low as below 10 % (Graber and Junge, 2009, Rakocy et al., 2004, Suhl et al., 2016, Blanchard et al., 2020, Shaw et al., 2022) to complete water exchange, i.e., 100 % replenishment (Nhan et al., 2019). Most of the studies perform water replenishment to cope with water loss due to evaporation or evapotranspiration. Moreover, a very limited number of scientific studies have been done on the effects of water replenishment on water quality and the ecosystem of Aquaponics. Similarly, only a few studies focus on the application of machine learning to analyze and control water quality and the impacts of water replenishment on fish and plants. This is surprising given the growing interest in the use of technology for intelligent monitoring of aquaponic systems to achieve automatic and precise control of nutrients, healthy growth of fish and vegetables, and improved resource efficiency. For example, intelligent management IoT-Cloud-based platforms and smart sensing systems for monitoring and controlling all operations, diagnostics of fish and crop health, and data analytics framework or remote assistance of Aquaponics have been developed (Karimanzira and Rauschenbach, 2019, Alselek et al., 2022, Gayam et al., 2022, Taha et al., 2022b). These systems include the use of real-time monitoring wireless sensors-based devices by InnovaSEA company for continued monitoring of dissolved oxygen (DO), salinity, chlorophyll, blue-green algae, and turbidity and an inter-digital FR4-based capacitive sensor with LoRa and WiFi communications for nitrate concentration monitor (Alahi et al., 2018). Some systems present an IoT system architecture for Aquaponics monitoring with relatively high number of metrics including pH, water temperature, DO, Oxidation-Reduction Potential (ORP), Electrical Conductivity (EC), Total Dissolved Solids (TDS, Total Suspended Solids (TSS), nitrite, nitrate and ammonium) (Alselek et al., 2022, Khaoula et al. 2021). Alselek et al., (2022) claimed that their developed low-cost 5G-enabled IoT system for fully monitoring fish farms performance has wide-area-enabled communications (>1 km^2) using NB-IoT, LTE-M, and LoRa/ LoRaWAN) with up to 11 metrics for real-time monitoring with low-power consumption, and thus a more sustainable system. Pu'Ad et al., (2020) proposed an IoT-based water quality monitoring system for Aquaponics using only pH as an indicator of the water quality which appears as a limit to this great work aiming at replacing human on-site daily routine works. Yanes et al. (2020) did a comprehensive literature study on various sensors used for sensing different water parameters in Aquaponics. This contribution helps to understand the IoT approaches used on Aquaponics in a commercial scale of production. However, the study mainly focuses on the sensing parameters and does not cover other smart technologies such as artificial intelligence applications, machine vision, or big data. In this paper "smart" and intelligent are used interchangeably, which means the use of machine learning, deep learning, IoT, big data analysis, decision-making systems, computer/machine vision, and remote control applications using mobile and web applications. The paper aims to review the literature on smart technologies used to monitor water quality and performance growth of fish and plants in an Aquaponics system and highlights research gaps and future directions. After the introductory part, the methodology used to collect information is presented followed by Section 3 on different types of Aquaponics. Factors and parameters affecting water quality are discussed in Section 4. Section 5 gives an overview of smart approaches including IoT, machine learning, deep learning, and machine vision used in Aquaponics focusing on water quality. The research gap identified through this review is presented in section 6 followed by the prospects in the area.

2. Research methodology

The review process has been systematically done for this article. Articles from 2013 to 2023 were selected for initial scrutiny. IEEE, Web of Science, and Google Scholar were chosen to be the main databases to be searched for articles. 374 articles were considered before applying the exclusion criteria and 53 articles were shortlisted. Articles written in non-English language have been avoided from shortlisting. Keywords to be used were confirmed to be "Smart Aquaponics" "Aquaponics 4.0" and "Aquaponics Water Quality". Then abstracts of the articles identified were analyzed to shortlist the most suitable articles for this review.

Papers have been segregated into categories such as AI in Aquaponics, Automation and remote sensing in Aquaponics, and Water Quality Management in Aquaponics. Overall, 56 articles were shortlisted, and data such as Algorithms used, tools and technology applied, materials and methods, and research findings were extracted. The article has been concluded with major research findings with a literature gap identified and future enhancements with suggestions and recommendations. Fig. 2 shows the process flow chart of the research methodology.

The main motivation of this article is to answer the following question. What are the smart approaches used in Aquaponics 4.0 with a focus on water quality? To address these questions, 56 articles were focused

