chemosensors

Review

Recent Advances of Smart Systems and Internet of Things (IoT) for Aquaponics Automation: A Comprehensive Overview

Mohamed Farag Taha [1,2,3], Gamal ElMasry [4], Mostafa Gouda [1,2,5], Lei Zhou [6], Ning Liang [1,2], Alwaseela Abdalla [1,2], David Rousseau [7,8] and Zhengjun Qiu [1,2,*]

1 College of Biosystems Engineering and Food Science, Zhejiang University, Hangzhou 310058, China; 11813051@zju.edu.cn (M.F.T.); mostafa-gouda@zju.edu.cn (M.G.); nliang@zju.edu.cn (N.L.); 11613051@zju.edu.cn (A.A.)
2 Key Laboratory of Spectroscopy Sensing, Ministry of Agriculture and Rural Affairs, Hangzhou 310058, China
3 Department of Soil and Water Sciences, Faculty of Environmental Agricultural Sciences, Arish University, North Sinai 45516, Egypt
4 Agricultural Engineering Department, Faculty of Agriculture, Suez Canal University, Ismailia 41522, Egypt; gamal.masry@irta.cat
5 Department of Nutrition & Food Science, National Research Centre, Dokki, Giza 12622, Egypt
6 College of Mechanical and Electronic Engineering, Nanjing Forestry University, Nanjing 210037, China; leizhou17@163.com
7 Laboratoire Angevin de Recherche en Ingénierie des Systèmes (LARIS), Université d'Angers, 49000 Angers, France; david.rousseau@univ-angers.fr
8 INRAE, UMR1345 Institut de Recherche en Horticulture et Semences, Beaucouzé, 49071 Angers, France
* Correspondence: zjqiu@zju.edu.cn; Tel.: +86-0571-88982728

check for updates

Citation: Taha, M.F.; ElMasry, G.; Gouda, M.; Zhou, L.; Liang, N.; Abdalla, A.; Rousseau, D.; Qiu, Z. Recent Advances of Smart Systems and Internet of Things (IoT) for Aquaponics Automation: A Comprehensive Overview. *Chemosensors* **2022**, *10*, 303. https://doi.org/10.3390/chemosensors10080303

Academic Editor: James Covington

Received: 19 June 2022
Accepted: 29 July 2022
Published: 1 August 2022

Abstract: Aquaponics is an innovative, smart, and sustainable agricultural technology that integrates aquaculture (farming of fish) with hydroponics in growing vegetable crops symbiotically. The correct implementation of aquaponics helps in providing healthy organic foods with low consumption of water and chemical fertilizers. Numerous research attempts have been directed toward real implementations of this technology feasibly and reliably at large commercial scales and adopting it as a new precision technology. For better management of such technology, there is an urgent need to use the Internet of things (IoT) and smart sensing systems for monitoring and controlling all operations involved in the aquaponic systems. Thence, the objective of this article is to comprehensively highlight research endeavors devoted to the utilization of automated, fully operated aquaponic systems, by discussing all related aquaponic parameters aligned with smart automation scenarios and IoT supported by some examples and research results. Furthermore, an attempt to find potential gaps in the literature and future contributions related to automated aquaponics was highlighted. In the scope of the reviewed research works in this article, it is expected that the aquaponics system supported with smart control units will become more profitable, intelligent, accurate, and effective.

Keywords: aquaponics; Internet of Things (IoT); smart systems; water quality; deep learning; convolutional neural network (CNN)

1. Introduction

The significant increase in the global population is accompanied by an increase in the demand for various food products. In the meantime, traditional farming and cultivation methods may not meet such increasing demand creating critical needs for sustainable and innovative agricultural practices. In this trend, aquaponics technology has emerged as a solution for improving agriculture production. Aquaponics is an integrated agri-aquaculture system (IAAS) that combines aquaculture (mostly fish), soil-less culture, and nitrifying bacteria in a symbiotic eco-system. Briefly, fish excrete their waste, which is instantly transformed into nutrients by nitrifying bacteria, and plants absorb such nutrients, as shown in Figure 1. Recently, aquaponics has attracted significant interest from researchers and producers as it has been perceived as highly water-efficient, soil-less, produces two food items simultaneously, does not pollute the environment, limits the use of chemical fertilizers, and eliminates the use of pesticides or antibiotics.

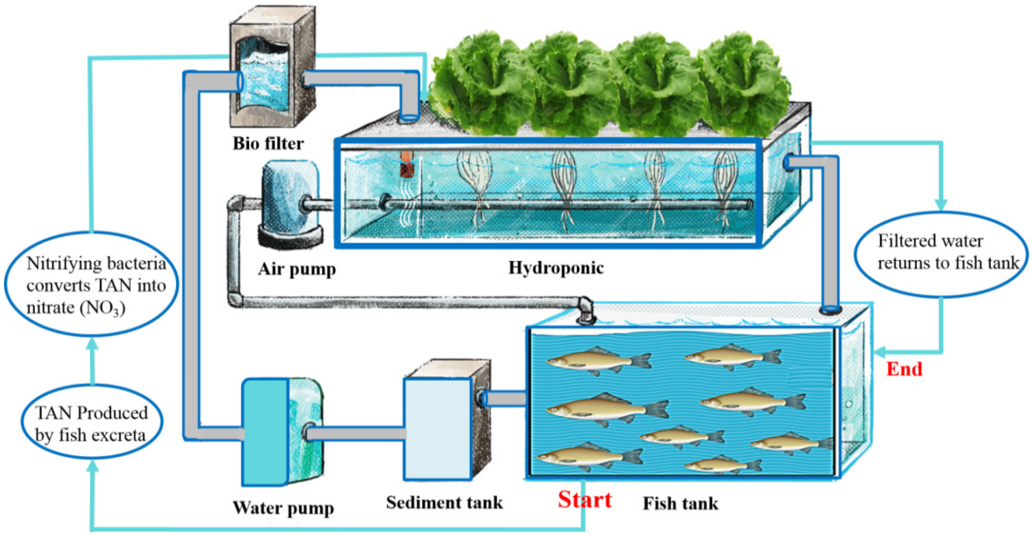

Figure 1. System diagram of aquaponics.

In some regions, such as North Africa and the Middle East zone, agricultural systems consume 90% of the total available freshwater. Recently, global trends have focused on different strategies of sustainable development depending on the circular economy, which is one of the best modes of economic prosperity [1]. In this trend, aquaponics was proposed as a promising and sustainable agricultural concept as it imitates natural systems in terms of reduced environmental impacts and the rationalization of water consumption [2]. It can play a crucial role in the future of socio-economic and environmental sustainability, and also promises to make outstanding contributions to global food and water security. Aquaponics can make significant contributions to increasing food production. The main concern about aquaponics was purifying aquaculture systems from toxic ammonia by using plants as a biofilter.

Currently, aquaponics is practiced in many countries as a hobby [3], and it is now commercially seen as a viable solution to tackle the recent global food crisis. However, only 31% of commercial aquaponics practices are reported to be economically viable and profitable due to lack of experience and poor management. Several literature articles have been written on aquaponics systems for reviewing various important topics such as species of cultured fish, plant species, management practices, new designs, and implementations of this system [4]. However, most of the recent reviews have not focused on research endeavors about automation techniques, communication platforms, or control units inside such systems. Therefore, a need to review such works arose to highlight recent advances in this trend.

The correct design, implementation, and management are the crucial procedures for the success of the aquaponics system and achieving the desired economic feasibility [5]. These tasks are not easy to achieve or optimize, especially when striving for high productivity and quality is required. This is due to its symbiotic nature and the multiplicity of its environmental parameters that must be monitored and controlled. For commercial levels, managing and optimizing such parameters is a big challenge and is difficult to handle manually.

Recently, smart automation and modern communication technologies have been introduced in all aspects of life, including agriculture. This opened new horizons for the development and enhancement of various agricultural systems such as aquaponics. Automation has several benefits including reducing manual work, increasing process control, predictability, and proactive, information-based decision-making [6]. The application of IoT, automation, communication, and sensing technologies in aquaponics systems has been one of the most important and recurrent research interests in the past few years. By analyzing the contributions that were presented, it is noted that there are many differences between the implemented automation systems. These differences reduce the success rate of commercial scales of aquaponic systems.

As a reference for automation experts who contribute to smart aquaponics systems, this article seeks to clarify a number of important concerns. In the scope of this review article, readers can easily determine the most important parameters affecting aquaponics systems, the importance of each parameter separately, the possibility of automatic monitoring, the methods of predicting quality parameters inside aquaponic systems, and the most important strategies of automation, monitoring, communications, and IoT technologies that are used in aquaponics. Therefore, a great number of recent research works about computer-integrated aquaponic systems supported with sensors, smart tools, or IoT capabilities were comprehensively reviewed and discussed in detail in the following sections.

This paper is divided into subsections including the essence of smart systems and the Internet of things (IoT), the parameters of the aquaponics systems, and the sensors used to sense such parameters. Then the smart and IoT systems integrated with aquaponics are listed and reviewed in terms of their practical implementation in aquaponics. The future of aquaponics using the automation pyramid (AP) is also considered and reported in this paper. Finally, the current limitations and main challenges that the automation of aquaponics systems may face are discussed.

2. Smart Systems

Recently, the term "Smartness" or "Smart Systems" appeared in various fields of life. In general, the concept of Smart Systems is to maximize and improve production through the application of Information and Communication Technology (ICT) [7,8], the usage of smart devices [9], and the implementation of artificial intelligence (AI) [10]. In aquaponic systems, the term "Smart Systems" refers to a broad class of miniaturized and intelligent devices to perform many functions such as operation, sensing, monitoring, and control either separately or simultaneously. These devices are usually self-powered and include advanced heterogeneous components and subsystems such as digital processing devices, sensors, actuators, telecommunication devices, multiple energy-storage units, and baseband computing units as shown in Figure 2.

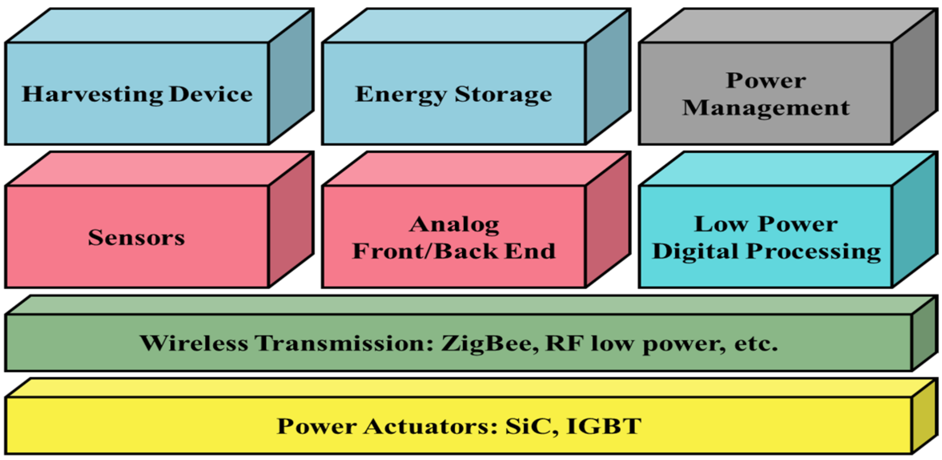

Figure 2. Typical components of smart systems.

3. Internet of Things (IoT)

The term Internet of Things (IoT) refers to executable machine-to-machine (M2M) communication. The most realistic and plausible definition of IoT was given by Smith [11] as "The dynamic global network architecture that includes independent self-configuration capabilities that based on standard communication protocols with interoperability so that physical "things" have virtual attributes, identities and virtual personalities using smart interfaces, and are seamlessly integrated into the information network, often connecting users' data and their environments".

IoT technology aims at the continuity of cyber-physical systems (CPSs) that include multiple intelligence capabilities [12]. Besides, IoT is an architecture related to the design and development of monitoring systems for ecosystems. Therefore, IoT is a powerful tool for granting systems and machines the ability to communicate with each other and make decisions based on data without human intervention. In general, the architecture of IoT is based on three basic layers: The perception layer (sensing), the network layer (data transmission), and the application layer (data storage and manipulation). One of the main features of IoT devices is networking capabilities, as evidenced by the term "Internet". IoT is used for communication between non-human entities, "things", which distinguishes it from the internet used for communications between human users.

As depicted in Figure 3, any IoT system's comprehensive architecture consists of several functional blocks, namely the device, communication, services, management, security, and applications. The importance of these blocks lies in facilitating the system utilities such as identification, monitoring, sensing, communication, actuation, control, and management. The device block performs the sensing, monitoring, control, and actuation functions. The communication block forms the communication protocols to perform the communication between the devices and remote servers. As for the services block, the IoT system provides many services, such as dissemination and data analysis services, device modeling, and control services. The management block provides multiple functions for controlling the IoT system to seek the basic governance of the IoT system. The applications block allows users to visualize and analyze the current state of the system and sometimes predict the future state [13].

