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Applications, technologies, and evaluation methods in smart aquaponics: a systematic literature review

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Abstract
Smart aquaponics systems are gaining popularity as they contribute immensely to sustainable food production. These systems enhance traditional farming with advanced technologies like the Internet of Things (IoT), solar energy, and Artificial Intelligence (AI) for increased proficiency and productivity. However, assessing the performance and effectiveness of these systems is challenging. A systematic literature review (SLR) was conducted to examine the applications, technologies, and evaluation methods used in smart aquaponics. The study sourced peer-reviewed publications from IEEE Xplore, Scopus, SpringerLink and Science Direct. After applying inclusion and exclusion criteria, a total of 105 primary studies were selected for the SLR. The findings show that aquaponics predictions (27%) have been under-explored compared to applications that involved monitoring or monitoring and controlling aquaponics (73%). IoT technologies have been used to create prototype aquaponic systems and collect data, while machine learning/deep learning (predictive analytics) are used for prediction, abnormality detection, and intelligent decision-making. So far, predictive analytics solutions for aquaponics yield prediction, return-on-investment (ROI) estimates, resource optimisation, product marketing, security of aquaponics systems, and sustainability assessment have received very little attention. Also, few studies (37.7%) incorporated any form of evaluation of the proposed solutions, while expert feedback and usability evaluation, which involved stakeholders and end-users of aquaponics solutions, have been rarely used for their assessment. In addition, existing smart aquaponics studies have limitations in terms of their short-term focus (monitoring and controlling of aquaponics not undertaken over a long time to assess performance and sustainability), being conducted mostly in controlled settings (which limits applicability to diverse conditions), and being focused on specific geographical contexts(which limits their generalizability). These limitations provide opportunities for future research. Generally, this study provides new insights and expands discussion on the topic of smart aquaponics.

Keywords Smart aquaponics · Internet of things (IoT) · Machine learning · Deep learning · Evaluation

Extended author information available on the last page of the article

1 Introduction

Aquaponics is a sustainable farming system that combines aquaculture (the farming of aquatic animals) with hydroponics (soilless gardening) (Amano et al. 2022; Dhal et al. 2022c; Murakami and Yamamoto 2023). Aquaponics is fast becoming a popular farming method as it uses far less water than conventional farming. The land area required for crops is also much less (Ekanayake et al. 2022) and it is a completely pesticide and fertiliser-free farming system (Murakami and Yamamoto 2023). Aquaponics is a promising technology that can produce fresh, healthy, organic food, including vegetables, fruits and fish. Water is a common medium for the three living organisms of an aquaponics system, namely fish, plants and bacteria (Thorarinsdottir et al. 2015; Shafeena 2016; Sallenave 2016; Lennard and Goddek 2019; Yanes et al. 2020; Singh et al. 2021).

There have been many advancements and innovations in the Internet of Things (IoT), communication and sensing technologies. These technologies have merged and integrated into aquaponics to ensure precision and efficiency and minimise human effort (Hardyanto and Ciptadi 2020; Abdullah and Mazalan 2022; Narvios et al. 2022; Taha et al. 2022a). Many fields have used machine learning to assist in achieving various objectives, including optimising farming practices (Lauguico et al. 2020b; Amano et al. 2022). Overall, addressing these research inquiries can provide valuable knowledge for the advancement of aquaponics systems, fostering sustainable agriculture practices and contributing to global food security and environmental conservation efforts.

The assessment and evaluation of various aquaponics solutions is of paramount importance to ensure their successful implementation. Different evaluation methods have been adopted to analyse the performance, reliability, and scalability of these systems. By exploring the evaluation methods used to assess the performance of aquaponics systems, the users can ensure the development of robust and reliable solutions. Effective evaluation methods enable researchers and practitioners to identify strengths and weaknesses, optimise system components, and implement corrective measures to achieve sustainable and efficient aquaponics practices. However, it is important to note that the evaluation method varies depending on the nature of the research and the technologies utilised in the studies.

A systematic literature review (SLR) is a secondary research method that employs a structured approach to identify, analyse, and interpret existing studies in order to address specific research questions or explore a particular topic area. An SLR is distinguished from conventional literature reviews by its structured approach. It begins with the development of a review protocol, which defines the research questions and methods. Next, a search strategy is formulated to identify and document relevant literature for evaluation. Additionally, the review employs explicit inclusion and exclusion criteria to assess the quality and relevance of the existing studies (Kitchenham and Charters 2007). This structured approach ensures a comprehensive and unbiased synthesis of research.

The primary aim of this systematic literature review (SLR) is to explore and evaluate the application areas of aquaponics solutions, focusing on the technologies used to implement these solutions—such as the Internet of Things (IoT), Artificial Intelligence (AI), including machine learning (ML) and deep learning (DL) and the evaluation methods employed to assess their quality.

The objective of the review sought to:

- Identify the various application areas where aquaponics solutions have been applied.
- Examine the technologies implemented in these solutions, specifically IoT, AI, ML, and DL.
- Assess the evaluation methods used to measure the performance and effectiveness of these systems.

To achieve these objectives, relevant publications were gathered from various databases, including Scopus, ScienceDirect, Springer Link, and IEEE. These databases were chosen for their valuable resources that allow researchers to stay at the forefront of scientific research. Inclusion and exclusion criteria were applied to focus on the specific areas of interest relevant to the review.

The unique contribution of this systematic literature review is its analysis of applications, technologies, and evaluation methods implemented across various studies to reveal the research gaps. The findings from this analysis will aid aquaponics researchers and stakeholders in determining suitable areas of applications, implementation technologies, and evaluation methods for smart aquaponics based on their research or business objectives.

The subsequent sections of this paper follow a structured format. Section 2 provides a comprehensive background on aquaponics, as well as key technologies like the Internet of Things, machine learning, and deep learning. Section 3 examines related work in the field of aquaponics to highlight the existing knowledge and gaps in research. In Sect. 4, the methodology used for conducting the current systematic literature review is detailed. Section 5 presents the findings obtained from answering the research questions. Section 6 addresses the limitations of the current review to acknowledge potential biases and constraints. Section 7 offers an in-depth discussion of the findings, providing the authors' insights and interpretations. Section 8 presents future research opportunities that stem from the findings of the study, while Sect. 9 concludes the study with a summary of findings and a brief note.

2 Background

This section provides a brief theoretical background on key concepts that are relevant to the topic of this systematic review.

2.1 Hydroponics

Hydroponics refers to the soilless cultivation of plants in nutrient-rich water/ nutrient solution with or without supporting medium such as gravel, rock wool, peat moss, pumice, vermiculite, coir (Jensen 1997; Resh 2013; Somerville et al. 2014; Sharma et al. 2018; Mason et al. 2018; Maucieri et al. 2019). The word hydroponics is a combination of two Greek words: 'hydro' means 'water' and 'ponos' means 'labour' together meaning 'working water' (Roberto 2003; Jones Jr 2005; Resh 2013). Compared to soil farming, soilless farming uses a nutrient solution to supply essential nutrients to the plant. There are different types of hydroponics systems available to deliver the nutrient solution to the plants (Berry 1996).

The hydroponics growing method involves two ways: either a liquid system/solution culture or an aggregate system/solid media. There is no physical support for the plant root in the liquid system, and the nutrient solution is directly transferred to the plant. In contrast, the aggregate system uses a support/growing/substrate medium to hold plant roots. If the excess nutrient solution is circulating/ recycling/recovering in the hydroponic system, then the system is a closed/recirculating system, or else it is an open system (Shrestha and Dunn 2010; Mason et al. 2018; Resh 2013). The implementation of a mechanical device in the hydroponics system to recirculate the nutrient water makes the system active. A passive system is where the roots absorb nutrients from the water without any mechanical device (gravity) and make use of capillary action (Roberto 2003; Jones Jr 2005; Shrestha and Dunn 2010). There are different types of hydroponics techniques: floating/raft system, ebb and flow (flood and drain), Nutrient Film Technique (NFT), drip system, wick system, water culture system and aeroponic system (Shrestha and Dunn 2010; Maucieri et al. 2019).

2.2 Aquaculture

Aquaculture means raising aquatic animals and plants in fresh or salty water (Pillay and Kutty 2005). Aquatic animals are mainly fish. The chemical, biological and physical qualities of the water affect optimal fish production (Bhatnagar and Devi 2013). Monitoring water quality is vital in aquaculture because low water quality influences fish growth, and the fish will not be able to harvest at the desired time (Dupont et al. 2018). An acceptable water quality brings down fish disease problems and encourages fish growth, and fewer chemical treatments are required (Francis-Floyd et al. 2009). Water quality is determined by different parameters such as pH, temperature, carbon dioxide, nitrate, nitrite, turbidity, dissolved oxygen, and watercolour (Pillay 2004; Bhatnagar and Devi 2013; Yildiz et al. 2019). However, the most essential parameters that need to be monitored are temperature, dissolved oxygen and pH (Abbink et al. 2012; Thorarinsdottir et al. 2015; Dupont et al. 2018).

2.3 Aquaponics

The word “Aquaponics” is a combination of “Aqua” and “Ponics”. “Aqua” refers to water or aquaculture, which is the raising of fish. “Ponics” stems from hydroponics and refers to growing plants in water without soil (Goddek et al. 2015; Underwood and Dunn 2016). Aquaponics is a combined system of a Recirculating Aquaculture System (RAS) and a horticulture system (Kledal and Thorarinsdottir 2018). In the aquaponics system, fish and plants can be cultivated simultaneously (Rakocy et al. 2006; Underwood and Dunn 2016). Fish consume the fish feed and excrete the waste in the form of ammonia through their gills and small amounts of their urine (Sallenave 2016; Espinal and Matulić 2019).

Compared to traditional agriculture, the aquaponics system requires less land and less water because both fish and plants can grow in one system and reuse the water. The aquaponics system can produce healthy organic food, use soil-less farming, and no chemical fertiliser is used (Rakocy et al. 2006; Manju et al. 2017; Dutta et al. 2018; Joyce et al. 2019; Kurian et al. 2019; Yanes et al. 2020). Aquaponics contributes towards food security and sustainability (Goddek et al. 2015; Singh et al. 2021; Obirikorang et al. 2021). Since aquaponics is a recirculating system, plants absorb the dissolved nutrient-rich water generated from fish waste. The plants send back the purified water to the fish, thus recycling the necessary nutrients in the system (Joyce et al. 2019). The plant’s food is the nutrient-rich water from the fish tank, which serves as a natural fertiliser. There is thus a reduction in pollution to the environment from fertilisers and other chemical products. The aquaponics system reduces the significant water exchange and discharged waste that is normally dumped into the environment (Rakocy et al. 2006). It also provides fresh organic produce and eliminates fertiliser usage.

An aquaponics unit produces fish and plants simultaneously in the same system. The fish grow in the fish tank, and the plants grow in the hydroponic growth system. The three main hydroponic grow systems are Media-based systems (MBS), Deep Water Culture (DWC), also known as the floating or raft method, and the Nutrient Film Technique (NFT) (Goddek et al. 2015; Azad et al. 2016; Shafeena 2016; Wongkiew et al. 2017; Singh et al. 2021).

2.4 Internet of things

The term "Internet of Things" (IoT) was coined in 1999 by Kevin Ashton (Corcoran 2016). IoT refers to any physical object or device connected or capable of being connected to the Internet. It is a system of embedded wired, wireless communication and sensors that can gather and transfer data over the Internet. A sensor is a device that collects data from the immediate environment and provides this information so that other devices can make use of it. Data can be collected from different IoT devices that are connected to large networks. The combined collected data can provide valid information to the user.

The emerging IoT integration in certain areas makes it more efficient, such as smart homes, smart cities, smart cars, agriculture, industries, health, and education (Chauhan 2018; Reddy et al. 2020). IoT sensors play a major role in agriculture for efficient monitoring and management of various soil properties, crop nutrient status, crop disease, and water quality (Ayaz et al. 2019; Idoje et al. 2021).

Generally, sensors are devices that detect and respond to variations in an environment or parameter/s that it is measuring. Sensors can be light, temperature, pH, motion or water quality. In the work of Saha et al. (2018), it is outlined that monitoring the water quality of aquaculture is implemented using Raspberry Pi, Arduino, and several sensors. Ulum et al. (2019) used an ultrasonic sensor, temperature sensor and pH sensor to retrieve the data and transmit it to the Ubuntu IoT Cloud server.

Valiente et al. (2018) utilised IoT to access and control pH levels and temperature in their study to monitor automated aquaponics systems. The status of the automated aquaponics was analysed using the Thingspeak platform sent by the Intel Edison microprocessor.

The majority of studies have shown that IoT was used for data collection, monitoring and controlling. Real-time monitoring has the advantage of providing a faster response time (Ayaz et al. 2019; Dupont et al. 2018). The farmers can monitor and control the farm remotely (Idoje et al. 2021). With data analysis and prediction, some Artificial Intelligence (AI) for farm management can be introduced. AI and IoT are coming together in more ways than imaginable. AI is assisting IoT in enabling real-time data analytics to help make informed decisions and drive agricultural productivity and efficiency.

2.5 Machine learning

Intelligence is the ability to learn from a changing environment (Ayodele 2010). Artificial intelligence (AI) is a way of simulating human intelligence in programming computers/ machines (Zhang and Lu 2021). These machines are programmed to think much like humans and copy their behaviour and actions. Machine learning is a subgroup and an application of AI that uses a machine to represent the human brain (Muhammad and Yan 2015; Nasteski 2017). Machine learning means the machine/computer can convert the set of data into actionable knowledge/intellectual actions using algorithms without any human intervention or acquiring knowledge from data (Lantz 2013; Müller and Guido 2016).

Machine learning is used to improve the performance of programs or machines over a period of time based on experience (Nandy and Biswas 2018). Tom Mitchell's definition that computer programs perform well through experience "A computer program is said to learn from experience *E* with respect to some class of tasks *T* and performance measure *P*, if its performance at tasks in *T*, as measured by *P*, improves with experience *E*" (Mitchell 2017). An algorithm is a well-defined set of instructions that a computer needs to be implemented to solve a problem. Machine learning is the study of algorithms and statistical models that are used to make inferences from samples (Ayodele 2010; Mahesh 2016).