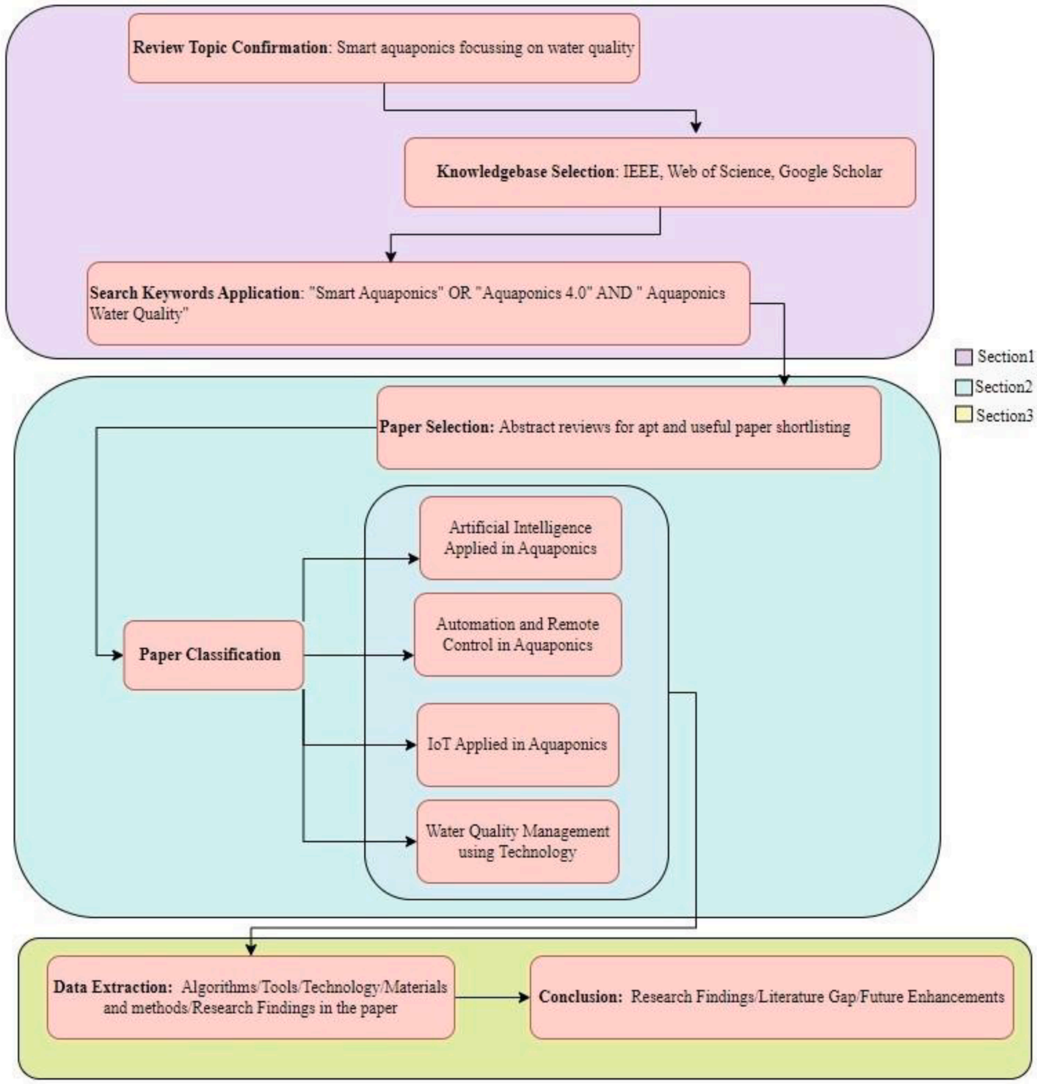

Fig. 2. Review Process Flowchart.

and categorized into the following:

- Factors affecting water quality and the effect of water recirculation and water replenishment in Aquaponics
- Aquaponics systems with different water replenishment rates with water quality assessment approaches
- Aquaponics and IoT-monitoring & control system
- Machine Vision in Aquaponics
- Artificial Intelligence in Aquaponics

3. Types of Aquaponics systems

Aquaponics systems can be classified mainly into couple and decoupled systems based on the engineering design (Table 1). A coupled Aquaponics system is a conventional Aquaponics where the aquacultural units and hydroponics unit are arranged in a closed loop. The water is recirculated from the fish tank to the hydronic unit directly and, then back to the fish tank. Decoupled systems are arranged in separate loops of fish tanks and hydroponics and water is recirculated to the respective units (Kloas et al., 2016). The system can also be classified based on the location and scale of production which includes indoor and outdoor Aquaponics systems and small-scale home/hobby-based systems intended for self-sufficient food production for local consumption when

Table 1
Comparison between coupled and decoupled Aquaponics systems.

Type	Features	Benefits	Demerits
Coupled	Mainly used as mini/ hobby/domestic/ backyard/ demonstrative/ small and semi-commercial level	Easy to implement, maintain, and manage	pH, temperature, and nutrient concentration are compromised
	May have short-term nutrient peaks and variations	Require less infrastructure	Less profitable
	Production depends on feed demand, no of plants and fish	Simple architecture	Lower commercial profile
	Gravity influenced water flow		
	Single loop systems/ scaling from small-medium-large		
Decoupled	Mainly used as semi/ full commercial level	More profitable	Complex design
	Multiloop systems	Improved nutrient stability	Implementation needs expertise
	Detached units	Improved pest management	Hard system maintenance

compared to industrial/commercial Aquaponics (Wu et al., 2018). An indoor system is set up inside a building making sure the necessary environmental conditions including artificial lighting are available for the system, which becomes popular in urban life (Tomlinson, 2015). Outdoor systems use controlled environments like greenhouses to provide suitable growth conditions for fish and plants. In this case, the system can be made even more sustainable by using solar energy to power the entire system (Nagayo et al., 2017, Khaoula et al.,2021).

The closed-loop principle can be applied for domestic purposes or demonstration. Coupled systems with the closed loop principle give more importance to the biological–chemical components of the process water. The uneaten feed particles in the fish waste make the water more nutrient-rich along with the digestive bacteria. Coupled systems yield better results than stand-alone Aquaponics systems (Goddek et al., 2019). However, the fish wastewater index increases with the increase of fish biomass which results in the accumulation of more ammonia and nitrate as time progresses, thereby making the coupled system less adequate for large-scale production. As the need for more commercially viable Aquaponics is growing with the precision farming concepts, the application of innovative technologies such as the Internet of Things (IoT) and artificial intelligence (e.g. machine learning, deep learning, and machine vision) and big data analytics become inevitable which converts the conventional Aquaponics into Aquaponics 4.0.

4. Aquaponics water

Water can be seen as the blood of any aquaponic system, and its quality unquestionably affects the ecological balance and the productivity of a recirculating Aquaponics system (Ngo Thuy Diem et al., 2017, Delaide et al., 2017). Potential factors affecting the water quality and key water quality parameters of an Aquaponics system are discussed in the following sections.

4.1. Factors affecting Aquaponics water quality

Four main baseline factors related to water that influence Aquaponics water quality are water sources, recirculation rate, replenishment rate, and water addition (Figs. 3 and 4). The chemical, physical, and biological composition of water depends on its source (e.g. sea, well, and municipal tap water) which in turn affects the AP systems since nutrients needs for fish and plant production should be met and balanced and water play a big role in maintaining the symbiotic relationship between them. It has been suggested that rainwater or water treated for chemical removal is the most preferred source of water for Aquaponics because it offers the producer a higher degree of flexibility to adjust the nutrient chemistry of the system as appropriate. Municipal-supplied water resources may contain chemicals such as chlorine and chloramine in concentrations that could be harmful to the fish, plants, or