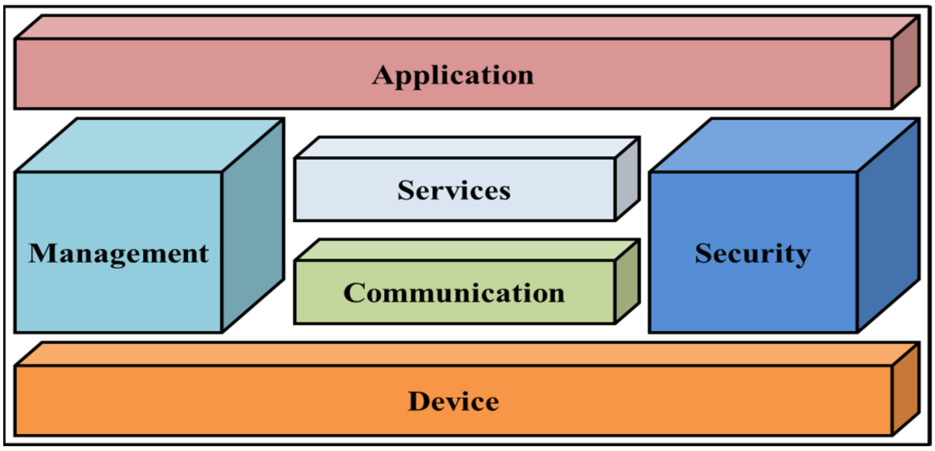

Figure 3. Main functional blocks of IoT.

4. Sensing of Aquaponics Parameters

Monitoring aquaponics parameters is the most important and complex task for better operation and optimizing all steps involved in operating the system to be more sustainable. Recently, after the emergence of microcontrollers and automated sensors, smart technologies can be used to monitor various environmental parameters to achieve sustainable and economically feasible systems by the continuous monitoring and safe and stable operation of aquaponics systems. Table 1 lists all sensed parameters, smart systems, and IoT systems used in the selected aquaponic or hydroponic publications. Figure 4 shows the proposed locations of the sensors in different aquaponics systems.

Table 1. List of sensed parameters, smart systems, and IoT systems in selected aquaponics, hydroponic, or aquaculture publications.

Eco-System	Sensing System		Water									Environment				References
	Smart	IoT	TAN	pH	EC	T	Level	DO	TDS	SL	Flow	T	RH	CO_2	Light	
Water quality	×	✓	×	✓	×	✓	×	×	✓	×	×	×	×	×	×	[14]
Aquaponics	×	✓	×	✓	×	×	×	✓	×	×	×	×	×	×	×	[15]
Aquaponics	×	✓	×	✓	×	×	✓	×	✓	×	×	×	×	×	×	[16]
Hydroponic	×	✓	×	✓	✓	×	✓	×	×	×	✓	×	✓	×	×	[17]
Aquaponics	✓	×	×	✓	×	✓	×	✓	×	×	×	×	×	×	×	[18]
Aquaponics	×	✓	✓	✓	×	✓	✓	×	×	×	×	×	×	×	×	[19]
Aquaculture	×	×	×	✓	×	✓	×	✓	×	✓	×	×	×	×	×	[20]
Water quality	×	×	×	×	×	✓	×	×	×	×	×	×	×	×	×	[21]
Irrigation sys.	×	×	×	×	×	✓	×	×	×	×	✓	×	×	×	×	[22]
Water quality	✓	×	×	×	×	✓	×	×	×	×	×	×	×	×	×	[23]
Aquaponics	✓	✓	✓	✓	✓	✓	✓	×	✓	×	×	✓	✓	✓	✓	[24]
Aquaponics	×	×	×	✓	✓	✓	✓	✓	×	×	×	✓	✓	×	✓	[25]
Aquaponics	✓	✓	×	✓	×	✓	✓	×	×	×	✓	✓	✓	×	✓	[26]
Aquaponics	×	✓	×	×	×	✓	✓	×	×	×	×	✓	✓	×	×	[27]
Water quality	×	✓	×	✓	×	✓	×	✓	×	✓	×	×	×	×	×	[28]
Aquaponics	×	×	×	✓	×	✓	×	✓	×	×	×	×	×	×	×	[29]
Water quality	✓	✓	×	✓	✓	✓	×	×	×	×	×	×	×	×	×	[30]
Aquaponics	×	✓	×	✓	✓	✓	×	✓	✓	✓	×	✓	✓	✓	×	[31]
Greenhouse	×	✓	×	×	×	×	×	×	×	×	×	✓	✓	✓	✓	[32]
Aquaponics	×	×	×	×	×	✓	✓	✓	×	×	×	×	✓	×	✓	[33]
Aquaponics	✓	×	×	×	×	×	✓	×	×	×	×	×	×	×	×	[34]
Aquaponics	✓	×	✓	✓		✓	✓	×	×	×	×	×	×	×	×	[35]
Aquaponics	✓	×	×	×	×	✓	✓	×	×	×	×	×	×	×	×	[36]
Aquaponics	✓	×	×	✓	×	✓	×	×	×	×	×	✓	×	×	✓	[37]
Aquaponics	✓	×	×	×	×	✓	✓	×	×	×	×	×	×	×	×	[38]
Aquaponics	✓	×	×	✓	×	✓	×	×	×	×	✓	×	×	×	✓	[39]

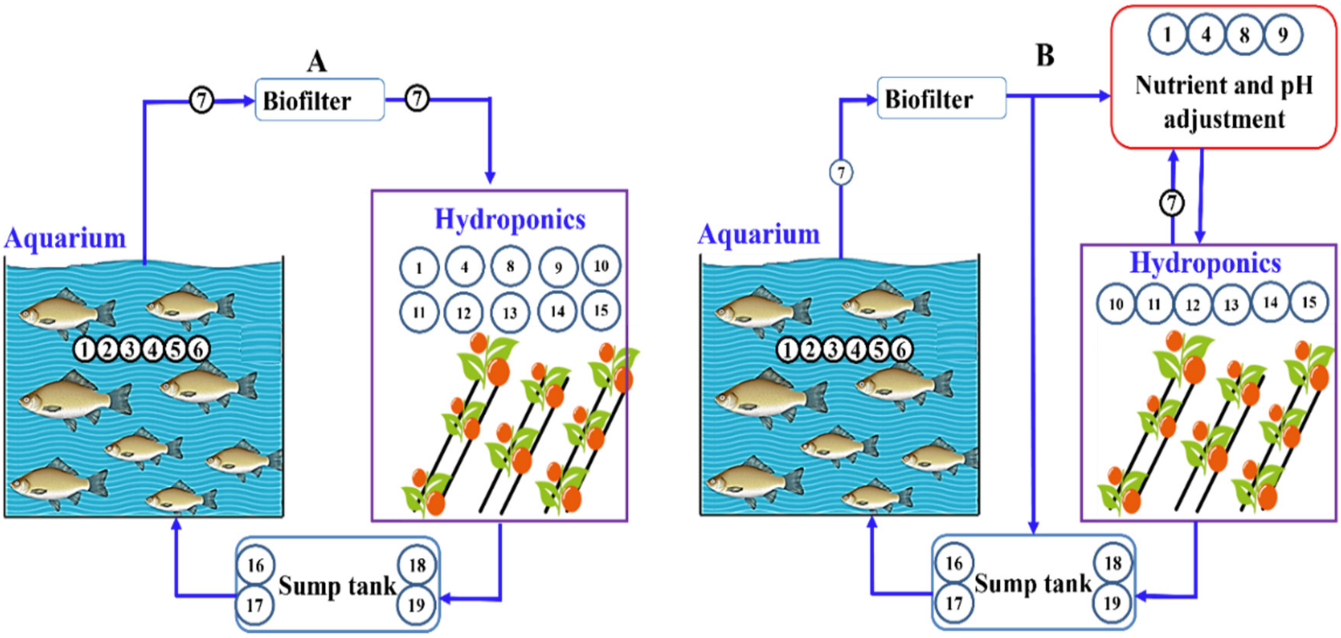

Figure 4. Location of sensors in coupled (**A**) and decoupled (**B**) aquaponics systems: pH 1, Water temperature. 2, Level 3, DO 4, TAN 5, NO_2 6, Flow 7, EC 8, NO_3 9, Air T. 10, RH 11, CO_2 12, Light 13, Moisture 14, Plant Height 15, TDS 16, SL 17, Water hardness 18, and Alkalinity 19.

4.1. Water Quality Parameters

In general, the term water quality refers to the suitability of this water for use, whatever the type of this use for drinking, agriculture, or aquaculture. In aquaponics, the quality of water could be viewed from different angles such as the concentrations of ammonia, nitrite (NO_2), and nitrate (NO_3), pH, temperature, and water level in the tank, dissolved oxygen (DO), electrical conductivity (EC), salinity (SL), water hardness, and water flow rate throughout the aquaponics systems. Table 2 shows the optimal ranges of different aquaponics parameters. In terms of automation, the most important and complex factor, and the priority for constantly monitoring and control in aquaponics, is water quality parameters due to the rapid fluctuations of these parameters within the aquaponics systems. Optimum monitoring and control of water parameters help in providing a healthy symbiotic environment for fish, plants, and bacteria [40,41]. There are many methods to sense or measure these parameters, which will be explained in detail in the following sections.

Table 2. The optimal ranges of different aquaponics parameters.

Parameter	Optimal Range	Reference
pH	6.5–8.0	[4]
Water T	17–34 °C	[42]
Water Level	0.02 kg/L	[41]
Dissolved Oxygen	>4 mg/L	[42]
Electro-Conductivity	30–5000 uS/cm	[43]
Total Dissolved Solids	<1000 mg/L	[41]
Salinity	0–2 ppt $CaCO_3$	[41]
Alkalinity	50–150 mg/L $CaCO_3$	[43]
TAN	<2 mg/L	[44]
Nitrites	0.25–1 mg/L	[4]
Nitrates	50–100 ppm	[45]
Flow	1–2 Liters/min	[41]
Air T	18–30 °C	[41]
Relative Humidity	60–80%	[41]
CO_2	340–1300 ppm	[41]
Light Intensity	600–900 PPFD	[46]

Table 3 lists the sensors used to monitor different water quality parameters found in the literature included in this review. Slight deviations from the minimum and maximum limits of some water quality parameters may lead to disastrous effects for the entire system. For example, fish mortality rates rise immediately if the ammonia level rises above the mentioned limits for a long time. In addition, at low concentrations of nitrite (NO_2), fish health problems begin to arise. Toxic levels of nitrites infect fish with "Brown-Blood Disease", which causes the blood to turn brown. In contrast, nitrates (NO_3) are not toxic to fish even at high levels. Fish may tolerate a nitrate concentration of 400 mg/L [41]. As for the acidity and alkalinity of the water, the pH value has a significant effect on all organisms in the aquaponics system. The rate of fish reproduction may decrease if the water is strongly acidic. Furthermore, a pH of less than 4.5 may affect the roots of plants and the appearance of symptoms of nutrient deficiency [41]. It is noteworthy that temperature (T) has the biggest effect on aquaponics parameters. If the temperature drops below 17 °C, it negatively affects the efficiency of the nitrification process, and bacteria will not be produced to the extent necessary to oxidize ammonia or nitrites. Maintaining the optimum temperature for the type of cultured fish reduces the risk of disease. High temperatures can restrict plant calcium absorption. Concretely, dissolved oxygen (DO) is one of the most important and critical parameters for water quality. During respiration, plants use their leaves and stems to absorb oxygen. The roots also need oxygen, as, without oxygen, fungi grow on the roots, die, and rot. For fish, the DO level in the water must not be less than 4–5 mg/L [47]. At higher densities, air pumps must be used to supply the system with the necessary oxygen. The suggested rate of the air pump is 5–8 L of air per minute per cubic meter of water. In nutrient solutions (e.g., aquaponics solution), the electrical conductivity (EC) measurement in addition to pH measurement is considered an indicator of the nutrient content without differentiating one nutrient from another. Monitoring changes in electrical conductivity may provide insight into the plant's nutrient consumption, helping to ensure nutrient utilization is maximized without over- or under-fertilization. Water hardness (W.H.) is the measure of all the divalent cations, particularly calcium and magnesium. Low concentrations of water hardness only stress the fish, but higher levels increase the pH of the water, which can cause fish death, lower nitrification, and, consequently, a lower plant nutrient uptake rate. There is no doubt that the salinity (SL) of the water causes physical and chemical changes to the water environment, which may lead to morphological changes in the digestive tube and gills, which remain in direct contact with the water [48]. Above all, it is necessary to detect the water flow rate within the system, filters, and the growing zone to maintain a constant water flow rate to avoid stressing the fish, as well as avoiding neglecting the plant nutrition.

Table 3. Sensors used to monitor different water quality parameters.

Parameter	Sensors	Reference
NH_3	WINSEN-MQ-137	[49]
NO_2	Apure-NO2-201 sensor	[50]
NO_3	WINSEN-MQ-137	[49]
pH	DFROBOT-SKU:SEN0169	[15]
	B&C Electronics–SZ 1093 model	[17]
	OMEGA PHE-45P pH sensor	[19]
	Orion 3 Star pH meter	[20]
T	DFROBOT-DS18B20	[24]
Level	Omron K8AK-LS1	[17]
	HC-SR04 ultrasonic sensor	[25]
	BC546 NPN transistor circuit	[51]
DO	DFROBOT-SEN0237	[15]
	Atlas DO probe	[18]
EC	DFROBOT-SKU:DFR0300-H	[31]
TDS	DFROBOT-Analog TDS sensor	[24]
SL	DFROBOT-SKU:DFR0300-H	[50]
W.H	DFROBOT-SKU:DFR0300-H	[50]
Flow	ETC1:YF-S201	[52]

4.2. Aquaponics Environment

Environmental climatic conditions, especially air temperature, relative humidity, carbon dioxide, and light intensity, have significant effects on fish and plant growth in general and on the absorption of plant nutrients specifically [53]. Therefore, these parameters must be monitored and controlled to obtain an ideal balance among these parameters to ensure the optimal stable growth conditions of both fish and plants. As an important parameter in greenhouse cultivation systems, especially in aquaponics, an optimum air temperature of 18–30 °C [41] is usually monitored with specific sensors, including DHT11 and DHT22, which have usually been used to measure air temperature and humidity [24,25]. The optimum RH varies according to the type of plant and the stage of growth. The most common value of RH is between 50 and 80%, depending on the indoor greenhouse temperature. The RH percentage is measured using the DHT11 sensor [24,25].