A machine-learning algorithm uses data as input and, in the learning process, discovers the pattern and statistical representation of data using abstraction and generalisation. Thus, it provides insight which can be used to take action (Lantz 2013; Nasteski 2017). An efficient machine learning algorithm helps to automate the decision-making process by generalising from common examples (Shalev-Shwartz and Ben-David 2014; Müller and Guido 2016). The selection of an algorithm depends on the type of problem that needs to be solved, parameters, business needs and so on (Lantz 2013; Mahesh 2016; Ray 2019).

There are mainly three categories of machine learning algorithms which are supervised, unsupervised and reinforcement learning (Shalev-Shwartz and Ben-David 2014; Mahesh 2016; Dangeti 2017; Chitralekha and Roogi 2021). Supervised learning utilises the known data to train the machine, whilst unsupervised learning utilises the unknown data, whereas reinforcement learning uses software agents to take action. A suitable machine learning algorithm is required to embark on the machine learning task. The selected algorithm inputs the gathered data to train the model. Machine learning algorithms analyse and recognise patterns from a given set of data, which allows a model to be created from the resulting data to take an action/recommendation (Lantz 2013).

2.6 Deep learning

Deep learning is a subset of machine learning. Artificial neural networks can be used to implement deep learning to generate a model for supervised or unsupervised problems using structured and unstructured datasets, respectively. Video, image, and voice are examples of an unstructured dataset (Dangeti 2017). There is a significant improvement in the performance of classifiers when deep learning is used as opposed to more conventional machine learning methods (LeCun et al. 2015; Mathew et al. 2021). Deep learning is capable of learning a large amount of data (Alzubaidi et al. 2021). Deep learning techniques have achieved great strides and much success in pattern recognition, speech recognition, handwritten classification, image analysis, Natural Language Processing (NLP) and many (Alzubaidi et al. 2021; Liu et al. 2017).

Several types of deep learning architectures exist to solve problems within different domains. Examples include Deep Belief Networks(DBN), Convolutional Neural Networks (CNN), Restricted Boltzmann Machine (RBM), Recurrent Neural Networks (RNN), Autoencoders, Generative adversarial network (GAN), and Long Short-Term Memory (LSTM)

(Liu et al. 2017; Shrestha and Mahmood 2019; Mathew et al. 2021; Alzubaidi et al. 2021; Reddy et al. 2021).

2.7 Recent advancements and emerging trends in smart aquaponics

The integration of Internet of Things (IoT) devices for real-time monitoring and control, as well as the application of artificial intelligence (AI) and machine learning algorithms to optimize system efficiency, are recent developments and developing trends in smart aquaponics. Figure 1 depicts an aquaponics system using IoT to monitor and control the parameters.

Automated systems are used to monitor and control various aspects of the aquaponics environment, including lighting, feeding, growth estimation sensors, humidity, temperature, water pumps, and water circulation, to increase efficiency and reduce manual labour. Energy-efficient innovations, such as solar panels and LED lighting, help lower operating expenses and minimise environmental impact (Haruo et al. 2020; Rozie et al. 2020; Mohd Ali et al. 2021; Murakami and Yamamoto 2023; Ahmad et al. 2022).

To maximise system performance, AI and machine learning algorithms analyse data collected from IoT devices. These technologies enable efficient resource usage management, optimisation of feeding schedules, and prediction of the health of plants, fish, and environmental parameters (Concepcion et al. 2021b; Karimanzira et al. 2021; Guo et al. 2022; Yang et al. 2023).

Aquaponics is a rapidly growing farming method due to its reduced resource consumption in water, soil and land. By optimising critical parameters, IoT technologies and AI

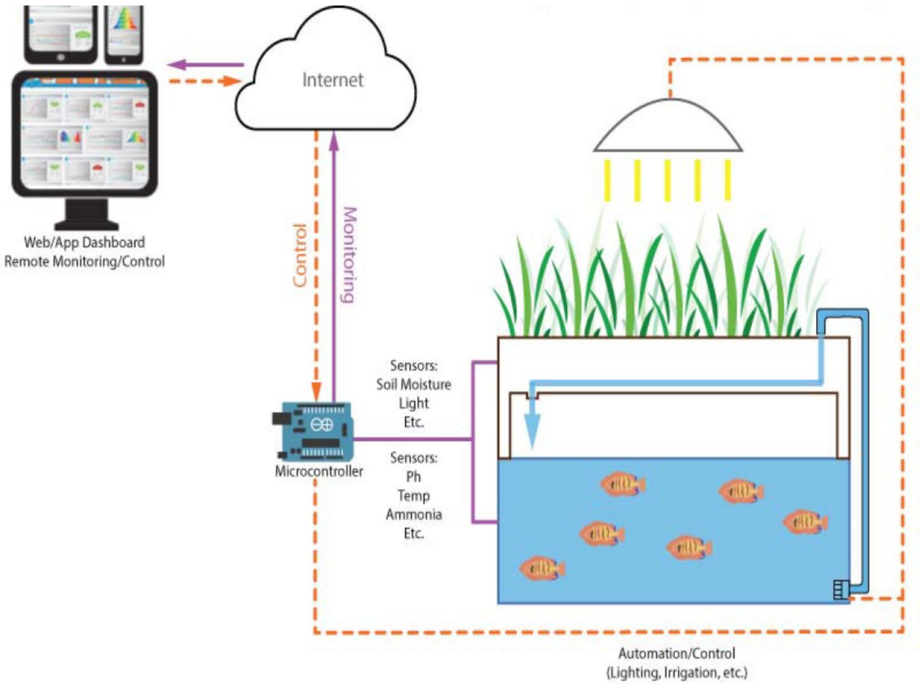

Fig. 1 An aquaponics system using IoT. Adopted from (Manju et al. 2017)

algorithms improve productivity and maximise yield in aquaponics systems (Khaoula et al. 2021; Abbasi et al. 2022a).

Real-world implementation of smart aquaponics can be seen in urban settings where IoT sensors and AI are used to maximise space utilisation and resource efficiency, producing high yields of vegetables and fish in compact environments (Kyaw and Ng 2017; Lee and Jhang 2019; Narvios et al. 2022).

For example, a study by Ghandar et al. (2021) titled "A Decision Support System for Urban Agriculture Using Digital Twin: A Case Study with Aquaponics" demonstrates the application of advanced digital technologies in urban farming to enhance efficiency and productivity further. Also, Ekanayake et al. (2022), in a study titled "A Smart Aquaponic System for Enhancing the Revenue of Farmers in Sri Lanka", addresses significant challenges in Sri Lanka's agricultural sector, such as fertiliser shortages and the scarcity of agriculture-related chemicals. By implementing aquaponic systems enhanced with IoT and machine learning technologies, the study provided Sri Lankan farmers with sustainable solutions to overcome these difficulties and boost their revenue.

3 Related work

This section presents an overview of previous reviews and surveys that have been done in the aquaponics field.

Wei et al. (2019b) presents an analysis of the equipment and intelligent control systems in aquaponics. The authors analysed the advantages and disadvantages of three different types of hydroponics cultivation methods: Nutrient Film Technique, Deep Flow Technique, and Floating Capillary Hydroponics. After that, the recirculating aquaculture equipment, such as physical and biological equipment, oxygenation unit and the recent developments were summarised. There was also a discussion about existing or intelligent technologies for monitoring and controlling water quality parameters, the greenhouse environment, and nutrient solutions. The challenges and shortcomings of the current situation and future development possibilities were also addressed in the paper. They concluded that in the future, aquaponics systems will become more intelligent, precise, focused and capable with the help of enhanced technologies.

Yanes et al. (2020) encouraged greater research for a commercially practical and feasible aquaponics plant or solution. In striving towards precision farming, many sensing, smart, and IoT technologies have gained traction in monitoring and controlling aquaponics automated processes. Research in the study was focussed on a feasible aquaponics solution through a detailed explanation of all relevant aquaponics systems and smart and IoT system technologies. The link that bridges between biological and electrical engineering expertise was fortified by collaboration with the technical expertise of aquaponics champions and professionals around automation, IoT, and smart systems, with experts who are knowledgeable about biological processes within the aquaponics field.

Taji et al. (2021) conducted a comparative study on IoT-based aquaponic architectures. In the paper, the authors considered the IoT and AI technologies, implementation factors, and the advantages and shortcomings of the existing architectures in the comparison process. The study provided a detailed perception of existing smart aquaponics techniques.

They concluded that further work is required to overcome the limitations addressed in the paper, which leads to improving the productivity and efficiency of the aquaponics system.

Ke and Zhou (2021) systematically analysed and summarised the utilisation of the Internet of Things to enhance the intelligent monitoring and control of the water quality environment parameters in aquaponics. The study concluded that the IoT process and the sensors were utilised to collect the parameters and transmitted with the help of communication technology through microprocessors, which control the actuators for adjusting the environmental parameters. Remote monitoring and control of parameters are achievable due to cloud data. With the use of real-time data in current analysis and modelling methods, artificial intelligence and automation are now conceivable in aquaponics.

Taha et al. (2022c) explored the recent development of smart systems and the Internet of Things for the automation of aquaponics. The study analysed and discussed the sensed water quality and aquaponics environmental parameters that were in line with smart and IoT sensing systems. The researchers provided an overview of how to control the aquaponics system at various levels. They described the process from the initial manual monitoring stage until the realisation of a smart aquaponics system that was automated. The study also discussed and analysed the various microcontrollers that were used in smart systems and the implementation of deep learning in smart aquaponics to perform different predictions. The study's intended objective was to build a bridge between electrical and biological engineers to assist in the advancement of aquaponics. Thus, the increased sustainability of these systems increases the progress within this domain and contributes to commercial solutions becoming more economically viable.

Thakur et al. (2023) highlighted the significance and necessity of biofilm-based bioreactors for aquaponics wastewater treatment. This approach ensured the reusability of the effluent water released from a bioreactor in an aquaculture system, encouraging the growth of plants and fish as well as the development of the essential bacteria in a bioreactor environment, leading to efficient bioremediation.

Gayam et al. (2022) focused on the use of wireless technology in aquaponics systems. The study examined how wireless technology has been implemented and its impact on water and environmental factors in the system. The study investigated the significance and function of wireless-based technologies for remote monitoring and the use of IoT, ML, and remote monitoring in aquaponics. Table 1 provides a summary of reviews previously reported in the literature.

From the analysis of previous review papers on aquaponics, the study established that most of the review papers that focused on smart aquaponics systems were descriptive reviews, lacking a systematic, methodical approach guided by specific research questions. Additionally, no prior review paper has focused on the evaluation methods or techniques used to assess aquaponics solutions. This gap highlights a significant shortcoming in the current literature. This paper addresses this gap by providing a systematic review that identifies different application areas in aquaponics, the technologies utilized, and the evaluation methods employed to assess the proposed solutions.

4 Research methodology

This section describes the methodological process that was followed to execute this study.

Table 1 Summary of related work

Author & Year	Study approach	Main Objective / Focus	MoA	ToA	EoA
Thakur et al. (2023)	Review	Elimination of Ammonia Nitrogen Contents.	Yes	Yes	No
Taha et al. (2022c)	Comprehensive Overview	Integrating automated, fully operated aquaponic systems with IoT and smart sensing technologies.	Yes	Yes	No
Taji et al. (2021)	Comparative study	Comparative analysis of existing aquaponic architectures and technologies, focusing on factors such as security, interoperability, renewable energy usability, and cost.	Yes	Yes	No
Ke and Zhou (2021)	Review (research progress)	A systematic analysis of research on aquaponics and a summary of components, parameters, monitoring, and control strategies for aquaponics.	Yes	Yes	No
Yanes et al. (2020)	Review	To identify, highlight, and provide an in-depth explanation of each of the parameters sensed in aquaponics, as well as the smart systems and IoT technologies.	Yes	Yes	No
Wei et al. (2019b)	Review	A summary of the current development of technology and methods in aquaponics and the prospects for future development trends.	Yes	Yes	No
Gayam et al. (2022)	Review	Latest developments and innovations in aquaponics monitoring and control.	Yes	Yes	No
Our paper	Systematic Literature review	Application, technologies, and evaluation methods used in smart aquaponics.	Yes	Yes	Yes

MoA Management of Aquaponics (Monitoring, Control), ToA Technologies of Aquaponics (AI / ML / IoT), EoA Evaluation of Aquaponics

The systematic literature review protocol proposed by Kitchenham and Charters (2007) was adopted for this study. A systematic literature review is a form of secondary study that makes use of a distinct methodology to identify, analyse, and interpret all the information in existing studies to answer specific research questions or investigate a particular topic area. A SLR also helps to identify the gaps in the published studies on a topic. Independent studies contributing to a systematic review are called primary studies (Kitchenham and Charters 2007; Xiao and Watson 2019; Page et al. 2020; van Klompenburg et al. 2020).

A systematic literature review encompasses three main activities: planning the review, conducting the review, and reporting the review (Kitchenham 2004; Kitchenham and Charters 2007; Brereton et al. 2007).

The activities associated with the planning phase are identifying the requirement for a review, specifying the research question/s and reviewing the protocol development. In the conducting phase, the activities are to identify the research and select the primary studies. After that, data will be extracted, analysed, and synthesised. In the final phase, the review findings are reported (Kitchenham 2004; Kitchenham and Charters 2007; Leão and Canedo 2018; van Klompenburg et al. 2020). The phases and activities of the literature review are depicted in Fig. 2.

4.1 Review protocol

A review protocol is a plan which specifies the methods that will be used for a proposed systematic literature review (Kitchenham and Charters 2007; van Klompenburg et al. 2020).