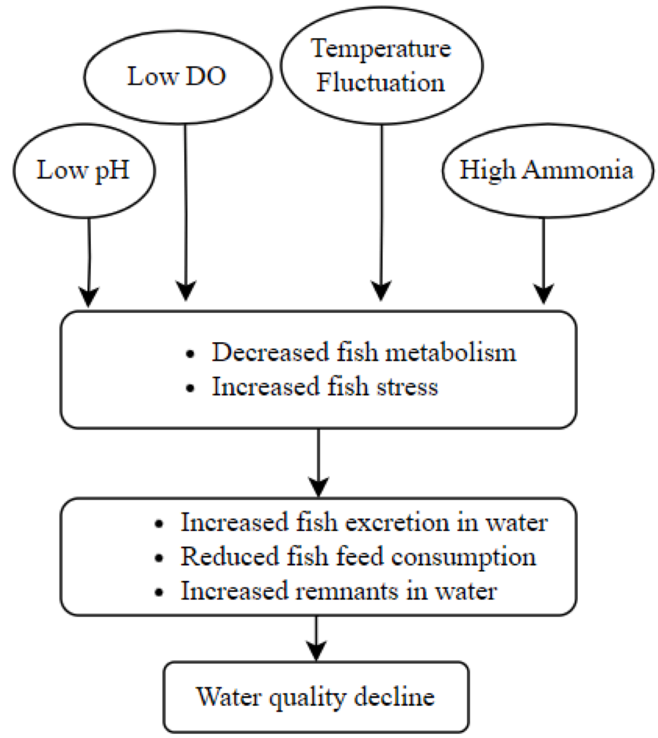

Fig. 4. Typical mechanism by which water quality parameters may cause a decline in water quality.

microorganisms within the aquaponic system (Goddek et al., 2019). However, sea water has been considered for growing halophytes in marine aquaponic systems (Boxman et al., 2017).

Water addition or topping up of water is done to replace the water lost by evapotranspiration or evaporation. The effect of recirculation water rate to continuously control the flow of fish water between plant grow bed and fish tank and that of water replenishment/water exchange on water quality are discussed in section 4.2.

4.1.1. Water quality and key definitions

The water quality of Aquaponics determines the overall productivity of fish and vegetables. Key parameters of water quality are water temperature, dissolved oxygen, water pH, water hardness, and total nitrogen (Fig. 4). Total nitrogen includes ammonia, nitrite, and nitrate in the water (Somerville, 2014). The tolerable levels of these parameters depend on the fish type, water type, type of Aquaponics system, and environmental conditions. Table 2 shows the acceptable and safe range of essential water quality parameters (Somerville, 2014, Goddek et al.,

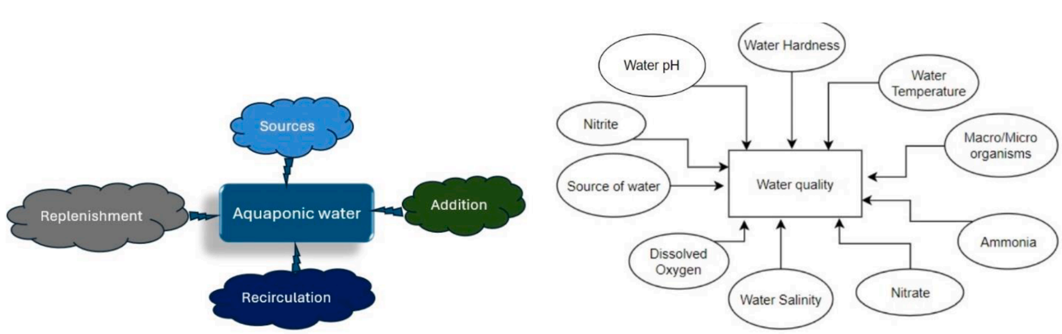

Fig. 3. Factors influencing water quality. (1) Influential factors affecting Aquaponics water quality (2) different water quality parameters as drawn based on the information from Hu et al., (2015), and Goddek et al., (0.2019).

Table 2
The acceptable and safe ranges of essential water quality parameters

Parameter	Acceptable range
pH	6.4–7.4
Dissolved Oxygen	> 5
Temperature	22–29 °C for warm water fish; <18 °C for cold water fish
Total Nitrogen	0.25–1.0 mg/litre
Water Hardness	60–140 mg/litre

adapted from Somerville (2014) and Goddek et al. (2019).

2019) which must be kept to maintain the optimal growth of both the fish and plants (Gnanasagar et al., 2020).

Water pH: pH is the level of hydrogen ion concentration present in a solution. Water pH can influence the availability of plant nutrients in the water and the development of nitrates and nitrites in water (Tyson et al., 2011). It's necessary to keep the water pH levels steady and any variations beyond the desired range are detrimental to the fish life. A low pH reading of water shows that it is more acidic and elevated pH makes the water more alkaline. High levels of pH eventually generate other toxic chemicals in fish water.

Dissolved Oxygen: Dissolved Oxygen is one of the most essential parameters for both fish growth and plant nutrients present in water. Dissolved oxygen plays a vital role in microorganisms' existence which turns the fish waste into useful plant nutrients (Sallenave, 2016). Dissolved oxygen supports the fish metabolism and low dissolved oxygen levels upset fish digestion and feeding patterns which eventually leads to water quality decline (Ren et al., 2018).

Temperature: Water temperature directly affects the growth pace and efficacy of both fish and vegetables. The tolerance level of water temperature varies with the types of fish such as cold-water fish and warm-water fish. Fish metabolism considerably drops as water temperature falls (Sallenave, 2016, Tyson et al., 2011) causing a deterioration in water quality through unfed food particles and fish extretes.

Ammonia: Ammonia in water is mainly produced through the fish excretes. Ammonia is present in the water primarily in two forms, NH3 which is highly dangerous to fish life, and NH4. The variation of fish water ammonia content is closely connected with the water temperature, dissolved oxygen, and the water pH (Goddek et al., 2019), Tyson et al., 2011). The level of ammonia needs to be monitored regularly as low nitrification can accumulate toxic ammonia in water which worsens the water quality.

Water hardness & Water Salinity: Water hardness indicates positively charged ions, such as calcium and magnesium. It is expressed as in ppm calcium carbonate. Hardness value varies from 0–75 ppm for soft water to as high as above 300 ppm for very hard water (Sallenave, 2016). Good water hardness values are between 60–140 mg/liter as dissolved calcium in the water contributes to osmoregulation and stress relief in fish. Both calcium and magnesium aid the fish's metabolic functioning and lower hardness may cause fish stress (Bhatnagar and Devi, 2013, Yanes et al., 2020). Water salinity is the measurement of salt in water. It is an essential factor for fish health and fish growth (Nagayo et al., 2017, Yanes et al., 2020). Thomas et al., (2021) showed that optimal water salinity can contribute to better plant productivity. Variations in salinity may affect other key water quality parameters which cause water quality decline (Fig. 4). These water parameters can be monitored and controlled using different smart approaches and devices reported in Table 3 which are mainly, IoT, machine learning, machine vision, or a combination of IoT and any of the AI methods.

