Smart Systems and IoT for Aquaponics Automation

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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.

aquaponics Internet of Things (IoT) smart systems

1. 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 [1][2]. **Table 1** 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 1. 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	[3]
		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.		[4]
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	[5]
		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		[6]
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	[7]

System Control Degree	Technique or Method	Component	Ways of Data Acquisition	Data Acquisition	Control Unit	Effect	Advantages/Disadvantages	References
		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%.		[8]
		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		[9]
		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	Autonomous monitoring	[10]
	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.		[11]
	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	[12]
	Raspberry Pi	Data acquisition,	T, pH, flow, light, and plant	T, pH, flow, light,	Water heater,	Self-sustainable,	Autonomous monitoring	[13]

1.1. 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, with Arduino or Raspberry pi devices [13][16][17].

System Control Degree	Technique or Method	Component	Ways of Data Acquisition	Data Acquisition	Control Unit	Effect	Advantages/Disadvantages	References
	[18]	alarm, unit, web application, mobile application, and cloud server	height sensors	plant height	water pump, LED grow light, and fish feeder	cost-effective, and eco-friendly urban farming		[19]
	Fuzzy logic	Microcontroller, relay control, and fuzzy interface system	Water T, air T, pH, and luminance [13] sensors	Water/air T, pH, light and intensity	Light, heater, and alarm	Accurate, low cost, and convenient	Continuous autonomous monitoring [7]	[14]
	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 [12] smart aquaponics remotely	Store data in cloud and analyzing data using smart technology	[15]
	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	[16]
		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		[17]

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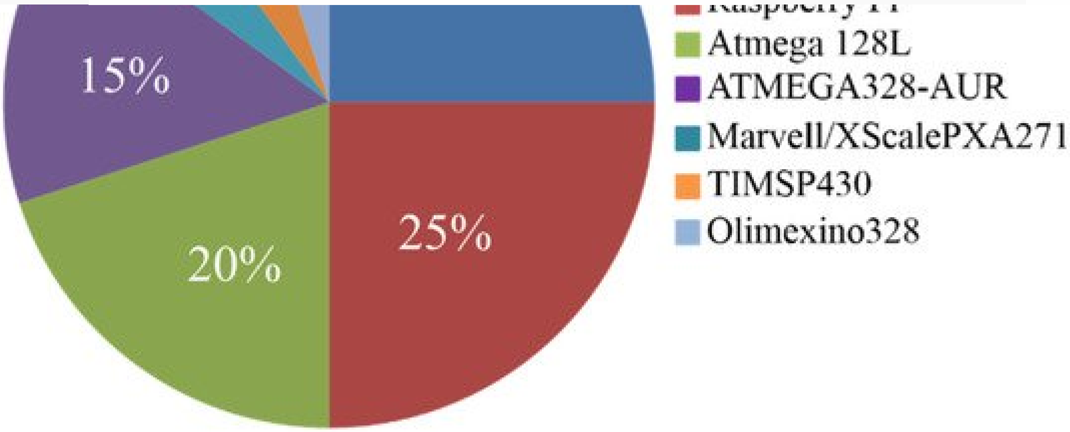

Figure 1. Distribution of research papers based on the types of microcontrollers.

1.2. 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 [20]. 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 [21], predicting plant water content [22], and identifying plant species [23]. In addition to the contributions of deep learning in the field of aquaculture, such as fish detection and classification [24], estimating the age and size of fish [25], behavior analysis [26], and feeding decisions [27], there are dozens of other potential applications of this approach in smart aquaponics systems. **Figure 2** shows deep-learning-enabled advanced applications for smart aquaponics.

