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Review

Optimisation of Small-Scale Aquaponics Systems Using Artificial Intelligence and the IoT: Current Status, Challenges, and Opportunities

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Abstract: Environment changes, water scarcity, soil depletion, and urbanisation are making it harder to produce food using traditional methods in various regions and countries. Aquaponics is emerging as a sustainable food production system that produces fish and plants in a closed-loop system. Aquaponics is not dependent on soil or external environmental factors. It uses fish waste to fertilise plants and can save up to 90–95% water. Aquaponics is an innovative system for growing food and is expected to be very promising, but it has its challenges. It is a complex ecosystem that requires multidisciplinary knowledge, proper monitoring of all crucial parameters, and high maintenance and initial investment costs to build the system. Artificial intelligence (AI) and the Internet of Things (IoT) are key technologies that can overcome these challenges. Numerous recent studies focus on the use of AI and the IoT to automate the process, improve efficiency and reliability, provide better management, and reduce operating costs. However, these studies often focus on limited aspects of the system, each considering different domains and parameters of the aquaponics system. This paper aims to consolidate the existing work, identify the state-of-the-art use of the IoT and AI, explore the key parameters affecting growth, analyse the sensing and communication technologies employed, highlight the research gaps in this field, and suggest future research directions. Based on the reviewed research, energy efficiency and economic viability were found to be a major bottleneck of current systems. Moreover, inconsistencies in sensor selection, lack of publicly available data, and the reproducibility of existing work were common issues among the studies.

Keywords: aquaponics; AgriTech; sustainable farming; Internet of Things; artificial intelligence; big data

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1. Introduction

Traditional farming methods are facing increasing threats from extreme weather events, resource scarcity, and urbanisation. These challenges are jeopardising food security, causing a shift towards more sustainable and resilient agricultural practices. Extreme weather events, like droughts, floods, and heatwaves, are causing widespread crop damage and yield losses. In 2018, heatwaves alone led to multiple crop failures and up to 50% yield reductions in central and northern Europe [1], highlighting the vulnerability of traditional farming systems to climate change. The escalating demand for food, coupled with urbanisation, is putting further strain on agricultural resources. Urban populations are projected to increase by about 50% by 2045 [2], and there is growing pressure to produce more food from a shrinking land base. This is further intensified by the depletion of water resources, deforestation, soil degradation, and greenhouse gas emissions associated with conventional farming practices [3]. There is a need to find new ways of food production that are more efficient, rely on fewer natural resources, and are resilient to climate change.

Aquaponics has emerged as one of the potential alternatives to overcome these challenges. It is a sustainable and innovative agricultural system that combines aquaculture (raising fish and other aquatic organisms) and hydroponics (growing plants without soil). In an aquaponics system, the nutrient-rich water from the fish tanks is used to fertilise the plants, and the plants help purify the water for the fish. This symbiotic relationship allows aquaponics systems to produce both fish and vegetables with significantly less water and land compared to traditional agriculture. Additionally, food can be grown indoors in a fully controlled environment, making it more resilient to climate change.

Despite its many benefits, aquaponics is a complex ecosystem with many critical parameters that must be closely monitored and maintained, such as dissolved oxygen (DO), ammonia, pH, temperature, and exposure to sunlight. Manually monitoring and maintaining all of these parameters is complicated, time-consuming, and requires multidisciplinary expert knowledge. However, the IoT and AI can help overcome these challenges by automating the monitoring and control process, analysing sensor data, and identifying patterns and trends that would be difficult or impossible for humans to detect. This could lead to the development of new and innovative ways to optimise aquaponics systems.

Recent studies have demonstrated the use of AI and machine learning to address various aspects of aquaponics systems. For example, Abbasi et al. [4] used machine learning algorithms to identify Foliage Chlorosis in lettuce, John and Mahalingam [5] tested the use of the You Only Look Once (YOLO) algorithm to detect excessive fish feed in a tank, and Karimanzira and Rauschenbach [6] used a convolutional neural network (CNN) to estimate plant growth parameters and a Long Short-Term Memory (LSTM) network to detect anomalies in the system. However, the majority of the AI-related literature on aquaponics focuses on visual observations using machine vision and image processing, whereas the use of data from IoT sensors remains largely unexplored.

Moreover, existing research on the use of the IoT for aquaponics often focuses on limited parameters. For instance, Wijayanto et al. [7] monitored pH, temperature, water level, and electrical conductivity but overlooked DO and other elements. Murakami and Yamamoto [8] detected DO but overlooked nitrate and solar radiation. There was no clear explanation about the parameter selection and use of sensors, suggesting that researchers are choosing sensors based on availability rather than on a thorough understanding of the needs of aquaponics systems. According to Yanes et al. [9], current aquaponics systems are still in their primitive stage, and not all the parameters of aquaponics have been thoroughly researched.

A comprehensive review is needed to consolidate the existing work on aquaponics, identify the crucial parameters to monitor, and survey the state-of-the-art AI and IoT technologies and sensing solutions available on the market.

1.1. Contributions

While there are several review papers on aquaponics, none of them provide an exhaustive evaluation of the current state-of-the-art use of AI and the IoT in this field. This paper aims to fill this gap by compiling and comparing the current literature. This review will cover the following key areas:

1. The key parameters that need to be monitored in aquaponics systems.
2. The sensors available for acquiring farm data.
3. The AI and ML algorithms used to optimise aquaponic processes and management.
4. The IoT systems and communication technologies used for remote monitoring and control.
5. The research gaps and new opportunities in this field.

1.2. Scope and Boundaries

The scope and boundaries of this study can be summarised as follows:

1. The scope of this study is mainly limited to small-scale experimental aquaponics systems within the academic domain. Commercial aquaponics systems, in contrast, exhibit significant variability in their technical specifications due to regional requirements, climate conditions, and resource availability. In addition, technical details about integrating AI and IoT technologies within commercial aquaponics systems appear to be limited in the public domain. Consequently, the comprehensive evaluation of commercial systems, particularly in relation to AI and IoT integration, proved challenging and, as a result, was excluded from the scope of this study.
2. Although commercial systems are excluded from this review, their fundamentals and operational theories are the same. Therefore, the knowledge acquired from this review can be applied to commercial systems.
3. This study is primarily focused on single-recirculation coupled aquaponics systems. While the identified IoT and AI technologies are applicable to both coupled and decoupled systems, optimising decoupled systems may require a separate study due to their distinct requirements. We have only included decoupled systems to provide a thorough overview of aquaponics systems.
4. This review only covers the technical aspects of aquaponics related to the integration of AI and the IoT. It does not delve into mechanical, chemical, biological, ecological, or any other domain.

1.3. Paper Organisation

This paper begins with a comprehensive literature review. Section 2 describes the methodology and search criteria used to select papers for review. Section 3 provides a brief introduction to typical aquaponics systems, their types, and grow techniques. Section 4 reviews the use of the IoT and AI in the existing literature, discusses the key parameters that need to be monitored, and surveys the progress of AI solutions for aquaponics. Section 5 outlines the research gaps and opportunities in the field. Finally, Section 6 concludes this review by identifying key research areas for future work.

2. Search Criteria and Methodology

This review is based on a comprehensive search of aquaponics publications on the Scopus database to synthesise the current knowledge of aquaponics systems and evaluate the use of the IoT and AI. All the papers published until August 2023 were searched in the Scopus database.

The initial search of the database using the keyword "aquaponics" resulted in 1176 records, whereas another search using "aquaponic" yielded 842 records. To cover both keywords, a third search was performed with an asterisk at the end of the keyword (aquaponic*), yielding 1405 results. To narrow down the search results, all aquaponics publications with specific keywords were filtered using advanced queries. The included keywords were 'internet of things', 'machine learning', 'smart', and 'intelligent'. Moreover, two additional keywords with an asterisk, "optim*" and "automat*", were used to cover any keyword that started with "opti" or "automat", such as optimal, optimisation, optimisation, automates, or automation. Publications that were not in the English language were excluded from the results.