Table 3
Water quality parameters with control actions and smart technologies approaches.

Main Parameters	Measurement & Control	Smart Approaches	References
Dissolved oxygen	Measured using manual probes and sensors. Maintained using aeration and improved water movements	Dissolved oxygen remote monitoring, measurement, and analysis using IoT. DO prediction using machine learning.	Ren et al., 2018
Temperature	Measured using manual probes. Water heaters are used to regulate temperature.	Automated temperature measurement and control using IoT. Temperature prediction using machine learning	Taufiqurrahman et al., 2020
Total Ammonia Nitrogen	Measured using ammonium strips, manual probes, and IoT sensors. Avoid overfeeding and increase the nitrification process to control water ammonia	Remote monitoring using IoT and sensors. Machine vision approach for uneaten fish food and dead fish detection which may lead to ammonia spike in water.	Yanes et al., 2020
Water pH	Measured using manual probes and IoT sensors. Chemicals and pH buffers are used to regulate pH levels	IoT and sensors for pH monitoring.PH prediction using machine learning	Mori et al., 2021

4.2. *Effect of water recirculation and replenishment*

Water recirculation makes the water safer for the fish as toxic chemicals such as Total Nitrogen will be absorbed by the plants. However, fish waste and uneaten fish feeds gradually change the water chemistry, and it can become increasingly acidic with time (Mori et al., 2021). In the conventional Aquaponics approach, farmers use chemicals such as calcium carbonate or potassium bicarbonate daily to achieve water stability (Sallenave, 2016). Different recirculating or water replenishment rates have been reported in the literature (Table 4). Ngo Thuy Diem et al., (2017) studied the effect of different water recirculation rates in a system where recirculation rates of 50 %, 200 %, and 400 % were tested. The study found that there was a huge mortality of fishes at 50 % of the recirculation rate and the survival was excellent when recirculated 400 % water. Ebeling and Timmons (2012) specified in their study that a water exchange rate between 5 % and 20 % is required for a recirculating aquaculture system. Rakocy et al. (2012) suggested that an early circulating aquaponic system would consume 0.5 % to 5 % of water daily. Delaide et al., 2017) reviewed the performance of fish and plant production including the mass balances for nutrients and water usage in a small-scale Aquaponics system. They found that 3.6 % of the daily water exchange caused a massive nutrient loss whereas Gnanasagar et al., (2020) reported that 5 to 10 % replenishment was sufficient for a recirculating Aquaponics system. Maucieri et al., (2018b) studied the water flow and daily water consumption in an Aquaponics system and identified that closed RAS has a daily water consumption of less than 1 %. This could be water loss through evaporation, plant evapotranspiration, splash during feeding, or sludge removal.

Diatin et al. (2021) analyzed the production performances of catfish farming with a water exchange system Aquaponics and biofloc technology and found that water exchange would benefit fish farming by removing the accumulated waste and toxic chemicals. Also, 30 % to 100 % water exchange was implemented in their aquaculture study. Huang et al. (2021) evaluated the water quality and growth in farming when an experimental farming group was compared with controlled farming which uses intelligent methods. The study shows that water pollution caused massive fish mortality and manual nitrification led to a sudden change in Nitrate and fish death. The optimum feeding rate was dependent on the water exchange rate of the Aquaponics system. Higher feeding rate and lower water exchange rate caused a rapid increase of Nitrite and toxic chemicals in the water (Rakocy et al., 2016). In

Table 4
Aquaponics systems with different water replenishment rates. The manual method refers to the standard approach of data collection using manual probes and chemical strips and data analysis using conventional statistical approaches.

Purpose of the study	Water Replenishment	Water quality monitoring	Smart Technology	Reference
Tomato production evaluation	6.3 %	Manual method	No	Suhl et al., 2016
Tilapia and vegetable production	0.26 to 0.46 %	Manual method	No	Rakocy et al., 2004
Effect of pH on cucumber growth	5 %	Manual method	No	Blanchard et al., 2020
Productivity enhancement of Snakehead	20 %	Manual method	No	Bich et al., 2020
Catfish production performance	20 %	Manual method	No	Diatin et al., 2021
Water circulation optimization	5–10 %	Manual method	No	Shete et al., 2013
Plant species effect calculation	20 %	Manual method	No	Hu et al., 2015
Effect of stocking densities on growth performance	100 %	Manual method	No	Nhan et al., 2019
Nutrient recycling from fish water	9 %	Manual method	No	Graber and Junge, 2009
Protein sources evaluation in fish feed	5 %	Manual method	No	Shaw et al., 2022
Aquaponics water management and nutrient removal	1 %	Manual method	No	Maucieri et al., 2018
Control Action in Aquaponics System	5 % to 10 %	Manual method	No	Gnanasagar et al., 2020
Water quality and plant performance in snakehead-mint Aquaponics	0 %	Manual method	No	T Nguyen et al., 2023
Aquaponics water quality comparison with separate RAS	0 %	Manual methods	No	Atique et al., 2022

conventional Aquaponics systems, daily water exchange is not mandatory. However, 5 to 10 % of daily water replenishments are done if required as nitrite levels were reported to increase linearly and quickly in the water of an Aquaponics system with no water exchange (Hu et al., 2015). Another study revealed that semi-closed and closed Aquaponics systems may have different water exchange rates whereas aquaculture systems have higher water exchange rates than Aquaponics systems. The water exchange rate may also depend on the fish type (Shete et al., 2013). Bich et al., (2020) analyzed the data and results produced when an Aquaponics system was compared with a normal aquaculture system to understand the economic viability of farming snakehead fish. They had a daily water exchange of 20 % and found that water quality was improved with a controllable level of NH_3 when compared with the normal system. Love et al. (2015) replaced 10 % of the water daily to top up the water loss due to evaporation and evapotranspiration when studying the use of water in a small Aquaponics system in Baltimore, United States. They used chemical combinations to stabilize the optimum water quality.