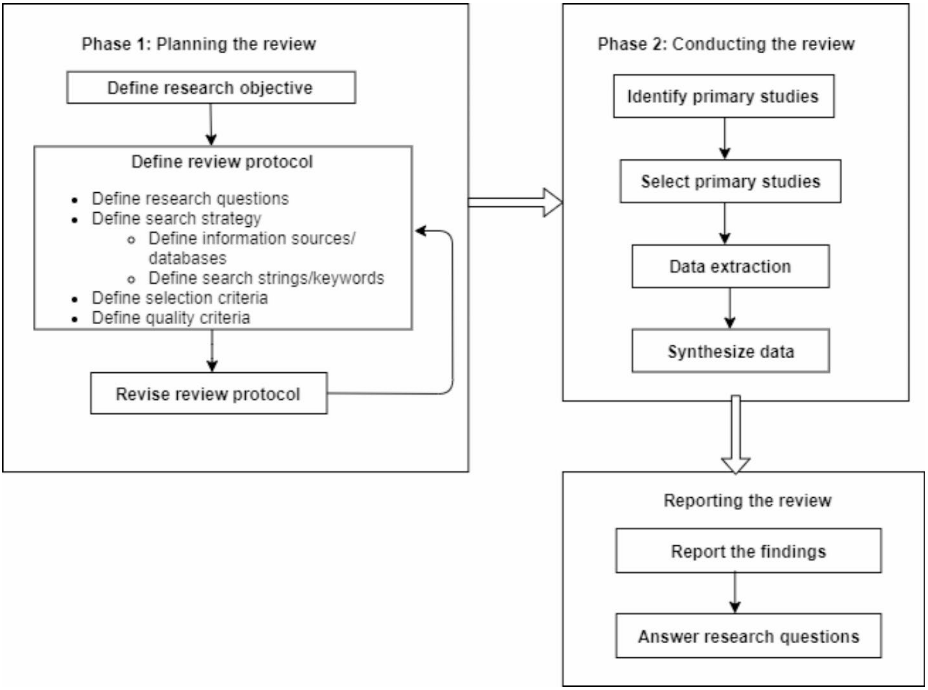

Fig. 2 Phases and activities of the systematic literature review (Kitchenham and Charters 2007; van Klompenburg et al. 2020)

The study adopted the review protocol proposed by Kitchenham and Charters (2007). The first activity of the review protocol was to define the research questions. Thereafter, digital databases and search strings were explored to identify the relevant papers (primary studies). These activities were carefully considered as they assisted in finding the answers to the research questions. The academic databases used for this study are IEEE Xplore, ScienceDirect, SpringerLink and Scopus. Primary studies selection was based on a set of inclusion and exclusion criteria.

4.2 Research questions

The systematic review aims to answer the following research questions:

RQ1: Which application areas have been addressed by aquaponics solutions?

RQ2: Which digital technologies have been used to implement aquaponics solutions?

RQ3: What methods were used to evaluate the proposed systems?

4.3 Search strategy

The adopted search strategy for this study is described in the subsequent sections.

4.3.1 Data sources

Various aquaponics studies published as journal articles and peer-reviewed conference papers can be found in different academic databases. However, the following databases, Scopus, ScienceDirect, SpringerLink and IEEE Xplore, were selected as the data sources for searching for relevant primary studies within the scope of the review. These databases are among the largest and most prominent academic databases, with a wide coverage of journals and conference proceedings and books/book chapters that pertain to aquaponics and related areas. A summary of selected databases is given in Table 2.

4.3.2 Search strings

An automatic search was conducted to find primary studies based on the research questions. Thus, keywords and synonyms were identified from the research questions. Thereafter, search strings were formulated by combining keywords and synonyms using the Boolean operators 'OR' and 'AND'. The search string was used to explore the appropriate publications from different databases.

The search resulted in four hundred and fifty-three (453) publications that were identified. The publications found were exported in RIS format The search strings used for specified databases are provided in Table 3. The search strings were meticulously selected to align with the review objectives, ensuring comprehensive coverage of the target literature.

Table 2 Description of the selected academic databases

Selected databases	About the database	Source
Scopus	One of the biggest academic databases is Scopus, which has peer-reviewed literature. It has books, conference proceedings and journals covering various fields. Scopus has smart tools to visualise research. Scopus ensures that important global research is identified properly. It further allows for experts to be identified and ensures the availability of analytical tools as well as access to reliable data.	https://www.scopus.com/
ScienceDirect	ScienceDirect is a digital platform that provides access to high-quality academic and scientific content that has been reviewed and accepted by field experts. In ScienceDirect, very intuitive functionalities and smart technologies have been incorporated into the full text, scientific, technical and health publications. Thus, it ensures users are informed in their respective fields and can also work optimally with the least hindrances and delays.	https://www.sciencedirect.com/
SpringerLink	Springer Link offers quick access to a wide range of online journals, eBooks, reference works, and protocols across various subject areas.	https://link.springer.com/
IEEE Xplore	The IEEE Xplore has a well-equipped digital library. It is a great resource for exploring scientific and technical content from various publishers. Millions of full-text documents from highly cited publications are available online on the IEEE Xplore platform. The publications include electronics, electrical engineering and science-related subjects.	https://ieeexplore.ieee.org/Xplore/home.jsp

Table 3 The search strings

Database	Search String
Scopus	(("Smart aquaponic*") OR ("Internet of Things" AND aquaponic*) OR ("IoT" AND aquaponic*) OR ("Machine Learning" AND aquaponic*) OR (intelligent AND aquaponic*) OR ("Artificial Intelligence" AND aquaponic*) OR (prediction AND aquaponic*) OR (forecast* AND aquaponic*)); (automation AND aquaponic*)
ScienceDirect	((“Smart Aquaponics” OR “Smart Aquaponic”) OR (“Machine Learning” OR “Artificial Intelligence”) OR (IoT OR “Internet of Things”)) AND (aquaponics OR aquaponic))
IEEE Xplore	“Smart aquaponic*” OR “Internet of Things” OR “IoT” OR “Machine Learning” OR Intelligent OR “Artificial Intelligence” OR prediction OR forecast* AND aquaponic*; automation AND aquaponic*;
Springer Link	“Smart Aquaponics” AND “IoT”; “Smart Aquaponics” AND “Prediction”; “Smart Aquaponics” AND “Machine learning”; “Smart Aquaponics” and “Artificial Intelligence”; “Aquaponics” AND “Prediction”

Table 4 Inclusion and exclusion criteria

Inclusion criteria	Exclusion Criteria
i. Papers published between 2016 to 2023 ii. Publications written in English iii. Publications only focus on aquaponics iv. Publications only focus on the technologies IoT/ AI/ Machine learning/Big Data v. Peer-reviewed Journals, conference proceedings and book chapters	i. Duplicate publication or already published in other databases ii. Incomplete publications iii. Review/survey publications iv. Non-peer-reviewed publications (i.e. not journal articles, conference proceedings, or book chapters) v. Publications which are not written in the English language vi. A publication which is not accessible vii. Publication which is not able to answer research questions

4.4 Inclusion and exclusion criteria

Inclusion and exclusion criteria are essential features of the selection process, which determines the scope, significance and quality of the study. Implementation of inclusion and exclusion criteria ensures that the studies are relevant and acceptable for review. Inclusion criteria assist the researcher in identifying the relevant primary studies from different databases, whereas the exclusion criteria help to exclude primary studies that are not suitable. The inclusion and exclusion criteria of the study are given in Table 4.

The title and abstract of the publication were analysed using the inclusion and exclusion criteria.

4.5 The selection process

The respective categorisation was achieved with the aid of the AI-powered open software Rayyan (https://rayyan.ai) (Ouzzani et al. 2016; Johnson and Phillips 2018). The RIS format document was uploaded to the Rayyan open-source software.

The first filtering process implemented exclusion criteria to the title and abstract to eliminate publications which would not be relevant to the study. The feature "Detect duplicates" identified the possible duplicated publications. However, it is difficult to identify and evaluate the relevant publications by only scanning the title and abstract, resulting in incomplete publications, and some abstracts do not express the publication objectives very well. Hence, a second filtering process was performed by the first author, which implemented inclusion and exclusion criteria by examining the introduction, methodology, result, and conclusion to eliminate the publications that will not be able to answer research questions. This process resulted in a total of 170 publications. Figure 3 depicts the stages of the primary study selection process.

4.6 Quality assurance

The quality of the selected paper was assessed by checking whether the selected paper could answer any of the research questions defined and labelled RQ1, RQ2, and RQ3. After that, the second author scrutinised and verified the selected relevant publications. Therefore, in the final refinement, a total of 105 primary study publications were selected to perform the systematic literature review. We also discovered that all the relevant papers that were contained in IEEE Xplore and SpringerLink were indexed in ScienceDirect or Scopus. Hence, no paper was selected from IEEE Xplore and SpringerLink. The summary of papers found in the different academic databases is shown in Table 5.

The number of selected publications associated with a particular year between 2016 and 2023 is depicted in Fig. 4.

Table 6 shows the relevance of each publication to the research questions of this systematic literature review. If a publication is relevant to a research question, it is denoted with the tick symbol (✔), and if it is not relevant, it is denoted by the cross symbol (✖). From the analysis of the selected papers, it was established that most of the selected publications were relevant to the research questions of our study.

4.7 Data extraction

Data from the selected papers were collected and consolidated to address the three research questions of this study. The information retrieved was primarily focused on answering the research questions and assessing whether the studies met the criteria for exclusion. Data extraction involved looking for relevant concepts that relate to any of the three research questions in the selected primary studies. For each paper, we looked for areas of application, the type of digital technology adopted, and the mode of evaluation used to assess the aquaponics solution. Data was extracted from the primary studies, combined, and analysed to arrive at the findings of this study. The findings are presented in Sect. 5.

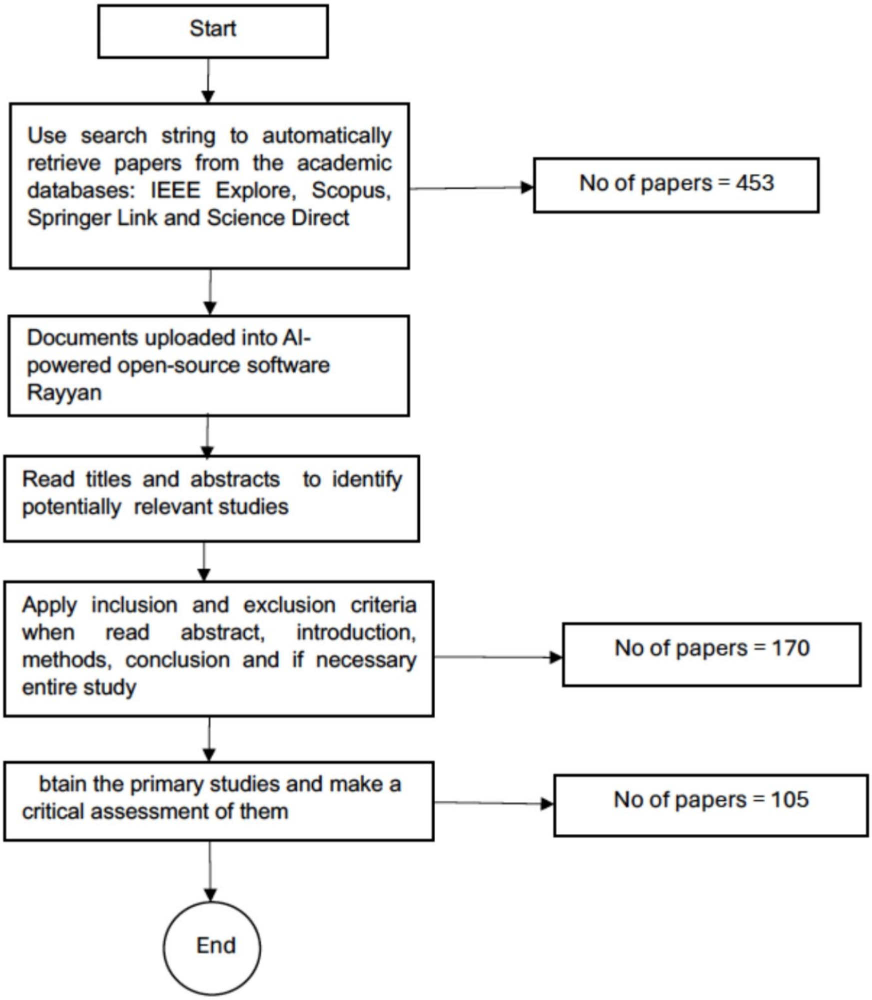

Fig. 3 Stages of the primary study selection process.(Adapted from Selleri et al. 2015)

Table 5 Number of papers selected

Electronic Database	Number of papers based on the search string	After applying inclusion and exclusion criteria	After quality assurance
Scopus	185	137	90
ScienceDirect	189	33	15
IEEE Xplore	77	0	0
Springer Link	2	0	0
Total	453	170	105

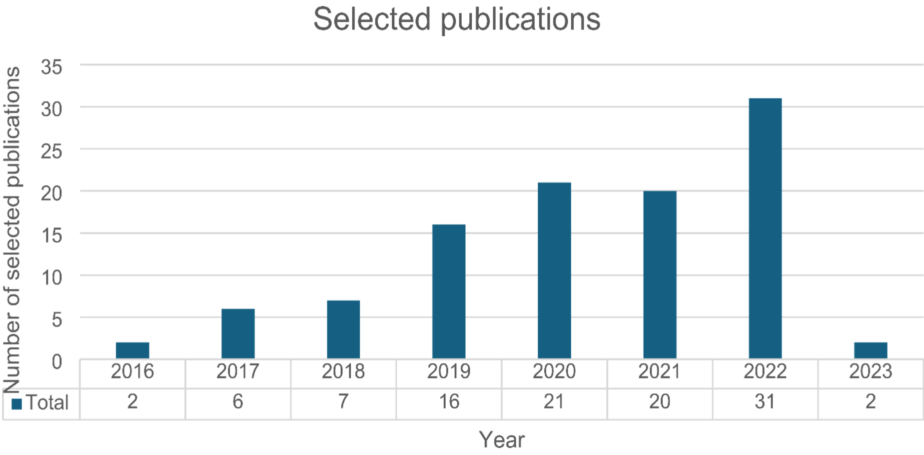

Fig. 4 Selected publications (2026–2023)

5 Results

The findings of this study, based on the three research questions, are presented in this section.