After refinement through a search query, a total of 479 results were returned, which were further evaluated by carefully checking the abstract of each paper. The papers that clearly focused on state-of-the-art aquaponics systems and their optimisation techniques, key parameters, and optimal ranges, as well as the use of the IoT and AI, were retained for full-text eligibility checks, leaving a total count of 198. After a full-text review, 45 papers were selected for inclusion in this article. Thirty of the selected papers mainly focused on the use of AI and the IoT in aquaponics systems, whereas the remaining papers covered the basics of aquaponics systems, the key parameters to monitor, and their optimal ranges to maintain. A diagram of the paper selection method can be seen in Figure 1.

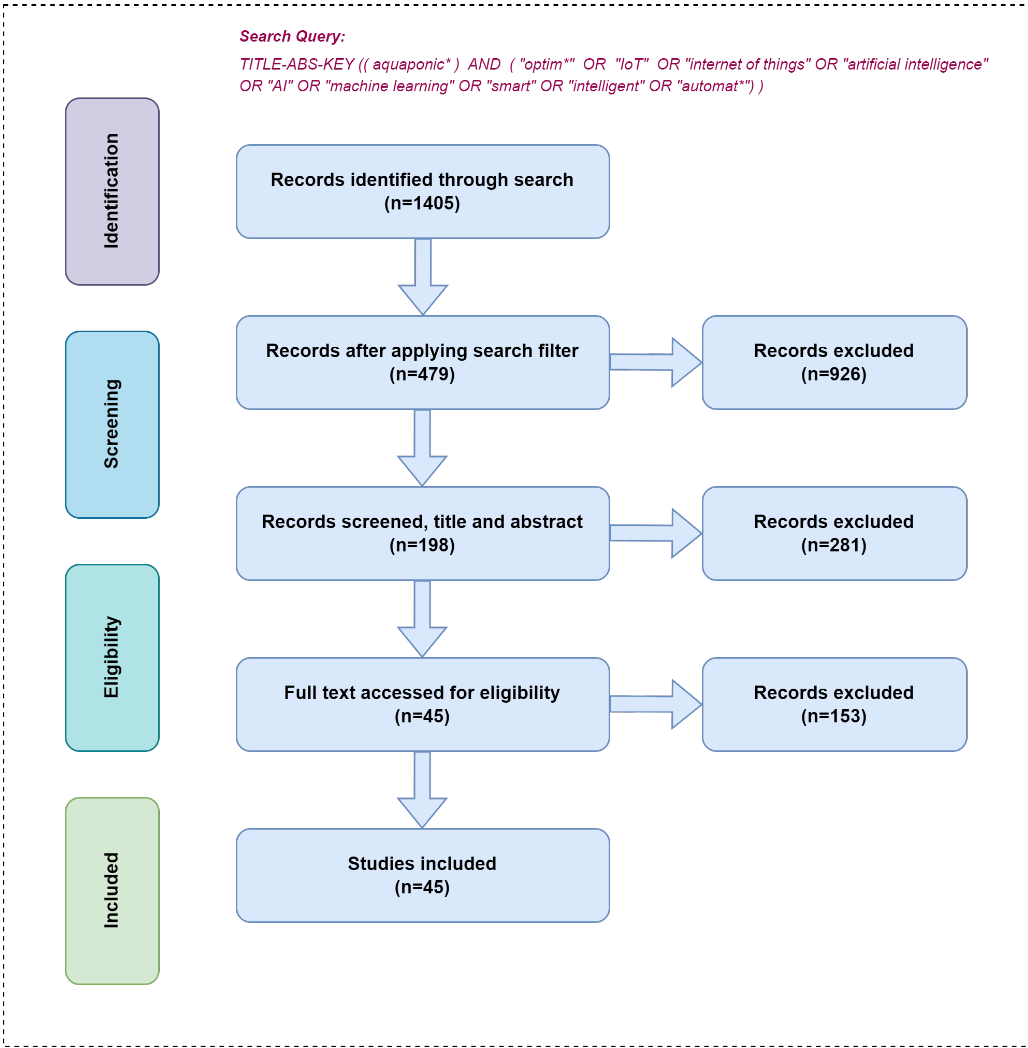

Figure 1. Flow diagram of paper selection method—adapted from PRISMA flow diagram www.prisma-statement.org/PRISMAStatement/FlowDiagram.

3. Aquaponics Systems

Growing plants and fish in integrated aquaculture systems dates back 2000 years to the early development of agriculture in China [10]. Modern aquaponics systems were first introduced by Dr James Rakocy and his team during the 1980s at the University of the Virgin Islands in the USA [11]. Aquaponics systems can be categorised into coupled aquaponics systems (CASs) and decoupled aquaponics systems (DASs), both of which are discussed in the following sections. For a quick overview, a block diagram is shown in Figure 2.

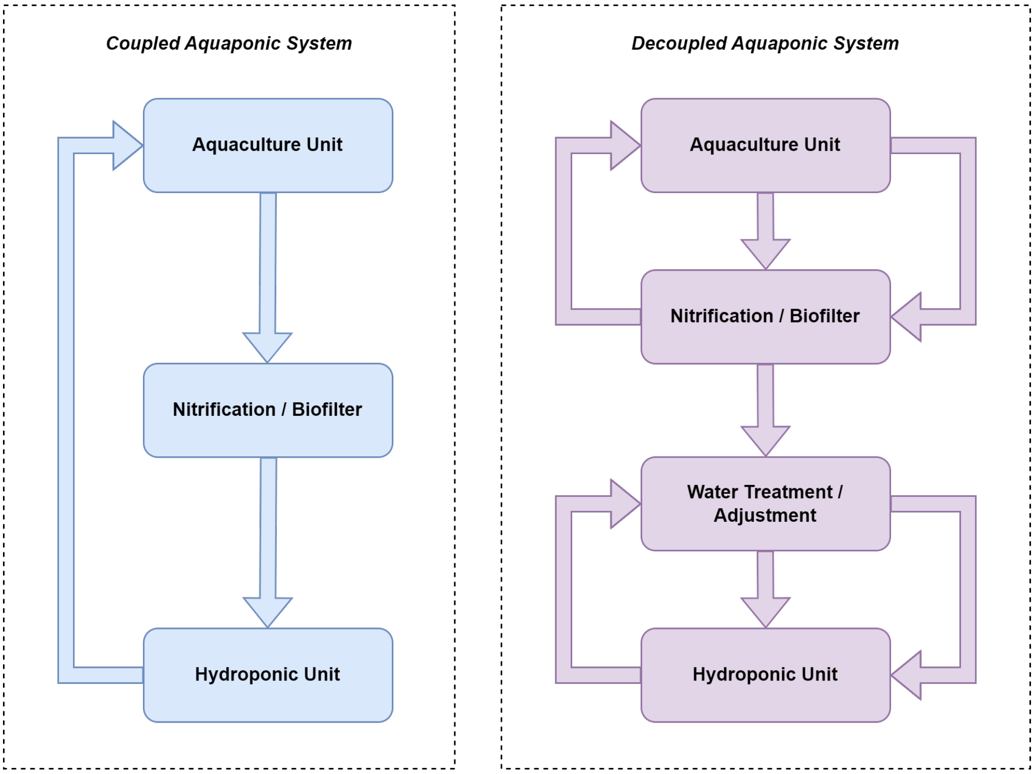

Figure 2. Block diagram for coupled and decoupled aquaponics systems.

3.1. Coupled Aquaponics Systems

Coupled aquaponics systems comprise a single loop where water flows in one direction only, moving from a fish tank to the plants and then returning to the fish tank. Plants and fish share the same water, and the waste produced by the fish is directly used as nutrients for the plants. A typical example of a coupled aquaponics system is the aquaponics system at the UVI (University of the Virgin Islands) [11]. The majority of the reviewed publications in this study tended towards CASs due to their simplicity and ease of setup and maintenance. However, one potential issue observed with CASs is that it is challenging to optimise the environment for both fish and plants due to the nature of a single recirculating system and different water quality requirements for both fish and plants [12].

3.2. Decoupled Aquaponics Systems

In DASs, fish and plant systems are separated, and water is not directly circulated from the fish tank to the hydroponics unit. Instead, it is first treated to remove any solid waste and excess nutrients before being supplied as needed. A decoupled system allows for greater control over the water quality in each unit. For example, the fish tank can be maintained at a different pH or temperature than the hydroponics unit, making it possible to maintain optimal conditions for both plants and fish. Kloas et al. [13] proposed a double-recirculation aquaponics system (DRAP), which is a type of decoupled system that provides optimum conditions for two components by separating plant and fish growth cycles. Using two independent recirculating units, the water circulation is separated by a one-way valve. The nutrient-rich water is supplied to the hydroponics part according to the plant's specific needs.