5. Smart approaches in Aquaponics 4.0

The productivity and yield of an Aquaponics system can be enhanced using technologies currently applied to Industry 4.0, such as the Internet of Things (IoT), robotics, big data analytics, and artificial intelligence (Abbasi et al., 2021a). As depicted by Fig. 5, different smart technologies can be used in combination with commercial or home Aquaponics farming.

IoT and robotics can help Aquaponics farmers with better monitoring, remote control, and full automation of the system (Eichhorn et al., 2019, Menon, 2020). Artificial intelligence explores the wider possibilities of prediction and classification through machine learning and deep learning approaches (Dhal et al., 2022, Liu et al., 2022). Cloud storage is used to store and retrieve commercial and personal Aquaponics data to be processed (Lee and Wang, 2020). Mobile and web applications are used to monitor and analyse the data and it helps farmers to operate on the system remotely.

5.1. Aquaponics and IoT-monitoring & control system

Khaoula et al. (2021) proposed an IoT-based monitoring system to control Aquaponics using sensors and solar power. The Aquaponics system was monitored for its water quality and other environmental parameters using sensors powered by solar energy. Zhang et al., (2021) had a study investigating the possibilities of implementing a sensor-based monitoring system focusing on water and air temperatures and dissolved oxygen in a greenhouse environment. The system contains an information perception layer, an information transmission layer, and a system architecture. Reyes-Yanes et al. (2020) used pH, electro-conductivity, air humidity, and water temperature sensors along with Raspberry Pi to monitor an Aquaponics system whereas Dhal et al., (2022) used machine learning and IoT to control the nutrient supply in a commercial Aquaponics system. Machine learning was then used to predict the important and optimal concentration of nutrients,

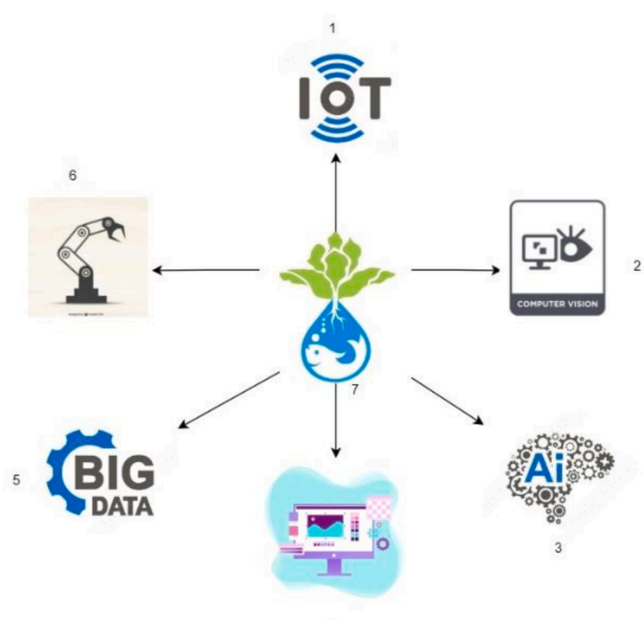

Fig. 5. Smart approaches to Aquaponics 4.0.(1) Internet of Things (2) Computer vision (3) Artificial intelligence (4) Software Applications (5) Big data (6) Robotics (7) Aquaponics system. (Color image preferred).

principally, ammonium and calcium where the concentration must be maintained to a certain level in the aquaponic solution to sustain the healthy growth of tilapia fish and lettuce plants in a coupled system. In that study, Actuators were used to supply the optimum nutrients. Sathyan et al. (2022) used an AVR microcontroller to analyze the water quality parameters and automated the Aquaponics using IoT. Menon (2020) compared the performance of an IoT-enabled Aquaponics system coupled with mobile applications with a normal Aquaponics system to see the enhancement in the productivity of fish and plants. The study was done in a controlled environment and the farmer was able to monitor and control the entire operations remotely. Karimanzira and Rauschenbach, (2019) investigated how IoT-enabled predictive analytics can be used for efficient utilization of information in Aquaponics management. They mainly focused on remote monitoring, predictive remote maintenance, and economical optimization of plant productivity. Lee and Wang (2020) developed a cloud-enabled IoT monitoring system to analyze the fish metabolism. They used regression analysis to track the fish activity and studied the fish's locomotion and resting state using a camera.

Khaoula et al., (2021) developed a solar-powered IoT enabled Aquaponics to control and monitor water quality and environmental parameters using actuators and artificial intelligence to improve its sustainability and productivity. Many sensors including water level, water temperature, electrical conductivity, CO2, and total ammonia - nitrogen were used. They also suggested that a combination of IoT-based technologies and artificial intelligence (AI) algorithms is required to boost the productivity of Aquaponics. Ezzahoui et al. (2021) reviewed IoT-enabled operations in Aquaponics systems categorizing their architecture, protocols, technologies applied, advantages, and limitations. The study also compares hydroponic systems with an Aquaponics system. They proposed a solution based on IoT to control and monitor the water quality using sensors. Abbasi et al., (2021b) developed an ontology model to address the challenges in heterogenic data of Aquaponics using IoT and artificial intelligence. This ontology model provides a sharing platform through which Aquaponics 4.0's knowledge base could be used to resolve inter-operation issues. Aquaponics operations are automated using Industrial IoT devices to monitor and control the water quality parameters (Odema et al., 2018). They used Modbus TCP communication protocol for the system. Riansyah et al. (2020) used sensors and actuators to automate fish feeding in an Aquaponics system. The study also focused on monitoring the pH value in real-time. Tolentino et al., (2017) developed an Android mobile application that helps to monitor and control urban Aquaponics remotely. The app analyses the water quality parameters and environmental parameters, and actuators were used to feed the fish. Cloud space was used to store data. Wongkiew et al., (2021) considered the nitrogen recovery via Aquaponics systems that used IoT for smart control operations. Dynamic nitrogen modeling was developed to predict and reduce dangerous nitrous oxide emissions. Connected Aquaponics can be established using open standard wireless sensor network protocols like 6LowWPAN to collect sensor information from nodes in a high bandwidth and low latency rate (Hari Kumar et al., 2016). Fig. 6 summarizes the different reasons for using the Internet of Things in Aquaponics which are remote operation and operation control, information acquisition, cloud data management, and parameters monitoring.