5.1 Which application areas have been addressed by aquaponics solutions?

From the selected primary studies, we established that the major areas where aquaponics solutions were applied are monitoring, controlling, and prediction. Figure 5 shows the percentage distribution of the different areas of aquaponics application. Fifty-six per cent (56%) of the studies focused on monitoring and controlling various aquaponics environmental parameters, seventeen per cent (17%) of studies concentrated only on monitoring the aquaponics environmental parameters, while twenty-seven per cent (27%) of the selected primary studies focussed on prediction (such as plant growth and plant size) within the aquaponics domain.

5.1.1 Monitoring and controlling of aquaponics

An aquaponic environment consists of aquaculture, hydroponics and the environment where the system is placed. Aquaponics systems are usually set up indoors or outdoors. The outdoor system can be a tunnel or a greenhouse. So far, many existing studies have focused on monitoring and controlling or monitoring alone in an aquaponics environment. Most of the aquaponics studies aimed to monitor and control the optimal growth of fish and plants, which necessitates frequent monitoring and controlling of various environmental parameters to maintain the most effective balance. Continuous monitoring of the aquaponics system is crucial for achieving maximum yield output. Parameters such as water quality, nutrient levels, temperature, environmental conditions, and fish health were monitored and controlled to ensure the best possible outcomes within the aquaponics system. Table 7 presents the studies that focus on aquaculture (breeding of fish and plants) in aquaponics.

Table 6 Selected publications after quality assurance

S/*n*	Author	RQ1	RQ2	RQ3
1	Friuli et al. (2021)	✓	✓	✓
2	Amano et al. (2022)	✓	✓	✓
3	Lauguico et al. (2020c)	✓	✓	✓
4	Omar et al. (2019)	✓	✓	✓
5	Ghandar et al. (2021)	✓	✓	✓
6	Wei et al. (2019a)	✓	✓	✖
7	Dhal et al. (2022c)	✓	✓	✓
8	Ren et al. (2018)	✓	✓	✓
9	Wan et al. (2022)	✓	✓	✓
10	Concepcion et al. (2022b)	✓	✓	✓
11	Ekanayake et al. (2022)	✓	✓	✓
12	Debroy and Seban (2022)	✓	✓	✓
13	Nandesh et al. (2022)	✓	✓	✖
14	Li et al. (2021)	✓	✓	✖
15	Lauguico et al. (2020a)	✓	✓	✓
16	Kumar et al. (2016)	✓	✓	✖
17	Karimanzira and Rauschenbach (2021)	✓	✓	✓
18	Udanor et al. (2022)	✓	✓	✖
19	Murdan and Joyram (2021)	✓	✓	✖
20	Abbasi et al. (2022b)	✓	✓	✓
21	Hadi et al. (2022)	✓	✓	✓
22	Khaoula et al. (2021)	✓	✖	✖
23	John and Mahalingam (2021)	✓	✓	✖
24	Silalahi et al. (2022)	✓	✓	✖
25	Defa et al. (2019)	✓	✓	✓
26	Dhal et al. (2022a)	✓	✓	✓
27	Nichani et al. (2018)	✓	✓	✖
28	Abbasi et al. (2022a)	✓	✓	✖
29	Yang et al. (2023)	✓	✓	✓
30	Taufiqurrahman et al. (2020)	✓	✓	✓
31	Sansri et al. (2019)	✓	✓	✓
32	Sriram and Shibu (2021)	✓	✓	✖
33	Rozie et al. (2020)	✓	✓	✓
34	Murad et al. (2017)	✓	✓	✖
35	Rahayu et al. (2021)	✓	✓	✓
36	Concepcion et al. (2021a)	✓	✓	✓
37	Haruo et al. (2020)	✓	✓	✓
38	Lee and Wang (2020)	✓	✓	✓
39	Tolentino et al. (2019)	✓	✓	✓
40	Banjao et al. (2020)	✓	✓	✖
41	Choi and Kim (2019)	✓	✓	✓
42	Reyes-Yanes et al. (2022)	✓	✓	✓
43	Guo et al. (2022)	✓	✓	✓
44	Arvind et al. (2020)	✓	✓	✓
45	Liu et al. (2022)	✓	✓	✓
46	Karimanzira and Rauschenbach (2019)	✓	✓	✖
47	Concepcion et al. (2020)	✓	✓	✓

Table 6 (continued)

S/n	Author	RQ1	RQ2	RQ3
48	Riansyah et al. (2020)	✓	✓	✓
49	Murakami and Yamamoto (2022)	✓	✓	✓
50	Tobias et al. (2020)	✓	✓	✓
51	Butt et al. (2019)	✓	✓	✖
52	Wijayanto et al. (2021)	✓	✓	✓
53	Alajas et al. (2021)	✓	✓	✓
54	Ong et al. (2019)	✓	✓	✓
55	Dawa et al. (2022)	✓	✓	✓
56	Valiente et al. (2018)	✓	✓	✓
57	Zaini et al. (2018)	✓	✓	✓
58	Zhang et al. (2022)	✓	✓	✓
59	Ahmad et al. (2022)	✓	✓	✓
60	Sunardi et al. (2021)	✓	✓	✖
61	Wibowo et al. (2019)	✓	✓	✓
62	Niranjan et al. (2022)	✓	✓	✓
63	Pu’ad et al. (2020)	✓	✓	✖
64	Prabha et al. (2020)	✓	✓	✖
65	Menon (2020)	✓	✓	✓
66	Jacob (2017)	✓	✓	✖
67	Kamil et al. (2020)	✓	✓	✓
68	Kassim et al. (2021)	✓	✓	✖
69	Ntulo et al. (2021)	✓	✓	✓
70	De Silva and De Silva (2016)	✓	✓	✖
71	Kjellby et al. (2019)	✓	✓	✖
72	Kim et al. (2022)	✓	✓	✓
73	Pramudita et al. (2022)	✓	✓	✓
74	Maulini et al. (2022)	✓	✓	✓
75	Elsokah and Sakah (2019)	✓	✓	✖
76	Concepcion et al. (2021b)	✓	✓	✓
77	Dhal et al. (2022b)	✓	✓	✓
78	Mohd Ali et al. (2021)	✓	✓	✓
79	Aquino et al. (2021)	✓	✓	✓
80	Mori et al. (2021)	✓	✓	✓
81	Manju et al. (2017)	✓	✓	✖
82	Reyes-Yanes et al. (2020)	✓	✓	✓
83	Benaya et al. (2022)	✓	✓	✓
84	Murakami and Yamamoto (2023)	✓	✓	✓
85	Mahkeswaran and Ng (2020)	✓	✓	✓
86	Ulum et al. (2019)	✓	✓	✓
87	Vernandhes et al. (2017)	✓	✓	✖
88	Hardyanto and Ciptadi (2020)	✓	✓	✖
89	Narvios et al. (2022)	✓	✓	✖
90	Odema et al. (2018)	✓	✓	✖
91	Kyaw and Ng (2017)	✓	✓	✖
92	Barosa et al. (2019)	✓	✓	✓
93	Abdullah and Mazalan (2022)	✓	✓	✓
94	Aishwarya et al. (2018)	✓	✓	✖

Table 6 (continued)

S/*n*	Author	RQ1	RQ2	RQ3
95	Lee and Jhang (2019)	✓	✓	✓
96	Pasha et al. (2018)	✓	✓	✓
97	Pantazi et al. (2019)	✓	✓	✖
98	Concepcion et al. (2022a)	✓	✓	✓
99	Wang et al. (2020)	✓	✓	✖
100	Taha et al. (2022a)	✓	✓	✓
101	Taha et al. (2022b)	✓	✓	✓
102	Alejandrino et al. (2020)	✓	✓	✓
103	Alselek et al. (2022)	✓	✓	✖
104	Hamza-Lup et al. (2019)	✓	✓	✖
105	Tolentino et al. (2020)	✓	✓	✓

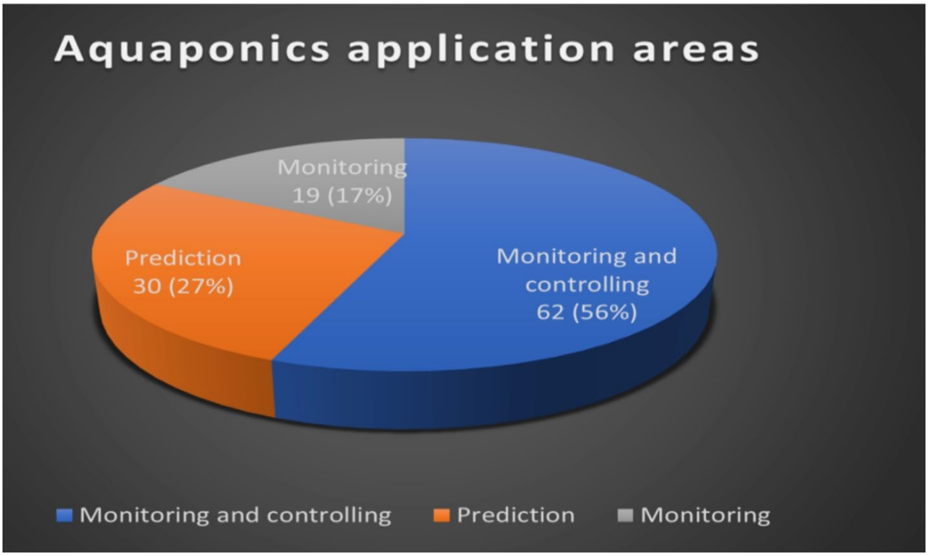

Fig. 5 Aquaponics application areas

5.1.1.1 Monitoring of aquaponics conditions So far, aquaponics monitoring is done in real-time from onsite and remote locations. The monitoring data are collected at regular intervals to serve various purposes. Aquaponics monitoring is done for general, observational, or predictive purposes. The specific objective of aquaponics monitoring is to get information on various parameters that affect the growth of the plants and fish in the system so that corrective actions can be taken should it be essential for controlling the system.

So far, the studies on aquaponics monitoring have focussed mainly on aquaculture, hydroponics and ambient environment. Aquaculture entails farming of aquatic organisms, primarily fish, shellfish, and algae in water. Hydroponics refers to the soilless cultivation of plants in nutrient-rich water/nutrient solution with or without a supporting medium such as

Table 7 A listing of studies that were focused on aquaculture

Author	Water quality parameter monitoring	Water quality parameters controlling
Friuli et al. (2021)	✓	✖
Omar et al. (2019)	✓	✖
Ghandar et al. (2021)	✓	✖
Dhal et al. (2022c)	✓	✖
Wan et al. (2022)	✓	✖
Ekanayake et al. (2022)	✓	✓
Lauguico et al. (2020a)	✓	✖
Kumar et al. (2016)	✓	✖
Karimanzira and Rauschenbach (2021)	✓	✓
Udanor et al. (2022)	✓	✖
Murdan and Joyram (2021)	✓	✖
Hadi et al. (2022)	✓	✓
Khaoula et al. (2021)	✓	✖
Silalahi et al. (2022)	✓	✖
Defa et al. (2019)	✓	✓
Nichani et al. (2018)	✓	✖
Abbasi et al. (2022a)	✓	✖
Taufiqurrahman et al. (2020)	✓	✓
Sansri et al. (2019)	✓	✖
Sriram and Shibu (2021)	✓	✖
Rozie et al. (2020)	✓	✖
Murad et al. (2017)	✓	✖
Rahayu et al. (2021)	✓	✖
Haruo et al. (2020)	✓	✖
Lee and Wang (2020)	✓	✖
Tolentino et al. (2019)	✓	✖
Banjao et al. (2020)	✓	✖
Choi and Kim (2019)	✓	✖
Reyes-Yanes et al. (2022)	✓	✓
Guo et al. (2022)	✓	✖
Arvind et al. (2020)	✓	✖
Riansyah et al. (2020)	✓	✖
Murakami and Yamamoto (2022)	✓	✖
Butt et al. (2019)	✓	✖
Wijayanto et al. (2021)	✓	✖
Ong et al. (2019)	✓	✓
Dawa et al. (2022)	✓	✖
Valiente et al. (2018)	✓	✖
Zaini et al. (2018)	✓	✓
Zhang et al. (2022)	✓	✖
Ahmad et al. (2022)	✓	✖
Sunardi et al. (2021)	✓	✖
Niranjan et al. (2022)	✓	✓
Pu'ad et al. (2020)	✓	✖
Prabha et al. (2020)	✓	✖

Table 7 (continued)

Author	Water quality parameter monitoring	Water quality parameters controlling
Menon (2020)	✓	✖
Jacob (2017)	✓	✓
Ntulo et al. (2021)	✓	✓
Pramudita et al. (2022)	✓	✖
Maulini et al. (2022)	✓	✖
Elsokah and Sakah (2019)	✓	✖
Mohd Ali et al. (2021)	✓	✖
Mori et al. (2021)	✓	✖
Manju et al. (2017)	✓	✖
Benaya et al. (2022)	✓	✖
Murakami and Yamamoto (2023)	✓	✓
Ulum et al. (2019)	✓	✖
Narvios et al. (2022)	✓	✓
Odema et al. (2018)	✓	✖
Kyaw and Ng (2017)	✓	✖
Barosa et al. (2019)	✓	✖
Abdullah and Mazalan (2022)	✓	✖
Aishwarya et al. (2018)	✓	✖
Lee and Jhang (2019)	✓	✖
Pasha et al. (2018)	✓	✖
Wang et al. (2020)	✓	✖
Alselek et al. (2022)	✓	✖
Tolentino et al. (2020)	✓	✖

gravel, rock wool, peat moss, pumice, vermiculite, coir (Jensen 1997; Resh 2013; Somerville et al. 2014; Sharma et al. 2018; Mason et al. 2018; Maucieri et al. 2019).