The importance of CO_2 to plants is that it is a critical reactant for the biochemical processes of plant photosynthesis to generate plant food. The optimum range of the CO_2 concentration for most plants is within 340–1300 ppm [54]. Different sensors, such as the K30 sensor [55] and the MG811 sensor, as well as the infrared gas sensor type (NDIR) [31], have been implemented for measurement of CO_2.

One of the limitations of indoor facilities is the unavailability or limited amount of direct sunlight, which is extremely important for the plant's growth. Therefore, artificial lighting sources are placed in aquaponics systems. For optimal plant growth, 14–18 h of light are recommended for daily needs. Some examples of sensors used for measuring light intensity in aquaponic systems are BH1750FVI (or BH1750) [26,32], the multi-channel digital light sensor based on the SI1145 sensor [24], and the light-dependent resistor (LDR) [27].

5. Smart System-Based Aquaponics

The application of smart systems in agriculture is known as precision agriculture (PA), which aims to gather, process, and analyze temporal, spatial, and plant morphological features and combine them with other available information to support management decisions for optimizing growth inputs and preserving resources in terms of water and nutrients. Aquaponics includes this feature and can be adopted as a precision technology if it is monitored and controlled by modern technologies such as IoT and ICT. Integrating smart technologies into aquaponics systems helps mitigate production times, reduce the need for labor to manage systems, improve product quality, and provide more sustainability. The applications of artificial intelligence to predict various parameters in aquaponics systems are still under intensive investigation by researchers. In general, the main goal is usually to build a smart, self-regulating aquaponic system using a wireless sensor network (WSN). In the smart aquaponics system, real-time monitoring of the essential parameters (e.g., pH, DO, temperature, flow rate, nutritional levels, etc.) is performed, along with building different modeling approaches for predicting other future values of these aquaponics parameters to take smart proactive action [56,57]. Table 4 shows a summary of the different degrees of control over the aquaponics system, showing the development of the aquaponics system from early manual monitoring to the construction of a smart system to employ automatic control.

Table 4. Summary of different control degrees implemented in traditional and modern aquaponic systems.

System Control Degree	Technique or Method	Component	Ways of Data Acquisition	Data Acquisition	Control Unit	Effect	Advantages/Disadvantages	References
Manual control	Manual control	A fish-rearing tank, a solids-removal unit, two hydroponic tanks, and a reservoir	Experience	Sludge, DO, and pH	Vertical-lift pump, drain valve, and add small amounts of base to regulate	Well suited for tropical regions where fresh water is scarce or level farmland is limited.	Low efficiency, inevitable mistakes, and more maintenance costs	[58]
		Fish rearing, Solids removal, and hydroponic components		DO, water T, and pH	Chillers and evaporative cooling towers, pump, and feeders	Meet the need for more food fish and plant crop production in small Caribbean islands.		[59]
Auto-Control	Control by using timers	Fish-holding tank, associated biofilter, and hydroponic growth bed	Meter and sonde probe, multiparameter meter, and various reagents.	Flow	Water pump, airlift, valve in the hydroponic bed drain line, and lighting unit	Managing the flow rate increases both biomass and yield.	Increased efficiency, automation control is realized, and higher management accuracy	[60]
		Recirculating aquaculture system (RAS).	YSI multi-probe meter (model YSI 550A) and pH cyber scan waterproof	DO, water T, and pH	Adjust the gate valves, air stones, and connected to an air blower	Effectively guarantee the flow rate of water, and stable operation of the system is guaranteed		[61]
Smart monitoring and control system	IoT	A fish-rearing tank, biofilter, Hydroponic growth bed	pH, EC, T, Level, Do, Air T, RH, Light sensors	pH, EC, water T, water level, Do, air T, RH, and light	Water heater, air pump, light-emitting diode grow lights, and exhaust fan	Effective and efficient aquaponics system	Efficacy automated aquaponics, minimal costs, and human intervention	[25]
		Microcontroller, sensor, web interface, display, pump, feeder, and emergency source	pH and T sensors	pH and water T	Water pump and fish feeder	The ultrasonic sensor has a 99.94% success rate, pH sensor of 92.35%, and T sensor of 97.91%.	Autonomous monitoring	[62]
		Source node, sink, database server, and visualization in mobile application	Level, T, pH, and TAN sensors	Water level, T, pH, and TAN	Water heater, coolant, fish feeder, and ammonia alarm	The plant growth was improved		[35]
		Fish feeder and water supplier	T, water level, and moisture sensors	T, water level, and moisture content	Water pump, oxygen pump, fish feeder, and LED light	The climate has the least or no interference in the aquaponics, cost-effective, and less water consumption		[63]
	IoT and deep learning	Recirculating aquaculture system, actuators, and sensors	DHT11, BH1750 light, soil moisture, HC-SR04 water level, and pH sensors	Air T, RH, soil moisture, light, water level, and pH	Water pump, and lamps,	Helped enhance the plant and fish growth.		[64]
	Websocket	pH, water temperature monitoring system and controlling system	DS18B20, DFROBOT analog pH, and water level sensors	Water T, water level, pH	Water pump, lights, fan, and lamp	Allows displaying multiple aquaponic parameter in specified delayed time	Automatic early warning	[34]
	Raspberry Pi	Data acquisition, alarm, unit, web application, mobile application, and cloud server	T, pH, flow, light, and plant height sensors	T, pH, flow, light, plant height	Water heater, water pump, LED grow light, and fish feeder	Self-sustainable, cost-effective, and eco-friendly urban farming	Autonomous monitoring	[39]

Table 4. *Cont.*

System Control Degree	Technique or Method	Component	Ways of Data Acquisition	Data Acquisition	Control Unit	Effect	Advantages/Disadvantages	References
	Fuzzy logic	Microcontroller, relay control, and fuzzy interface system	Water T, air T, pH, and luminance sensors	Water/air T, pH, light and intensity	Light, heater, and alarm	Accurate, low cost, and convenient	Continuous autonomous monitoring	[37]
	Open Wrt and WRT node	Data acquisition, mobile transfer, and smart application	Water T, water level, and RH sensors	Water T, light, water level, DO, and RH	Water pump, air pump, feeder, and lamps	Monitoring and controlling smart aquaponics remotely	Store data in cloud and analyzing data using smart technology	[33]
	Arduino microcontroller	controller, actuators, and sensors	Water T, and float sensors	Water T, water level, amount of food	Feeder, pump, and dimmer	Closed loop control system, and plant grow successfully	Continuous autonomous monitoring	[38]
		Hydroponics, aquaculture, and water reservoir	Water level and water T sensors	Water level and water T	DC motor, LED, an alarm	All functionality of the system were working as intended		[65]

5.1. Microcontrollers Used in Smart Aquaponics

A microcontroller is an integrated circuit designed to control a specific operation in an integrated system. It includes a processor, memory, and input and output peripherals on a single board or chip. Such circuits could be circuits embedded in vehicles, robots, industrial machines, medical devices, mobile radio transceivers, vending machines, and household appliances. Most of these devices are rather compact compared to large computers. Microcontrollers, therefore, represent perfect tools for the control of smart aquaponics devices. Different technologies may differ in their computational capabilities, speed, and energy consumption. None of these criteria constitute critical parameters in smart aquaponics since the process of growth is relatively slow. Consequently, low-cost systems have been introduced for possible use in the literature, as shown in Table 3 with Arduino or Raspberry pi devices [38,39,65].

The microcontroller acts as a cornerstone in providing smart services as it enables devices to work together as a single system [66]. The information sensed by the sensors is used as an input to the microcontroller, then the microcontroller generates signals for the actuators and controls the system to reach the target state [67]. So, it is not possible to create a sensor system without using some kind of microcontroller. Many microcontrollers are available on the market, such as Arduino, Raspberry Pi, Atmega 128L, etc. The distribution of research papers based on the types of microcontrollers used is shown in Figure 5. The Arduino Mega microcontroller was used to feed the sensor outputs to the actuators and Raspberry Pi was used as the central control unit for the smart aquaponics system designed by Kyaw and Ng [39]. In the smart aquaponics system, Mahkeswaran and Ng [25] used an Arduino Mega 2560 microcontroller as the central processing unit. Pasha et al. used a Raspberry Pi microcontroller as the gateway to the sensor readings and control of those read by Arduino [34]. All microcontrollers integrated with the aforementioned aquaponics have been verified to be efficient and accurate in receiving signals from sensors and sending commands to actuators.

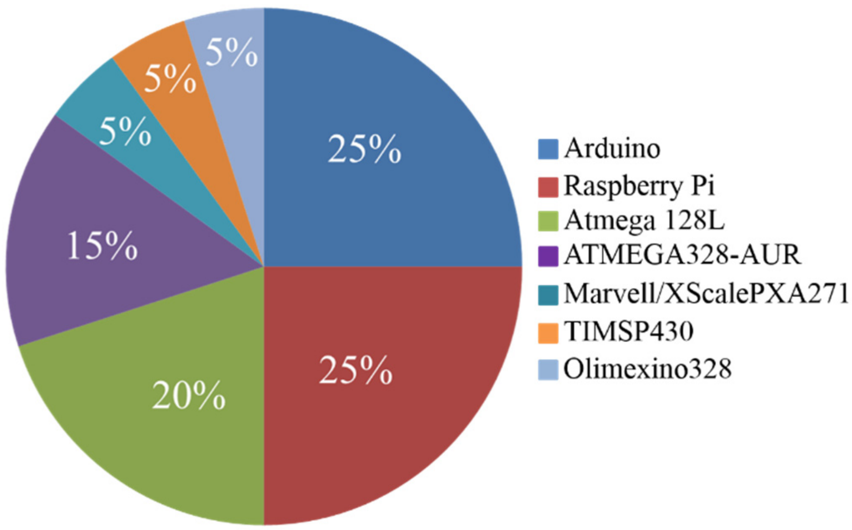

Figure 5. Distribution of research papers based on the types of microcontrollers.

5.2. Neural Networks and Deep Learning Methods for Smart Aquaponics

The development of computational systems, especially Graphical Processing Unit (GPU)-embedded processors, became a necessity in modern computer-integrated artificial intelligence applications. This has led to the emergence of new methodologies and models that now constitute a new category, namely deep learning [68]. Deep learning methods are based on networks of artificial neurons. When optimized, they have been demonstrated to be of high value for various tasks (classification, regression, image segmentation, object detection, etc.) where both feature extraction and decision making are trained end-to-end.

Deep learning models have achieved remarkable success in many agricultural applications such as detecting and diagnosing plant disorders [69], predicting plant water content [70], and identifying plant species [71]. In addition to the contributions of deep learning in the field of aquaculture, such as fish detection and classification [72], estimating the age and size of fish [73], behavior analysis [74], and feeding decisions [75], there are dozens of other potential applications of this approach in smart aquaponics systems. Figure 6 shows deep-learning-enabled advanced applications for smart aquaponics.

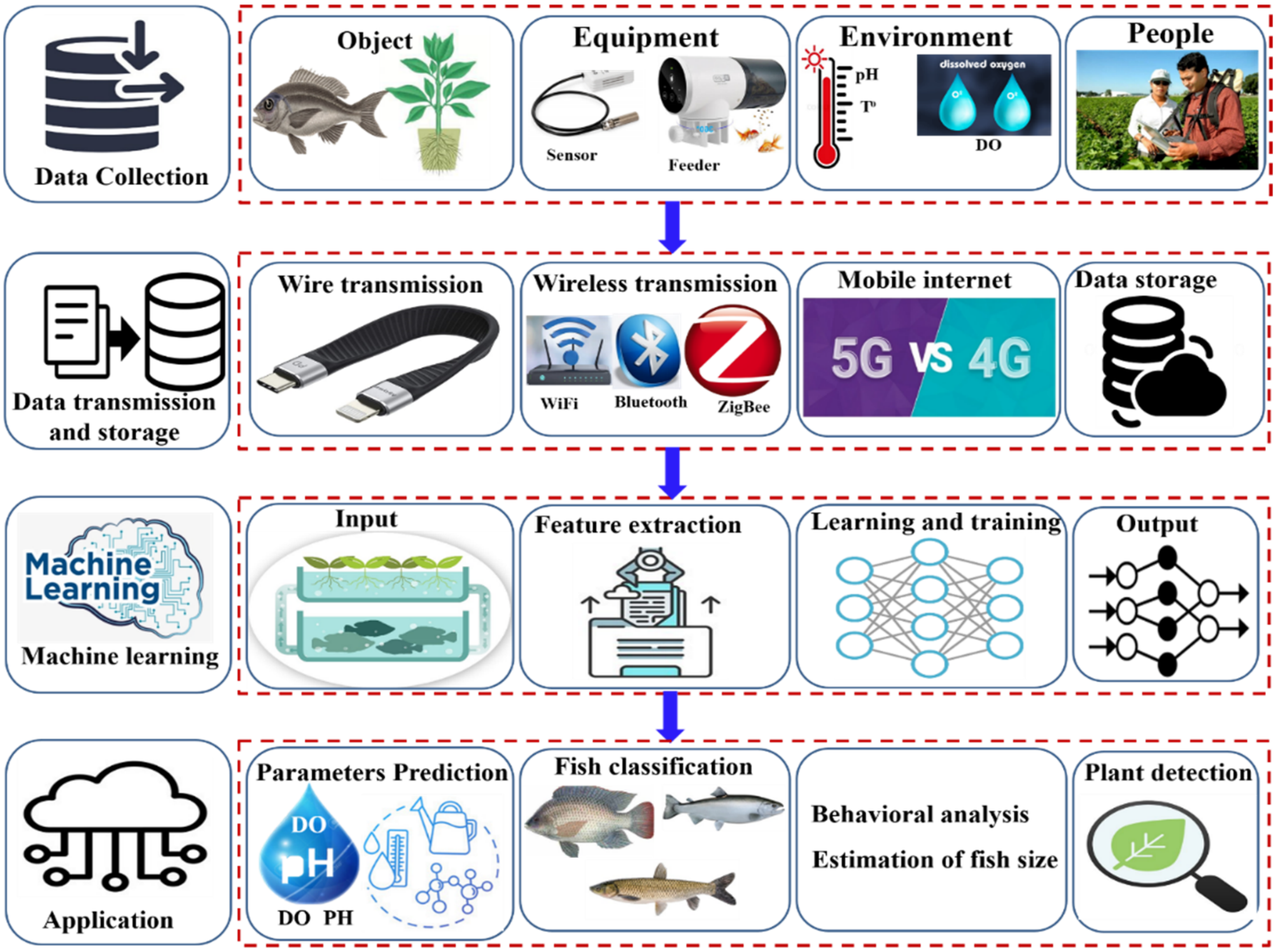

Figure 6. Neural networks and deep-learning-enabled advanced analytics applied for different tasks in smart aquaponics.