In another study, Suhl et al. [14] compared the performance of a DRAP with that of a conventional hydroponics system by growing tomatoes and found a 40% higher yield with the DRAP. A DRAP offers greater flexibility over the hydroponics part of the system. The water can be supplemented to increase nutrient concentration and achieve optimal plant growth. An experiment conducted by Delaide et al. [15] demonstrated a 39% increase in the growth rate of lettuce with a supplemented aquaponic solution. A DAS can provide independent regulation of water chemistry for each component. Monsees et al. [12] demonstrated a 36% higher fruit yield with more effective management of fertilisers and pH levels using a DAS.

Despite the apparent benefits of DASs, this article mainly focuses on coupled aquaponics systems due to their easier setup and the vast number of related publications. DASs are comparatively complex systems and require a high initial investment. Therefore, they are often appropriate for large-scale commercial setups.

3.3. Hydroponics—Grow Techniques for Plants

Aquaponics is the combination of aquaculture and hydroponics to produce fish and vegetables in a sustainable manner. Fish are generally grown in a simple tank that is sufficient to accommodate the densities of fish proportional to crop size. However, in hydroponics, three techniques have been widely discussed in the literature for growing plants [16,17]: deep water culture (DWC), the nutrient film technique (NFT), and media beds. Each has its advantages and disadvantages, which are explained in the following sections. Commercial setups often combine these techniques to obtain all the benefits of each.

3.3.1. Media-Based Systems

These systems use large trays or boxes filled with solid growth media, such as gravel, expanded clay pebbles, or stones, to provide support for plants and serve as a biofilter for converting fish waste into plant nutrients [16]. They use flood and drain cycles to ensure adequate aeration and supply nutrients to plant roots. This is the ideal technique for beginners and is comparatively more fault-tolerant [17]. Media-based systems provide good support to plant roots, natural filtration, and a large area for bacterial growth. Depending on which media are used, they can become very heavy, be labour labour-intensive to construct and maintain, and may not be suitable for large-scale setups [18].

3.3.2. Nutrient Film Technique

In NFT systems, horizontal pipes are used to grow plants. Small holes are drilled into the pipes to support plants and keep their roots inside. A continuous stream of nutrient-rich shallow water is pumped from the fish tank, and the plants absorb the nutrients they need for growth before the water is returned to the tank. This technique uses the least amount of water, allows for easy harvesting, and is most suitable for rooftops because it is lightweight and does not use soil [17]. However, this technique requires careful monitoring and management to ensure that the water and nutrient levels are maintained within the optimal range for plant growth. Water quality issues can quickly escalate if the water circulation is interrupted for any reason, such as power failure or clogging of pipes with debris [18].

3.3.3. Deep Water Culture

In the DWC technique, plants are generally grown on a floating polystyrene sheet over a water bed [16]. Small holes are made in the sheets to support plants and keep their roots in water. The nutrient-rich water is typically recirculated from a fish tank or other nutrient source, and an air pump is used to provide oxygen to the roots of the plants. The roots of the plants grow down into the water, absorbing the nutrients they need for growth. DWC is a cost-effective technique that allows for easy harvesting and planting and a high density of plants to be grown in a small space, but it requires more complex filtration methods and is unsuitable for large plants [18]. Moreover, the roots of the plants can become tangled and overcrowded if the plants are not spaced properly or if they grow too large for the size of the tank or tray. This can lead to a reduction in plant growth and can also increase the risk of disease and pest infestations [17].

3.4. System Sizes of Domestic and Commercial Systems

The design and size of aquaponics systems vary greatly depending on production requirements and specific needs, ranging from small-scale domestic systems to large-scale commercial setups. Commercial systems are typically designed to meet the demand for fresh produce in local shops and supermarkets. On the other hand, domestic systems can allow each home to achieve self-sustainability and produce its own food. According to Palm et al. [10], these systems have the potential to become an integral part of future homes and smart cities.

Aquaponics is a versatile system that can be adopted for domestic and commercial needs. Domestic aquaponics systems typically involve cultivating fish and plants in closed-loop systems, typically consisting of a single fish tank, such as an aquarium, and a small hydroponics unit with a maximum area below 50 m^2 [19]. Commercial systems are relatively complex to build, requiring a dedicated mechanical filter for solid separation and a biofilter for the nitrification and growth of bacteria. Water flows from the fish tank to the solid separator, then to the biofilter, and from the biofilter to plants. Finally, the water from plants is dumped into a sump, and from there, it is pumped back to the fish tank. The sizes of both domestic and commercial systems, their required site area, and their mechanical complexity can be seen in Table 1.

Table 1. Sizes of aquaponics systems for domestic and commercial setups.

Aquaponics System	Market	Site Area	Mechanical Complexity
Domestic systems	Home use or direct sales	Below 50 m^2	Low
Small-scale commercial	Retail or wholesale	50 to 100 m^2	Medium
Medium-scale commercial	Wholesale	100 to 500 m^2	High
Large-scale commercial	Wholesale	Above 500 m^2	High

4. Use of the IoT and AI in Aquaponics

Aquaponics is a complex ecosystem, and manually monitoring and maintaining each parameter is a difficult task for cultivators. The IoT and AI can greatly increase the efficiency of aquaponic farms by eliminating operational complexities, enabling process automation, and ensuring stable operation [8]. Recent research has trended toward automation to optimise processes such as climate control, anomaly detection, and remote access with the goal of reducing operational costs and making aquaponics more sustainable. The Scopus database reveals an upward trend in the use of the IoT and AI in aquaponics systems. Figure 3 shows the total number of publications on aquaponics involving the IoT and AI for each year based on the following search term:

TITLE-ABS-KEY ((aquaponic*) AND (“IoT” OR “internet of things” OR “artificial intelligence” OR “AI” OR “machine learning” OR “smart” OR “intelligent”)) AND (LIMIT-TO (LANGUAGE , “English”)).

Various electronic sensors were used in the reviewed studies to monitor farm parameters, the most common of which were water and air temperature, humidity, pH, DO, light intensity, and ultrasonic level sensors to monitor water level and plant height. Sensor data were used to control farm environments, including climate control (lighting, heating, and cooling), aerator control, water pumps, and automated fish feeders. However, not all studies provided complete control of the farm environment, with many limited to one or two control elements.

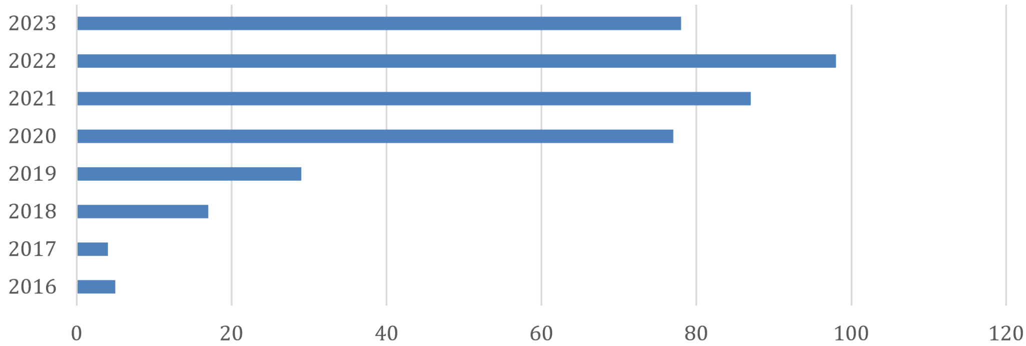

Figure 3. Number of publications in Scopus from 2016 to August 2023 discussing the use of the IoT and AI in aquaponic systems.

The use of Arduino-based microcontrollers and Raspberry PI hardware was common among the reviewed papers, where control logic was implemented locally, and cloud connectivity was used for remote monitoring of farm health and to switch some actuators via a web interface.

Table 2 outlines the key sensing and control elements used in recent publications.

Table 2. Use of sensing and control elements in recent publications.

