water
MDPI

Review

IoT-Based Water Monitoring Systems: A Systematic Review

Che Zalina Zulkifli [1,*], Salem Garfan [1], Mohammed Talal [2], A. H. Alamoodi [1], Amneh Alamleh [3], Ibraheem Y. Y. Ahmaro [4], Suliana Sulaiman [1,*], Abu Bakar Ibrahim [1], B. B. Zaidan [5], Amelia Ritahani Ismail [6], O. S. Albahri [7], A. S. Albahri [8], Chin Fhong Soon [9], Nor Hazlyna Harun [10] and Ho Hong Chiang [1]

1 Computing Department, Universiti Pendidikan Sultan Idris, Tanjung Malim 35900, Malaysia
2 Department of Electronic Engineering, Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia (UTHM), Parit Raja 86400, Malaysia
3 Department of Artificial Intelligence, Faculty of Information Technology, Zarqa University, Zarqa 13100, Jordan
4 Computer Science Department, College of Information Technology, Hebron University, Hebron P.O. Box 40, Palestine
5 Future Technology Research Center, National Yunlin University of Science and Technology, Douliu 64002, Taiwan
6 Kulliyyah of Information and Communication Technology (KICT), International Islamic University Malaysia, Kuala Lumpur 50728, Malaysia
7 Computer Techniques Engineering Department, Mazaya University College, Nasiriyah 362Q + FC9, Iraq
8 Informatics Institute for Postgraduate Studies (IIPS), Iraqi Commission for Computers and Informatics (ICCI), Baghdad 10021, Iraq
9 Microelectronics and Nanotechnology-Shamsuddin Research Centre (MINT-SRC), Universiti Tun Hussein Onn Malaysia (UTHM), Parit Raja 86400, Malaysia
10 Data Science Research Lab, School of Computing, College Arts & Sciences, Universiti Utara Malaysia, Sintok 06010, Malaysia
* Correspondence: chezalina@fskik.upsi.edu.my (C.Z.Z.); suliana@fskik.upsi.edu.my (S.S.)

Citation: Zulkifli, C.Z.; Garfan, S.; Talal, M.; Alamoodi, A.H.; Alamleh, A.; Ahmaro, I.Y.Y.; Sulaiman, S.; Ibrahim, A.B.; Zaidan, B.B.; Ismail, A.R.; et al. IoT-Based Water Monitoring Systems: A Systematic Review. *Water* **2022**, *14*, 3621. https://doi.org/10.3390/w14223621

Academic Editors: George Arhonditsis and Dimitrios E. Alexakis

Received: 26 August 2022
Accepted: 1 November 2022
Published: 10 November 2022

Abstract: Water quality monitoring plays a significant part in the transition towards intelligent and smart agriculture and provides an easy transition to automated monitoring of crucial components of human daily needs as new technologies are continuously developed and adopted in agricultural and human daily life (water). For the monitoring and management of water quality, this effort, however, requires reliable models with accurate and thorough datasets. Analyzing water quality monitoring models by utilizing sensors that gather water properties during live experiments is possible due to the necessity for precision in modeling. To convey numerous conclusions regarding the concerns, issues, difficulties, and research gaps that have existed throughout the past five years (2018–2022), this review article thoroughly examines the water quality literature. To find trustworthy peer-reviewed publications, several digital databases were searched and examined, including IEEE Xplore®, ScienceDirect, Scopus, and Web of Science. Only 50 articles out of the 946 papers obtained, were used in the study of the water quality monitoring research area. There are more rules for article inclusion in the second stage of the filtration process. Utilizing a real-time data acquisition system, the criteria for inclusion for the second phase of filtration looked at the implementation of water quality monitoring and characterization procedures. Reviews and experimental studies comprised most of the articles, which were divided into three categories. To organize the literature into articles with similar types of experimental conditions, a taxonomy of the three literature was created. Topics for recommendations are also provided to facilitate and speed up the pace of advancement in this field of study. By conducting a thorough analysis of the earlier suggested methodologies, research gaps are made clear. The investigation largely pointed out the problems in the accuracy of the models, the development of data-gathering systems, and the types of data used in the proposed frameworks. Finally, by examining critical topics required for the development of this research area, research directions toward smart water quality are presented.

Keywords: water quality monitoring; internet of things; systematic review

1. Introduction

Water is significant to all forms of life [1]. The implementation of urbanization and industrialization plan has caused serious public concern on the growth of pollutants in water resources [2,3]. Dumping solid wastes and littering by humans in rivers, lakes, and oceans, air pollution equally contributes to the contamination of water bodies and affects the food chain adversely [4]. In water distribution systems through pipes, water could trap unwanted substances like rust and metals from the wall of old distribution pipes, silt and mud from damaged pipes, and sediments during the pipe repairing process [5]. Therefore, innovative means of monitoring and mitigating water pollution are required [6]. According to the United States Geological Survey, water quality is "a measure of the acceptability of water for a particular purpose based on specified physical, chemical, and biological parameters" (USGS). As a result, it is a measurement of the state of the water for human needs or purposes or even the needs of different kinds of land or aquatic animals [7,8].