Deep neural networks consist of several deep layers (hidden layers), which means there are many layers between the input and output. The huge increase in both dataset size and the huge surge in computing power have led to the emergence of a new class of deep neural networks, Convolutional Neural Networks (CNNs), with huge potential in big data analysis. CNNs are very powerful in object recognition and image classification. CNNs are trained on the images to be analyzed, and during the training process, the network automatically recognizes the high-dimensional features of all the input images. Once the training process is completed, the trained networks are used to identify and classify the different images.

5.2.1. Prediction of Water Quality Parameters

Predicting changes in water quality parameters is critically important for better management of aquaponics systems, in order to take precautionary actions before harm occurs to the fish or the whole system. For instance, the concentration of dissolved oxygen in aquaponics was predicted based on both neural networks and genetic algorithms [76,77]. Furthermore, the water temperature, pH, salinity, water level, relative humidity, and light intensity were modeled by developing a smart IoT-based hydroponic system using deep neural networks and a Long-Short Term Memory (LSTM) algorithm. More importantly, the trained model was installed in a microcontroller (e.g., Raspberry Pi) to control the output and manage the operation of the whole system [78–80]. For the prediction of EC and pH, Pitakphongmetha et al. used an artificial neural network with temperature, light intensity, humidity, plant age, pH, and EC as inputs of the network. Then, the error between the expected values and the sensor output was used to monitor and control the factors [81].

5.2.2. Fish Detection and Species Classification

The availability of an accurate mechanism for automatic fish detection and species classification would support the sustainability of aquaponics systems, especially in large-scale commercial systems. For instance, an efficient framework for the automatic detection of fish in underwater videos was developed with an accuracy of 95.47% using ResNet-50 with the YOLO (You Only Look Once) deep neural network model [82]. Another approach to detecting moving live fish in open aquatic environments was suggested, using an area-based CNN with a detection accuracy of 87.44% [83]. The detection is also extended to include the detection of fish diseases, such as in the work of Hasan et al. who developed a CNN model for the detection of two fish diseases, namely red spot and white spot, with a detection accuracy of 94.44% [84]. A multi-procedure method for classifying tuna fish was also developed by integrating image processing with a network (Mask R-CNN), and then all segmented images were categorized by the ResNet50V2 network. The proposed method achieved a classification accuracy of 70% [72].

5.2.3. Estimation of Fish Size

Fish size estimation is one of the most key variables for both making short-term management decisions and modeling stock trends. In this regard, Region-based Deep Convolutional Neural Network (R-CNN) algorithms were the most widely used algorithms in the literature for the length measurement of fish [73,85,86] as detailed in Table 4. To estimate the length of pond fish, Lu and Ma used a multi-camera CNN, and their results proved that the model had a very good accuracy of 93.93% [87]. Junior et al. compared a set of convolutional neural networks (InceptionV3, Exception, VGG19, VGG16, and ResNet50) for the automatic estimation of the mass of Pintado Real fingerlings. ResNet50 achieved the highest accuracy of 67.08% [88].

5.2.4. Feeding Decisions

Apart from the loss of profits due to overfeeding, food waste accumulating from poor feeding strategies of aquaculture farms can harm the aquaponics environment. The integration of smart systems with the aquarium helps in evaluating the level of fish satiety, controlling the quantity of food, as well as making feeding decisions. Ubina et al. developed a smart system for assessing the feeding intensity of fish in aquaculture using convolutional neural networks, with an accuracy of 95% [75]. Måløy et al. developed a deep video classification model to identify salmon feeding behavior or non-feeding. The proposed Dual-Stream Recurrent Network captures the Spatio-temporal behavior of salmon species with a prediction accuracy of 80% [89]. Adegboye et al. evaluated feeding behavior predicated on Noda and Gleiss's research sample dataset used in prior research. The results revealed that when the Fourier descriptor threshold was 0.5, the accuracy was 100%. Thus, the intelligent feeding of fish could be accurately achieved [90].

5.2.5. Plant Detection

In general, convolutional neural networks are extensively used to assess crop quality. In this vein, Mohanty et al. compared two well-established structures in identifying 26 plant diseases. Their results were very promising, with automatic recognition success rates reaching 99.35% [91]. Recently, convolutional neural networks were also applied to monitor the growth rate of lettuce in hydroponic systems [92]. Furthermore, a novel deep recurrent neural network (RNN) in combination with the long-term memory (LSTM) neuron model was used to predict the tomato yield and stem growth of Ficus Benjamina in a greenhouse. The proposed method performed well [93]. More recently, Taha et al. used a CNN (ResNet18 and Inceptionv3) to diagnose the nutrient deficiencies of lettuce grown in aquaponics. The results demonstrated that the proposed deep model (Inceptionv3) obtained an accuracy of 96.5 % [69]. Table 5 summarizes the results and outcomes obtained from these research endeavors in terms of the prediction of water quality parameters, detection and species classification, estimation of fish size, feeding decisions of fish, and plant detection using deep learning.

Table 5. Prediction of water quality parameters, detection and species classification, estimation of fish size, feeding decisions of fish, and plant detection using deep learning.

Application	Models/Algorithm Technology	Results/Accuracy	Reference
Predicting DO	DCNN and genetic algorithms	—	[76]
Predicting water temperature, pH, salinity, water level, relative humidity, and light intensity	DCNN	—	[78]
Monitoring and predicting temperature, DO, salinity, and pH of water using	DCNN and LSTM algorithm	—	[79]
Predicting dissolved oxygen	DCNN	—	[77]
Prediction of EC and pH	artificial neural network	—	[81]
Predicting the content of both chlorophyll (Chl-a) and DO using CNN-LSTM prediction model	Hybrid CNN–LSTM deep learning model	—	[80]
Detecting fish in underwater videos	ResNet-50 with YOLO (You Only Look Once)	95.47%	[82]
Detecting moving live fish	DCNN	87.44%	[83]
detection of fish disease	DCNN	94.44%	[84]
Classifying tuna fish	R-CNN and ResNet50V2	70%	[72]
Estimating fish length	R-CNN	99%	[73]
Fish length	R-CNN	97.8%	[85]
Estimation of fishs length	Local gradient technique and Mask RCNN	0.89	[86]
Estimation the pond fish length	CNN	93.93%	[87]
Estimation of fingerlings mass	InceptionV3, Exception, VGG19, VGG16, and ResNet50.	67.08%	[88]
Assessing the feeding intensity of fish	Convolutional neural networks,	95%	[75]
Identify salmon feeding behavior or non-feeding	Dual-Stream Recurrent Network	80%	[89]
Prediction feeding behavior	Artificial neural networks	100%.	[90]
Plant disease detection	CNN	99.35%	[91]
Diagnose nutrient deficiencies of lettuce	ResNet18 and Inceptionv3	96.5%	[69]
Monitor the growth rate of lettuce	Mask R-CNN	97.63%	[92]
Prediction tomato yield and stem growth	RNN with LSTM	Performed well	[93]

5.3. Aquaponics and Industry 4.0

Industry 4.0 is an initiative that integrates many emerging technologies such as artificial intelligence (AI), the Internet of Things (IoT), big data and analytics (BDA), cyber-physical systems (CPS), wireless sensor networks (WSN), autonomous robot systems (ARS), interconnectivity, automation, machine learning, real-time data acquisition, and cloud computing [94,95]. Accordingly, the concept of a smart system is closely related to Industry 4.0 itself, involving algorithms and complex logical processes [50]. To implement the commercial aquaponics systems, enhance its capabilities, and increase its production efficiency, there is an urgent need to integrate Industry 4.0 technologies in such systems [96]. Hence, the term Aquaponics 4.0 emerged as a counterpart of Industry 4.0 as it is a digital agricultural ecosystem based on the use of the aforementioned technologies for operation, monitoring, autonomous control, and intelligent decision making in all aquaponics operations [96]. At the industry level, the realization of aquaponics 4.0 makes the aquaponics system more flexible and adaptable to ecosystems. The realization of aquaponics 4.0 requires the effective integration of data from different sources or from a whole web different sensing devices. These data are stored, classified, extracted, and processed to extract useful knowledge to solve real-world problems in real-time, not only to improve the system efficiency but also to revolutionize the way in which the system is operated and managed [96].

6. IoT-Based Aquaponics

As shown in Figure 7, the structure of the IoT applied in aquaponics systems and protected agriculture scenarios consists of five layers [97]:

1. Perception Layer: This layer consists of various sensors for acquiring aquaponics parameters (such as DO, T, pH, and EC), various actuators and microcontrollers, a wireless sensor network (WSN), Radio-frequency identification (RFID) tags, readers, and so on.
2. Network layer: This is the infrastructure of an IoT system, which includes a group of different wired (CAN bus and RS485 bus) and wireless (Zigbee, Bluetooth, and LoRa) communication networks. This network transmits the information collected by the perception layer to the upper layer and sends control commands from the application layer to the perception layer to take appropriate action in devices related to the sensing layer.
3. Middleware Layer: This layer collects data and procedures received from IoT devices to provide developers with a more versatile tool for building their applications. There are different types of middleware such as HYDRA, UBIWARE, UBIROAD, SMEPP, SOCRADES, GSN, and SIRENA.
4. Common platform layer: This layer consists of common processing technologies such as fog computing, cloud computing, machine, and deep learning algorithms, as well as their establishment models. This layer is responsible for storing, making decisions, statistics, and creating intelligence algorithms such as control, decision making, forecasting, and early warning.
5. Application layer: This is the highest level of the IoT structure and the position in which the importance and value of IoT is more clearly visible to the final users. This layer includes many smart platforms and systems for monitoring, real-time environmental control, and early warning of various diseases and disorders. All of these measures can contribute to improving the final product and saving effort, time, and costs.

In brief, if IoT in agriculture was applied correctly, it can bring a new green revolution. The capacity of networks can be enhanced by using 4G and 5G technologies, which makes the use of IoT technologies more feasible, in addition to creating new communication technologies. In the modern era of artificial intelligence of things (AIoT) and 5G, early warning and remote monitoring based on an autonomous wireless sensing system are critical. In this paper, most of the publications used IoT in their proposed systems. IoT has been used in three axes: Monitoring interfaces, remote applications, and Wireless Sensor Networks (WSN).