5.2. Artificial intelligence in Aquaponics

Artificial intelligence (AI) and machine learning have been used widely in agricultural applications for various purposes (Table 5). AI can allow farmers to predict the values of the parameters and classify crops or plants. AI can be used in selecting suitable fish or vegetables to be farmed in the Aquaponics system in specified conditions. It is also applied in water quality prediction of various critical parameters of Aquaponics like dissolved oxygen, pH, salinity, water hardness, dissolved solids, and total ammonia and nitrogen (TAN). Machine learning and deep learning techniques have also been applied to detect fish and plant diseases and optimization of fish feed delivery and fish feed to fish biomass conversion (Debroy and Seban, 2022).

Ghandar et al., (2021) used a digital twin system and IoT to predict the production of Aquaponics with a decision support system (DSS). The decision support system applied machine learning algorithms for predictive data analytics of the sensor data. Lauguico et al.(2020) applied machine learning algorithms for the classification of lettuce life stages grown in an Aquaponics system. Stochastic gradient descent and other approaches in machine learning have been used. The plant texture was analyzed using the machine vision technique. Machine learning algorithms have been applied in predicting fish biomass (Debroy and Seban, 2022). Various approaches like artificial neural networks and hybrid fuzzy logic may be applied to identify the biomass of a fish, which helps the farmers avoid any market supply imbalances. Taha et al., (2022a) diagnosed the nutrient deficiencies of plants grown in an Aquaponics system using images and deep convolutional neural network.

Fertigation can be made adaptive using hybrid vision and machine learning (Concepcion et al., 2021) and a controlled supply of nutrients can be obtained using IoT and fuzzy logic techniques. Decision tree regression may be used for predicting the water temperature in an Aquaponics system (Taufiqurrahman et al., 2020). Machine learning algorithms are applied to forecast and Aquaponics ecosystems. A combination of image segmentation, deep learning, and regression analysis has been used to estimate the size of the crops as they grow. This was followed by modeling the relationship between crop size and fresh

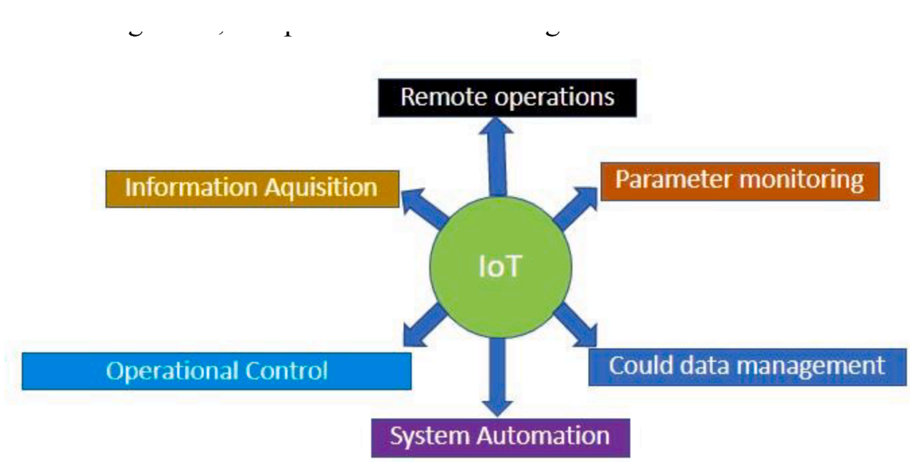

Fig. 6. IoT approaches in Aquaponics, based on the information from (Dhal et al., 2022, Karimanzira et al., 2019, Reyes-Yanes et al., 2021, Ruan et al., 2019) (Color image preferred).

Table 5
Machine learning and deep learning approaches in Aquaponics are used for classification, prediction, decision support, and estimation of data.

Algorithm/Approach	Purpose	Parameter(s) focused	Paper & year
Classical machine learning (ML)	Prediction	water pH	Mori et al., 2021
Machine learning	Classification	Leaf Disease Detection	Yang et al., 2021
Fuzzy logic, Genetic Algorithm	Prediction	Dissolved oxygen	Ren et al., 2018
Classical machine learning-Support vector machines, regression	Prediction	Seed quality	Mendigoria et al., 2021
Classical machine learning	Classification	Lettuce growth	Sabino et al., 2020
Deep learning	Estimation	Leaf water stress	Concepcion et al., 2020b
Recurrent neural network (RNN)	Prediction	Sensor drift fault	Shaif et al., 2021
Machine learning, digital twin	Decision support	Nutrient exchange	Ghandar et al., 2021
Machine learning, Genetic algorithm	Prediction	Water nitrate	Alajas et al., 2021
Artificial neural network, Fuzzy logic	Prediction	Fish biomass	Debroy and Seban, 2022
Genetic Algorithm	Prediction	Organic carbon and Hydrogen	Concepcion et al., 2020a
Fuzzy logic	Prediction	Lettuce growth	Tobias et al., 2020
Classical machine learning	Prediction	Fish health and activity	Lee and Wang, 2020
Classical machine learning, Regression	Prediction	Tilapia and Lettuce production	Estrada-Perez et al., 2018
Recurrent neural network model, ML algorithms	Prediction	Aquaponics system behavior	Cardenas-Cartagena et al., 2022

weight (Reyes-Yanes et al., 2020) since these are key performance metrics. The authors were able to monitor the growth rate and estimate the fresh weight and crop size of a little gem romaine lettuce with an overall accuracy of 81 % and 92 % respectively.

Machine learning algorithms have been applied to predict the real-time nitrogen concentration in aquaponic water, which is crucial for fish and plant health. Moving-horizon algorithm-based adaptive filtering was used to predict the nitrogen concentration in a study by Li et al. (2021). Machine learning and optimization algorithms have been used to estimate the biophysical signature of an aquaponic lettuce by Concepcion et al. (2022). They used an artificial bee colony optimization algorithm for the estimation. Water physical sensors, regression-based machine learning algorithms, and genetic algorithms were used for predicting the nutrients in an Aquaponics system in the study by Concepcion et al. (2021b). Deep convolutional neural networks and machine vision can be applied to diagnose plant nutrient deficiency in lettuce grown in an Aquaponics system. Image classification using machine learning algorithms is used to detect the nutrient status in this approach (Farag Taha et al., 2022). Concepcion et al. (2020) measured the canopy area of an aquaponic-grown lettuce using a statistical supervised learning technique and texture analysis. The study used machine learning models for the area measurement. Bracino et al., (2021) studied how to determine the optimal biofilter size for an aquaponic pond using optimization algorithms. The study also focused on ammonia prediction using machine learning algorithms. Concepcion et al. (2020c) proposed an approach for estimating the biophysical signature of lettuce grown in an Aquaponics system using deep learning algorithms. The study also focused on the variations of lightness of the environment. Using ontology models, it was possible to design Aquaponics systems that automatically determine the characteristics based on the crops selected (Abbasi et al., 2021a). This approach uses machine learning models for decision support systems and knowledge modeling. SLauguico et al. (2020) proposed an approach to predict the attributes and features of lettuce grown in an Aquaponics system using machine vision and deep learning algorithms. In summary machine learning and deep learning approaches found many applications in Aquaponics ranging from classification, growth prediction, decision support, and estimation of data to disease early detection (Table 5).