Sensors															Controls				IoT	AI	Publication
Water Temp.	pH	Dissolved Oxygen	Ammonia	Nitrite	Nitrate	Total Dissolved Solids	Water Salinity	Electrical Conductivity	Flow	Level	Air Temp.	Humidity	Light	Machine Vision	Heating	Lighting	Water Pump	Feeder	-	-	-
	x										x	x					x		x		Mansor et al. [20]
x	x	x	x	x	x	x	x	x											x		Alselek et al. [21]
x	x	x									x	x				x	x		x		Wan et al. [22]
x	x							x			x	x	x		x	x	x		x	x	Reyes Yanes et al. [23]
										x	x	x				x		x	x		Kodali and Sabu [24]
x	x	x									x	x	x	x					x	x	Murakami and Yamamoto [8]
x	x					x				x	x	x					x		x		Wijayanto et al. [7]
	x										x	x					x		x		Ntulo et al. [25]
x	x	x				x				x	x		x	x	x	x	x	x	x	x	John and Mahalingam [5]
x	x	x						x		x	x	x	x		x	x	x	x	x		Mahkeswaran and Ng [26]
x	x	x						x			x								x		Banjao et al. [27]
														x						x	Concepcion II et al. [28]
														x						x	Lauguico et al. [29]
x	x	x													x		x	x			Mandap et al. [30]
x	x							x		x	x	x	x			x		x			Jie Ong et al. [31]
x	x								x	x			x		x	x	x	x			Kyaw and Ng [32]

x = used.

The complexity of aquaponics lies in the interdependent relationship among its core components: fish, bacteria, plants, nutrient cycles, and system maintenance. Fish generate nutrient-rich waste, primarily ammonia, which beneficial bacteria transform into nitrites and then nitrates, serving as essential nutrients for plants [17]. These plants, in turn, filter the water, creating a healthier environment for fish. Managing this relationship involves maintaining a delicate balance of nutrient levels, water quality, and system functionality.

The IoT and AI can play a vital role in managing these interdependencies. IoT sensors can continuously monitor crucial parameters like water quality pH, ammonia, nitrites, nitrates, temperature, oxygen levels, and water flow rates. These real-time data are pivotal for understanding the health of the system. For example, IoT sensors can promptly detect an imbalance in nutrient levels or a fluctuation in water quality and alert operators to take corrective actions.

The following section delves into the potential ways in which AI and the IoT can manage these complexities, optimise aquaponics operations, and enhance their efficiency over traditional aquaponics systems.

4.1. The Synergy of AI and the IoT in Revolutionising Aquaponics

The convergence of AI and the IoT holds immense potential for transforming aquaponics systems and enhancing their efficiency, sustainability, and overall productivity. By integrating these technologies, aquaponics operators can harness real-time data, automate system control, optimise component performance, and make data-driven decisions, leading to a more efficient, sustainable, and productive aquaponics system [33].

4.1.1. Real-Time Monitoring and Predictive Analytics

AI algorithms can analyse real-time data from IoT sensors to monitor critical parameters such as water quality, nutrient levels, fish health, and plant growth indices [6,8]. This enables the early detection of potential issues, such as imbalances, contamination, or disease outbreaks, allowing for proactive interventions to minimise disruptions and maintain optimal system performance.

4.1.2. Remote Monitoring and Management

IoT-enabled remote monitoring provides aquaponics operators with the ability to access and analyse system data from anywhere, enabling real-time adjustments and interventions even when away from the site [34,35]. This promotes continuous optimisation and ensures optimal system performance even from remote locations.

4.1.3. Automated System Control and Maintenance

IoT sensors can trigger automated tasks, such as adjusting water flow, aeration, nutrient dosing, and filtration cycles, based on real-time data and AI-generated recommendations [6,36]. This reduces manual labour requirements and ensures consistent system performance, minimising the risk of human error.

4.1.4. Predictive Maintenance and Anomaly Detection

AI algorithms can analyse historical data and sensor readings to identify patterns and predict potential breakdowns or malfunctions in system components [6,33]. This enables proactive maintenance, preventing downtime and disruptions to production. By anticipating failures, aquaponics operators can efficiently schedule maintenance tasks and ensure uninterrupted operation.

4.1.5. Nutrient Management

Nutrient management is a crucial aspect of aquaponics, as it involves maintaining the right balance of nutrients in the water to ensure healthy plant growth and fish health. The use of AI and the IoT can help optimise nutrient management in aquaponics by providing real-time data on water quality parameters such as pH, DO, ammonia, nitrate, and nitrite. These data can be used to identify potential imbalances in these water quality parameters, which can help efficiently manage the nutrients in the system [37].

4.1.6. Data-Driven Decision Making and Optimisation

AI-powered decision support systems can aggregate and analyse data from IoT sensors [23], system performance logs, and market trends to provide actionable insights for aquaponics operators. This facilitates data-driven decision making and the optimisation of system operations, leading to improved resource utilisation, cost savings, and increased productivity.

4.1.7. Optimising Fish Health and Feeding

AI coupled with IoT sensors offers continuous monitoring capabilities for crucial water quality parameters such as temperature, dissolved oxygen (DO), pH, ammonia, nitrite, and nitrate levels within the fish tank. These real-time data can serve as a valuable resource for understanding fish health, facilitating the early detection of potential issues such as ammonia or nitrite poisoning, as well as identifying signs of diseases or abnormalities within the system [31,38]. In addition to functioning as early warning systems for fish health, AI algorithms can also play a pivotal role in optimising feeding practices. By leveraging machine vision, AI can analyse video streams and images from the fish tank to track fish movement and behaviour, providing real-time estimations of feed intake and fish growth rates. This capability assists in refining feeding schedules to ensure the optimal quantity of food is dispensed, mitigating the risk of overfeeding and subsequent waste generation. This precise feeding regimen not only safeguards water quality but also sustains a healthy aquatic environment [31]. Furthermore, through the analysis of historical feeding data, growth patterns, and nutritional content, machine learning algorithms can help optimise feed formulations or dynamically adjust feeding schedules based on real-time data. This adaptive approach ensures the provision of adequate nutrition to the fish while minimising costs [33].

4.1.8. Optimising Filtration and Bioconversion

The use of AI and the IoT can enhance the efficiency of both mechanical filters and biofilters in aquaponics. Mechanical filters are responsible for removing solid waste and debris from the water, whereas biofilters provide a habitat for beneficial bacteria that convert harmful ammonia and nitrite into less harmful nitrate [18]. For a healthy bacterial colony, it is important to maintain adequate levels of pH, DO, water temperature, and UV light [17]. IoT sensors can monitor these parameters in real time and ensure they remain within their optimal ranges by alerting farmers of any deviations or suggesting they take other corrective measures, such as activating aerators to increase DO levels or heaters to increase temperature [35]. The key indicators of bacterial activity are the ammonia and nitrite levels; they should always be under 1 mg/L in a balanced system [17]. IoT sensors can monitor the ammonia and nitrate levels, identify changes in the nitrification rate, and ensure they remain within their optimal ranges [21].

To ensure mechanical filter functionality, a flow-rate sensor can be used [32]. Typically, a blockage would impact water flow, and AI algorithms can analyse historical flow-rate data, identifying trends and deviations from established patterns. This analysis, in turn, can detect potential blockages within the filter or performance degradation over time. Additionally, a turbidity sensor mounted inside the filter tank can continuously monitor water clarity. Increased turbidity levels indicate a rise in suspended solids, which could result from filter clogging or excessive organic matter buildup. By analysing flow-rate and turbidity data using ML algorithms, it is possible to determine the optimal time for filter media replacement or cleaning [39].

Moreover, AI algorithms can analyse historical data from all these sensors and make recommendations for bacterial management [6], such as dosing nitrifying bacteria cultures to boost bacterial activity and address ammonia spikes, adding or removing specific microbial strains to maintain a healthy and balanced community of microbes for effective ammonia and nitrite conversion [40,41], and water recycling or periodic filter tank cleaning to manage bacterial populations and prevent nitrite build-up.

These combined approaches optimise filtration and bioconversion by maintaining a healthy aquaponics system and reducing human error.