In traditional water quality monitoring methods [9]; the farmer or healthy society responsible for water quality will visit the fond or the specific areas to monitor and control the water quality manually [10]. They take the water sample to the lab to know the values of the water quality parameters and then employ appropriate controlling measures [11]. This entire process is tiresome, costly lengthy, and less efficient due to the many processes involved in identifying the pollutants, pollution level, and the source of the pollutants [12]. The advent of the internet of things and wireless sensor networks that emerged simultaneously with the development of data acquisition has been utilizing the best part in water and air quality monitoring systems [4]. The current trends in water quality monitoring systems are focused on continuous sensing, multiple sensors, automated control, and wireless data acquisition mechanism [5]. In addition, artificial intelligence, technologies like machine learning [13], deep learning [14], and fuzzy logic [15], integrated with the IoT are emerging technologies which is recognized as efficient ways to monitor water quality [16].

Although the term "Internet of Things" (IoT) is widely used in many different contexts, we can define it as a global network of uniquely addressable networked items that are based on established communication protocols [17]. The concept of IoT is helpful in a variety of application scenarios, including healthcare and wellness, home and building automation, increased energy efficiency [18], industrial automation, smart metering and smart grid infrastructures, asset management, and logistics, vehicular automation and smart transport, precision agriculture, smart shopping, aquaculture [19], and water quality assessment [20]. Owing to the advancement in the Internet of Things [21], many modern technologies are now utilising IoT [22] as a platform for monitoring and evaluating water quality [23]. Conclusively, with the help of cutting-edge ICT technology; The water quality has a significant impact on property values, and keeping the water quality in good condition would please people as well as benefit the aquatic ecosystems [24,25].

Development of research on water quality management integrated with recent advances in IoT technology continuously is the pinnacle for this research as it aims to conduct a systematic literature review to examine the latest research trends on water quality management. It provides valuable insights into technological environments and support researchers by understanding the available options and gaps in this area of research. It also aims to shed light on the researchers' efforts in mapping the research landscape into a coherent taxonomy and categorization, analyze this categorization providing discussion including motivations, recommendations, issues, and challenges encountered by researchers along with the proposed solutions for these challenges and issues.

To expedite the advancement of this field of study, future research directions are offered. As a result, the primary objectives of this study are to examine prior research, summarize their conclusions on crucial criteria for determining water quality levels, choose methods, estimate procedures, and offer taxonomic literature. This research focuses on experiments-based studies. The following inquiries are being addressed in this review article:

This systematic Literature review is aimed to answer the current research questions:

1. What kinds of data acquisition system (DAS) are now employed to gather water samples for testing and monitoring?
2. How are DAS evaluations in the literature made?
3. What kind of approach is employed to categorize water quality?
4. What are the characteristics used in earlier research studies to measure water quality?

The remaining of this paper is structured as follows: in Section 2, the systematic literature review protocol is proposed, Section 3 illustrates the taxonomy and its analysis, Section 4 bibliography, and lastly, Section 5 the conclusion.

2. Systematic Review Protocol

This study used a systematic literature review (SLR) to analyses the topic of water quality monitoring and inspection in detail. An extensive, thorough review of the subjects related to the research area is provided by this method. Strategies and guidelines in the research plans are described along with key insights and points of understanding. Additionally, SLR offers thorough interpretations and identifies problems and difficulties that are widely discussed or given less consideration by researchers [26]. The SLR process is an important one that is actively used in research methodologies. SLR should be used to draw attention to research gaps and researcher effort [27,28].

2.1. Information Source

This study followed the literature review style recommended by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses. *three digital databases, namely, Web of Science (WoS), ScienceDirect (SD), and IEEE Xplore were selected*. WoS is an extremely reliable resource on social sciences, engineering, science, arts, humanities, and cross-disciplinary studies. SD provides access to a highly reliable journal in the field of science and technology. IEEE Explore contains updated research papers in the field of computer science, electronic engineering, and the applications of engineering and computer technology in medical applications.

2.2. Search Strategy

The search was initiated in the advanced search boxes of the previously mentioned scientific databases on. Boolean operators (i.e., *AND* and *OR*) were used for the search and two groups of keywords (i.e., *queries*) were utilized in the process, as shown in Figure 1 as follows:

("Water Quality" OR "Water Management") AND (IoT OR "internet of things")

The previous process was performed to retrieve the most related articles. In searching and filtration, content based on various types of publication articles (reviews and research articles) was chosen. This option was deemed efficient for covering the latest and most relevant publications in the designated topic of this review.