From the primary studies, we found that the monitored parameters for aquaculture were water quality parameters such as pH, temperature, dissolved oxygen, total dissolved solids (TDS), electrical conductivity (EC), ammonia, nitrate, nitrite and turbidity, the water flow rate in the tank, nitrogen cycle monitoring, water levels, fish growth and fish feeder (Manju et al. 2017; Haruo et al. 2020; Arvind et al. 2020; Wang et al. 2021; Tolentino et al. 2019; Alselek et al. 2022; Maulini et al. 2022). The hydroponics monitored parameters were plant growth and grow bed temperature (Sharma et al. 2018; Mason et al. 2018; Maucieri et al. 2019) while the parameters regularly monitored in the ambient environment were temperature, humidity, light and CO_2 (Guo et al. 2022; Yang et al. 2023).

5.1.1.2 Controlling of aquaponics conditions Parameter control is based on monitored parameters. It is important to maintain the specific parameter range for plants and fish species. The findings show that real-time data was used to automate interventions such as a control mechanism. This approach ensured the optimal plant and fish growth in the aquaponics system. If parameter values deviate from the optimal values, some studies used manual control interventions, whilst others incorporated an automated system for automatic parameter regulation. Studies have also leveraged the combination of manual and automated systems (Vernandhes et al. 2017; Valiente et al. 2018). For manual control, if the monitored parameter has deviated from the predefined optimal range, notifications were sent to the responsible user of the system via various communication technologies, namely SMS, email, buzzer and light display.

Since water is a common medium of aquaponics living organisms, monitoring and controlling studies were undertaken in various tank-based environments. Variations in parameters were controlled automatically through various actions such as:

- Automatic dispensing of chemical solutions into water to correct pH variation (Defa et al. 2019).
- Water pumps were automatically activated when poor water circulation was detected (Jacob 2017).
- Fish feeders were automatically triggered at a predetermined time on a regular basis (Hadi et al. 2022).
- A heater was used to regulate the temperature when required (Valiente et al. 2018).

5.1.2 Predictions in aquaponics

Some studies have focussed on aquaponics prediction and these studies used historical or external data to perform their predictions. Predictions have been mainly on specific parameters such as plant and fish growth. Usually, from the gathered historical data, a dataset is created, and selected algorithms are used on the dataset to generate predictions based on the dataset. Predictive modelling has been applied in several aspects such as prediction of plant and fish growth, leaf disease, water quality parameters (temperature, pH, dissolved oxygen), fruit biomass, macronutrient concentrations, air temperature, leaf nutrient level, photosynthetic growth signatures at canopy scale, fish locomotion (Ren et al. 2018; Concepcion et al. 2021a, b; Ekanayake et al. 2022; Taufiqurrahman et al. 2020; Debroy and Seban 2022; Yang et al. 2023);

The two main approaches used for prediction are regression and classification. We will discuss these next.

5.1.2.1 Regression for aquaponics prediction Regression is a technique for modelling the relationship between independent variables, often called regressors, and the dependent variable to be predicted (Molin 2021). Regression analysis aims to build mathematical models that explain the existing relationships between variables (Seber and Lee 2012). Table 8 presents the instances of regression applied for aquaponics prediction.

5.1.2.2 Classification for aquaponics prediction In classification, the objective is to determine which category each data point belongs to based on its features or attributes. The performance of classification models is assessed by examining the accuracy with which each class in the data is predicted (Molin 2021).

The studies where classification was used for prediction were mainly hydroponics-based, as shown in Table 9.

Table 8 Regression in aquaponics

Author	Application
Ren et al. (2018)	Dissolved oxygen in the aquaculture water
Ekanayake et al. (2022)	Predicting aquaponics environmental parameters
Debroy and Seban (2022)	Tomato fruit biomass prediction
Li et al. (2021)	Total nitrogen concentration in the fish pond
Lauguico et al. (2020)	Macronutrients in the fishpond
Yang et al. (2023)	Prediction of greenhouse aquaponics air temperature
Taufiqurrahman et al. (2020)	Water temperature prediction
Reyes Yanes et al. (2022)	The growth rate and fresh weight of the plant
Guo et al. (2022)	Water temperature prediction
Alajas et al. (2021)	Aquaponics water nitrate
Ong et al. (2019)	Plant and fish growth rate
Aquino et al. (2021)	Lactuca Sativa Leaf Chlorophyll-b Prediction
Mori et al. (2021)	pH in aquaponics systems
Murakami and Yamamoto (2022)	Plant and fish growth
Haruo et al. (2020)	Estimate the growth condition of the plants
Taha et al. (2022b)	Nutrient content detection
Concepcion et al. (2022b)	Plant growth
Concepcion et al. (2021a)	Aquaponic pond water macronutrient
Concepcion et al. (2021b)	The nutrient and pigment concentrations

5.1.3 Strengths and weaknesses of reviewed studies on areas of application in aquaponics

The analysis of the different areas of application in aquaponics reveals strengths in comprehensive system monitoring, technological advancement, diverse applications, and collaboration identification. The areas of weakness are the short-term focus of most studies, limited environmental variability, and the narrow focus of solutions on specific regions. Table 10 provides a detailed description of each of these aspects.

5.2 Which digital technologies have been used to implement aquaponics solutions?

Aquaponics, combining fish farming and soil-less plant cultivation, offers a sustainable food production method that efficiently utilizes limited resources like land and water. This system significantly reduces environmental impact by minimizing the use of fertilizers and pesticides, contributing to a greener food production process. However, to fully realize its potential, aquaponics requires technological advancements for precise control and optimization to overcome challenges in scalability and commercialization.

Table 9 Classification in aquaponics

Author	Application
Lauguico et al. (2020c)	Machine vision-based lettuce growth stage
Amano et al. (2022)	To identify the Bok Choy leaf disease
Alejandrino et al. (2020)	Visual classification of lettuce growth stage based on morphological attributes
Dhal et al. (2022a)	Nutrient regulation: Optimal nutrients required for fish and plant growth
Dhal et al. (2022b)	Regulate nutrient concentrations in aquaponic irrigation water
Hadi et al. (2022)	Control water temperature and pH in an aquaponics system
Tobias et al. (2020)	Aquaponic Lettuce Growth Stage Classification Based on Canopy Texture Descriptors
Taha et al. (2022a)	Diagnosis of nutrient deficiencies in plants grown
Concepcion et al. (2020)	Predicting the cultivation period in weeks after germination and estimating
Concepcion et al. (2022a)	Moisture stress predictive model
Barosa et al. (2019)	Leaf Disease Detection

Table 10 Analysis of strengths and weaknesses of studies on areas of application in aquaponics

Theme	Strength	References
Comprehensive system monitoring	Current research efforts have extensively explores critical plant and fish health indicators, providing an in-depth understanding of aquaponic environments	(Amano et al. 2022; Concepcion et al. 2022b; Murakami and Yamamoto 2022; Zhang et al. 2022)
Technological advancement	Improving aquaponic efficiency	(Reyes-Yanes et al. 2020; Manju et al. 2017; Sriram and Shibu 2021; Ong et al. 2019)
Diverse applications	Studies cover a broad range of uses, highlighting the adaptability and potential of aquaponics across various contexts	(Dhal et al. 2022c; Amano et al. 2022; Nandesh et al. 2022; Abbasi et al. 2022a)
Collaboration identification	Research has explored the synergistic benefits of combining aquaponics with other systems or technologies to enhance its impact	(Hadi et al. 2022; Udanor et al. 2022; Ekanayake et al. 2022; Wan et al. 2022)
Theme	**Weakness**	**References**
Short-term focus	Limited long-term research hinders understanding of aquaponics' sustainability and long-term performance	(Dhal et al. 2022c; Ntulo et al. 2021; Niranjan et al. 2022; Ahmad et al. 2022)
Limited environmental variability	Some studies are conducted in controlled settings, potentially limiting the applicability of findings to diverse conditions	(Abbasi et al. 2022a; Tolentino et al. 2019; Yang et al. 2023)
Focus on specific regions	Many studies are region-specific, limiting the generalizability of findings to other geographical contexts	(Amano et al. 2022; Ekanayake et al. 2022; Udanor et al. 2022; Hadi et al. 2022)

In this SLR, the focus was on digital technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI), as well as its subsets, namely machine learning (ML) and deep learning (DL). From the reviewed papers, we found that IoT technologies were used to create most of the prototype aquaponic systems. In contrast, ML and DL algorithms were used to enable prediction, abnormality detection, and intelligent decision-making. 66% of the studies utilised IoT devices to develop their proposed aquaponics system. 17% of the studies utilised the data from various resources and performed prediction using ML/DL by applying regression or classification algorithms, and 17% of the studies incorporated IoT for data collection and ML/DL for prediction and anomaly detection, as shown in Fig. 6.

5.2.1 IoT applications domain in aquaponics system

The study found that IoT technologies were utilised in several studies for both monitoring and controlling (56%) as well as for monitoring alone (44%). Figure 7 illustrates the percentage distribution of IoT applications domain in aquaponics system. The most common area of application of IoT in aquaponics is monitoring and controlling.

Sensors in the aquaponics system are used to continuously monitor and measure various parameters such as water temperature, pH levels, Total Dissolved Solids (TDS), Electric Conductivity(EC), Dissolved Oxygen (DO), light intensity, CO_2, ammonium (NH4+), nitrate (NO3−), nitrite (NO2−), turbidity, water level, flow rate, ambient humidity, ambient temperature, fish feeder, food level, plant growth and nutrient concentrations (Manju et al. 2017; Zaini et al. 2018; Omar et al. 2019; Ghandar et al. 2021; Ekanayake et al. 2022; Friuli et al. 2021; Sunardi et al. 2021; Nandesh et al. 2022; Murakami and Yamamoto 2022; Niranjan et al. 2022; Dawa et al. 2022).

These real-time data streams enable farmers to closely monitor and maintain optimal conditions for both fish and plant growth.

Furthermore, the integration of IoT technology enables remote monitoring, empowering users to oversee their aquaponics systems from any location. The users can promptly receive alerts in the form of short messages, emails, buzzers, LED lights or notification formats regarding possible concerns and take timely actions (Kyaw and Ng 2017; Ong et al. 2019; Dawa et al. 2022). The corrective action can take place manually or automatically (Sansri et al. 2019). IoT-enabled automation allows the systems to adjust parameters like temperature, humidity, water flow, fish feeding, nutrient supply, water supply and light of the environment. To attain these goals, actuators controlling devices such as the cooler, aerator, humidifier, fan, water pump, fish feeder, LED light, and water heater were used (Jacob 2017; Valiente et al. 2018; Pasha et al. 2018; Aishwarya et al. 2018; Tolentino et al. 2020; Mahkeswaran and Ng 2020; Abdullah and Mazalan 2022; Benaya et al. 2022).

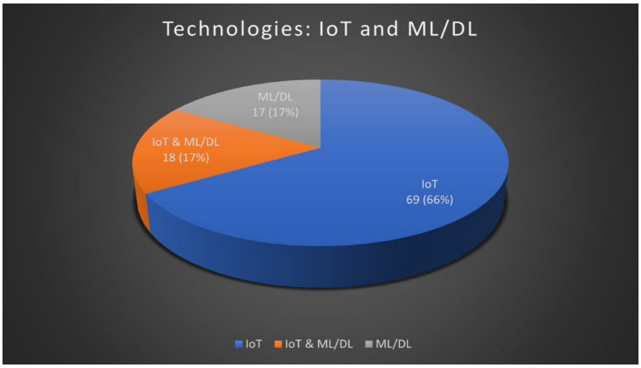

Fig. 6 The technologies: IoT and AI/ML/DL

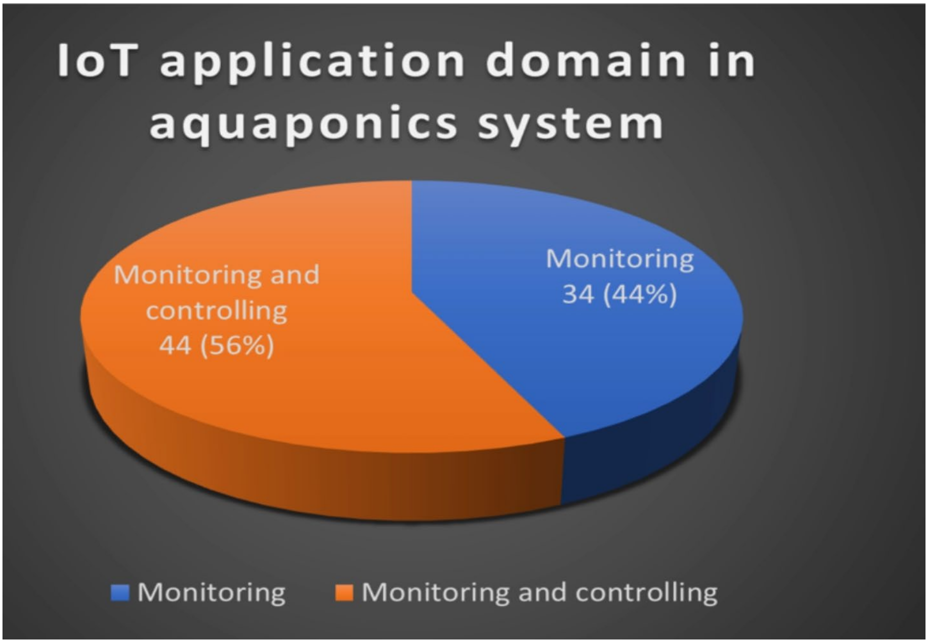

Fig. 7 IoT applications domain in aquaponics system

Also, found that data from sensors were stored via a variety of network connection technologies and protocols on SD cards, MySql database, Google Spreadsheets, and a cloud platform (Karimanzira and Rauschenbach 2019, 2021; Sansri et al. 2019; Butt et al. 2019; Ong et al. 2019; Riansyah et al. 2020; Wijayanto et al. 2021).

Given the diverse applications of physical internet objects, relying on a singular layer is deemed insufficient. Various studies have proposed different layers within the architecture of the Internet of Things (IoT) (Gubbi et al. 2013; Sethi and Sarangi 2017; Jamali et al. 2020a). However, according to most of the researchers (Jamali et al. 2020b; Mouha 2021; Wan et al. 2022) the standard IoT architecture comprises three fundamental layers: Perception Layer (Sensing), Network Layer (Data transmission) and Presentation Layer (Data storage and Manipulation).