4.1.9. Optimising Plant Growth

AI and IoT technologies can also be employed to optimise plant growth in aquaponics systems [28]. By continuously monitoring plant health metrics, such as leaf nutrient levels, chlorophyll content, and photosynthetic efficiency, AI algorithms can identify potential growth limitations and suggest adjustments to nutrient dosing, light intensity, and environmental conditions. For instance, AI can analyse leaf nutrient levels to detect deficiencies or imbalances [37], prompting automated nutrient dosing adjustments to ensure optimal nutrient availability for plant growth. Additionally, AI can monitor plant photosynthetic efficiency, which reflects a plant's ability to convert light energy into biomass. By analysing photosynthetic efficiency data, AI can optimise the light intensity and spectral distribution to maximise plant growth rates and yield. Furthermore, IoT sensors can track plants' water uptake and moisture levels in the growing media, allow control of water circulation to ensure consistent water availability for plants and prevent water stress.

By harnessing the power of AI and the IoT, aquaponics can be transformed into a highly efficient, sustainable, and productive form of agriculture, offering a promising solution for addressing global food security challenges while minimising the environmental impact [33].

4.2. IoT Sensors, Controllers, and Communication Technologies

To enable the IoT in aquaponics, three essential components need to be integrated: sensors, controllers, and a network communication interface. There is a variety of standalone sensors available in the industry that can be selected based on project requirements. These sensors generate electrical signals that need to be translated by a controller. A computer program inside the controller tells it what these electrical signals mean, how to translate them, and what action needs to be taken next. For example, turning off the water pump when the water tank is filled or activating aeration when the DO level drops below a certain point. Together, they can perform various automation tasks that are preprogrammed. However, without IoT connectivity, their data handling and AI capabilities are very limited. The communication interface enables internet connectivity in the controllers, which opens up many possibilities, including massive data handling and storage capabilities using big data. It also enables the ability to remotely monitor and control aquaponic farms, run complex AI algorithms, and train models, which were never before possible.

4.2.1. Key Parameters and Electronic Sensors

There are several key parameters that need to be monitored to ensure optimal growth performance. The optimal ranges for these parameters can vary greatly depending on the species of fish and plants in the system, as well as the specific design and setup of the aquaponics system. To avoid system failures and achieve better efficiency, it is crucial to regularly monitor the key parameters and ensure that they remain within the appropriate range for the healthy growth of fish and plants in the system. The next sections discuss the key parameters, the available sensors, and their optimal ranges as a general guideline.

4.2.2. Temperature and Humidity

All aspects of an aquaponics system are affected by temperature. The water temperature is considered the most important parameter, as it greatly impacts the whole process, fish health, and plant growth. The temperature requirements of plants and fish vary greatly between species, but generally, plants can tolerate between 16 and 30 °C, cold water fish between 10 and 18 °C, warm water fish between 22 and 32 °C, and nitrifying bacteria between 14 and 34 °C [17,42]. To avoid any production issues, it is important to choose a combination of plants and fish that matches their optimal temperature as closely as possible. The ambient temperature of the farm's location is also a key factor to consider, as controlling the temperature is an energy-intensive operation that could lead to high energy bills and thus make the business unprofitable.

Temperature and humidity can be easily monitored using basic electronic sensors. Two types of sensors have been discussed in the studied literature: standalone sensors and sensors that combine temperature and humidity sensing elements in a single unit. It has been found that combined sensors are only suitable for monitoring air temperature and humidity, whereas standalone sensors are suitable for monitoring water temperature due to their ability to be submerged in the water.

The lack of consistency in the literature regarding the specific models of sensors used could be due to the limited availability of some sensors or the numerous options that perform similarly. Each study may have conducted experiments using the sensor that was most easily accessible. The reviewed studies used various sensors, as detailed in Table 3. The resolution and accuracy of each sensor differed. The sensors used by Murakami and Yamamoto [8] appear to be the best due to their higher accuracy and reliability. The PT-1000 is widely used in industrial applications, and the SHT-31-D is from Sensirion, a reputable manufacturer. However, the DS18B20 also seems to have the second-best accuracy and resolution, with easy accessibility and a lower price tag.

Table 3. Use of temperature sensors in the reviewed studies.

Sensor	Accuracy	Range	Resolution	References
DHT11	±2 °C	0 to 50 °C	1 °C	Nagayo et al. [35] Kodali and Sabu [24] Yanes et al. [9] Bolte et al. [43] Ng and Mahkeswaran [44] Murakami and Yamamoto [8]
PT-1000	±0.15 °C	−200 to +850 °C	-	Murakami and Yamamoto [8]
DS18B20	±0.5 °C	−55 to +125 °C	0.0625 °C	Ghandar et al. [45] Nagayo et al. [35] Mandap et al. [30] Khaoula et al. [34] Yanes et al. [9] Ng and Mahkeswaran [44] Wijayanto et al. [7] Mohd Ali et al. [46] Reyes Yanes et al. [23]
SHT-31-D	±0.2 °C	−40 to +125 °C	0.01	Murakami and Yamamoto [8]
DHT22	±0.5 °C	−40 to +80 °C	0.01	Mansor et al. [20] Wijayanto et al. [7] Ntulo et al. [25] Reyes Yanes et al. [23]
LM35	±0.5 °C	−55 to +150 °C	-	Prabha et al. [47]

4.2.3. pH

pH (Potential of Hydrogen) is the measure of acidity or alkalinity of a solution. It is one of the key parameters to maintain in an aquaponics system and can be described as a master variable that affects several chemical and biological processes essential for plant growth. It controls the nutrient availability to plants [48]. The pH scale is logarithmic, meaning that a change of one pH unit represents a tenfold change in the hydrogen ion concentration. For instance, a pH of 7 has ten times fewer hydrogen ions than a pH of 6, and a pH of 9 has

1000 times fewer hydrogen ions than a pH of 6. This significant decline in hydrogen ions can significantly impact the survival of fish and plants. For optimum growth and better nutrient uptake, most plants require a pH value between 6 and 6.5 [49]. Nitrifying bacteria prefer the pH to be above 6. In an acidic environment, their ability to convert ammonia to nitrate is reduced. This can lead to an increase in ammonia in the system, which can be harmful to fish and plants. The optimum pH for nitrifying bacteria is above 7 [49], and the efficiency of nitrification increases linearly by 13% with each unit of pH between a range of 5 and 9 [50]. The optimum level of pH for fish varies between fish species. According to Goddek et al. [49], Tilapia fish achieve the best growth performance between a pH range of 7.0 and 9.0, yet they can survive large fluctuations in the range of 3.7 to 11.0. Generally, the optimum pH range for most fish is between 6 and 8.5 [42]. The monitoring of pH has been broadly discussed in the reviewed papers. Wijayanto et al. [7] implemented an IoT system for aquaponics, where a pH sensor was used to monitor the level of acidity in the aquaponic water. The system was tested by artificially adding the alkaline and acidic solutions with the help of peristaltic pumps. Jie Ong et al. [31] used a sensor to monitor the pH level, which was reported to an online application. A variety of sensors have been used, mostly with identical specifications, from low-end manufacturers targeting hobbyists and enthusiasts. One of the better-quality sensors is from Atlas Scientific, which was used in Murakami and Yamamoto [8]'s study. The specifications for both categories of sensors are shown in Table 4.

Table 4. Use of pH sensors in the reviewed studies.

Sensor	Accuracy	Range	Resolution	References
DF Robot/Grove pH probe	±0.1	0 to 14	0.15	Khaoula et al. [34] Ntulo et al. [25] Udanor et al. [51] Wijayanto et al. [7] Mahkeswaran and Ng [26] Jie Ong et al. [31]
Atlas Scientific pH probe	±0.002	0 to 14	0.001	Alselek et al. [21] Murakami and Yamamoto [8]

4.2.4. Dissolved Oxygen

Oxygen is essential for all living things in aquaponics: fish, plants, and bacteria. Dissolved oxygen is a relative measure of the oxygen concentration in the water, and it is measured in milligrams per litre. It is the most critical parameter in aquaponics, which, if disregarded, could have catastrophic results. If, for any reason, the DO level drops, fish can die within hours, depending on the size of the tank and fish density. Particularly in small aquaponics systems, if aeration is stopped, DO levels can quickly decrease due to a limited time buffer. A pump or aerator failure is a common cause. Therefore, a drop in DO must be detected as soon as possible, and countermeasures should be taken to avoid any failures. According to Somerville et al. [17], the optimum level of DO for all organisms to thrive is between 5 and 8 mg/litre.