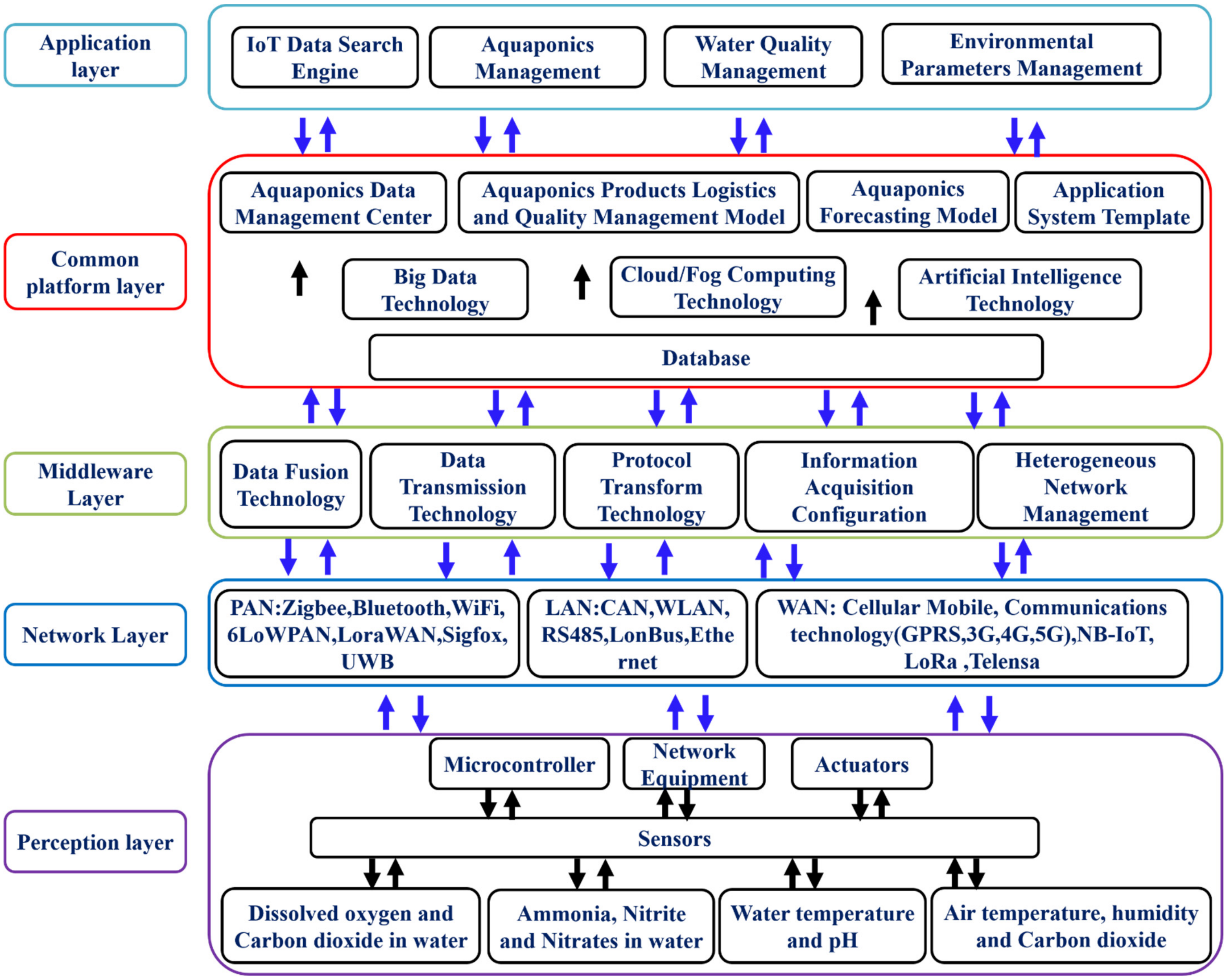

Figure 7. Structure of IoT in aquaponics.

6.1. Remote Monitoring Interfaces

Remote monitoring interfaces are often the medium that humans use to interact with computers or machines. Currently, IoT is applied in many monitoring activities for agricultural environments such as hydroponics and aquaponics. IoT technologies allow us to improve the quality of aquaponics products (plants and fish), increase their sustainability, and support the decision-making of aquaponic systems managers. Recently, the wireless monitoring system that integrates monitoring interfaces, wireless networks, multiple types of electronic devices, and sensors with connectivity capability is widely distributed in multiple scenarios such as smart farming, smart city, and environmental detection. IoT technology enables monitoring interfaces to display values sensed by wireless networks in real-time. In this context, aquaponics parameter-monitoring systems were designed using IoT in combination with microcontrollers. The sensed parameter data are sent to a web-based platform to be stored and displayed on a graphical user interface (GUI) in real-time [19,98–100]. Recently, Elsokah and Sakah developed an iOS app that allows for real-time and continuous monitoring of an aquaponics ecosystem through data obtained directly from sensors and microcontrollers [101]. These collaborations are heading towards information reliability and real-time mobility (through mobile applications, not only on the web). More recently, a remote monitoring system was designed using IoT combined with Convolutional Neural Networks (CNN) to monitor the greenhouse environment using an

A6 GSM module to develop an android mobile application for notifying operators of any changes that occurred in the system by sending an alert in case of an anomaly [32]. Continuous monitoring of these parameters will provide a healthy environment for fish and plants while saving approximately 90% of the water used in traditional farming systems [98].

6.2. Remote Control Applications and Strategies

Remote control refers to the ability to send certain signals to system operators to interact or change the state of a certain environmental parameter. The potential of these applications does not stop at mere monitoring, but also extends to control systems and actuators. Using remote control applications, operators can control pumps, artificial lights, fans, ventilation pumps, and other different actuators.

Wang et al. developed an Intelligent Voice Control System (IVCS) combined with IoT to monitor and control aquaponic parameters [102].

Many applications of remote control were found in the reviewed literature using various communication technologies and microcontrollers. To design an IoT-based monitoring and control system for aquaponics environmental parameters, a NodeMCU microcontroller with a Wi-Fi module was used to connect to the Internet. The data are sent to the Blynk–IoT (a multi-language platform that enables remote control of different microcontrollers), and finally, the local server receives the measurements and sends them to the mobile phone. In these systems, the operators control the different actuators in real-time by sending a message to the receptor [24,25,81]. A simple GSM Arduino-based monitoring and control system was developed to notify farmers when aquaponics parameter measurements are outside the specified ranges where the measurements were displayed on a GUI. This system enables operators to control various parameters in real-time [31,63]. An IoT-based monitored and controlled aquaponics system using a microcontroller (Raspberry Pi and Arduino) was also applied to monitor water quality parameters in aquaponics systems. System information was displayed to enable operators to control different actuators [18,103]. Using the Modbus TCP protocol, another IoT-based remote monitoring and control system for aquaponics was created to extract data from sensing nodes [104]. Lastly, an IoT system was utilized to monitor and control the parameters of the aquaponics system using a microcontroller connected to the web via Ubuntu IoT Cloud [62].

The monitoring and control framework of the aquaponics system consists of three basic stages, as shown in Figure 8. The first stage is data acquisition using various sensing devices. In aquaponics, there are two main components from which data are sensed: Water and the environment. There are many methods of sensing water, from the traditional methods (e.g., the floating method, the volumetric method) to modern methods using different sensors [105]. Then the data are stored and processed using different algorithms and processing tools [106]. At the end, the processing commands are sent to different actuators, and the operation and control are then performed automatically.

Generally, three different types/levels of monitoring and control strategies were observed. The main control strategies are to monitor the various quality and operation parameters using various sensors and control them using microcontrollers, such as the contribution of Murad et al., who used sensors controlled by an Arduino microcontroller and connected to the GSM interface to send alarms/notifications to the operator as a proactive action based on the defined levels of the sensors [107]. The next level involves wireless data collection and analysis using a cloud server. In the contribution of Wang et al., Arduino, OpenWrt, and WRTnode were used to connect field monitoring and remote monitoring centers for collecting information and managing the aquaponics system. The information was collected and sent wirelessly to the management and control center for storage, processing, and transmission to a remote server. The data stored in the server are analyzed and decisions are made regarding the different actuators, such as artificial lights, water, and air pumps [33]. Finally, the control systems found in the contributions listed in this paper aim to implement autonomous systems by using a variety of techniques that shift from traditional linear regression to complex prediction approaches such as convolutional neural networks (CNN). In Kumar et al.'s system, WSN (6LoWPAN PROTOCOL) was included to monitor and control the nitrate level, pH, and temperature [56]. Their network conceived a 10 m communications range and a transfer rate of 250 kbit/s. Moreover, in this system, the IBM Mote Runner (run-time platform) is used as a sensor network. In addition, to collect and store information from the set of sensors, a cloud data storage system was used. Then the time-series values of different variables were predicted with the help of a trend analysis. To predict the levels of pH and nitrates, linear regression was implemented to create an automated aquaponics system concerning these two parameters.

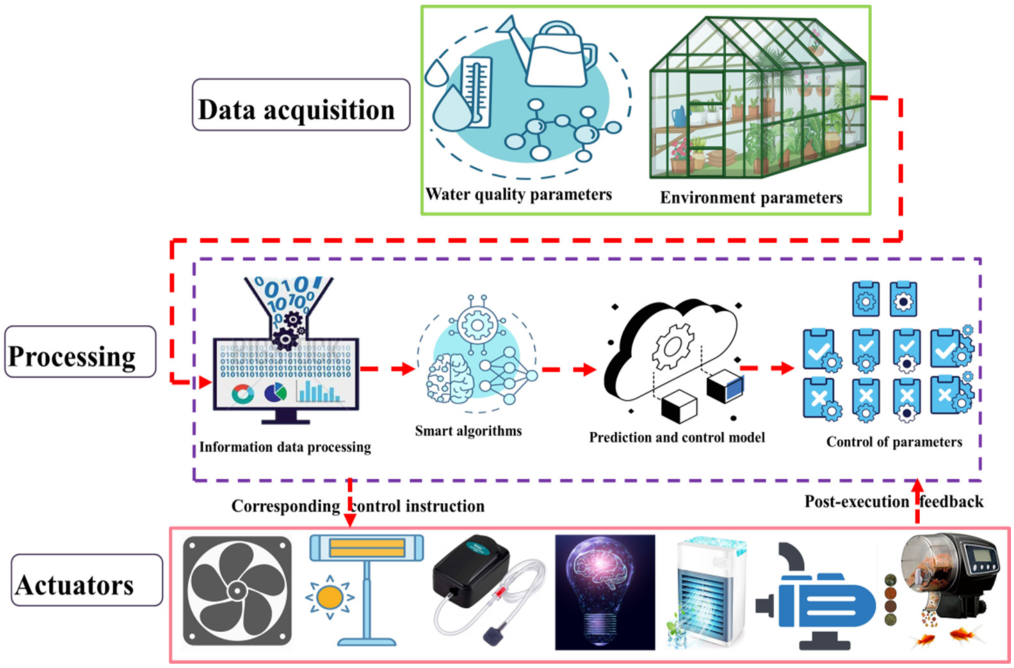

Figure 8. Schematic diagram of detection and control system for aquaponics system.

6.3. Wireless Sensor Network (WSN)

WSN consists of a group of smart devices used to collect application-oriented data requirements called "nodes", as shown in Figure 9. Sensing, communication, and computation using software and algorithms are the main functions of sensor networks. There are two types of nodes based on the function the node performs. The nodes that collect basic information from the field are called the source node and they also act as routing nodes due to the multiplicity of routing hops. Meanwhile, the node that collects information from the source nodes is called the sink node or the gate node. Applications of wireless technologies are often not presented alone and are mostly associated with remote monitoring or control interfaces. However, contributions focused on the application of wireless networking techniques to develop connectivity in aquaponics were found. Wang et al. designed a smart system to monitor and control aquaponics using wireless sensor network (WSN) technologies and an Arduino microcontroller with a Wi-Fi module. The data are stored on the WRT nodes and then transmitted via Wi-Fi to the OpenWrt server [33]. Kumar et al. Used the 6LOWPAN protocol and WSN to design a monitored and controlled aquaponics system [56]. To monitor the temperature and pH of the water in the aquaponics system, GSM technology was used to send an alert message to the operator if the values were outside the specified range [107]. To collect and store data from the aquaponics system, Mamatha and Namratha used the ThingSpeak data logging platform [108]. Sreelekshmi and Madhusoodanan monitored aquaponics using the ThingSpeak IoT platform combined with an Arduino Uno microcontroller and a transceiver (ESP8266-01 Wi-Fi) [27]. To design an IoT-monitored and -controlled aquaponics system, Jacob used a Raspberry Pi microcontroller equipped with a Wi-Fi module. Cloud-based platforms integrating an IoT dashboard and Freeboard were used to collect, store, and control target parameters [51]. The application of wireless technologies for transmitting data and integrating them with sensors is a promising field in the development and improvement of monitoring and control techniques. Table 6 lists current wireless communication technologies.

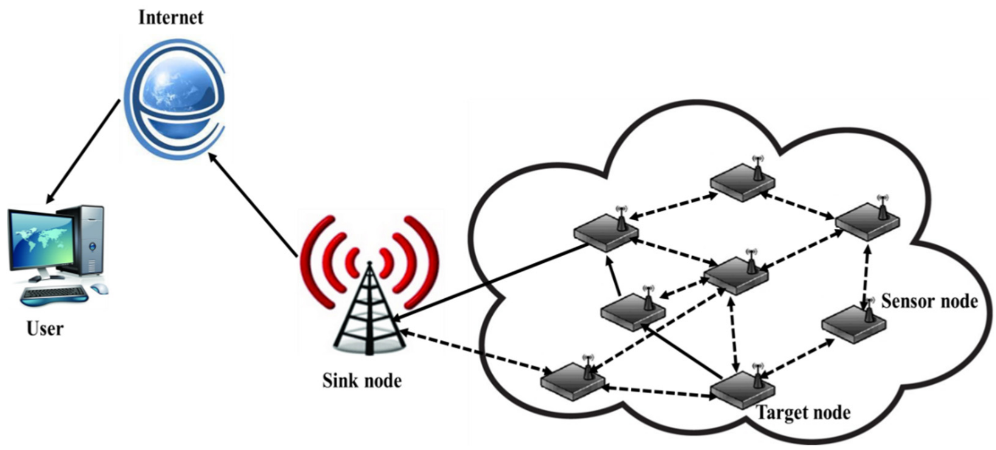

Figure 9. Wireless Sensor Network (WSN).

Table 6. Wireless communication technologies.