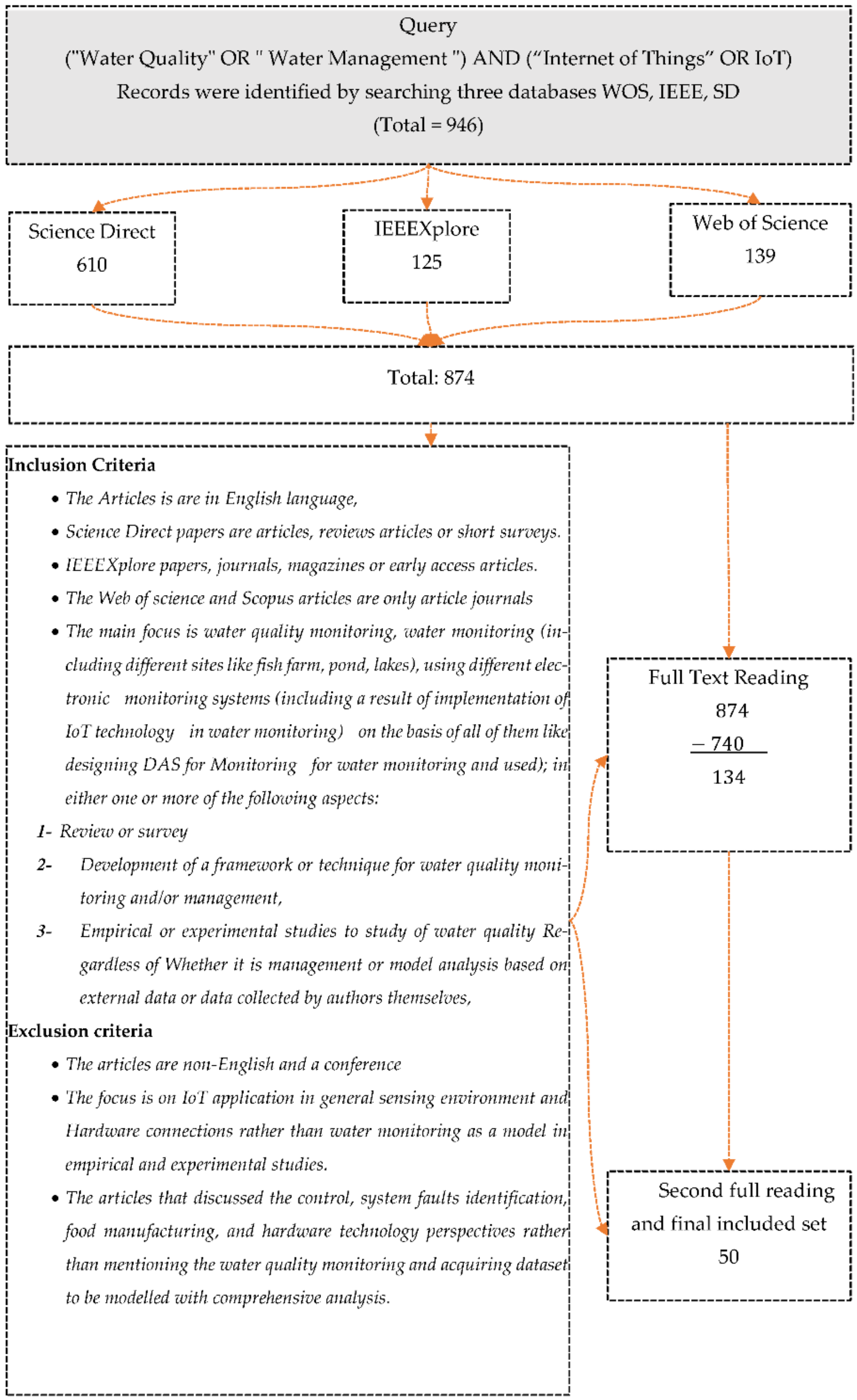

Figure 1. Systematic review protocol.

2.3. Study Selection

The three steps that in this research procedure were article gathering, title and abstract scanning, and full-text reading. In the first step, using Endnote software, papers published between 2018 and 2022 (5 years) were collected and duplicate articles from all the databases were discarded, the articles with the initial number n = 946 were collected from the chosen databases. The second step involved searching through the abstracts, titles, and keywords of papers to find those that were relevant. By carefully examining the titles and abstracts of each retrieved article, it was determined whether it satisfied the inclusion requirements. An article was included in the final round when it matched. The final step involved reading the entire manuscript. A total of 50 related papers were found. This final set of articles that met the inclusion criteria defined in this study underwent full-text reading, and usable and important information (i.e., data extraction) was extracted. 50 papers made up the final set of articles that were reviewed. The systematic review protocol is depicted in Figure 1.

2.4. Inclusion and Exclusion Criteria

2.4.1. Inclusion Criteria

The articles are in English language and the papers are based in Science Direct which are articles, reviews articles or short surveys. IEEEXplore papers, journals, magazines, or early access articles. The Web of science articles are filtered to article journals merely. The main focus in the inclusion criteria is water quality monitoring, data collection from water sites (including different sites like fish farm, pond, lakes, etc.), using different electronic monitoring systems (including a result of implementation of IoT technology in marine monitoring topics) on the basis of all including all the components of DAS designing and implementation for monitoring water quality) and used; in either one or more of the following aspects:

1- Review or survey
2- Development of a framework or technique for water quality monitoring and/or management,
3- Empirical or experimental studies to study of water quality regardless of Whether it is management or model analysis based on external data or data collected by authors themselves. However, the articles with no clear data collection procedure (no DAS) and comprehensive analysis are neglected in the three proposed tables of analysis.