In aquaponics systems, DO can be measured using three types of sensors: polarographic, galvanic, and optical. Both polarographic and galvanic sensors are electromechanical sensors that work by diffusing the dissolved oxygen from the water sample. Electrical voltages are generated when the oxygen passes inside the sensor from a membrane, causing a chemical reaction. Polarographic sensors require a constant voltage to be applied, which must be polarised. In contrast, galvanic sensors are self-polarising, reducing the warm-up time by 5–15 min. Optical sensors measure the DO concentration in water based on the quenching effect. This process decreases the fluorescence intensity of a given substance. A photodiode inside the sensor detects the quenched luminescence and compares it against a reference value to calculate the DO concentration in the water. The advantage of optical sensors is that they do not require frequent calibration and are not dependent on the velocity of water flow, making them the preferred choice in commercial setups. Many of the reviewed studies used electromechanical sensors. For example, Udanor et al. [51] used a DF Robot DO sensor probe for Arduino. Mandap et al. [30] and Murakami and Yamamoto [8] used the DO probe from Atlas Scientific, which is considered to be a better-quality probe with a wider measurement range of 0–50 mg/L compared to 0–20 mg/L for the DF Robot probe.

There was no use of optical probes in the reviewed studies. This could be due to the limited availability and higher cost of these probes, generally above GBP 500 at the time of writing this paper.

4.2.5. Total Nitrogen: Ammonia, Nitrite, and Nitrate

Nitrogen is an essential water quality parameter in aquaponics systems. It enters the system through fish feed as crude protein, and the fish utilise a portion for growth while releasing the rest as waste. The waste consists primarily of ammonia and is expelled through the gills and urine, with some unconsumed feed waste being converted into ammonia by microbes. Bacteria in the system convert ammonia into nitrite and then further into nitrate through a process called nitrification. Although nitrogen compounds can be toxic to fish, they serve as a valuable nutrient source for plants and are the basis of plant fertilisers. In a well-functioning aquaponics system with proper biofiltration, ammonia and nitrite levels should be minimal, ideally close to zero or ranging from 0.25 to 1.0 mg/L. The bacteria in the biofilter should effectively convert ammonia and nitrite into nitrate before any harmful buildup occurs. Fish can generally tolerate up to 300 mg/L, but above 250 mg/L, plants will start accumulating excessive nitrate into their leaves, which is unsafe for human health. The optimum nitrate level to maintain is between 5 and 150 mg/L [17]. The nitrification process is dependent on the water temperature, pH, and DO levels. Optimal nitrification can be achieved when the temperature is between 25 °C and 30 °C, pH is between 7 and 9, and DO levels are below 20 mg/L [16].

Generally, ammonia is measured manually using chemical tests, which is a cumbersome process, especially in small-scale systems. It often requires colour comparison with a reference chart by the human eye. The colours in the reference chart are generally very close to each other and could easily deceive human judgement, resulting in incorrect findings. Electronic sensors are available, but they are generally very expensive, often costing thousands of pounds. This is likely the reason they were often not used in the reviewed studies.

4.2.6. Water Level

In aquaponics, adequate water levels need to be maintained in the system, particularly in the fish tank, so that fish can move freely and thrive. Water is typically consumed in the system through evaporation and transpiration, or it is manually drained to remove waste from the system. Water levels can be monitored in the system using basic float switches or ultrasonic sensors. Ultrasonic distance sensors, such as the HC-SR04 from Sparkfun, have often been discussed in the reviewed literature. They work by emitting high-frequency sound waves beyond the range of human hearing. These waves propagate through the air and reflect back when they encounter a surface, such as water. By measuring the time it takes for the waves to travel to the water's surface and return, the level of water can be calculated. This method allows for accurate monitoring and measurement of water levels in aquaponics. However, the HC-SR04 is not appropriate or reliable for long-term use, particularly in commercial applications. Furthermore, the electronics are not protected against water, and a few accidental splashes of water can easily damage them. To ensure reliable operation, water-level sensors should be at least water-resistant or ideally, IP68-rated. IP68 is an Ingress Protection (IP) rating for dust and water protection, indicating that a device is dust-tight and can withstand temporary immersion in water up to 1.5 m (4.9 feet) for 30 min.

4.2.7. Water Flow Rate

The flow rate is an important factor in maintaining the overall balance of an aquaponics system. It influences the rate of nutrient cycling, oxygen availability, and waste removal. A consistent flow rate in the system can help maintain stability and ensure that fish and plants receive optimal conditions for growth. It is important to note that the ideal flow rate varies depending on the size of the system, the specific fish and plant species, and the design of the aquaponics setup. During the initial setup, the flow rate is typically set using a manual valve, but adjustments may be required if changes in pressure are observed during operation. While electronic sensors or water meters can be used to monitor flow rates, the reviewed literature suggests that they are not commonly utilised in small-scale systems. This may be due to the preference for manual observation, as flow rates tend to remain relatively stable in a well-functioning system, thereby reducing complexity and cost.

4.2.8. Light Intensity

Light is the primary energy source for photosynthesis, and it is the process by which plants convert light energy into chemical energy. Through photosynthesis, plants produce sugars and other organic compounds necessary for their growth. Without adequate light, plants may struggle to photosynthesise effectively, resulting in stunted growth or even death.

When setting up an aquaponics system, it is essential to consider the lighting needs of the plants being grown. Factors such as light intensity, duration, and spectrum should be taken into account. The use of electronic sensors was widely observed in the reviewed literature for detecting light intensity and controlling artificial light. For example, Nagayo et al. [35] used an LDR (Light-Dependent Resistor) to automatically activate artificial grow lights when it is dark, and Sunardi et al. [52] used an LDR to monitor solar lighting. Table 5 shows the types of sensors used in the various studies.

Table 5. Use of light-intensity sensors in the reviewed studies.

Sensor	Range	References
LDR (Photoconductive cell)	5 k to 100 k Ohms @ 10 Lux	Ghandar et al. [45] Nagayo et al. [35] Sunardi et al. [52] Prabha et al. [47]
TLS2561 (Photojunction device)	0.1 Lux to 40,000 Lux	Murakami and Yamamoto [8] Mahkeswaran and Ng [26]

4.2.9. Total Dissolved Solids, Electrical Conductivity, and Salinity

Electrical conductivity (EC) is a measurement of the electrical charge that passes through water in aquaponics systems, whereas Total Dissolved Solids (TDS) refers to the measure of anything dissolved in the water, usually mineral salts. The more salt dissolved in the water, the higher the electrical conductivity, making them highly correlated. Therefore, TDS and salinity are often estimated from the EC in electronic sensors to reduce processing time and hardware complexity. It is recommended to maintain a TDS level between 200 and 400 ppm in aquaponics systems [49]. Salinity levels may vary depending on the plant species, but it is generally advised to keep the water salinity below 1500 µS/cm [17].

Wijayanto et al. [7] used an EC sensor to detect TDS levels in aquaponic water. The system was tested by dissolving a salt solution in the fish water until it reached a set threshold. Another experiment by Mahkeswaran and Ng [26] used an EC sensor to monitor the electrical conductivity of water and report it to a mobile-based GUI application.

4.3. Controllers—Microprocessor or Microcontroller

To process sensor data and perform any kind of automation in aquaponics, a microcontroller or a microprocessor is required. The difference between a microcontroller and a microprocessor is that a microcontroller contains a CPU (Central Processing Unit), memory, and all I/O-related hardware in a single chip. In contrast, microprocessors often contain a CPU only. Comparatively, the processing power of a microcontroller is very limited; it is an inexpensive part, usually does not require an OS (Operating System) to run, and is used in a range of applications from calculators to washing machines. Almost all modern electrical appliances contain one or more microcontrollers. The use of both microcontroller- and microprocessor-based systems was observed in the reviewed works. Microcontroller-based systems were largely Arduino-based, such as Atmega, ESP32, ESP8266, etc. Microprocessor-based systems included Raspberry Pi and other SBCs (Single-Board Computers) like the NVIDIA Jetson Xavier, etc. Table 6 shows the usage of controllers in the reviewed studies.

The use of Arduino-based microcontrollers and Raspberry PI hardware was most common among the reviewed papers. Control logic was implemented locally, and the cloud connectivity was used for remote monitoring of a farm's health and to switch some actuators via a web interface.