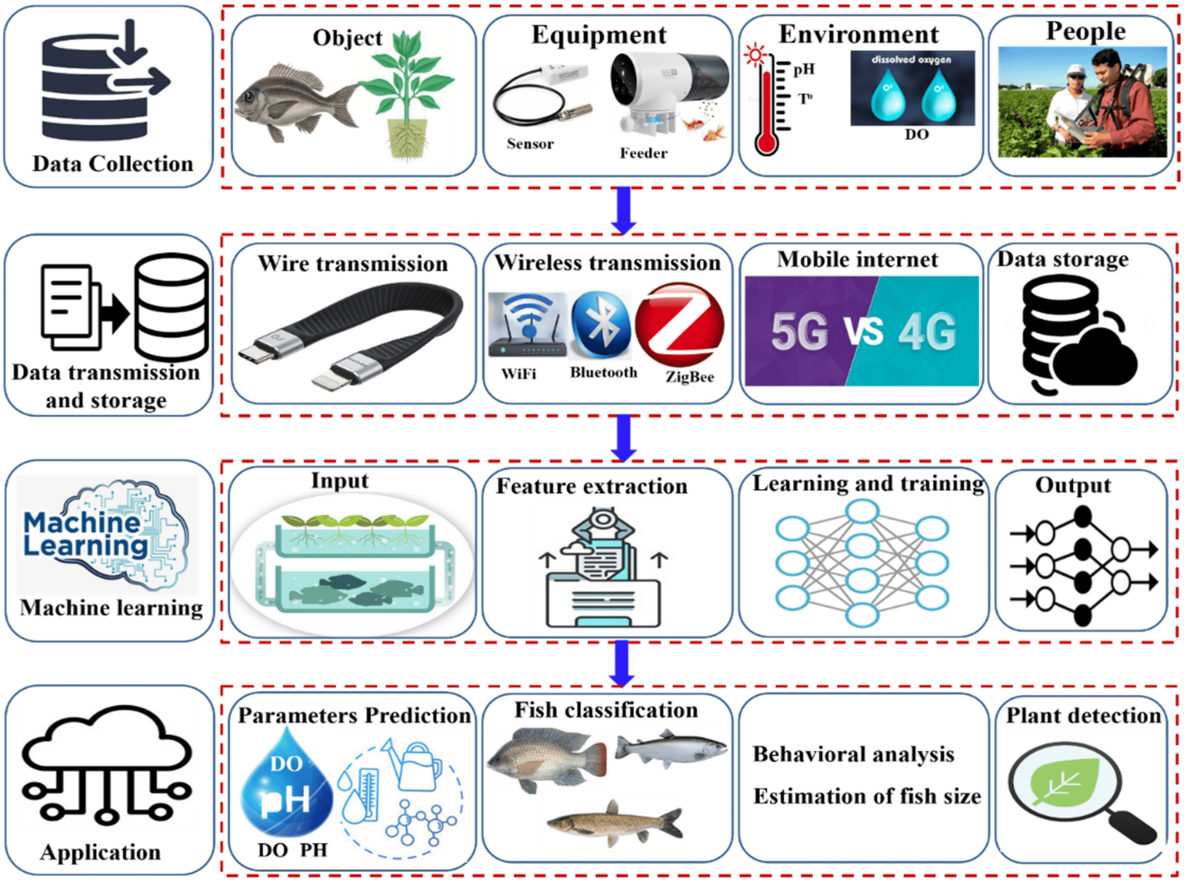

Figure 2. Neural networks and deep-learning-enabled advanced analytics applied for different tasks in smart aquaponics.

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.

1.2.1. 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 [28][29]. 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 [30][31][32]. 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 [33].

1.2.2. 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 [34]. 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% [35]. 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% [36]. 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% [24].

1.2.3. 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 [25][37][38] as detailed in **Table 1**. 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% [39]. 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% [40].

1.2.4. 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% [27]. 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% [41]. 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 [42].

1.2.5. 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% [43]. Recently, convolutional neural networks were also applied to monitor the growth rate of lettuce in hydroponic systems [44]. 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 [45]. 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 % [21]. **Table 2** 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 2. 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	—	[28]
Predicting water temperature, pH, salinity, water level, relative humidity, and light intensity	DCNN	—	[30]
Monitoring and predicting temperature, DO, salinity, and pH of water using	DCNN and LSTM algorithm	—	[31]
Predicting dissolved oxygen	DCNN	—	[29]
Prediction of EC and pH	artificial neural network	—	[33]
Predicting the content of both chlorophyll (Chl-a) and DO using CNN-LSTM prediction model	Hybrid CNN–LSTM deep learning model	—	[32]
Detecting fish in underwater videos	ResNet-50 with YOLO (You Only Look Once)	95.47%	[34]
Detecting moving live fish	DCNN	87.44%	[35]
detection of fish disease	DCNN	94.44%	[36]