2.4.2. Exclusion Criteria

The articles are non-English written and are conference papers. Also, other articles excluded due to its focus is on IoT application in general sensing environment and hardware connections rather than water monitoring as a framework/model in empirical and experimental studies. Other publications, particularly those that focused on hardware control, system optimization, identifying system defects, and big data analysis without an IoT hardware perspective, were excluded in favor of those that examined water quality and collected datasets for detailed analysis.

3. Taxonomy

In this section, the taxonomy of the study is drawn and explained. Drawing the taxonomy assists in understanding the various works accomplished in the respected area from the authors' points of view by grouping the related articles into sections and subsections. Figure 2 demonstrates the taxonomy of the study. This taxonomy contains two main categories; AI-based methods articles and non-AI-based methods articles.

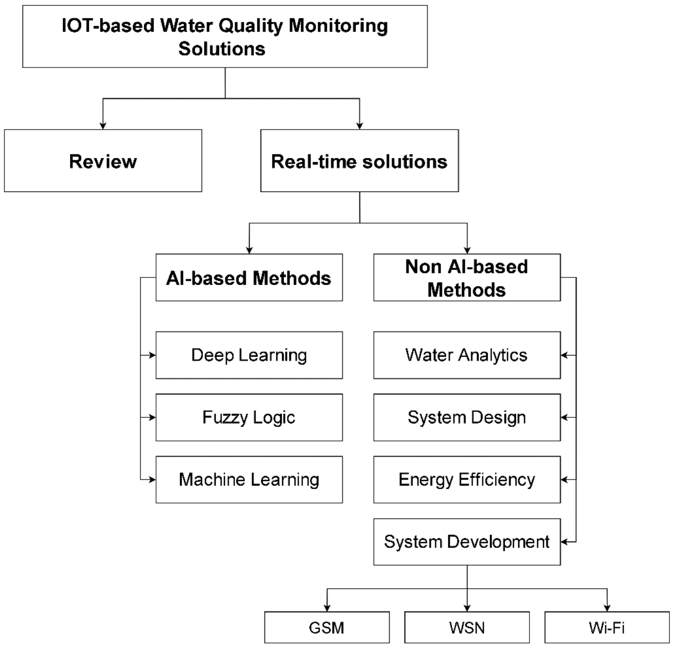

Figure 2. The taxonomy of the study.

3.1. AI-Based Methods

In this section, nine (n = 9) articles utilized different AI-based methods to develop a real-time system to monitor and analyze water along with IoT solutions. The AI-based methods section consists of three sub-categories; machine learning methods, fuzzy logic methods, and deep learning methods.

3.1.1. Machine Learning Methods

This sub-category includes all the articles that utilized machine learning algorithms to develop systems and methods to provide a real-time IoT-based system to monitor and analyze water. Five (n = 5) articles are included in this sub-sub category. In the first article, an unsupervised machine learning algorithm, namely, K means was utilized to monitor the quality of water and detect any abnormality by processing instantly the data collected from Turbidity, Conductivity, and pH sensors implemented in IoT devices [29]. In the second article, an IoT-based fish farming and tracking control system equipped with a pH sensor, water electrical conductivity sensor, water turbidity sensor, dissolved oxygen sensor, and temperature sensor was developed [7]. In this system, a forecasting method was introduced by using a local outlier factor algorithm to enable automatic water quality management along with tracking the fish breeding and fish sale. The system utilized the Random Forest algorithm, a supervised machine learning algorithm, and fuzzy dynamic to build and merge a tree of decisions and, hence, to provide an accurate water quality result. In the fourth article, a real-time water quality and groundwater level monitoring system of the entire area is developed based on IoT devices that are equipped with pH, TDS, ultrasonic water level, and salinity sensors [13]. A linear regression model was implemented to predict the level of groundwater in the future based on the current consumption. In the last article, an IoT-based water quality evaluation model for Black Tiger Prawn farming was developed utilizing a decision tree algorithm to reach the optimum water quality [30].

3.1.2. Fuzzy Logic Methods

In this sub-category, all the articles that utilized fuzzy logic algorithms to develop systems and methods to provide a real-time IoT-based system to monitor and analyze water are included. One (n = 1) article is included in this sub-category. In the article, an IoT-based water quality monitoring system was proposed using wireless sensor networks equipped with water quality sensors, namely, turbidity, conductivity, temperature, pH, and oxidation-reduction potential sensors [31]. Fuzzy logic was implemented in the system to predict at the local level the water contamination risk in the water distribution pipelines.

3.1.3. Deep Learning Methods

This sub-category includes all the articles that utilized deep learning algorithms to develop systems and methods to provide a real-time IoT-based system to monitor and analyze water. Three (n = 3) articles are included in this sub-category. In the first article, an IoT-based smart water quality monitoring system was developed with the assessment of big data and long short-term memory (LSTM) deep neural networks to utilize time-series prediction in predicting the quality of drinking water [32]. In the second article, the LSTM algorithm was utilized to monitor and predict the quality of water in aquaculture and fisheries for an IoT-based real-time water quality system using salinity, dissolved oxygen, temperature, and pH sensors [14]. In the third article, a water demand forecasting method was developed using the LSTM algorithm for a real-time IoT-based water distribution monitoring system, and based on the results, a water distribution network system was designed for the development of a smart water distribution system [33].