Table 6. Controllers used in the reviewed studies.

Controller	Usage	References
Atmega	Reads sensor data and controls actuators	Nagayo et al. [35]
ESP8266 ESP32	Reads sensor data, controls actuators, and provides cloud connectivity	Wan et al. [22] Khaoula et al. [34] Udanor et al. [51] Kodali and Sabu [24]
Raspberry Pi	Reads sensor data, controls actuators, and runs web applications	Wijayanto et al. [7]
ESP8266 + Raspberry Pi	ESP32 reads sensor data and controls actuators; Raspberry Pi for analyses data and provides cloud connectivity	Ghandar et al. [45]
Atmega + ESP32	Atmega reads sensor data; ESP32 provides cloud connectivity	Mansor et al. [20] Banjao et al. [27] Ng and Mahkeswaran [44]
Atmega + esp8266	Atmega reads sensor data and controls actuators; ESP8266 provides cloud connectivity	Ntulo et al. [25] Ng and Mahkeswaran [44]
Atmega + Raspberry Pi	Atmega reads sensor data and controls actuators; Raspberry Pi runs web applications and provides cloud connectivity	Mandap et al. [30] Sunardi et al. [52] Jie Ong et al. [31] John and Mahalingam [5]
Raspberry Pi + PIC32	Processes sensor data, runs pre-trained models, and controls actuators	Dhal et al. [53]
MSP430 + ESP8266	MSP430 microcontroller processes sensor data; ESP8266 provides cloud connectivity	Lee and Wang [54]
Jetson Xavier + nRF52840	nRF52840 reads sensor data and provides Bluetooth connectivity; Jetson Xavier processes image processing and runs ML algorithms.	Murakami and Yamamoto [8]

The controller acts as the brain of the system. Electrical signals from all connected sensors are transmitted to it, which are then processed according to the program running inside, and automated decisions are made to activate or deactivate specific actuators.

Microprocessor-based systems were mostly used where image processing was required or for running local app servers, data storage, and visualisation. For example, Murakami and Yamamoto [8] used an NVIDIA Jetson Xavier NX to capture images from multiple depth cameras and run ML algorithms to estimate growth. Mandap et al. [30] used Raspberry Pi to run a local web server and database storage. John and Mahalingam [5] used Raspberry Pi to capture images from a CMOS camera and detect fish feed in the fish tank.

4.4. Communication Technologies to Enable the IoT

Any physical device that has a sensor attached to it and can transmit data to the internet is referred to as an IoT device. All IoT devices must have some communication interface that allows them to transmit and receive data from the internet. There are many communication technologies available on the market, which can be categorised into two types: ones that provide direct IP (Internet Protocol) connectivity, such as WiFi and cellular, and ones that provide indirect connectivity with the help of gateways such as Zigbee, LoRaWAN, LPWAN, etc. Table 7 shows the available technologies that can be used in aquaponic farms.

Table 7. Available communication technologies.

Technology	Communication Range	Data Rate	Frequency	Power Consumption
WiFi	Up to 100 m	Up to 9.6 Gbits/s	2.5 GHz, 5 GHz, and 6 GHz	Higher
Cellular (GPRS)	-	Up to 171.2 Kbps	850/900/1800/1900 MHz	Higher
LoRaWAN	Up to 10 km	27 kbit/s	868 MHz, 900 MHz, 2.4 GHz	Lower
Sigfox	Up to 40 km	100/ 600 bps	868 MHz, 902 Mhz	Lower
LTE-M	-	300/375 kbps	-	Lower
NB-IoT	-	30/60 kbps (NB1) - 127/169 kbps (NB2)	-	Lower

Devices with indirect connectivity are generally ultra-low power; they can last on coin cell batteries for years. However, their use in aquaponic studies is very limited. Bolte et al. [43] designed a sensor node using LoraWAN for long-range transmission. Murakami and Yamamoto [8] designed an aquaponics system where sensor data were transmitted using Bluetooth. Despite the range of communication technologies available on the market, the majority of experiments were conducted using WiFi connectivity. This is probably due to the easy availability and lower cost of WiFi modules.

4.5. Use of AI in Aquaponics

In recent years, the use of machine learning and AI has become the focus of studies in aquaponics to optimise plant growth and improve resource efficiency. Machine learning algorithms can be used to analyse data from image sensors or sensors that measure environmental factors such as temperature, pH, DO, and nutrient levels in the water. By using these data, machine learning models can be trained to predict the optimal conditions for plant growth in aquaponics, monitor the growth of fish and plants, or identify problems in the system. In the studied literature, AI methods were effective at visually classifying plant growth stages, estimating fish size, detecting nutrient deficiencies and plant diseases, detecting anomalies, and optimising processes. This section discusses the common applications of AI and ML in aquaponics. In essence, it is not meant to cover all AI and ML research conducted in the aquaponics industry but rather give an idea of current research interests. The AI methods used in the reviewed studies can be seen in Table 8.

Table 8. Usage of AI methods in aquaponics.

Usage	AI Methods	References
Prediction of dissolved oxygen	Deep Convolutional Neural Network (DCNN), K-Nearest Neighbour (KNN), Support Vector Machine (SVM), Decision Tree (DT)	Taha et al. [55]
	LSTM, CNN, CNN-LSTM	Barzegar et al. [56]
	Back Propagation (BP), CNN	Ta and Wei [57]
Growth estimation of plant	Mask-RCNN	Murakami and Yamamoto [8]
	Artificial Neural Network (ANN), Latent Dirichlet Allocation (LDA), Quantum Support Vector Machine (QSVM)	Concepcion II et al. [28]
	DCNN, KNN, SVM, DT	Lauguico et al. [29]
Detection of nutrient deficiencies	DCNN, KNN, SVM, DT	Taha et al. [55]
Detection of disease	YOLOv5s, Fast-RCNN	Abbasi et al. [36]

4.5.1. Prediction of Dissolved Oxygen

One of the important parameters that need to be monitored in aquaponics is the DO level in the water, which is crucial for the health and growth of fish and plants. Machine learning algorithms can help predict DO levels in aquaponics systems, making it easier for farmers to maintain optimal DO levels. Various machine learning models, such as LSTM and CNN, can be used. These models can use data such as water temperature, pH levels, and EC to predict DO in the water. A study by Ta and Wei [57] proposed a simplified reverse-understanding CNN model to predict DO. The results showed that the accuracy of the model was adequate for use in commercial farms. Another study by Barzegar et al. [56] tested various machine learning models, specifically CNN and LSTM, to predict concentrations of DO in water. Time-series data of 1 year, which included water temperature, pH, oxidation–reduction potential (ORP), electrical EC, and DO, were used for model development. The findings indicated that the LTSM model performed better compared to the CNN. However, a new approach using a coupled CNN-LSTM model outperformed the standalone models.

4.5.2. Growth Estimation of Plants

One of the most common applications of ML in aquaponics was found to be the growth estimation of plants and fish using vision-based systems. Various papers focused on plants, specifically lettuce. Concepcion II et al. [28] used three ML approaches, namely LDA, ANN, and QSVM, to identify the growth stage of lettuce. In the study, the LDA model was found to be very unstable. The ANN achieved the highest accuracy of 90% during the training phase but fell to 85% during testing. QSVM was shown to be the best-performing model, with testing and training accuracies of 87.90% and 88.33%, respectively. Another study by Murakami and Yamamoto [8] used a sensor network and two types of cameras for the growth estimation of fish and plants. The environmental data were collected using an air temperature and humidity sensor, illuminance sensor, pH sensor, water temperature sensor, and dissolved oxygen sensor. Data were transmitted via Bluetooth low-energy (BLE) wireless sensors to a Jetson Xavier NX. To capture plant images, a RealSense depth camera D415 module was used, and a ZED Mini stereo camera was used to capture fish images. Both cameras were directly connected to a Jetson Xavier board, and Mask-RCNN was used to extract pixels from the captured images. The accuracy of the method was evaluated using the RMSE (Root-Mean-Squared Error), and the average RMSE was 6.92%. This indicates that the proposed method was sufficiently accurate to track changes in plant growth conditions over time.