Application	Models/Algorithm Technology	Results/Accuracy	Reference
Classifying tuna fish	R-CNN and ResNet50V2	70%	[24]
Estimating fish length	R-CNN	99%	[25]
Fish length	R-CNN	97.8%	[37]
Estimation of fishs length	Local gradient technique and Mask RCNN	0.89	[38]
Estimation the pond fish length	CNN	93.93%	[39]
Estimation of fingerlings mass	InceptionV3, Exception, VGG19, VGG16, and ResNet50.	67.08%	[40]
Assessing the feeding intensity of fish	Convolutional neural networks,	95%	[27]
Identify salmon feeding behavior or non-feeding	Dual-Stream Recurrent Network	80%	[41]
Prediction feeding behavior	Artificial neural networks	100%.	[42]
Plant disease detection	CNN	99.35%	[43]
Diagnose nutrient deficiencies of lettuce	ResNet18 and Inceptionv3	96.5%	[21]
Monitor the growth rate of lettuce	Mask R-CNN	97.63%	[44]
Prediction tomato yield and stem growth	RNN with LSTM	Performed well	[45]

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 [46][47]. Accordingly, the concept of a smart system is closely related to Industry 4.0 itself, involving algorithms and complex logical processes [48]. 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 [49]. 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 [49]. 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 [49].

2. IoT-Based Aquaponics

As shown in **Figure 3**, the structure of the IoT applied in aquaponics systems and protected agriculture scenarios consists of five layers [50]:

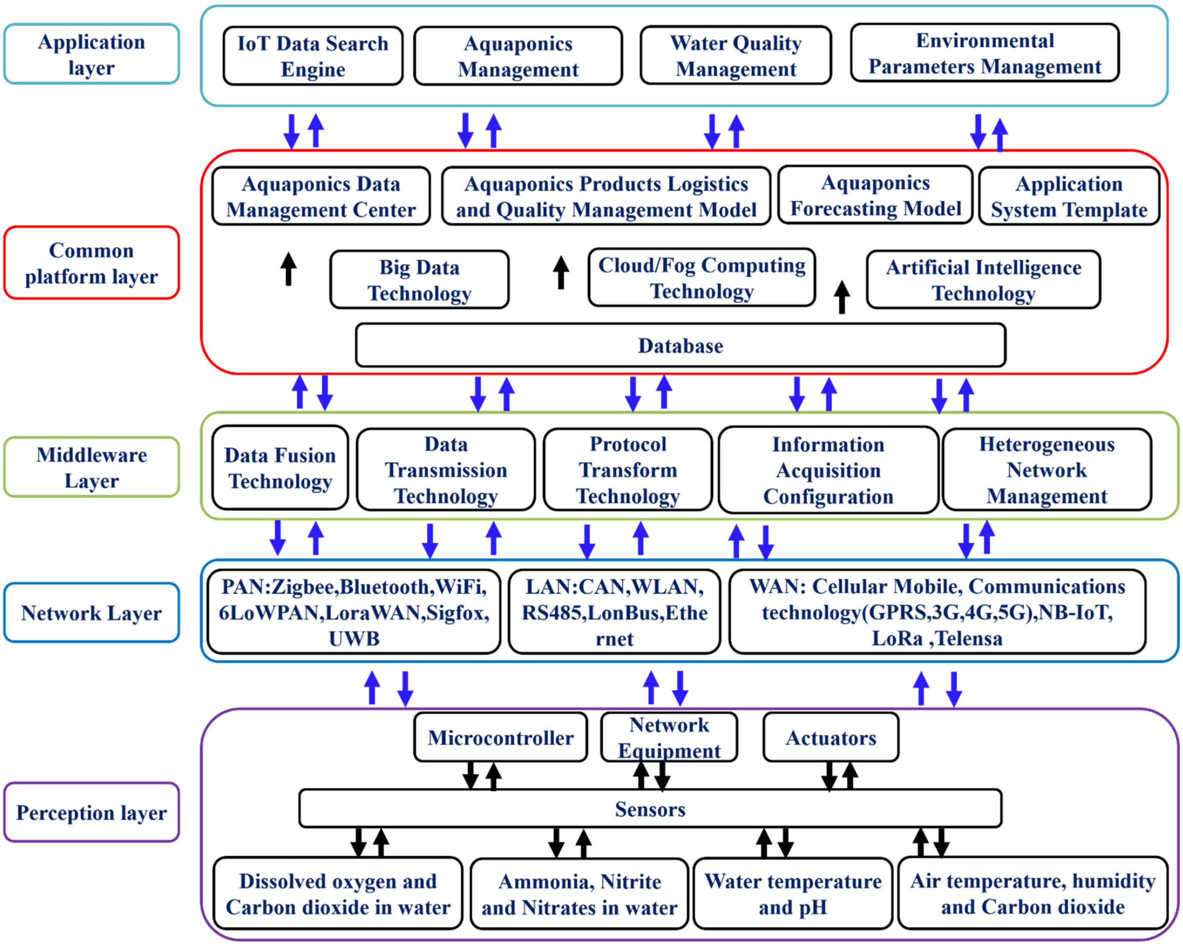

Figure 3. Structure of IoT in aquaponics.

- 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.

- 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.

- 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.

- 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.

- 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. IoT has been used in three axes: Monitoring interfaces, remote applications, and Wireless Sensor Networks (WSN).

2.1. 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 [51][52][53][54]. 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 [55]. 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 [56]. 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 [52].

2.2. 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 [57].

Many applications of remote control were found in the 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 [7][33][58]. 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 [10][59]. 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 [60][61]. Using the Modbus TCP protocol, another IoT-based remote monitoring and control system for aquaponics was created to extract data from sensing nodes [62]. 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 [8].

The monitoring and control framework of the aquaponics system consists of three basic stages, as shown in **Figure 4**. 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 [63]. Then the data are stored and processed using different algorithms and processing tools [64]. At the end, the processing commands are sent to different actuators, and the operation and control are then performed automatically.