3.2. Non-AI-Based Methods

In this section, all the IoT-based water monitoring designs, and solutions without utilizing artificial intelligent methods are included. This section consists of forty (n = 40) articles, and it includes four sub-sections; efficiency optimization, water analytics, system design, and system development.

3.2.1. Energy Efficiency

This sub-section discusses the optimization methods or framework of energy efficiency consumption using IoT devices, and this sub-section includes two (n = 2) articles. In the first article, an approach was developed to the allocation of resources in an IoT sensor network for optimal and sustainable use of resources to monitor the quality of water by developing a successive wireless power sensor network system embedded with a scheduling algorithm and operating as a non-orthogonal multiple access system [34]. In the other study, different energy-efficient solutions are presented for wireless sensor systems to assist in reducing the energy consumption and energy scarcity of real-time water quality monitoring systems [18].

3.2.2. Water Analytics

This sub-section discusses the articles that concentrate on water analytics with the use of data analytics platforms or big data analytics. In this sub-section, three (n = 3) articles are included. In the first article, the data of IoT sensors were acquired in real-time for water management in cities to monitor water quality and alert water leaks [35]. Due to the huge data acquired at the same time, big data analytics is utilized with the use of the Supervisory controller and data acquirement approach. In the second article, a cloud-based analytical platform was developed for an IoT-based real-time water quality system using big data analysis technology [36]. In this platform, the data for water quality monitoring are collected, cleaned, and analyzed automatically. In the third article, water quality monitoring was developed using the IoT-based ThingSpeak platform using MATLAB programming software [37]. This platform provides analytic tools and visualization to test water samples using turbidity and TDS sensors.

3.2.3. System Design

In this sub-section, articles that designed a system but were not implemented fully are discussed. This sub-section includes seven (n = 7) articles. In the first article, a real-time IoT-based smart river monitoring system was designed with the use of unmanned aerial vehicles (UAVs) or drones and lower power wide area communication technology [16]. In the second article, a real-time IoT-based drinking water quality monitoring system was designed using ZigBee and pH, turbidity, temperature, broken-down oxygen, and conductivity sensors [38]. Another study utilized ZigBee with Wasp mote to design a real-time IoT-based continuous water monitoring and water quality controlling system using pH, temperature, turbidity, dissolved oxygen, Calcium, and Chloride sensors [39]. In the next study, an integration between amphibious UAV and hovercraft was designed and a prototype was developed for an IoT-based monitor water quality system in a large area utilizing pH, DO, electrical conductivity, and turbidity sensors [40]. In this study, real-time IoT-based water quality monitoring was proposed for fish pond owners to maintain normal water levels in fish tanks using pH and ultrasonic sensors [41]. In this study, a remote real-time water and soil quality monitoring system was designed using pH, turbidity, electrical conductivity, and moisture sensors [42]. In the last study, an IoT-based portable drinking water quality monitoring system was proposed [43]. This prototype system consists of various types of parameters to analyze the taste, odor, color, Nitrate, Floride, Lead, Arsenic, and Chromium.

3.2.4. System Development

This sub-section discusses the articles that developed IoT-based water monitoring systems. In this sub-section, twenty-eight (n = 28) are included and the articles are divided into three categories based on the way of transferring the data, and these categories are GSM, wireless sensor node (WSN), and Wi-Fi.

GSM: Three articles (n = 3) are included in this category. In the first article, a real-time IoT-based water quality monitoring system was developed using temperature, pH, turbidity, ultrasonic, and flow sensors [44]. In this system, Data are sent to a cloud via GSM installed in the Arduino in a text-based notification. In the second article, integration between a Supervisory Control and Data Acquisition system and the IoT was proposed for real-time water quality monitoring to identify contaminated water and water leakage in pipelines [45]. In this system, temperature, pH, flow, and color sensors were utilized and data were sent using the GSM module. In a study, a real-time IoT-based portable water quality monitoring and notification system were developed using pH, temperature, conductivity, TDS, turbidity, dissolved oxygen, and salinity sensors [46]. In the system, the data are transferred to a cloud server "thingspeak" via GSM.

WSN: In this category, thirteen (n = 13) are included. In the literature, different studies integrated WSN with IoT to transfer the collected data from pH, temperature, turbidity and dissolved oxygen sensors to monitor the quality of water in real time [47–52]. In some articles, IoT-based real-time water quality monitoring systems were designed and developed using the Zigbee module to transmit the data via WSN [2,4,19,53–55]. Also, blockchain technology was integrated with IoT, WSN, and GIS technologies for real-time water pollution source tracing [56].

Wi-Fi: In this category, twelve (n = 12) are included. In the literature, various studies developed water quality monitoring systems based on IoT attached with sensors such as pH, temperature, and dissolved oxygen and send the readings of these data via Wi-Fi in real-time to ensure the quality of water is maintained and early detect any changes in the water [17,57–65]. A study has developed a real-time automated IoT-based system for water quality monitoring using pH, temperature, ammonia, and nitrate level of water sensors, and the data are transferred with the help of Wi-Fi for aquaponics farmers [66]. In another study, a real-time web-based water turbidity monitoring system was developed based on IoT to measure the water's cloudiness in pipes and the data were transferred via WiFi [5].