Perception layer This is the lower layer in the IoT architecture. This layer, embedded with sensors, actuators, and any other physical devices, passes the collected or converted data transfer to the upper layer in the architecture. The actuators in this layer control the environment (Jamali et al. 2020b).

Network layer This layer is responsible for secure data transmission between the perception layer and application layer over the Internet. For effective communication, various communication network technologies and protocols must be incorporated (Jamali et al. 2020b).

Application layer This is the top layer in the IoT standard architecture. It uses various applications and technologies to interpret the received signals and provide insight to users. Thus, this layer shares information with the end user (Jamali et al. 2020b).

From the review of the selected primary studies, we found various types of technologies that have been used across the different layers of the IoT architecture. At the application layer, data analytics technologies like machine learning and deep learning have been deployed to deliver services/functionality that are consumed by web/mobile client applications. These could be for the purpose of monitoring or monitoring and controlling aquaponics systems. Also, other smart applications for managing aquaponics have been implemented for the application layer.

The network layer of the IoT architecture has network communication technologies and protocols. The network communication technologies that have been used include Wireless Fidelity (Wi-Fi), Cellular Networks (3G, 3G, 5G), Bluetooth Low Energy (BLE), Wireless Sensor Networks (WSN), Low Power Wide Area Networks (LPWAN), and Long Range Wide Area Network (LoRaWAN). The data transmission protocols that are used include Zigbee, WebSocket, TCP/IP, Internet Protocol Version 6 (IPV6), IPV6 over Low Power Personal Area Networks (6LoWPAN), Message Queuing Telemetry Transport (MQTT).

In the perception layer, various types of equipment such as sensors, actuators, cameras, and other devices have been used. In Fig. 8, we present a conceptual overview of the three layers of the IoT architecture, including the relevant devices, technologies, protocols, and applications.

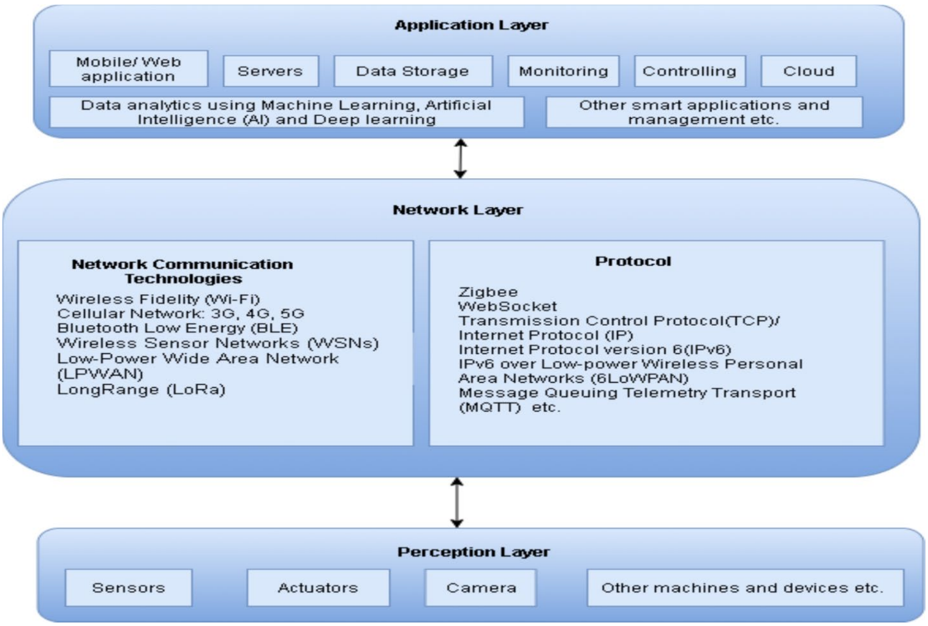

Fig. 8 Overview of technologies across layers in the IoT architecture

5.2.2 Machine learning and deep learning

Machine learning (ML) — 49% and deep learning (DL) — 51% algorithms have been applied in several studies to predict plant and fish growth, leaf disease detection, water quality parameters (temperature, pH, dissolved oxygen), fruit biomass, macronutrient concentrations, air temperature, leaf nutrient level, Chlorophyll-b, leaf pigmentation, photosynthetic growth signatures at canopy scale, fish locomotion detection. Figure 9 outlines the percentage of the utilisation of ML and DL in aquaponics studies.

Supervised learning (regression, classification) and unsupervised machine learning (clustering) models have been used in aquaponics studies. Supervised learning involving classification and regression is used more frequently in aquaponics studies than unsupervised learning (clustering), as shown in Fig. 10.

5.2.3 Strengths and weaknesses of reviewed studies on Aquaponics technologies

In this section, we present an analysis of the strengths and weaknesses of the studies on technologies that have been used to implement aquaponics technologies. We noticed strengths in the aspects of advanced technological integration, real-time optimization, data-driven decision-making, and versatility and adaptability. Also, data management complexity and technology dependence are perceived to be areas of weakness where improvements are required. Further elaboration on each of these strengths and weaknesses is provided in Table 11.

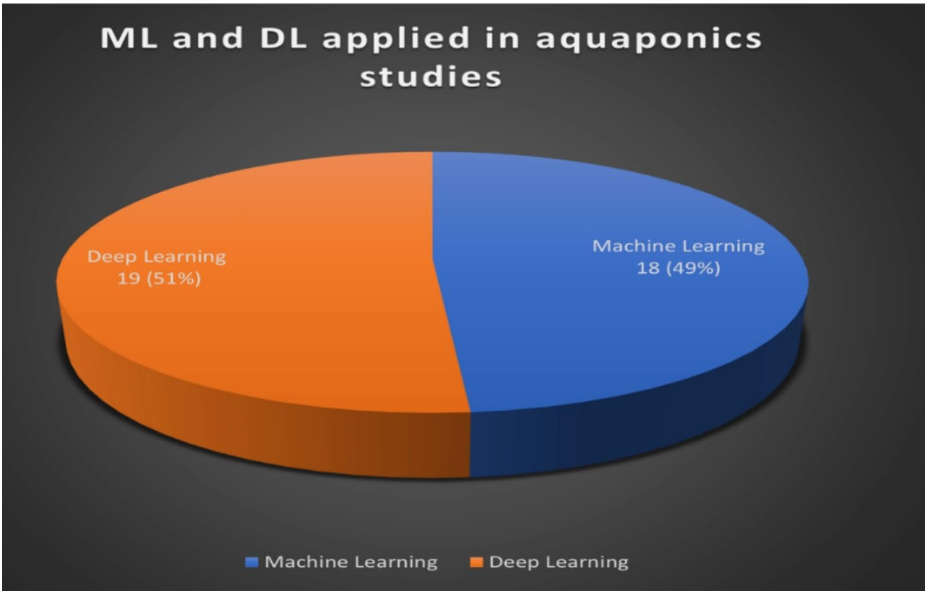

Fig. 9 ML/DL applied in aquaponics studies

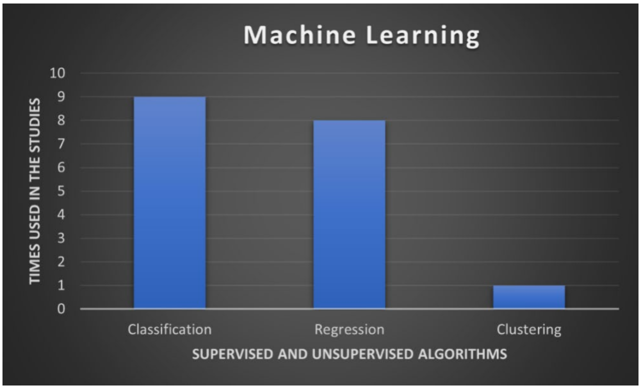

Fig. 10 Machine learning: supervised and unsupervised algorithms

Table 11 Analysis of strengths and weaknesses of studies on digital technologies for aquaponics

Theme	Strengths	References
Advanced technological integration	The effective integration of IoT and AI drives innovation, enabling precise monitoring, control, and predictive capabilities within aquaponics systems.	(Zhang et al. 2022; Ahmad et al. 2022; Dhal et al. 2022c; Debroy and Seban 2022)
Real-time optimization	Continuous data monitoring facilitates immediate responses to system changes, optimizing conditions for plant and fish health.	(Hadi et al. 2022; Dawa et al. 2022; Abdullah and Mazalan 2022)
Data-driven decision-making	Predictive models and anomaly detection enhance decision-making processes, improving overall system management.	(Amano et al. 2022; Ekanayake et al. 2022; Debroy and Seban 2022; Murakami and Yamamoto 2022)
Versatility and adaptability	IoT and AI applications span various aquaponic domains, showcasing the technologies' potential for diverse systems.	(Ahmad et al. 2022; Concepcion et al. 2022a).
Theme	**Weakness**	**References**
Data management complexity	There is efficient handling of datasets while maintaining accuracy, consistency and security poses significant obstacles.	(Benaya et al. 2022; Pramudita et al. 2022; Niranjan et al. 2022; Zhang et al. 2022; Nichani et al. 2018)
Technology dependence	The reliance on technology increases the risk of system failures and necessitates robust security measures.	(Alselek et al. 2022; Ghandar et al. 2021; Khaoula et al. 2021)

5.3 What methods were used to evaluate the proposed systems?

So far, aquaponics research and development primarily comprised two methods: the development of prototypes and the execution of computational models (Manju et al. 2017; Murad et al. 2017; Kyaw and Ng 2017; Reyes et al., 2020; Murdan and Joyram 2021; Ntulo et al. 2021; Abdullah and Mazalan 2022; Debroy and Seban 2022; Ekanayake et al. 2022).

The development of IoT-based prototypes provides real-time monitoring and control, leading to stable and optimal environmental conditions. The execution of computational models has proven to be an effective method in enhancing the performance of aquaponics systems. Computational models offer predictive insights that help optimize system parameters and improve overall productivity. Both approaches contribute significantly to the advancement of smart aquaponics, demonstrating their practical viability and potential for scalability. The following sections describe how these methods have been evaluated.

5.3.1 Evaluation approaches for IoT-based prototypes in aquaponics

Evaluation approaches in IoT-based prototypes in aquaponics involve ways to check if using the Internet of Things (IoT) makes aquaponics systems better.

For example, Riansyah et al. (2020) developed a prototype aimed to monitor water quality and control fish feeding in an aquaponics system. To assess the prototype's effectiveness, a direct comparison between the embedded sensors (pH and TDS) and their corresponding laboratory-grade meters is essential. Zaini et al. (2018) developed a prototype to monitor and control water quality. To evaluate the effectiveness of their system, they employed several methods. Sensor accuracy was tested by comparing temperature sensors with infrared thermometers, height sensors with rulers, pH sensors with electric pH meters, and ammonia gas levels with tetra test kits. The plant growth was observed and compared between the monitored aquaponic NFT system and a conventional hydroponic setup. The results confirmed that the prototype's sensors provided accurate measurements and that plants in the IoT-enhanced aquaponic system showed improved growth and health compared to those in the traditional hydroponic system, demonstrating the system's efficacy in optimizing both water quality and plant productivity. Also, Dawa et al. (2022) developed an IoT-based aquaponics system and rigorously tested it through unit, integration, system, and acceptance testing. Experts evaluated hardware, software, and network connectivity. Overall, the system earned an average approval rating of 4.32, indicating strong reliability, efficiency, applicability, portability, and economic feasibility.

The evaluation process of IoT-based prototypes encompassed various aspects, including comparison, observations and feedback from domain experts (Valiente et al. 2018; Defa et al. 2019; Friuli et al. 2021; Dawa et al. 2022). These evaluation techniques provided valuable insights and critical assessments of the system's performance and functionality. Figure 11 provides an overview of IoT evaluation approaches.

Comparison The majority of studies — 32 (82%) used comparison as the basis for evaluation. They conducted a comprehensive range of comparisons across diverse domains, examining the growth rates of plants in aquaponics versus traditional methods. This evaluation approach included analysing pH meter values in comparison to pH sensor readings, as well as validating temperature sensor values against those obtained from thermometers. Furthermore, the efficacy of aquaponic plants in water purification was assessed through microwave reflectometry (MR) measurements, comparing water samples from tanks, taps, and filtered sources. System-recorded data for parameters such as Dissolved Oxygen, light intensity, and plant height were compared with manually sampled data. Additionally, the studies delved into comparisons related to power consumption. Moreover, the estimation results were cross-referenced with the actual area measured manually (Barosa et al. 2019; Defa et al. 2019; Menon 2020; Friuli et al. 2021; Rahayu et al. 2021; Niranjan et al. 2022).

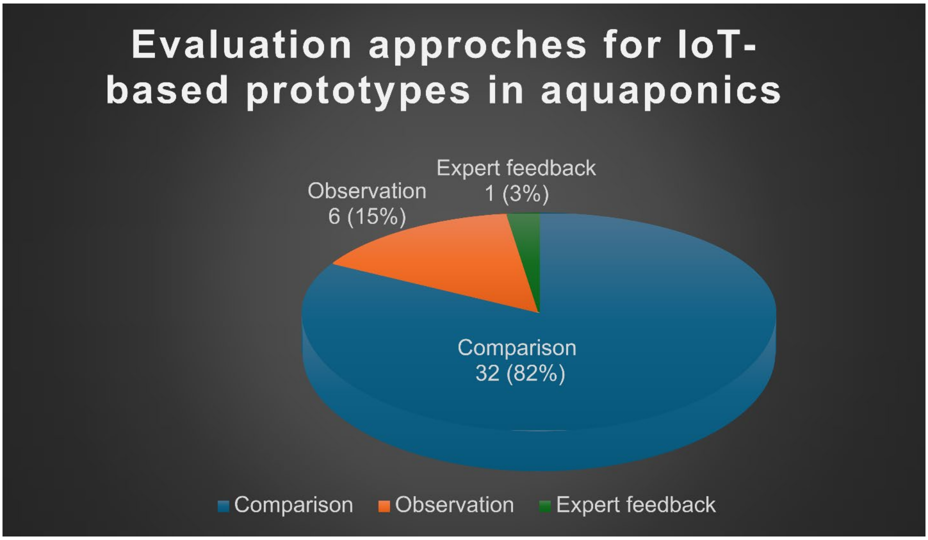

Fig. 11 Evaluation approaches for IoT-based prototypes in aquaponics

Observation Six studies (15%) used direct observation as a means of evaluation. The direct observations were conducted over designated periods, ranging from 7 days to 1 month, to evaluate the growth rates of both fish and plants. These observations also involved an examination of the variations in collected data, such as pH levels and total dissolved solids (TDS) (Valiente et al. 2018; Defa et al. 2019; Ahmad et al. 2022; Ahmad et al. 2022; Friuli et al. 2021).