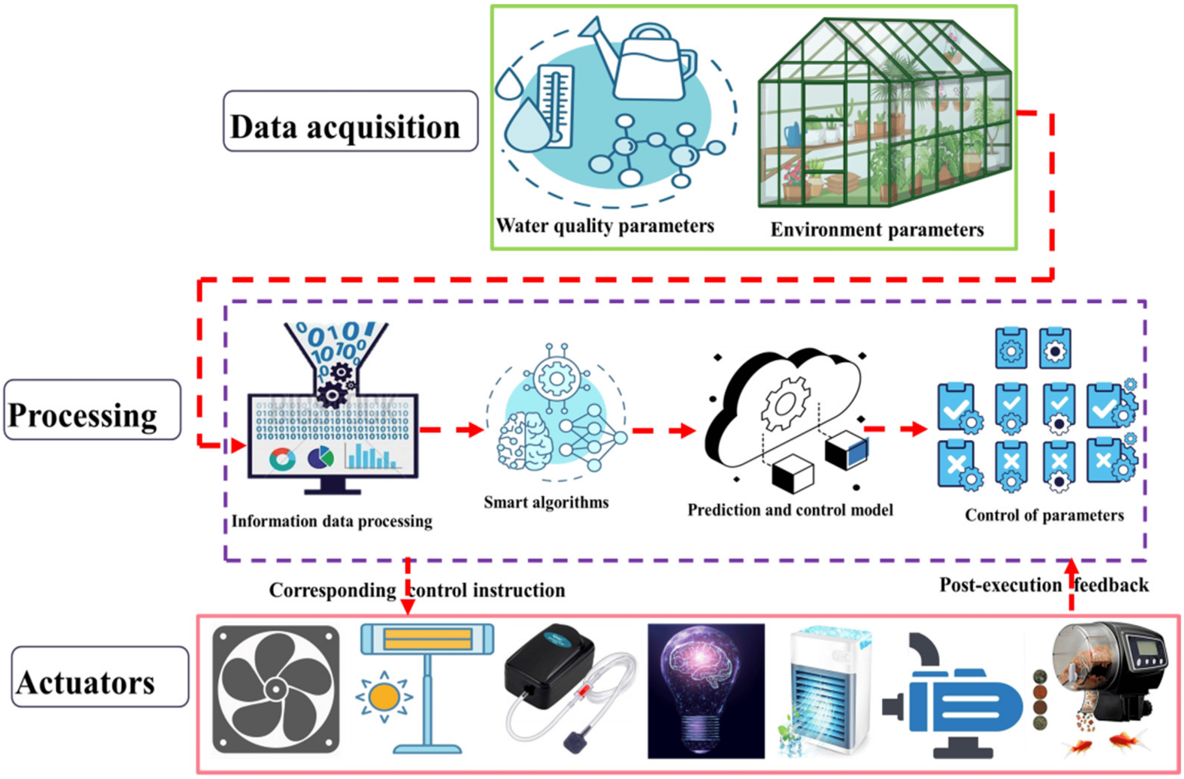

Figure 4. Schematic diagram of detection and control system for aquaponics system.

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 [65]. 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 [15]. 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 [1]. 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 trend analysis. To predict the levels of pH and nitrates, linear regression was implemented to create an automated aquaponics system concerning these two parameters.

2.3. 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 5**. 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 [15]. Kumar et al. Used the 6LOWPAN protocol and WSN to design a monitored and controlled aquaponics system [1]. 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 [65]. To collect and store data from the aquaponics system, Mamatha and Namratha used the ThingSpeak data logging platform [66]. Sreelekshmi and Madhusoodanan monitored aquaponics using the ThingSpeak IoT platform combined with an Arduino Uno microcontroller and a transceiver (ESP8266-01 Wi-Fi) [67]. 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 [68]. 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 3** lists current wireless communication technologies.

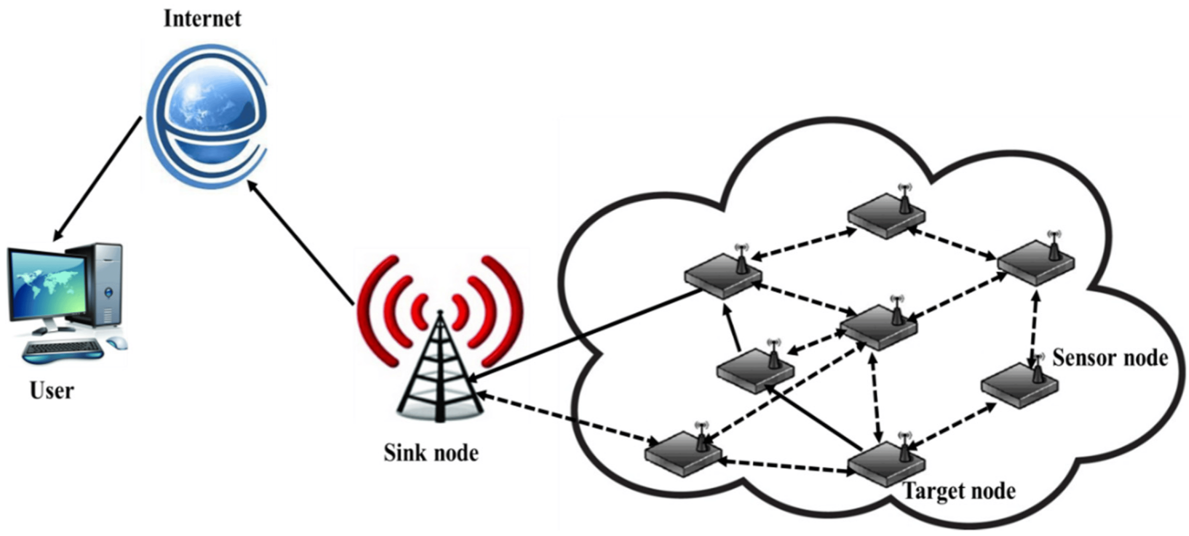

Figure 5. Wireless Sensor Network (WSN).

Table 3. 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

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