3.3. Review and Survey Articles

This section presents the article(s) that was proposed to investigate the literature on water quality monitoring. Authors in [18] reviewed the energy-efficient solutions for WSN for water quality monitoring systems. Only one article is presented in this section, indicating a research gap covering this important research area.

4. Discussion

In this section, included articles are analyzed and discussed. In this section, challenges, and recommendations are presented.

4.1. Challenges

In IoT-based water monitoring solutions, various challenges occur. This section discusses the main challenges found in IoT-based water monitoring solutions. Five main challenges are discovered in the literature related to water pollution, water management, farm management, traditional monitoring methods, limited water sources, and increasing population. Figure 3 demonstrates the main challenges of the study.

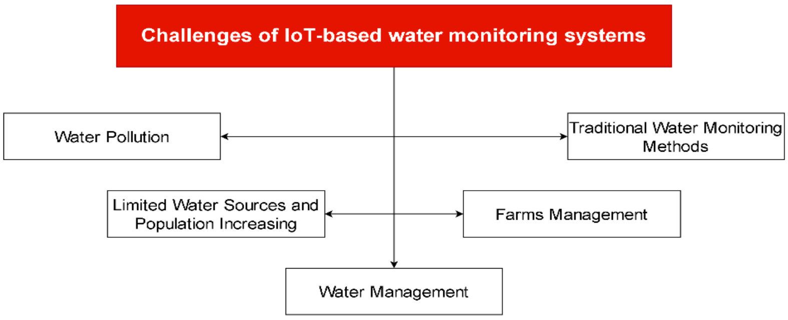

Figure 3. Main challenges.

4.1.1. Water Pollution

Water pollution is one of the main challenges globally. It is one of the major threats to sustainability. Currently, the water resources (i.e., rivers, lakes, seawater) are contaminated due to the rapid growth of human beings and the industrial companies that dump their wastes in the water [4,13,29,34,45,48,49,51,55,64,65]. However, water pollution contributes to various disasters despite the reduction of the available sources of drinking water. Heavy metal contamination that resulted from the illegal discharge of wastewater via irrigation channels is threatening agricultural production, public health, and the environment severely [56]. For instance, the pollution of water leads to an imbalance of the ecosystem and, hence, a threat to life [16]. Also, due to continuous water contamination, the quality of water is reduced [16,17,46,50]. Further, cleaning up the pollution will cost very high [16]. Moreover, the scarcity of the drinking water will result in the increase of water tariffs cost [16]. Contaminated drinking water is the main medium of transmitting serious diseases (e.g., diarrhea, typhoid, polio, cholera, and dysentery), which may cause serious health issues [31,44,48,50]. Also, the quality of aquaculture farms' production is affected large scale by the different water pollutions such as leakages in the sea and coastal discharges, and therefore, consumers' health is jeopardized [67]. Further, consumption of drinking water from water resources using complex buried pipe networks to commercial and residential areas may put the quality of water at risk being contaminated [5].

4.1.2. Limited Water Sources and Increasing Population

With the restricted natural water assets, providing resources for drinking water is getting challenging [17,38]. Over the earth, 71% is covered with water. However, only 2.5% of this water is freshwater [2]. In many regions of the world, water demand has exceeded supply and more regions are expected to face the same soon [13]. Finding natural drinking water resources is becoming harder over time due to the increasing population of the world, which results in increased water consumption [13,39]. Infact, the major sources of water are depleting rapidly [13]. Further, climate change and global warming has impacted the water resources significantly[13,14,39,49]. Due to the effects of water resources by climate changes, aquaculture and agricultural farmers suffered from economic losses due to the impacts of climate changes on production alongside with the costs of recovering from the damage [14].

4.1.3. Water Management

Managing and distributing drinking water and water supplies properly in urban areas is an extremely challenging task. The current distribution of water systems contribute to reducing the quality of drinking water due to pipes' erosion, pipes' breakdown, and interaction with pipe materials [33,49]. The procedure of distributing drinking water and water supply in urban areas is causing water supply tainting; whether incidental or intentional, which contributes to being a medium of transmitting microbes and bacteria and may cause serious health problems [44]. Also, with this procedure, drinking water is lavished in various ways such as wasteful use and poor water distribution [36]. Further, poor water management makes it challenging to keep up a water consumption record [36]. Moreover, the current irrigation process causes a large amount of water to be wasted due to the automated schedule of irrigation at a certain time, which is not considering the moisture in the soil and irrespective of the weather condition [35].

4.1.4. Farms Management

Managing fish farms and aquaculture production is an extremely challenging task due to the sensitivity and vulnerability of these creations to the quality of water. A few factors in a controlled cultivation environment could affect the quality of aquaculture lives such as human interventions, agricultural wastes, and pollution [53]. Poor management of farm management may cause viral diseases in fish and lead to significant losses to aquaculture and the death of fish [7,19,52,53,57]. In most aquaculture farms, agricultural managers have no enough media and techniques to forecast environmental factors, which is making risk management an impossible task [14]. Managing the quality of water in aquaculture farms manually is a complex task due to the need for a systematic approach to be alleviated [52].