5.3. Machine vision in Aquaponics

Machine vision is a system that retrieves useful data about a visual from its two-dimensional projections. Machine vision uses machine learning and deep learning algorithms to process the acquired data and produce output information and the core principle is based on image capture and analysis. Machine vision techniques can be used for fish and plant growth surveillance which would help farmers with timely alerts, suggestions, and decision-making processes. Fig. 7 explains various applications of machine vision in Aquaponics and aquaculture.

In Aquaponics and aquaculture, machine vision is used in plant growth stage classification, fish and plant disease detection, fish biomass prediction, fish counting, fish behavioral monitoring, and fish length estimations (Li & Du, 2021). Aquaponic pond water macronutrient prediction can be done using machine vision (Concepcion et al., 2021a). Water quality analysis is always pivotal in precision Aquaponics because it is directly correlated to the quality of fish and plant growth. Barosa et al (2019) investigated how plant leaves can be monitored for their health using machine vision. They used IoT and mobile applications to communicate with the farmer if any disease was identified on the leaf. Liu et al. (2022) used machine vision to demonstrate that fish locomotion is higher in Aquaponics compared to other aquaculture systems. Ii et al. (2021) implemented adaptive fertigation and nutrient control for Aquaponics lettuce using machine vision. The fish population was counted automatically by Zhang et al., (2020) using machine vision and a hybrid neural network. Lee et al. (2013) proposed a vision-based automated vaccine injection method for flatfish. A machine vision-based fish length estimation and species identification are possible (White et al., 2006).

6. Discussion

6.1. Overview

After the articles have been closely analyzed, it is found that sensors, IoT enabled solutions are used mainly for remote monitoring and control of the Aquaponics systems whereas AI plays a vital role in Aquaponics 4.0 by providing solutions to the complex problems, enhancing the productivity of the system. Table 6 gives an idea about the common approaches and the nature of the proposed solutions. Indeed, web applications and mobile applications have been developed and used to monitor water quality, control, and automate the AP system. AP data have been stored and processed using cloud storage and wireless sensor networks have been created among different sensors used in IoT applications for data transfer. Most of the articles reviewed focused on these IoT-based solutions.

More complex Aquaponics problems have been proposed to be dealt with by machine learning, deep learning along machine vision. Most of the studies focussed on parameters prediction using machine learning and the most studied parameter was the prediction of pH. This is probably because water pH determines plant nutrient availability and the nitrification rate (Yanes et al 2020), thus the growth rate and health of both fish and plants. Moreover, Aquaponics systems are very sensitive to changes in the water pH, and variation in pH as low as 0.3 in about 21 h can significantly affect the health of the fish (Somerville, 2014.). Water pH is easily measured and data availability to validate different models could play a role. Solutions to perplexing problems such as fish and plant classification, disease detection, fish locomotion detection, biomass

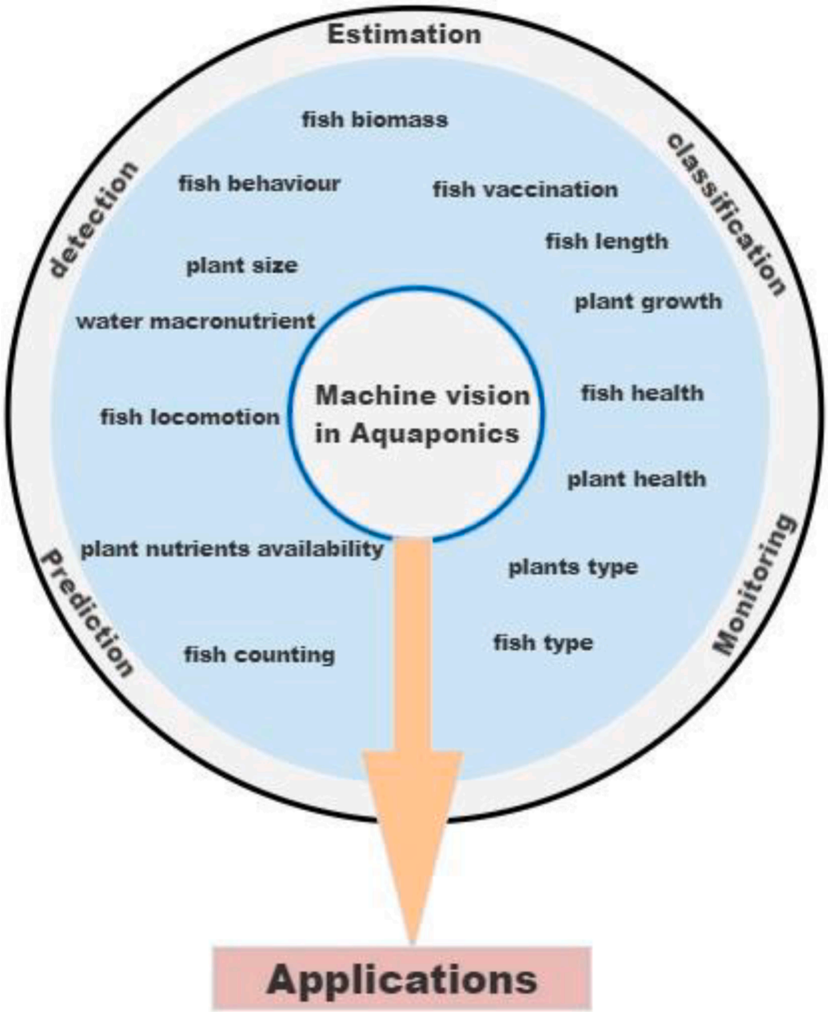

Fig. 7. A schematic diagram showing various applications using machine vision in Aquaponics 4.0. The outer layer of the diagram shows the general purposes of the vision-based approach. (Color image preferred).