Feedback Feedback has been rarely used for evaluation. The only study (3%) that used expert evaluation (Dawa et al. 2022) was performed by a panel consisting of individuals possessing specialised knowledge in their respective domains, including hardware, software, and network connectivity.

5.3.2 Evaluation methods for computational models in aquaponics

The evaluation of computational models has focussed mainly on assessing the performance of different machine learning algorithms using various metrics. For example, Amano et al. (2022) aimed to identify the most effective machine-learning algorithm for detecting diseases in Bok Choy. The study involved training three machine learning algorithms—K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest (RF) on images with extracted features using image processing techniques. The comparative analysis revealed that KNN achieved the highest accuracy of 98.21%, outperforming SVM, which had an accuracy of 73.81%, and RF, which had an accuracy of 64.29%. Debroy and Seban (2022) conducted a performance evaluation of prediction models for forecasting tomato biomass in an aquaponic system. The analysis showed that the proposed models were effective, with the Adaptive Neuro-Fuzzy Inference System (ANFIS) model outperforming the Artificial Neural Network (ANN) model. ANFIS demonstrated superior performance, as evidenced by the best values in Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R^2) metrics.

A comprehensive understanding of performance measurement is integral to the study of machine learning techniques. Several metrics, have been defined to assess the performance of different types of machine learning systems (Lauguico et al. 2020a, b; Ghandar et al. 2021; Amano et al. 2022; Ekanayake et al. 2022; Concepcion et al. 2021b; Taufiqurrahman et al. 2020; Yang et al. 2023).These metrics play a crucial role in evaluating the effectiveness and efficiency of machine learning algorithms, allowing researchers and practitioners to make informed decisions and improvements in their models (Joshi 2020). Table 12 shows the metrics used for classification.

The metrics for the evaluation of regression algorithms are presented in Table 13.

Table 14 presents the view of the level of utilisation of different evaluation metrics in aquaponics studies.

Table 15 presents a comparative overview of evaluation methods for IoT-based prototypes and computational models in aquaponics in terms of their advantages and disadvantages, which can inform the selection of appropriate evaluation approaches.

5.3.3 Strengths and weaknesses of reviewed aquaponics evaluations studies

Understanding the technologies used to implement aquaponics solutions is essential for evaluating their effectiveness, scalability, and innovation. This section analyses the strengths and weaknesses of the reviewed studies on evaluation methods.

From the selected primary studies for this SLR, we observe that the strengths of evaluation methods on IoT-based prototypes are the use of a comprehensive approach and the real-world grounding of evaluations. The weaknesses of the evaluation methods stem from the underutilization of expert knowledge and the challenges around the methodological rigour of evaluations (see Table 16). Regarding the evaluation of machine learning algorithms in aquaponics (computational methods), the strengths are in the aspects of quantitative accuracy and data-driven optimization, while the weakness is the absence of contextual adaptation (see Table 17).

Evaluation methods that focus on IoT-based prototypes and computational (machine learning) algorithms present opportunities and challenges. Combining the strengths of both approaches, such as incorporating expert feedback into quantitative assessments and using diverse metrics to evaluate IoT system performance, could enhance the overall evaluation process. Additionally, addressing the weaknesses identified, like increasing the frequency of expert evaluations and extending observation periods, can improve the reliability and validity of the evaluation results.

6 Limitations

In this section, the limitations of the current review are addressed, with acknowledgement of potential biases and constraints.

The publications were selected from Scopus, IEEE Explore, SpringerLink and Science Direct. Some relevant papers could have been overlooked from other less popular databases. Only publications written in English were considered; some relevant publications in other

Table 12 Classification evaluation metrics

Classification metrics	Formula	References
Precision (P)/Positive Predictive Value (PPV)	$P = \frac{TP}{TP+FP}$	Dangeti (2017)
Recall (R) /sensitivity/ True Positive Rate (TPR)	$R = \frac{TP}{TP+FN}$	Chicco and Jurman (2020); Dangeti (2017)
F1 score (F1)/ *F-measure* or *F1 score*	$F_1 = \frac{2}{\frac{1}{P}+\frac{1}{R}}$	Dangeti (2017)
Accuracy (Acc)	$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)}$	Dangeti (2017)
Specificity (Sp)/ True Negative Rate (TNR)	$TNR = \frac{TN}{TN+FP}$	Chicco and Jurman (2020); Dangeti (2017)
False Positive Rate (FPR) / fallout	$FPR = \frac{FP}{FP+TN}$	Chicco and Jurman (2020)
Matthews Correlation Coefficient (MCC)	$MCC = \frac{TP.TN-FP.FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$	Chicco et al. 2021a); Chicco and Jurman (2020); Zhu (2020);
Average Precision	$AP = \frac{\sum_{i=1}^{n} \frac{TP_i}{TP_i+FP_i}}{n}$	Hossin and Sulaiman (2015)
mean Average Precision	$mAP = \frac{1}{n} \sum_{i=1}^{n} AP_i$	Chen et al. (2022)
Averaged Recall	$AR = \frac{\sum_{i=1}^{n} \frac{TP_i}{TP_i+FN_i}}{n}$	Hossin and Sulaiman (2015)
Hamming Loss	$HammingLoss\ (H_{ML}, D_t) = \frac{1}{n} \sum_{i=1}^{n} \frac{\lvert Y_i\, \Delta\, Z_i \rvert}{\lvert L \rvert}$	Krstinić et al. (2020)

True Positive (TP); True Negative (TN); False Positive (FP); False Negative(FN);

D_t = Data set of multi-label patterns; H_{ML} = value of the Hamming Loss calculated for this dataset;

Y_i = Ground Truth set of labels for data instance i; Z_i= prediction of the classifier of i^{th} instance;

L=total number of labels; Δ =symmetric difference of two sets;

n=number of classes in the classification.

Table 13 Regression evaluation metrics

Regression metrics	Formula	References
Mean Squared Error (MSE)	$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \widehat{y}_i)^2$	Chicco et al. (2021b)
Root Mean Squared Error (RMSE)	$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \widehat{y}_i)^2}{n}}$	Chicco et al. (2021b)
Mean Absolute Error (MAE) / Absolute Mean Error (AME)	$MAE = \frac{1}{n} \sum_{i=1}^{n} \lvert y_i - \widehat{y}_i \rvert$	Chicco et al. (2021b)
Coefficient of determination (R^2 or R-squared)	$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \widehat{y}_i)^2}{\sum_{i=1}^{n} \left(y_i - \bar{y}\right)^2}$	Chicco et al. (2021b)
Mean absolute percentage error (MAPE)	$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left\lvert \frac{y_i - \widehat{y}_i}{y_i} \right\rvert$	Chicco et al. (2021b); Ren et al. (2018)
Nash-Sutcliffe efficiency (NSE) — only relevant to hydrological models	$NSE = 1 - \frac{\sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} (O_i - O)^2}$	Duc and Sawada (2023)
Root Relative Squared Error (RRSE)	$RRSE = \frac{\sqrt{\sum_{i=1}^{n} (y_i - \widehat{y}_i)^2}}{\sqrt{\sum_{i=1}^{n} \left(y_i - \bar{y}\right)^2}}$	Guo et al. (2022)
Root Mean Squared Percentage Error (RMSPE)	$RMSPE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(\frac{y_i - \widehat{y}_i}{y_i}\right)^2 X\ 100}$	Kumar et al. (2023)

n=total number of observations; y=actual value of the observation; $\widehat{y}$ =predicted value of the observation; s_i = simulations ; o_i= observations; O= observed mean languages, such as French and Spanish, could have been omitted. Whilst all efforts have been made for maximum accuracy, there always exists a remote possibility of human error.

7 Discussion

This section offers an in-depth discussion of the findings, incorporating the authors' insights and interpretations of the following research questions.

7.1 Application of aquaponics (RQ1)

So far, aquaponics solutions have been applied the most in the area of monitoring and controlling the aquaponics environment, with over 70% of efforts focusing on either monitoring and controlling or just monitoring (see Fig. 5). Many of the aquaponics monitoring studies pertain to aquaculture, hydroponics and ambient environment. Generally, the most commonly monitored and controlled parameters are water quality, nutrient levels, temperature, environmental conditions, and fish health. Thus far, there are many instances where aquaponics parameters were monitored but not controlled. As shown in Table 7, regarding the studies that focus on aquaculture in aquaponics, only 13 out of 70 studies (18.6%) delved into controlling monitored parameters. This observation suggests that more instances of the combination of monitoring and controlling are needed since it will enable effective management of the aquaponics system to ensure maximum aquaponics yield.

For aquaculture, the water quality parameters that are most commonly monitored are pH, temperature, dissolved oxygen, total dissolved solids (TDS), electrical conductivity (EC), ammonia, nitrate, nitrite and turbidity, the water flow rate in the tank, nitrogen cycle monitoring, water levels, fish growth and fish feeder (Arvind et al. 2020; Tolentino et al. 2019; Alselek et al. 2022; Maulini et al. 2022). For hydroponics, the most monitored parameters were plant growth and grow bed temperature (Sharma et al. 2018; Mason et al. 2018; Maucieri et al. 2019). The parameters regularly monitored in the ambient environment were temperature, humidity, light and CO2 (Guo et al. 2022; Yang et al. 2023). Approaches for controlling the aquaponics environment can largely be described as manual (where the environment is physically adjusted), automated (where the environment is regulated by a system), or a combination of manual and automated.

Predictive modelling has been applied for aquaponics prediction with more emphasis on aspects such as prediction of plant and fish growth, leaf disease, water quality parameters (temperature, pH, dissolved oxygen), fruit biomass, macronutrient concentrations, air temperature, leaf nutrient level, photosynthetic growth signatures at canopy scale, fish locomotion. There are more instances where regression algorithms (see Table 8) have been used than classification methods (see Table 9). The prevalence of regression is because most of the input (independent) variables used as predictors were measured as continuous values, which dictates that regression be used to estimate the target variable (such as plant size, fish growth, water quality parameters — temperature, pH, dissolved oxygen (Alajas et al. 2021; Yang et al. 2023).

The application of prediction in aquaponics (27%) has been under-explored compared to monitoring and controlling or monitoring of aquaponics (73%). Most of the predictions focus on estimating specific parameters that require monitoring and not aspects that pertain

Table 14 Frequency of utilisation of evaluation metrics in aquaponics studies

Evaluation metrics	Classification	Regression	Percentage
Root Mean Squared Error (RMSE)	✖	✓	15%
Mean Absolute Error (MAE)/ Absolute Mean Error (AME)	✖	✓	12%
R-squared/ correlation coefficient of determination (R^2)	✖	✓	11%
Mean Squared Error (MSE)	✖	✓	5%
Mean Absolute Percentage Error (MAPE)	✖	✓	3%
Root Relative Squared Error (RRSE)	✖	✓	1%
Root Mean Squared Percentage Error (RMSPE)	✖	✓	1%
Precision	✓	✖	9%
F1-Score	✓	✖	8%
Recall (R) /sensitivity/ True Positive Rate (TPR)	✓	✖	9%
Accuracy	✓	✖	7%
Specificity	✓	✖	4%
Matthews correlation coefficient (MCC)	✓	✖	2%
False Positive Rate (FPR)/fallout	✓	✖	3%
Hamming loss	✓	✖	1%
mean average precision (mAP)	✓	✖	1%
Average Precision	✓	✖	1%
Average Recall	✓	✖	1%
Receiver Operating Characteristic (ROC)	✓	✖	1%

to aquaponics yield prediction. The implication is that the end users and stakeholders of the aquaponics system do not have the mechanism to forecast the yield. In the business domain, this creates uncertainty, which causes a lack of confidence, resulting in less investment in aquaponics (Bosma et al. 2017; Hao et al. 2020; Turnsek et al. 2020).

7.2 Technologies used to implement aquaponics solutions (RQ2)

So far, IoT technologies have been used to create most of the prototype aquaponic systems and data collection. In contrast, machine learning and deep learning algorithms have been used to enable prediction, abnormality detection, and intelligent decision-making. IoT was used mostly in the area of monitoring and controlling or just for monitoring (see Fig. 7).