4.1.5. Traditional Monitoring Methods

The existing water monitoring systems and devices suffer from various shortages. Current traditional systems are big and costly to keep up in monitoring [15]. Traditional monitoring systems require a lot of human effort in water quality monitoring, which consumes a lot of time and labor costs [17,37,40,50,57,65,66,68]. In the traditional water quality prediction model, some factors cannot be considered such as biology, chemistry, physics, hydraulics, and meteorology factors [32]. Some traditional monitoring systems lack analysis and processing of the collected data [7]. Also, existing water quality monitoring systems are dismissing data analysis and the water quality data resource attributes and focus on water quality data monitoring [36]. Due to transmission failures and power failures sometimes, some data loss and dirty data may occur, which affects the quality of data monitoring and analysis [36,57].

The existing communication technologies (e.g., 3G, Bluetooth, WiFi, and Zigbee) suffer from short communication ranges and high power consumption [16,18]. Transferring the data between the sensors and core network using satellite-based communication is considered slow and very costly [45]. Currently, water quality parameters are collected using fixed location sensors, which reduces the accuracy of the measured data [16,45]. Usually, measuring the water quality is accomplished based on a single spot with no spatial coverage [2,50]. Besides that, the manual lab-based water quality monitoring approach suffers from low sampling frequency [2,47]. Some sensor nodes utilize radio frequency identification (RFID), which makes it challenging to main and cannot be used in applications with restricted access [47]. For the water distribution network, the wireless sensor networks have a limited number of sampled locations at a certain time and the equipment operating is costly [31]. The use of radio frequency energy harvesting in monitoring systems is insufficient due to the nondeterministic and uncontrollable, which makes these systems difficult to be reliable [34]. Employing the model of a simultaneous wireless information power transfer is practically costly and the interference may suffer from problems [34]. Water quality sensor nodes in water quality monitoring systems include various resource constraints such as limited processing capabilities, limited energy, limited data storage memory, lack of communication capabilities, and energy limitation [18]. With the lack of real-time values, the accuracy of data is reduced due to the continuous change of water parameters, and hence, farmers are unable to be warned of the changes in water parameters, which makes them fail to make any preventive actions [30,50–53,65].

4.2. Recommendations

This section demonstrates the main recommendations of the previous studies to improve the field of IoT-based water monitoring solutions. This section includes three main categories as presented in Figure 4, namely, sensors-related, technology-related, and factors related.

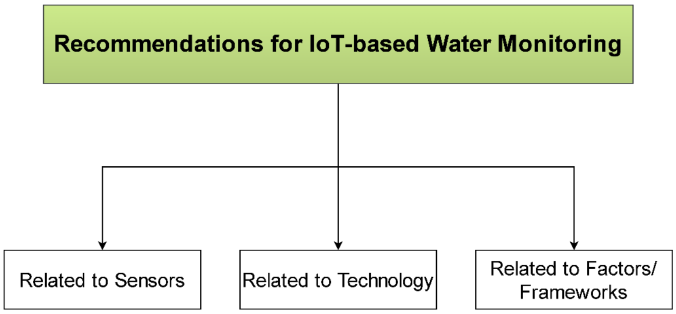

Figure 4. Main recommendations.

4.2.1. Sensor Related

To solve difficulties in the primary sector of the economy, additional research using cutting-edge remote sensing technologies and IoT-based solutions can be resorted [54]. Authors in [36] suggested that the water quality monitoring indicator database can be enlarged in the following step by increasing the number of water quality monitoring sensors to detect provide a comprehensive water quality indication. Authors in [44] discussed the future aspect of their implementation for future models by using flow sensors that could accurately measure up to 60 milliliters of water in place of the current model, which can only measure up to 30 milliliters of water. Authors in [58] mentioned their future steps by removing GSM hardware. Then authors can test to see if the system can receive emergency warnings from a cloud server over the internet to a mobile phone. Authors in [56] discussed that additional sensors established at appropriate upstream channels within the irrigation unit should be included in future studies using their blockchain tracing process to address any concerns caused by a lack of upstream water monitoring station data. Authors in [51] recommended that more sensors should be used in the future to collect more data that can be used for modeling.

4.2.2. Technology Related

In [6], the creation of intelligent water quality solutions utilizing cutting-edge technology that provide real-time data access is essential for the management of water resources. Designing structures that are adaptable, modular, scalable, and simple for the user to install is essential. Better real-time monitoring tools that combine notifications and social media alerts are likely to be the subject of future research. Additionally, it is advised to use a mobile application to scan the water's colorization and monitor red tides using image processing [54]. Authors in [33] proposed a system that may be expanded in the future to include the creation of a software agent-based model for underground pipe health monitoring and consumption monitoring utilizing intelligent agents that will alert the SCADA engineer for prompt control action and supply restoration. This intelligent agent would introduce automation of control during crucial periods as a safeguard. The authors proposed to concentrate on [57] evaluating and improving measuring procedures to increase the lifespan of sensor probes. Authors in [13] suggested that a Machine Learning technique can be expanded in the future to investigate the various physical characteristics of the water and forecast the location of a source of water experiencing an abrupt abnormal change in water quality, which can be useful in identifying and preventing contaminants from seeping into or being deposited into a source of water. The authors in [16] proposed to focus on a study in the future regarding the optimization of UAVs for sample WQ in rivers based on flying limits, power consumption, load, and river size in the usage of UAVs with LPWA communication technology. Miniature smart multi-parameter sensors for WQ will elevate the interest of study due to the load which plays a significant role.