Parameters	Standard	Frequency Band	Data Rate	Transmission Range	Consumption	Cost
WiFi	IEEE 802.11a/c/b/d/g/n	5–60 GHz	1 Mb/s–7 Gb/s	20–100 m	High	High
ZigBee	IEEE 802.15.4	2.4 GHz	20–250 kb/s	10–20 m	Low	Low
LoRa	LoRaWAN R1.0	868/900 MHz	0.3–50 kb/s	<30 Km	Very low	High
RFID	ISO 18000-6C	860–960 MHz	40 to 160 kb/s	1–5 m	Low	Low
Mobile communication	2G-GSM, CDMA 3G-UMTS, CDMA2000, 4G-LTE, GPRS	865 MHz, 2.4 GHz	2G: 50–100 kb/s 3G: 200 kb/s 4G: 0.1–1 Gb/s	Entire Celluar Area	Low	Low
Bluetooth	IEEE 802.15.1	24 GHz	1–24 Mb/s	8–10 m	Very low	Low

7. Future of Smart Aquaponics

Modern aquaponics systems could be more effective and successful provided that intensive monitoring, control, and management are practiced in all steps of the system. Consequently, the Automation Pyramid (AP), with its layers of Supervisory Control and Data Acquisition (SCADA), Enterprise Resource Planning (ERP), and Manufacturing Execution System (MES), integrated with IoT technologies, is applied for process control, which makes aquaponics operations more efficient and sustainable.

Generally, systems such as aquaponics are managed using an automation pyramid (AP) as shown in Figure 10. The automation pyramid consists of five layers divided into two different sections: The first section represents the production process with its various equipment (actuators, sensors, Programmable Logic Controls (PLCs), etc.), and the enterprise resource planning systems for business management (i.e., the Supervisory Control and Data Acquisition (SCADA) network, Manufacturing Execution System (MES), and Enterprise Resources Planning (ERP)) build the top-level.

Supervisory Control and Data Acquisition (SCADA) is a tool that helps supervisors make decisions about the stages of the production process, but it does not help in making important decisions as it does not provide an overview of the production system [109]. SCADA can be enhanced with IoT technologies by providing real-time information in addition to analyzing the historical information available for the production process, and accordingly, SCADA can help in predictive analytics and making important decisions.

For more prosperity, processes and information within the enterprise must be linked in an innovative, intelligent way [110]. Enterprise Resource Planning (ERP) represents one of the most important connectivity tools within enterprises as it is a back office for all information and also provides a comprehensive and updated (real-time) view of all major activities within the organization. In short, cloud-based IoT provides ERP with real-time agility, flexibility, and predictability [111]. Many of the simple routine activities and operations that take place in many aquaponics systems, such as reading manual sensors, can be automated.

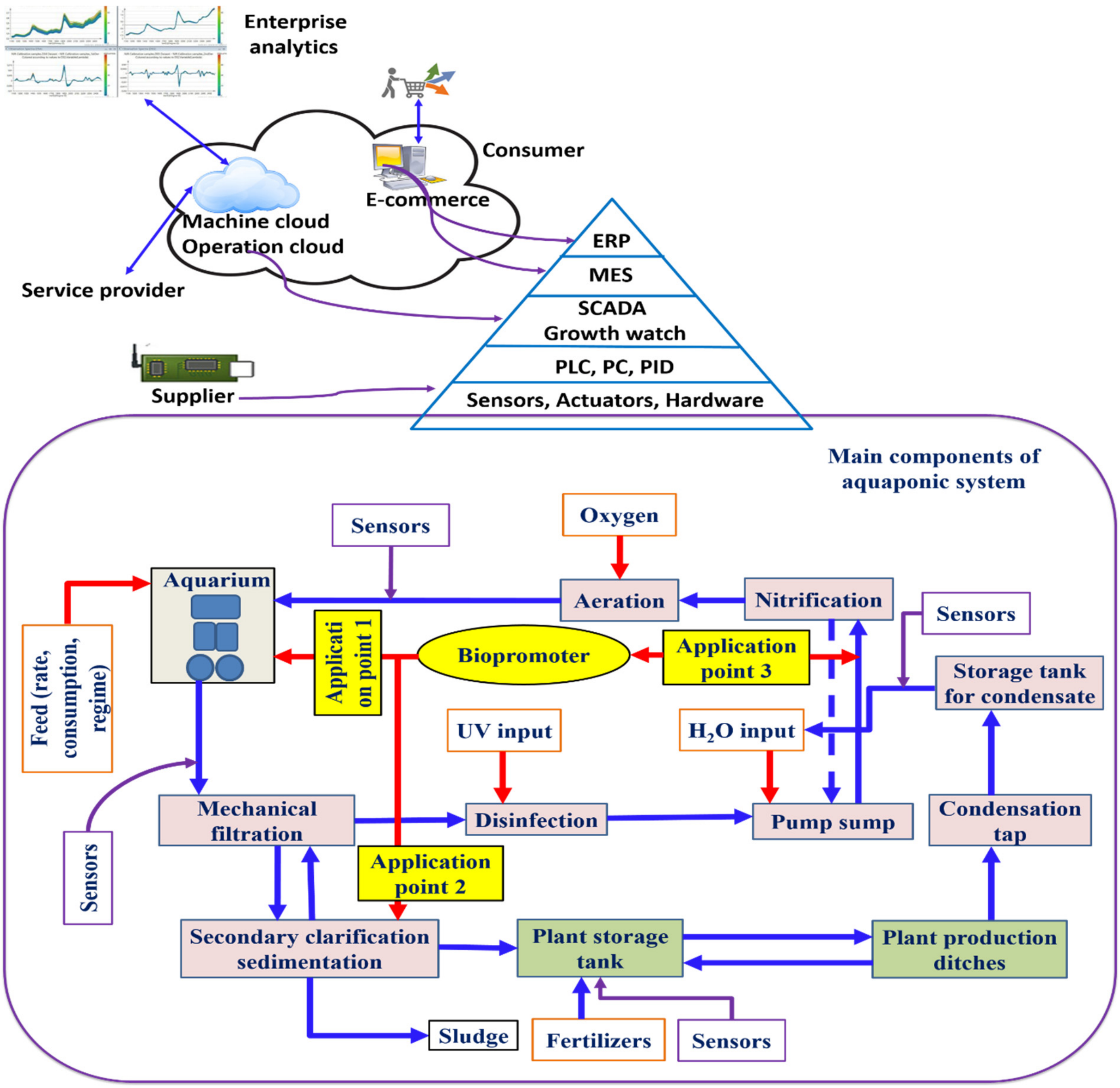

Figure 10. The future for aquaponics process automation systems with IoT.

MES provides an overview of the aquaponics environment, as well as the activities practiced that contribute to the decision-making of managers, and it provides an effective foundation for the application of IoT. MES stands out because it employs smart equipment to gather, process, and transfer information to various controllers. MES can become more flexible and can be easily designed to suit the different requirements of enterprises by enhancing them with the IoT in addition to what the IoT draws from the huge amount of ecosystem data. The real-time data collection and processing that IoT provides enhances MES and makes it very easy for aquaponics operators to measure the efficiency and productivity of different systems [111].

The application of SCADA, ERP, and MES and its enhancement with IoT in aquaponics systems enable operators to implement applications based on predictive analytics that provides new insights for all levels of decision-making, as well as the ability to communicate and work with different types of modern media devices such as mobile phones. In summary, IoT systems can produce unprecedented improvements in many areas of the aquaponics system, especially if they are enhanced with MES, ERP, and SCADA to leverage their true potential and benefits.

8. Current Limitations in Aquaponics

Some limitations were detected in the reviewed literature, as there are important parameters that were neglected by academic contributors. Therefore, further research is needed to provide operators and practitioners with a comprehensive view of the impact of different parameters of aquaponics systems, in addition to making an effort to proactively work on important criteria while improving previous contributions.

The aim of applying IoT technologies to monitor and control aquaponics systems is to achieve precision farming and the feasibility of these systems. When moving to larger scales, such as the commercial and industrial levels, the reliance on modern equipment and technologies increases, and this becomes imperative. Upgrading to more powerful and intensive monitoring and control methods such as powerful sensors, the application of pyramid automation with its different layers (SCADA, ERP, and MES), as well as the use of PLC, is essential for the automation of commercial aquaponics systems.

Currently, off-the-shelf monitoring software and devices are available that are capable of extracting information on ecosystem parameters in real-time, such as pH, temperature, relative humidity, and salinity, which are, nowadays, used to improve crop yield and quality in greenhouses. However, the failure of these devices is that they are inefficient in dealing with closed circular food systems such as aquaponics, where it is necessary to monitor and control external variables and devices to push aquaponics towards smart applications. Besides, some of these systems are not suitable for combination with microcontrollers.

It is crucial to design aquaponics monitoring and control systems with a high degree of adaptability. It is frequently challenging to forecast and might not be understood due to the high interaction and intricacy between several parameters (such as how water temperature changes affect DO and pH). Therefore, the control system must be flexible enough to allow the monitoring and control of a diverse set of actuators and sensors in aquaponics components (aquaculture and hydroponics).

The introduction of industrial control systems such as SCADA, ERP, and MES, as well as PLCs, along with wireless and IoT technologies can significantly influence decision-making and the development of the aquaponics industry. PLC systems are highly flexible when dealing with various combinations of actuators (pumps, fans, ventilation equipment, etc.), sensors, and other devices used in the aquaponics industry.

While machine-learning-based algorithms are already largely widespread in real-time information processing, they have certain limitations in the way they operate. Indeed, most of the approaches are trained in a supervised way based on data at rest. This means that the model should have seen representative data of all growth stages accessible in the aquaponic system. More active approaches would enable us to face the development of the grown organisms more dynamically. This includes the possible use of reinforcement learning, active learning, and edge computing to embed the retraining of the algorithm on the microcontrollers.

9. Conclusions

Recently, the contributions of the academic community in the fields of hydroponics and aquaculture have been increasing, which has attracted the attention of practitioners. Given the importance of aquaponics and its positioning as a sustainable and promising industrial food system, in this paper, we have presented a systematic analysis to explore the recent global status and trends of these systems. Emphasis was placed on sensor parameters, wireless network technologies, IoT technologies, and smart technologies. In this work, by studying the field as a whole, the decision-making processes related to the setup of sensors in aquaponics are simplified, and the recent trends in intelligent automated aquaponics are clearly shown. The intended purpose of this paper is to create a bridge between electrical and biological engineering to contribute to the development of aquaponics. This work helps aquaponics operators and experts to learn about automation technologies, smart systems, and IoT technologies, as well as introducing automation experts to the vital processes in aquaponics systems. The created bridge will lead to greater sustainability of these systems in addition to accelerating contributions in this field and enabling the economic feasibility of commercial solutions.

Author Contributions: Conceptualization, M.F.T. and G.E.; investigation, M.G., L.Z., A.A. and N.L.; writing—original draft preparation, M.F.T.; writing—review and editing, M.F.T., G.E., M.G., D.R. and Z.Q.; visualization, A.A., L.Z., N.L. and D.R.; supervision, Z.Q.; funding acquisition, Z.Q. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the key projects of international scientific and technological innovation cooperation among governments under the national key R&D plan (2019YFE0103800) and the Zhejiang province key research and development program (2021C02023).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: Authors would like to appreciate the support from the Distinguished Scientist Fellowship Program (DSFP) of King Saud University.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

IoT: Internet of Things; CPSs: Cyber-physical systems; DO: Dissolved oxygen; TAN: Total ammonia nitrogeyn; ICT: Information and Communication Technology; EC: Electrical conductivity; RH: Relative humidity; TDS: Total dissolved solids; SL: Salinity; PA: Precision Agriculture; WSN: Wireless Sensor Network; CNN: Convolutional neural network; BDA: Big data and analytics; ARS: autonomous robot systems; LSTM: Long-short term memory; YOLO: You Only Look Once; R-CNN: Region-based deep convolutional neural networks; AIoT: Artificial intelligence of things; IVCS: Intelligent Voice Control System; GSM: Global System for Mobile; GUI: Graphical user interface; AP: Automation Pyramid; SCADA: Supervisory Control and Data Acquisition; ERP: Enterprise Resource Planning; MES: Manufacturing Execution System; PLCs: Programmable Logic Controls.