4.5.3. Nutrient Deficiencies

One of the challenges of aquaponics is ensuring that plants receive the necessary nutrients for healthy growth. Nutrient deficiencies can lead to stunted growth, reduced yield, and even death. Traditional methods of monitoring plant nutrition in aquaponics involve manual testing of water quality and plant tissue samples, which can be time-consuming and labour-intensive. Machine learning can be used to automate the detection of nutrient deficiencies in aquaponics. By analysing data from sensors that measure water quality and plant growth, machine learning algorithms can identify patterns that indicate nutrient imbalances. For example, a machine learning model can be trained to recognise when the levels of nitrogen, phosphorus, or potassium in the water are too low or too high, based on their effects on plant growth.

Taha et al. [55] used deep CNNs to detect nutrient deficiencies in plants. The model was evaluated using 3000 images of lettuce, and it successfully classified the images with 96.5% accuracy into four categories: (1) potassium deficiency, (2) nitrogen deficiency, (3) phosphorous deficiency, and (4) full nutrition.

4.5.4. Disease Detection

Plant disease is a common problem that can destroy a whole crop. The early detection of diseases is crucial for farmers, enabling them to take prompt action to prevent further spread and minimise losses. Machine learning algorithms can aid in plant disease detection by analysing various parameters, including plant growth patterns, leaf colour, and texture. Abbasi et al. [36] evaluated YOLOv5s and Fast-RCNN to detect diseases in leafy greens. The system works in three stages: first, it identifies the crop type; then, it checks whether it is diseased or healthy; and finally, it identifies the disease. Both models were initialised using transfer learning and then trained on datasets. In the experiment, the YOLOv5s outperformed Fast-RCNN with a detection speed of 52.8 FPS and an mAP@0.5 of 82.13.

5. Research Gaps and Future Work

Despite the significant progress made in recent years, there are still many challenges and research gaps present in the field of aquaponics. The following sections outline some of these challenges to our understanding.

5.1. Energy Efficiency and Profitability

Energy efficiency is crucial in aquaponics, and one of the major issues is high energy costs. In Europe and the UK, a large portion of the running costs may be attributed to energy consumption. Specifically, in cold weather, climate control becomes an essential requirement, and it is an energy-intensive operation.

The energy consumption of aquaponic farms can vary greatly depending on the location of the farm, weather conditions, and selection of fish and plant combinations. One small-scale aquaponic farm experiment conducted by Love et al. [58] in the USA reported 56 kWh of energy consumption to produce 1 kg of vegetables and 159kWh to increase the weight of tilapia fish by 1 kg. Another experiment by Delaide et al. [59] in Belgium reported 84.5 kWh of electricity consumption to grow 1 kg of vegetables and 96.2 kWh to increase tilapia weight by 1 kg. Considering the market prices of produce and the current energy rates in the UK, the economic viability of aquaponics remains a challenge. Table 9 shows the total cost to produce 1 kg of vegetables and fish. To make aquaponics a viable food production system, energy consumption needs to be optimised. This can be achieved by using renewable energy sources, finding ways to reduce energy usage, and developing smart environmental control systems to optimise energy usage on farms.

Table 9. Cost to produce 1 kg of fish and vegetables.

Reference	Product	Total Consumption	Cost/kWh	Total Cost
Love et al. [58]	Vegetables Fish	56 kWh 159 kWh	GBP 0.34 [60]	GBP 19.05 GBP 54.06
Delaide et al. [59]	Vegetables Fish	84.5 kWh 96.2 kWh	GBP 0.34 [60]	GBP 28.73 GBP 31.35

5.2. Anomaly Detection

Aquaponics systems are subject to environmental variability, such as changes in temperature, pH, and nutrient levels. Building robust detection methods to distinguish between normal fluctuations and genuine anomalies is a research challenge. Future research should focus on combining data from multiple sources, such as water quality data, fish behaviour data, and plant growth data, to develop reliable anomaly detection systems. Additionally, real-time anomaly detection is crucial for preventing and mitigating issues in aquaponics systems. Integrating anomaly detection into the local control systems of aquaponics setups can help automate responses to anomalies.

By addressing these research gaps, scientists and engineers can develop more effective and reliable anomaly detection systems for aquaponics. This will help aquaponic farmers in identifying and mitigating problems early on, improving the productivity and efficiency of their systems, and reducing the risk of losses.

5.3. System Design and Optimisation

There is a need for more research on how to design and optimise aquaponics systems for different climates, fish and plant species, and production goals. AI and the IoT could help analyse regional climate data, recommend the most productive fish–plant pairings, and seamlessly fine-tune the operational parameters. This not only minimises uncertainties for novice farmers but also avoids unexpected failures. Furthermore, the setup of an automated aquaponic farm often involves the installation of multiple sensors and actuators, coupled with the challenging task of configuring them to individual requirements. Addressing this hardware complexity is another key area that needs improvement. Introducing simplified control and monitoring systems could lower the entry barriers for traditional farmers and encourage the adoption of cutting-edge technologies.

5.4. Lack of Data

One challenge with aquaponics is the lack of publicly available data. The training process of an ML model heavily depends on large datasets and the selection of data. In most of the reviewed studies, only a general description of the methodology used was provided, and the datasets and codes used to train the ML models were excluded. This could be due to the work being proprietary, but it restricts the work from being verified or reproduced, which limits its adoptability by other researchers.

While many aquaponics systems already have electronic sensors installed, archiving the raw data in its most detailed form in public repositories could help accelerate the development of new intelligent systems.

5.5. Nutrient Management and Crop Variability

Understanding nutrient dynamics in aquaponics systems and optimising nutrient delivery to different crop types remains a research challenge. Studying crop-specific nutrient requirements and addressing potential nutrient imbalances can improve crop yield and quality. Public repositories of sensor data from a variety of crops and regions across the world could help in the study of nutrient dynamics and suggest nutrient supplements in real time to maximise farm efficiency.

5.6. Interoperability and Standardisation

Despite the variety of sensors and actuators used in aquaponics systems, there are no established standards defining how each component should work, what the most important parameters are, the allowable tolerances for each sensor, or guidelines for dataset selection. As a result, the selection of sensors and monitoring parameters in the reviewed studies was found to be questionable or unjustified. It seems that researchers are selecting sensors based on their personal preference or ease of use and programming them to meet their individual needs. This can lead to the production of datasets or results that are unique to their specific environment and sensor selection, making them less useful to other researchers. Unless there are plug-and-play-type sensors that are easy to install and interoperable among manufacturers, it would be difficult for a typical farmer or someone with less technical knowledge to adapt or access modern technologies.

5.7. Parameter Prediction

To optimise the performance of an aquaponics system, real-time monitoring of key parameters is essential. Sensors for basic parameters, such as temperature, light, and pH, are readily available and affordable, but sensors for ammonia, nitrate, and nitrite are often costly and difficult to obtain. It may be possible to use machine learning to predict these parameters based on data from basic sensors, which would reduce the initial investment and maintenance costs of aquaponics systems.

6. Conclusions

This study provides an up-to-date review of the work conducted on the optimisation of small-scale aquaponics systems using artificial intelligence and the IoT. This review focused on identifying key parameters and their optimal ranges, utilising electronic sensors, and incorporating state-of-the-art IoT and AI technologies into aquaponics.

One of the major concerns identified in aquaponic farming is energy efficiency and economic viability, particularly due to high energy costs. Current systems often prove unprofitable, especially in cold weather conditions. For aquaponics to achieve success, a reduction in energy costs is crucial. This could be attained by effectively managing available resources. Renewable energy sources, such as solar and wind power, offer promising solutions, as they have the potential to significantly decrease energy costs. Furthermore, the IoT and AI can contribute to optimising the aquaponic process by gathering more data for in-depth analysis and facilitating better decision making. Moreover, aquaponics systems are susceptible to environmental variability, including fluctuations in temperature, pH, and nutrient levels. Developing robust detection methods to distinguish between normal variations and genuine anomalies poses a significant research challenge.

Future studies could explore the integration of data from various sources, such as water quality, fish behaviour, and plant growth data, to create reliable anomaly detection systems. Another challenge is the scarcity of publicly available data for training and testing machine learning models, making it difficult to optimise systems or apply AI techniques to a variety of crops. Additionally, interoperability and standardisation issues among sensors and actuators create barriers for farmers and the general public to adopt these technologies.

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