Table 6
Smart approaches in Aquaponics 4.0 with their main purposes.

Approach	Main Purpose
Machine learning and deep learning, Machine vision	Water parameter Prediction, Fish and Plant Feature Detection, Fish and Plant classification
IoT, cloud management, Wireless sensor network, web applications	APs system Remote monitoring and control

calculation, length estimation, and leaf health monitoring have been made easy with the help of machine learning, deep learning, and machine vision.

Out of the total short-listed articles,26 % of the articles focused on remote monitoring and control using IoT in Aquaponics whereas 23 % of the articles discussed parameter or feature prediction. 21 % of the articles studied feature detection and classification while 19 % of the articles researched on water quality monitoring using smart technologies. 6 % of the total papers looked at smart approaches in water recirculation and 3 % discussed water replenishment in Aquaponics. Remote operations have been widely discussed followed by the classification and prediction problems while smart innovations. Machine learning-enabled solutions for Aquaponic water management issues have been less explored. The trend is shown in Fig. 8.

6.2. *Current limitation and future work*

It is evident that whilst in-depth research has happened to specific Aquaponics water parameters like pH, there are still possibilities for better exploration of more parameters that could be pivotal in Aquaponics water chemistry. Research studies that applied IoT, cloud management, and wireless sensor networks mainly focused on general Aquaponics system automation and control while more sensor-based applications involving machine learning would provide an advanced research prospect. Studies based on the combination of blockchain technologies with IoT, and cyber-physical systems were not found which opens a wider chance of research especially on commercial Aquaponics.

Most importantly, research studies concerning the Aquaponics water quality have not been explored much to its potential depth. There are studies on water recirculation and water quality monitoring using IoT, but the prospects of water replenishment and its aftereffects have not been greatly identified. Conventional Aquaponics conserve water without much replenishment. However enhanced study on possible benefits of water replenishment and calculated water addition to the system and impacts of water chemistry when freshwater addition is not investigated thoroughly.

7. Conclusion

Research studies on Aquaponics are attracting research scholars and

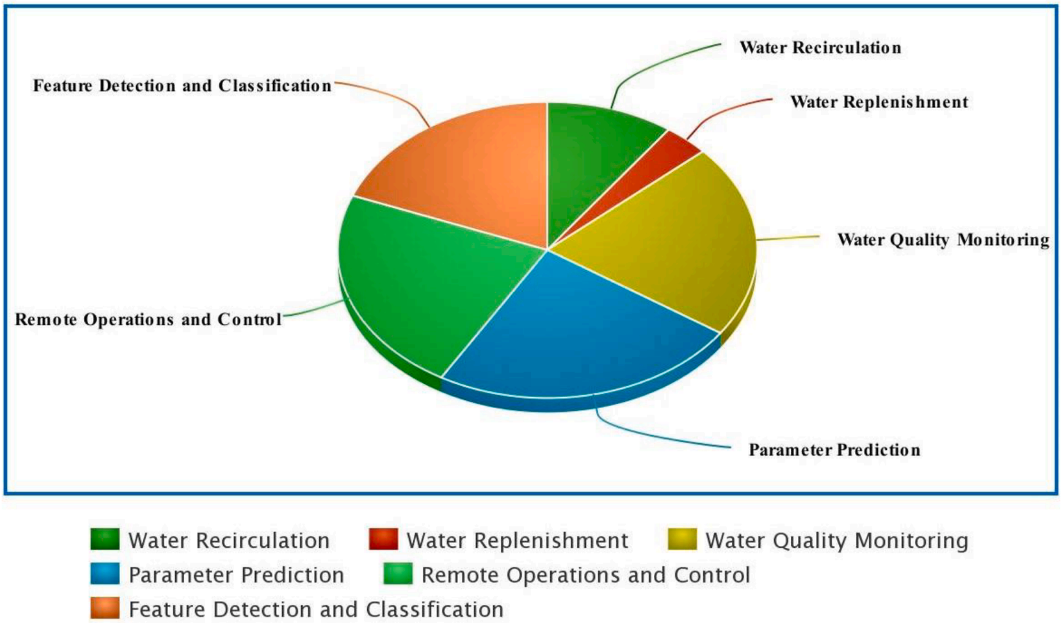

Fig. 8. Categories of applications where smart technologies are applied in Aquaponics 4.0. (Color image preferred).

industrial practitioners worldwide. The use of smart technologies and their impacts in Aquaponics with a focus on water quality aspects has been reviewed and discussed. The paper gives the idea of the current research on Aquaponics 4.0. The main highlights of this study include the following:

- Highlights of various studies regarding Aquaponics water quality and how the quality parameters relate to water recirculation and water replenishment where water replenishment was given a special focus. Effective research towards smart approaches that implement controlled water replenishment would unquestionably improve fish and plant productivity.
- Evidence of the impact of water quality parameters on aquaponic fish and plants' health and these parameters could be monitored and controlled using smart approaches.
- This review emphasizes various Aquaponics challenges that are addressed with different artificial intelligence and IoT-based solutions. This information gives insight into which technology could be best suited to a specific Aquaponics problem, though trends towards a combination of technologies were apparent.

Smart applications are widely researched in fields such as parameter prediction, water quality monitoring, remote monitoring and control, and feature detection and classification in Aquaponics. Important aspects identified as the literature gap, which could be given more attention in the future are outlined as follows. (1) Less focus is given to water replenishment and water recirculation using innovation (2)Very few studies discuss the possibilities of AI and Machine Learning in Aquaponics water management (3) Machine Vision, Machine Learning, and Deep Learning are mostly used in parameter prediction while IoT, Wireless sensor applications, cloud data storage are used mostly in remote monitoring and control applications(4) Lack of research in the use of AI in plant and fish productivity and water quality optimization. These research gaps identified will be useful for aquaponic researchers and experts to work towards better research and implementation of smart technology in Aquaponics water and other areas.

CRediT authorship contribution statement

Praveen Chandramenon: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Amar Aggoun:** . **Fideline Tchuenbou-Magaia:** Writing – review & editing, Validation, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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