References

1. Wei, Y.; Li, W.; An, D.; Li, D.; Jiao, Y.; Wei, Q. Equipment and intelligent control system in aquaponics: A review. *IEEE Access* **2019**, *7*, 169306–169326. [CrossRef]
2. Blidariu, F.; Grozea, A. Increasing the economical efficiency and sustainability of indoor fish farming by means of aquaponics-review. *Anim. Sci. Biotechnol.* **2011**, *44*, 1–8.
3. Love, D.C.; Fry, J.P.; Genello, L.; Hill, E.S.; Frederick, J.A.; Li, X.; Semmens, K. An international survey of aquaponics practitioners. *PLoS ONE* **2014**, *9*, 102662. [CrossRef] [PubMed]
4. Yep, B.; Zheng, Y. Aquaponic trends and challenges—A review. *J. Clean. Prod.* **2019**, *228*, 1586–1599. [CrossRef]
5. Tyson, R.V.; Treadwell, D.D.; Simonne, E. Opportunities and challenges to sustainability in aquaponic systems. *HortTechnology* **2011**, *21*, 6–13. [CrossRef]
6. Martinez, P.; Ahmad, R.; Al-Hussein, M. A vision-based system for pre-inspection of steel frame manufacturing. *Autom. Constr.* **2019**, *97*, 151–163. [CrossRef]
7. Blau, B.; Kramer, J.; Conte, T. Service value networks. In Proceedings of the 2009 IEEE Conference on Commerce and Enterprise Computing, Vienna, Austria, 20–23 July 2009.
8. Li, Q.; Tang, Q.; Chan, I.; Wei, H.; Pu, Y.; Jiang, H.; Li, J.; Zhou, J. Smart manufacturing standardization: Architectures, reference models and standards framework. *Comput. Ind.* **2018**, *101*, 91–106. [CrossRef]
9. El Hendy, M.; Miniaoui, S.; Fakhry, H. Towards strategic information & communication technology (ICT) framework for smart cities decision-makers. In Proceedings of the 2nd Asia-Pacific World Congress on Computer Science and Engineering (APWC on CSE), Nadi, Fiji, 2–4 December 2015.
10. Wolter, D.; Kirsch, A. Smart environments: What is it and why should we care? *KI-Künstliche Intell.* **2017**, *31*, 231–237. [CrossRef]

11. Smith, I.G. *The Internet of Things 2012 New Horizons*; CASAGRAS2: Halifax, UK, 2012.
12. Ighalo, J.O.; Adeniyi, A.G.; Marques, G. Internet of things for water quality monitoring and assessment: A comprehensive review. *Artif. Intell. Sustain. Dev. Theory Pract. Future Appl.* **2021**, *912*, 245–259.
13. Ali, O.; Ishak, M.K.; Bhatti, M.K.L.; Khan, I.; Kim, K. A Comprehensive Review of Internet of Things: Technology Stack, Middlewares, and Fog/Edge Computing Interface. *Sensors* **2022**, *22*, 995. [CrossRef]
14. Hong, W.J.; Shamsuddin, N.; Abas, E.; Apong, R.A.; Masri, Z.; Suhaimi, H.; Gödeke, S.H.; Noh, M.N. Water Quality Monitoring with Arduino Based Sensors. *Environments* **2021**, *8*, 6. [CrossRef]
15. Lee, C.; Wang, Y. Development of a cloud-based IoT monitoring system for Fish metabolism and activity in aquaponics. *Aquac. Eng.* **2020**, *90*, 102067. [CrossRef]
16. Rozie, F.; Syarif, I.; Al Rasyid, M.U.H. Design and Implementation of Intelligent Aquaponics Monitoring System based on IoT. In Proceedings of the International Electronics Symposium (IES), Surabaya, Indonesia, 29–30 September 2020.
17. Zamora- Izquierdo, M.A.; Santa, J.; Martínez, J.A.; Martínez, V.; Skarmeta, A.F. Smart farming IoT platform based on edge and cloud computing. *Biosyst. Eng.* **2019**, *177*, 4–17. [CrossRef]
18. Mandap, J.P.; Sze, D.; Reyes, G.N.; Dumlao, S.M.; Reyes, R.; Chung, W.Y.D. Aquaponics ph level, temperature, and dissolved oxygen monitoring and control system using raspberry pi as network backbone. In Proceedings of the TENCON IEEE Region 10 Conference, Jeju, Korea, 28–31 October 2018.
19. Manju, M.; Karthik, V.; Hariharan, S.; Sreekar, B. Real time monitoring of the environmental parameters of an aquaponic system based on Internet of Things. In Proceedings of the International Conference on Science Technology Engineering & Management (ICONSTEM), Chennai, India, 23–24 March 2017.
20. Kuhn, D.D.; Drahos, D.D.; Marsh, L.; Flick, G., Jr. Evaluation of nitrifying bacteria product to improve nitrification efficacy in recirculating aquaculture systems. *Aquac. Eng.* **2010**, *43*, 78–82. [CrossRef]
21. Tang, Z.; Wu, W.; Gao, J. A wireless passive SAW delay line temperature and pressure sensor for monitoring water distribution system. In Proceedings of the IEEE SENSORS, New Delhi, India, 28–31 October 2018.
22. Singh, P.; Saikia, S. Arduino-based smart irrigation using water flow sensor, soil moisture sensor, temperature sensor and ESP8266 WiFi module. In Proceedings of the IEEE Region 10 Humanitarian Technology Conference (R10-HTC), Agra, India, 21–23 December 2016.
23. Muhammad, D.; Endro, A.; Sidik, P. Design and implementation of smart bath water heater using Arduino. In Proceedings of the 6th International Conference on Information and Communication Technology (ICoICT), Bandung, Indonesia, 3–5 May 2018.
24. Khaoula, T.; Abdelouahid, R.A.; Ezzahoui, I.; Marzak, A. Architecture design of monitoring and controlling of IoT-based aquaponics system powered by solar energy. *Procedia Comput. Sci.* **2021**, *191*, 493–498. [CrossRef]
25. Mahkeswaran, R.; Ng, A.K. Smart and Sustainable Home Aquaponics System with Feature-Rich Internet of Things Mobile Application. In Proceedings of the 6th International Conference on Control, Automation and Robotics (ICCAR), Singapore, 20–23 April 2020.
26. Nichani, A.; Kumar, A.; Iyer, S.; Ramya, M.A. Environmental Parameter Monitoring and Data Acquisition for Aquaponics. *Int. J. Emerg. Technol. Comput. Sci. Electron.* **2017**, *24*, 29–34.
27. Sreelekshmi, B.; Madhusoodanan, K. Automated aquaponics system. In *Emerging Trends in Engineering, Science and Technology for Society, Energy and Environment*; CRC Press: Boca Raton, FL, USA, 2018; pp. 719–724.
28. Hassan, Z.; Hossain, G.J.; Islam, M.M. Internet of Things (IoT) Based Water Quality Monitoring System. *Educ. Res.* **2020**, *2*, 168–180.
29. Bárta, A.; Souček, P.; Bozhynov, V.; Urbanová, P. Automatic multiparameter acquisition in aquaponics systems. In Proceedings of the International Conference on Bioinformatics and Biomedical Engineering, Garanda, Spain, 26–28 April 2017.
30. Manoharan, S.; Sathiyaraj, G.; Thiruvenkadakrishnan, K.; Vetriselvan, G.; Kishor, P. Water quality analyzer using IoT. *Int. J. Innov. Technol. Explor. Eng.* **2019**, *8*, 34–37.
31. Nagayo, A.M.; Mendoza, C.; Vega, E.; Al Izki, R.K.; Jamisola, R.S. An automated solar-powered aquaponics system towards agricultural sustainability in the Sultanate of Oman. In Proceedings of the IEEE International Conference on Smart Grid and Smart Cities (ICSGSC), Singapore, 23–26 July 2017.
32. Mellit, A.; Benghanem, M.; Herrak, O.; Messalaoui, A. Design of a Novel Remote Monitoring System for Smart Greenhouses Using the Internet of Things and Deep Convolutional Neural Networks. *Energies* **2021**, *14*, 5045. [CrossRef]
33. Wang, D.; Zhao, J.; Huang, L.; Xu, D. Design of a smart monitoring and control system for aquaponics based on OpenWrt. In Proceedings of the 5th International Conference on Information Engineering for Mechanics and Materials, Huhhot, Inner Mongolia, 25–26 July 2015.
34. Pasha, A.K.; Mulyana, E.; Hidayat, C.; Ramdhani, M.A.; Kurahman, O.T.; Adhipradana, M. System design of controlling and monitoring on aquaponic based on Internet of Things. In Proceedings of the 2018 4th International Conference on Wireless and Telematics (ICWT), Nusa Dua, Indonesia, 12–13 July 2018.
35. Zaini, A.; Kurniawan, A.; Herdhiyanto, A. Internet of Things for monitoring and controlling nutrient film technique (NFT) aquaponic. In Proceedings of the International Conference on Computer Engineering, Network and Intelligent Multimedia (CENIM), Surabaya, Indonesia, 26–27 November 2018.

36. Aishwarya, K.; Harish, M.; Prathibhashree, S.; Panimozhi, K. Survey on IoT based automated aquaponics gardening approaches. In Proceedings of the Second International Conference on Inventive Communication and Computational Technologies (ICICCT), Coimbatore, India, 20–21 April 2018.
37. Shaout, A.; Scott, S.G. IoT fuzzy logic aquaponics monitoring and control hardware real-time system. In Proceedings of the International Arab Conference on Information Technology, Giza, Egypt, 28–30 November 2020.
38. Saaid, M.; Fadhil, N.; Ali, M.M.; Noor, M. Automated indoor Aquaponic cultivation technique. In Proceedings of the IEEE 3rd international conference on system engineering and technology, Shah Alam, Malaysia, 19–20 August 2013.
39. Kyaw, T.Y.; Ng, A.K. Smart aquaponics system for urban farming. *Energy Procedia* **2017**, *143*, 342–347. [CrossRef]
40. Sheikh, B. Hydroponics: Key to sustain agriculture in water stressed and urban environment. *Pak. J. Agric. Agril. Eng. Vet. Sci.* **2006**, *22*, 53–57.
41. Somerville, C.; Cohen, M.; Pantanella, E.; Stankus, A.; Lovatelli, A. *Small-Scale Aquaponic Food Production: Integrated Fish and Plant Farming*; FAO Fisheries and Aquaculture Technical Paper; FAO: Rome, Italy, 2014.
42. Þórarinsdóttir, R.I.; Kledal, P.R.; Skar, S.L.G.; Sustaeta, F.; Ragnarsdóttir, K.V.; Mankasingh, U.; Pantanella, E.; Ven, R.v.d.; Shultz, C. *Aquaponics Guidelines*; Haskolaprent: Reykjavik, Iceland, 2015.
43. Stone, N.M.; Thomforde, H.K. *Understanding Your Fish Pond Water Analysis Report*; Cooperative Extension Program, University of Arkansas at Pine Bluff, US Department of Agriculture and County Governments Cooperating: Washington, DC, USA, 2004; pp. 1–4.
44. Espinal, C.A.; Matulić, D. Recirculating aquaculture technologies. In *Aquaponics Food Production Systems*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 35–76.
45. Eck, M.; Körner, O.; Jijakli, M.H. Nutrient cycling in aquaponics systems. In *Aquaponics Food Production Systems*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 231–246.
46. García- Rodríguez, A.; García-Rodríguez, S.; Díez-Mediavilla, M.; Alonso-Tristán, C. Photosynthetic active radiation, solar irradiance and the CIE standard sky classification. *Appl. Sci.* **2020**, *10*, 8007. [CrossRef]
47. Bhatnagar, A.; Singh, G. Culture fisheries in village ponds: A multi-location study in Haryana, India. *Agric. Biol. J. N. Am.* **2010**, *1*, 961–968. [CrossRef]
48. De Azevedo, R.V.; de Oliveira, K.F.; Flores-Lopes, F.; Teixeira-Lanna, E.A.; Takishita, S.S.; Tavares-Braga, L. Responses of Nile tilapia to different levels of water salinity. *Lat. Am. J. Aquat. Res.* **2015**, *43*, 828–835. [CrossRef]
49. Petric, M.; Dodigović, F.; Grčić, I.; Markužić, P.; Radetić, L.; Topić, M. Ammonia concentration monitoring using arduino platform. *Environ. Eng. Inženjerstvo Okoliša* **2019**, *6*, 21–26. [CrossRef]
50. Yanes, A.R.; Martinez, P.; Ahmad, R.J. Towards automated aquaponics: A review on monitoring, IoT, and smart systems. *J. Clean. Prod.* **2020**, *263*, 121571. [CrossRef]
51. Jacob, N.K. IoT powered portable aquaponics system. In Proceedings of the Second International Conference on Internet of things, Data and Cloud Computing, Cambridge, UK, 22–23 March 2017.
52. Nichani, A.; Saha, S.; Upadhyay, T.; Ramya, A.; Tolia, M. Data Acquisition and Actuation for Aquaponics using IoT. In Proceedings of the 2018 3rd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT), Bangalore, India, 18–19 May 2018.
53. Cortella, G.; Saro, O.; De Angelis, A.; Ceccotti, L.; Tomasi, N.; Dalla Costa, L.; Manzocco, L.; Pinton, R.; Mimmo, T.; Cesco, S. Temperature control of nutrient solution in floating system cultivation. *Appl. Therm. Eng.* **2014**, *73*, 1055–1065. [CrossRef]
54. Blom, T.; Straver, W.; Ingratta, F.; Khosla, S.; Brown, W. *Carbon Dioxide in Greenhouses*; Ministry of Agriculture and Food: Guelph, ON, Canada, 1984.
55. Salamone, F.; Belussi, L.; Danza, L.; Ghellere, M.; Meroni, I. How to control the Indoor Environmental Quality through the use of the Do-It-Yourself approach and new pervasive technologies. *Energy Procedia* **2017**, *140*, 351–360. [CrossRef]
56. Kumar, N.H.; Baskaran, S.; Hariraj, S.; Krishnan, V. An autonomous aquaponics system using 6lowpan based wsn. In Proceedings of the IEEE 4th International Conference on Future Internet of Things and Cloud Workshops (FiCloudW), Vienna, Austria, 22–24 August 2016.
57. Da Silva, L.F.; Yang, Z.; Pires, N.M.; Dong, T.; Teien, H.-C.; Storebakken, T.; Salbu, B. Monitoring aquaculture water quality: Design of an early warning sensor with Aliivibrio fischeri and predictive models. *Sensors* **2018**, *18*, 2848. [CrossRef]
58. Rakocy, J.E. Aquaponics-integrating fish and plant culture. In *Book Aquaculture Production Systems*, 1st ed.; James, H., Tidwell, A., Eds.; John Wiley & Sons, Ltd.: Oxford, UK, 2012; pp. 344–386.
59. Rakocy, J.E.; Shultz, R.C.; Bailey, D.S. Commercial aquaponics for the Caribbean. In Proceedings of the 51st Gulf and Caribbean Fisheries Institute (GCFI). 2000. Available online: http://hdl.handle.net/1834/29306 (accessed on 15 July 2022).
60. Lennard, W.A.; Leonard, B.V. A comparison of reciprocating flow versus constant flow in an integrated, gravel bed, aquaponic test system. *Aquac. Int.* **2004**, *12*, 539–553. [CrossRef]
61. Endut, A.; Jusoh, A.; Ali, N.; Nik, W.W.; Hassan, A. A study on the optimal hydraulic loading rate and plant ratios in recirculation aquaponic system. *Bioresour. Technol.* **2010**, *101*, 1511–1517. [CrossRef]
62. Haryanto, M.U.; Ibadillah, A.; Alfita, R.; Aji, K.; Rizkyandi, R. Smart aquaponic system-based Internet of Things (IoT). In Proceedings of the Journal of Physics: Conference Series, Medan, Indonesia, 19–20 July 2019.