Table 15 Comparison of evaluation methods, advantages, and disadvantages of prototype development and computational models in aquaponics

Application	Evaluation method	Advantages	Disadvantages	References
Prototype Development using IoT	Comparison of prototype performance with benchmarks, feedback from users, and observation of real-time operation.	Delivers instant, actionable insights and responses. Enables prompt user-system interaction.	High costs and time commitment. Potential hardware malfunctions. Limited scalability.	(Ong et al. 2019; Sunardi et al. 2021; Wibowo et al. 2019; Menon 2020; Kamil et al. 2020; Benaya et al. 2022; Abbasi et al. 2022a)
Computational Models	Performance metrics: accuracy, precision, recall etc. for classification; MSE, RMSE, AME etc. for regression.	High accuracy and scalability. Effective for complex and large-scale data analysis.	Requires a significant amount of processing power. Models may be intricate and difficult to understand. Training may take a long period	(Dhal et al. 2022b; Amano et al. 2022; Concepcion et al. 2020; Debroy and Seban 2022; Murakami and Yamamoto 2022)

Table 16 Analysis of strength and weakness of studies evaluation of IoT-based prototypes

Theme	Strength	References
Comprehensive evaluation approach	A variety of methods offers a general view of IoT-enhanced aquaponics system performance, cost-effectiveness, and user-friendliness	(Wibowo et al. 2019; Niranjan et al. 2022; Zhang et al. 2022; Zaini et al. 2018)
Real-world grounding	Direct observation and expert input ensure practical relevance and applicability of findings	(Dawa et al. 2022; Ahmad et al. 2022; Wibowo et al. 2019)
Theme	**Weakness**	**References**
Underutilization of expert knowledge	Limited use of expert feedback hinders the potential for in-depth qualitative assessment and improvement recommendations.	(Wijayanto et al. 2021; Riansyah et al. 2020; Sansri et al. 2019)
Methodological rigour challenges	Variations in comparison studies and short observation periods can compromise data reliability and generalizability	(Abdullah and Mazalan 2022; Pramudita et al. 2022; Ntulo et al. 2021; Wibowo et al. 2019; Ahmad et al. 2022)

Table 17 Analysis of strength and weakness of studies on machine learning evaluation

Theme	Strength	References
Quantitative accuracy	Precise mathematical metrics enable objective performance assessment and benchmarking.	(Concepcion et al. 2021a; Murakami and Yamamoto 2022; Dhal et al. 2022b)
Data-driven optimization	Performance metrics inform model improvement and better decision-making in aquaponics management.	(Yang et al. 2023; Hamza-Lup et al. 2019)
Theme	**Weakness**	**References**
Contextual adaptation	Careful selection of metrics is essential to avoid misleading evaluations and ensure accurate performance assessment	(Debroy and Seban 2022; Ghandar et al. 2021; Amano et al. 2022)

Different types of technologies that pertain to different layers of the IoT architecture have been used to create aquaponics solutions. These include technologies such as data analytics (machine learning, deep learning, and smart applications) for the construction of end-user services which pertain to the application layer. Some technologies enable the network layer of IoT architecture to ensure network communication and data transmission. Some technologies enable the perception layer of the IoT architecture, ensuring that signals/precepts are continuously picked from the environment to allow monitoring and controlling of the aquaponics system (see Fig. 8).

In addition, IoT is the dominant technology used for aquaponics control because it allows the adjustment of parameters like temperature, humidity, water flow, fish feeding, nutrient supply, water supply, and light of the environment. In many instances, IoT-enabled devices such as coolers, aerators, humidifiers, fans, water pumps, fish feeders, LED lights, and water heaters were used to control the aquaponics environment. There are far more cases of application of supervised learning involving classification and regression than unsupervised learning involving clustering.

As IoT applications for smart aquaponics continue to grow, the issues of security and sustainability will be more critical. So far, not much attention has been paid to the security of aquaponics systems. The increased uptake of smart aquaponics will lead to increased security threats, which will compel the need for secure IoT technologies and methods to mitigate the security threats and attacks such as man in the middle and denial of service (DoS), which can have a negative effect on smart aquaponic systems. Generally, IoT systems are susceptible to security attacks that target IoT devices or layers of the IoT architecture. The attacks through IoT devices could target memory, firmware, physical interfaces, network resources, faulty parts, vulnerable update systems, dangerous factory settings, and communication channels. IoT devices can also be affected by spoofing, denial of service, and unauthorized user access (Mazhar et al. 2023). The security challenges of the IoT architecture are authentication, confidentiality, mobile security, secure middleware, access control, privacy, policy enforcement, and trust (Torğul et al. 2016; Mazhar et al. 2023). An IoT system is susceptible to different security attacks and risks that may be unknown. Thus, a thorough investigation is always required to identify areas of vulnerability and tackle them. The application of AI methods especially machine learning and deep learning techniques could be an effective way to improve security of IoT architectures ((Mazhar et al. 2023).

In addition, the application of technologies like digital twinning and blockchain to ensure decentralised storage of valuable data that pertain to smart aquaponics will be essential (Reyes-Yanes et al. 2020; Taji et al. 2023). The sustainability concerns of aquaponics refer to the need to ensure good yield (production) of fish and plants in a way that minimises waste and ensures resource efficiency with no adverse effect on humans and other living things in the environment (Hao et al. 2020; Arakkal Thaiparambil and Radhakrishnan 2022; Goddek et al. 2015). There will be a need to evolve IoT technologies to foster sustainability.

To some extent, the application of AI technologies such as machine learning/deep learning have been applied mainly for monitoring and, to a lesser extent, for prediction. More attention needs to be directed at implementing AI methods that will enable predictive analytics to be applied in aspects such as aquaponics yield prediction, return-on-investment (ROI) estimates, resource optimisation, product marketing, and sustainability assessment (Hao et al. 2020), which have not received very little attention so far.

7.3 Methods for the evaluation of aquaponics solutions (RQ3)

The findings of the study reveal that many studies did not apply any form of evaluation to assess the performance or effectiveness of the proposed aquaponics solution. As shown in Fig. 10, only 39 out of a total of 105 selected primary studies (37%) on smart aquaponics have at least a form of evaluation. Therefore, more attention needs to be given to the validation of proposed smart aquaponics solutions to promote the credibility of such proposals.

Generally, evaluation methods can be divided into two categories: evaluation of IoT-based prototypes in aquaponics and evaluation of computational (machine learning) methods. The evaluation process encompasses various aspects, including comparison, observations, and, to a lesser extent, feedback from domain experts.

So far, expert feedback has rarely been used to evaluate aquaponic solutions (Dawa et al. 2022). Hence, there is a need for a more thorough approach to evaluation that will focus not just on performance metrics but on qualitative assessment by domain experts. This form of evaluation will enhance the credibility of aquaponics solutions. Also, thus far, there is no emphasis on usability evaluation by end-users of aquaponics systems. The study did not find any study where end-users like aquaponic farmers were involved in the evaluation of aquaponic solutions. Researchers and technical experts tend only to propose solutions and evaluate them based on some scientific metrics but do not consider the opinion of stakeholders like end-users and domain experts on the fitness for purpose and usability of such solutions. More studies focused on stakeholder perspectives will be required to increase the uptake of smart aquaponics.

Related to this is the need for participatory design and human-centred development of aquaponic systems. So far, there has been few or no cases where the conception, design, and development of aquaponic systems were based on an agile methodology that involved the active participation of end-users and critical stakeholders. This limitation must be addressed to enhance the quality and credibility of smart aquaponics solutions.

Although several aquaponics studies applied machine learning (ML) or deep learning (DL) for prediction (using regression or classification methods), there is hardly any study that looked at the explainability and interpretability of the ML/DL models. Therefore, the application of Explainable AI (XAI) in smart aquaponics is scarce (Lowe et al. 2022; Taji et al. 2023). Explainability ensures that relevant justifications are provided for results (predictions, suggestions) made by AI systems (Guidotti et al. 2018; Gunning et al. 2019; Kolajo and Daramola 2023). Powerful machine learning algorithms such as artificial neural networks (ANN), support vector machines, and ensemble learning models (such as extreme gradient boosting, random forest) are opaque models that have poor explanation capability (Gunning et al. 2019). XAI enables justifications that explain the rationale for the result generated by these opaque models to be generated (Gunning et al. 2019; Kolajo and Daramola 2023). Explainability will enable end-users of machine-generated results to understand the basis for the results, which will improve trust. The aspects of XAI and trustworthy AI are still unexplored in smart aquaponics. More solutions based on XAI are required to ensure increased uptake of smart aquaponics systems. New metrics to evaluate XAI smart aquaponics solutions will also have to be developed.

Thus far, there is a paucity of decision support systems for smart aquaponics. Relatively few instances of decision support systems for aquaponics have been reported in the literature. So far, most of the proposed aquaponic solutions that employ predictive analytics focus on the prediction of certain parameters either for monitoring or controlling the aquaponics system. Solutions that are designed to enable strategic decision-making or day-to-day operational decision-making by stakeholders of smart aquaponics are rare. This scenario makes it essential to explore other technologies like expert systems, Explainable AI, and Large Language Models (LLMs) (to realise Generative Pre-trained Transformers (GPT)) to facilitate the development of decision support systems for smart aquaponics. The metrics for the evaluation of these types of decision support systems for smart aquaponics also have to be developed.

The study noticed the absence of end-to-end aquaponics solutions that cover the whole spectrum of monitoring, controlling, prediction, and decision support. Technologies that support a holistic approach to smart aquaponics will be necessary in the near future. This will also compel the need for the development of new evaluation methods that will focus not just on the performance of prediction algorithms but also on the effectiveness and fitness of smart aquaponics to meet specific business and organisational objectives.

8 Future research opportunities

There are several research opportunities that can be inferred from the findings of this study. These are outlined as follows:

1) **Long-term and longitudinal studies**: most of the existing are cross-sectional studies where aquaponics data were collected within a short period(most 3–6 months) and analysed to arrive at the findings. There is need for more studies that enables data collection over a long time, and also at different times and seasons for analysis. This will provide a stronger basis for the validation of findings from smart aquaponics studies and enrich the theoretical body of knowledge.
2) **Studies in different geographical contexts and settings**: Most of the existing studies are focus on a specific geographical context and conducted within a specific controlled environment. There is a need for more studies that are conducted across different geographies and diverse settings, which will enhance the generalizability of results. Cross-national studies and replicative case studies will be vital in the smart aquaponics field.
3) **More combined studies on monitoring and controlling of aquaponics**: In most cases, aquaponics parameters were monitored but not controlled. More instances of the combination of monitoring and controlling are needed since it will enable effective management of the aquaponics system to ensure maximum aquaponics yield. Also, aquaponics predictions (27%) have been under-explored compared to instances that involved either monitoring or monitoring and controlling aquaponics (73%).
4) **More studies on aquaponics yield prediction**: Most of the aquaponics predictions focussed on estimating specific parameters that require monitoring and not aspects that pertain to aquaponics yield prediction. This observation implies that the end users or stakeholders of the aquaponics system do not have the mechanism to forecast the yield.
5) **Explainable AI for smart aquaponics**: Although there have been many studies on predictive analytics for aquaponics, instances of the application of Explainable AI (XAI) in smart aquaponics are scarce. There is hardly any study that looks at the explainability and interpretability of the ML/DL models in aquaponics.

6) **Predictive analytics for new aspects of aquaponics**: There is a need for more attention on predictive analytics solutions that pertain to the aspects of aquaponics yield prediction, return-on-investment (ROI) estimates, resource optimisation, product marketing, and sustainability assessment, which have received very little attention so far. Also, not much attention has been given to the security of aquaponics systems. More research on secure architectures for smart aquaponics are required.
7) **Stakeholders and user-centric evaluation of smart aquaponics solutions**: So far, few studies (37.7%) have paid attention to the validation of proposed aquaponics solutions by attempting to evaluate the performance or effectiveness of the proposed solution. Expert feedback and usability evaluation, which involved stakeholders and end-users (e.g. farmers and business owners) of aquaponics solutions, have been rarely used to assess smart aquaponics solutions. Generally, there is a lack of participatory design and a human-centred development approach to the creation of proposed aquaponic solutions. There are very few cases where the conception, design, and development of aquaponic systems were based on an agile methodology that involved the active participation of end-users and critical stakeholders.
8) **Decision support systems for aquaponics**: Currently, there is a paucity of decision support systems for aquaponics. In most cases predictive analytics methods have been applied, but not in a way that translates to practical decision-making by end-users. Hence, there is a need for more decision support systems for aquaponics that can enable strategic decision-making and day-to-day operational decision-making by stakeholders of smart aquaponics.
9) **End-to-end smart aquaponics solutions**: There is an absence of end-to-end aquaponics solutions that cover the whole spectrum of monitoring, controlling, prediction, and decision support in aquaponics. Most studies have focused on one aspect at the expense of others. End-to-end systems that embrace multiple aspects of smart aquaponics are highly desirable in the field.
10) **Application of new technologies**: The introduction of new technologies that have not been widely applied in aquaponics will be valuable. These include expert systems, LLM, Explainable AI, and blockchain to facilitate a holistic approach to the development of smart aquaponics in the near future.
11) **New evaluation methods and metrics**: The need for new types of aquaponics solutions, such as decision support systems and end-to-end aquaponics solutions, and the introduction of new technologies like expert systems, LLM, Explainable AI, and blockchain will require that new evaluation methods and metrics be developed. The evaluation methods and metrics must focus not just on performance but also on the fitness for purpose and capability of smart aquaponics systems to meet specific business and organisational objectives.

9 Conclusion

This study examines three questions focused on the application of aquaponics, the technologies used to implement aquaponics solutions, and the methods used to evaluate aquaponics solutions by using a systematic literature review methodology. After applying relevant search strings to search for relevant papers in specific academic databases (viz. Scopus, ScienceDirect, SpringerLink, and IEEE Explore), we applied the inclusion and exclusion criteria to select a total of 105 primary studies from which data was extracted to answer the three research questions of the study.

The findings of this study reveal that aquaponics predictions (27%) have been underexplored compared to the monitoring or monitoring and controlling aquaponics (73%). IoT technologies have been used to create prototype aquaponic systems and collect data, while machine learning and deep learning algorithms are used for prediction, abnormality detection, and intelligent decision-making. So far, predictive analytics solutions for aquaponics yield prediction, return-on-investment (ROI) estimates, resource optimisation, product marketing, security of aquaponics systems, and sustainability assessment have received very little attention. Also, few studies (37.7%) validated the proposed solutions by assessing the performance or effectiveness of the proposed solution. Expert feedback and usability evaluation, which involved stakeholders and end-users (e.g. farmers and business owners) of aquaponics solutions, have been rarely used to assess smart aquaponics solutions. In addition, existing aquaponics studies have some limitations because they: (i) have a short-term focus since the monitoring and controlling of aquaponics was not undertaken over a long time to assess performance and the sustainability of the proposed solutions; (ii) are conducted mostly in controlled settings which limits applicability to diverse conditions; and (iii) are conducted in specific geographical contexts, which limits their generalizability.

As a contribution, this study offers a new perspective on the applications, technologies, and evaluation methods in smart aquaponics, which could aid future researchers in determining suitable methods to implement in their studies based on the strengths and weaknesses of these technologies and evaluation methods. It also provides recommendations on future research opportunities in smart aquaponics.

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Declarations

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