63. Aishwarya, K.; Harish, M.; Prathibhashree, S.; Panimozhi, K. Survey on automated aquaponics based gardening approaches. In Proceedings of the 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT), Coimbatore, India, 20–21 April 2018.
64. Arvind, C.; Jyothi, R.; Kaushal, K.; Girish, G.; Saurav, R.; Chetankumar, G. Edge Computing Based Smart Aquaponics Monitoring System Using Deep Learning in IoT Environment. In Proceedings of the 2020 IEEE Symposium Series on Computational Intelligence (SSCI), Canberra, Australia, 1–4 December 2020.
65. Cheong, C.; Iskandar, A.; Azhar, A.; Othman, W.J. Smart Aquaponics System: Design and Implementation using Arduino Microcontroller. *Int. J. Res.* **2018**, 2348–6848.
66. Wu, Z.; Qiu, K.; Zhang, J. Smart microcontroller architecture for the Internet of Things. *Sensors* **2020**, *20*, 1821. [CrossRef]
67. Verma, S.; Bhatia, A.; Chug, A.; Singh, A.P. Recent advancements in multimedia big data computing for IoT applications in precision agriculture: Opportunities, issues, and challenges. In *Multimedia Big Data Computing for IoT Applications*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 391–416.
68. LeCun, Y.; Bengio, Y.; Hinton, G. Deep learning. *Nature* **2015**, *521*, 436–444. [CrossRef]
69. Taha, M.F.; Abdalla, A.; ElMasry, G.; Gouda, M.; Zhou, L.; Zhao, N.; Liang, N.; Niu, Z.; Hassanein, A.; Al-Rejaie, S. Using Deep Convolutional Neural Network for Image-Based Diagnosis of Nutrient Deficiencies in Plants Grown in Aquaponics. *Chemosensors* **2022**, *10*, 45. [CrossRef]
70. Zhou, L.; Zhang, C.; Taha, M.; Qiu, Z.; He, L. Determination of Leaf Water Content with a Portable NIRS System Based on Deep Learning and Information Fusion Analysis. *Trans. ASABE* **2021**, *64*, 127–135. [CrossRef]
71. Zhou, L.; Zhang, C.; Taha, M.F.; Wei, X.; He, Y.; Qiu, Z.; Liu, Y. Wheat Kernel Variety Identification Based on a Large Near-Infrared Spectral Dataset and a Novel Deep Learning-Based Feature Selection Method. *Front. Plant Sci.* **2020**, *11*, 575810. [CrossRef]
72. Lekunberri, X.; Ruiz, J.; Quincoces, I.; Dornaika, F.; Arganda-Carreras, I.; Fernandes, J.A. Identification and measurement of tropical tuna species in purse seiner catches using computer vision and deep learning. *Ecol. Inform.* **2022**, *67*, 101495. [CrossRef]
73. Álvarez-Ellacuría, A.; Palmer, M.; Catalán, I.A.; Lisani, J. Image-based, unsupervised estimation of fish size from commercial landings using deep learning. *ICES J. Mar. Sci.* **2020**, *77*, 1330–1339. [CrossRef]
74. Han, F.; Zhu, J.; Liu, B.; Zhang, B.; Xie, F. Fish shoals behavior detection based on convolutional neural network and spatiotemporal information. *IEEE Access* **2020**, *8*, 126907–126926. [CrossRef]
75. Ubina, N.; Cheng, S.-C.; Chang, C.-C.; Chen, H.-Y. Evaluating fish feeding intensity in aquaculture with convolutional neural networks. *Aquac. Eng.* **2021**, *94*, 102178. [CrossRef]
76. Ren, Q.; Zhang, L.; Wei, Y.; Li, D. A method for predicting dissolved oxygen in aquaculture water in an aquaponics system. *Comput. Electron. Agric.* **2018**, *151*, 384–391. [CrossRef]
77. Ta, X.; Wei, Y. Research on a dissolved oxygen prediction method for recirculating aquaculture systems based on a convolution neural network. *Comput. Electron. Agric.* **2018**, *145*, 302–310. [CrossRef]
78. Mehra, M.; Saxena, S.; Sankaranarayanan, S.; Tom, R.J.; Veeramanikandan, M. IoT based hydroponics system using Deep Neural Networks. *Comput. Electron. Agric.* **2018**, *155*, 473–486. [CrossRef]
79. Thai-Nghe, N.; Thanh-Hai, N.; Chi Ngon, N.J. Deep learning approach for forecasting water quality in IoT systems. *Int. J. Adv. Comput. Sci. Appl.* **2020**, *11*, 686–693. [CrossRef]
80. Barzegar, R.; Aalami, M.T.; Adamowski, J. Short-term water quality variable prediction using a hybrid CNN–LSTM deep learning model. *Stoch. Environ. Res. Risk Assess.* **2020**, *34*, 415–433. [CrossRef]
81. Pitakphongmetha, J.; Boonnam, N.; Wongkoon, S.; Horanont, T.; Somkiadcharoen, D.; Prapakornpilai, J. Internet of things for planting in smart farm hydroponics style. In Proceedings of the 2016 International Computer Science and Engineering Conference (ICSEC), Chiang Mai, Thailand, 14–17 December 2016.
82. Jalal, A.; Salman, A.; Mian, A.; Shortis, M.; Shafait, F. Fish detection and species classification in underwater environments using deep learning with temporal information. *Ecol. Inform.* **2020**, *57*, 101088. [CrossRef]
83. Salman, A.; Siddiqui, S.A.; Shafait, F.; Mian, A.; Shortis, M.R.; Khurshid, K.; Ulges, A.; Schwanecke, U. Automatic fish detection in underwater videos by a deep neural network-based hybrid motion learning system. *ICES J. Mar. Sci.* **2020**, *77*, 1295–1307. [CrossRef]
84. Hasan, N.; Ibrahim, S.; Aqilah Azlan, A.J. Fish diseases detection using convolutional neural network (CNN). *Int. J. Nonlinear Anal. Appl.* **2022**, *13*, 1977–1984.
85. Monkman, G.G.; Hyder, K.; Kaiser, M.J.; Vidal, F.P. Using machine vision to estimate fish length from images using regional convolutional neural networks. *Methods Ecol. Evol.* **2019**, *10*, 2045–2056. [CrossRef]
86. Garcia, R.; Prados, R.; Quintana, J.; Tempelaar, A.; Gracias, N.; Rosen, S.; Vågstøl, H.; Løvall, K.J. Automatic segmentation of fish using deep learning with application to fish size measurement. *ICES J. Mar. Sci.* **2020**, *77*, 1354–1366. [CrossRef]
87. Lu, H.; Ma, X. Hybrid decision tree-based machine learning models for short-term water quality prediction. *Chemosphere* **2020**, *249*, 126169. [CrossRef]
88. Junior, A.D.; Sant'Ana, D.A.; Pache, M.C.B.; Garcia, V.; de Moares Weber, V.A.; Astolfi, G.; de Lima Weber, F.; Menezes, G.V.; Menezes, G.K.; Albuquerque, P.L. Fingerlings mass estimation: A comparison between deep and shallow learning algorithms. *Smart Agric. Technol.* **2021**, *1*, 100020. [CrossRef]
89. Måløy, H.; Aamodt, A.; Misimi, E. A spatio-temporal recurrent network for salmon feeding action recognition from underwater videos in aquaculture. *Comput. Electron. Agric.* **2019**, *167*, 105087. [CrossRef]

90. Adegboye, M.A.; Aibinu, A.M.; Kolo, J.G.; Aliyu, I.; Folorunso, T.A.; Lee, S. Incorporating intelligence in fish feeding system for dispensing feed based on fish feeding intensity. *IEEE Access* **2020**, *8*, 91948–91960. [CrossRef]
91. Mohanty, S.P.; Hughes, D.P.; Salathé, M. Using deep learning for image-based plant disease detection. *Front. Plant Sci.* **2016**, *7*, 1419. [CrossRef]
92. Lu, J.Y.; Chang, C.L.; Kuo, Y.F. Monitoring growth rate of lettuce using deep convolutional neural networks. In Proceedings of the ASABE Annual International Meeting, Boston, MA, USA, 7–10 July 2019.
93. Alhnaity, B.; Pearson, S.; Leontidis, G.; Kollias, S. Using deep learning to predict plant growth and yield in greenhouse environments. In Proceedings of the International Symposium on Advanced Technologies and Management for Innovative Greenhouses, Angers, France, 16–20 June 2019.
94. Hazra, A.; Adhikari, M.; Amgoth, T.; Srirama, S.N. A comprehensive survey on interoperability for IIoT: Taxonomy, standards, and future directions. *ACM Comput. Surv.* **2021**, *55*, 1–35. [CrossRef]
95. Lelli, F. Interoperability of the Time of Industry 4.0 and the Internet of Things. *Future Internet* **2019**, *11*, 36. [CrossRef]
96. Rabiya, A.; Martinez, P.; Ahmad, R. An ontology model to represent aquaponics 4.0 system's knowledge. *Inf. Process. Agric.* **2021**, *100*, 55–60.
97. Ge, W.; Zhao, C. State-of-the-art and developing strategies of agricultural internet of things. *Nongye Jixie Xuebao Trans. Chin. Soc. Agric. Mach.* **2014**, *45*, 222–277.
98. Abraham, S.; Shahbazian, A.; Dao, K.; Tran, H.; Thompson, P. An Internet of Things (IoT)-based aquaponics facility. In Proceedings of the 2017 IEEE Global Humanitarian Technology Conference (GHTC), San Jose, CA, USA, 19–22 October 2017.
99. Dutta, A.; Dahal, P.; Prajapati, R.; Tamang, P.; Kumar, E.S. IOT based aquaponics monitoring system. In Proceedings of the 1st Kantipur Engineering College (KEC) Conference Proceedings, Dhapakhel, Nepal, 27 September 2018.
100. Raju, K.R.S.R.; Varma, G.H.K. Knowledge based real time monitoring system for aquaculture using IoT. In Proceedings of the IEEE 7th International Advance Computing Conference (IACC), Hyderabad, India, 5–7 January 2017.
101. Elsokah, M.M.; Sakah, M. Next generation of smart aquaponics with internet of things solutions. In Proceedings of the 19th International Conference on Sciences and Techniques of Automatic Control and Computer Engineering (STA), Sousse, Tunisia, 24–26 March 2019.
102. Wang, S.S.C.; Lin, W.L.; Hsieh, C. To improve the production of agricultural using IoT-based aquaponics system. *Int. J. Appl. Sci. Eng.* **2020**, *17*, 207–222.
103. Vernandhes, W.; Salahuddin, N.S.; Kowanda, A.; Sari, S.P. Smart aquaponic with monitoring and control system based on IoT. In Proceedings of the Second International Conference on Informatics and Computing (ICIC), Jayapura, Indonesia, 1–3 November 2017.
104. Odema, M.; Adly, I.; Wahba, A.; Ragai, H. Smart aquaponics system for industrial Internet of Things (IIoT). In Proceedings of the International Conference on Advanced Intelligent Systems and Informatics, Cairo, Egypt, 9–11 September 2017.
105. Llaban, A.; Ella, V. Conventional and sensor-based streamflow data acquisition system for sustainable water resources management and agricultural applications: An extensive review of literature. In Proceedings of the IOP Conference Series: Earth and Environmental Science, Bogor, Indonesia, 11–13 October 2021.
106. Lelli, F.; Frizziero, E.; Gulmini, M.; Maron, G.; Orlando, S.; Petrucci, A.; Squizzato, S. The many faces of the integration of instruments and the grid. *Int. J. Web Grid Serv.* **2007**, *3*, 239–266. [CrossRef]
107. Murad, S.; Harun, A.; Mohyar, S.; Sapawi, R.; Ten, S. Design of aquaponics water monitoring system using Arduino microcontroller. In Proceedings of the AIP Conference Proceedings, Bydgoszcz, Poland, 30 September 2017.
108. Mamatha, M.; Namratha, S. Design & implementation of indoor farming using automated aquaponics system. In Proceedings of the IEEE International Conference on Smart Technologies and Management for Computing, Communication, Controls, Energy and Materials (ICSTM), Chennai, India, 2–4 August 2017.
109. Peharda, D.; Ivanković, I.; Jaman, N. Using data from SCADA for centralized transformer monitoring applications. *Procedia Eng.* **2017**, *202*, 65–75. [CrossRef]
110. Jacobs, F.R. Enterprise resource planning (ERP)—A brief history. *J. Oper. Manag.* **2007**, *25*, 357–363. [CrossRef]
111. Da Xu, L.; He, W.; Li, S. Internet of things in industries: A survey. *IEEE Trans. Ind. Inform.* **2014**, *10*, 2233–2243.