The usage of multi-criteria network-aware service composition algorithms and some pertinent access control systems can be used in the interim to ensure access control and boost service quality [36]. Additionally, utilizing deep learning, neural networks, and other artificial intelligence technology can be tried to create a smart data analysis scheme to evaluate and forecast water quality [36]. Authors in [60] discussed the implementation of a prediction algorithm, that might be utilized to use the analytical data to predict the sources of pollution in the water. More data should be gathered in the future to improve the AI prediction model they have created [7]. Additionally, more detection tools like NO2 and heavy metals, which are the main contaminants that harm consumers and fish farms should be included [7].

Additionally, authors in [18] anticipated that their research can improve the development of wireless sensor network-based water quality monitoring within the context of environmentally friendly network operations. Also, they stated that proper discovery and exploitation of wireless energy transfer and optimization will enable sensors in a network used to monitor water quality to remain operational for an extended period. Authors in [64] elaborated that their research can be expanded to an automatic farm programmed in the future using the big data collected from the sensors, and we will use artificial intelligence to determine the best conditions for eels to grow. Additionally, it's crucial to safeguard wireless sensor data communication from interference [45].

4.2.3. Factors/Framework Related

Authors in [17] suggested that the analysis of additional characteristics such as electrical conductivity, free residual chlorine, nitrates, and dissolved oxygen in the water is also advised as part of their proposed system reliability check. Authors in [30] used an IoT device and decision tree algorithm to construct a water quality evaluation system specifically for the aquaculture of Penaeus monodon. However, the system can still be improvised by including an evaluation of other aquaculture to provide more assistance to fish farmers. The creation of a mobile application as the primary graphical user interface for the user is also advised for future researchers to make the system more direct and user-friendly than having users access it through a web browser.

Authors in [38] proposed that their designed system might be used to check the water quality for an entire town or city, depending on where the water supply is coming from, as well as for individual households. The appropriate period for cleaning the city water tank can be determined using this framework. Sooner rather than later, a cross-city or cross-town quality monitoring framework can be developed using a combination of different sensors. The researcher in [54] suggests changing the method to track how many heavy metals are added, removed, and reduced in the soil and water studies.

Authors in [63] proposed that future water quality estimate methods will take into account on the factors such as conductivity, hardness, chloride, smelling salts, press, fluoride, and others. These factors are used to assess the water's cleanliness for uses like drinking water and daily needs. Authors in [53] clarified that their future work will focus on the framework's applicability to pond areas between 2 and 5 acres in size as well as its deployment in the western Godavari region. Additionally, efforts are being made to create new ergonomic and cost-effective designs with the assistance of the industry in preparation for the product's commercialization for use by aquaculture farmers. Authors in [31] discussed the concentration of model optimization by merging the various water quality characteristics, to increase the model's accuracy by using multi-dimensional input datasets to forecast the target values.

5. Bibliography Analysis

In this section of the study, the researchers concentrated on compiling statistics for previous studies regarding the author's country, as shown in Figure 5, and it provides statistical information about the years of publication for the selected articles as shown in Figure 6.

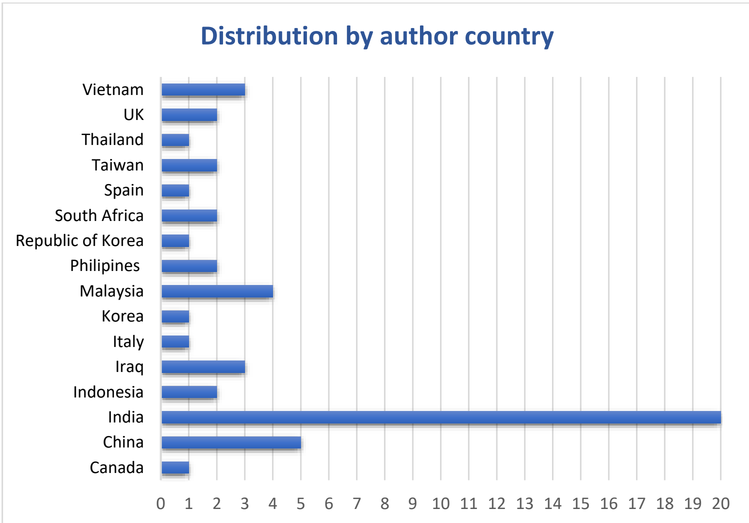

Figure 5. Distribution by country of author.

Figure 5 shows the corresponding author's country or the first author's country if the corresponding author was not clarified, for each study included in this review. There are 16 countries overall. Geographical distribution of the selected articles in terms of numbers and percentages reveal that India, with 20 study cases, is the country that contributes to the most, followed by China with five studies, Malaysia with four, Vietnam and Iraq with three, Indonesia, the Philippines, South Africa, and the United Kingdom with two each, Canada, Italy, Korea, the Republic of Korea, Spain, and Thailand with one study case each.

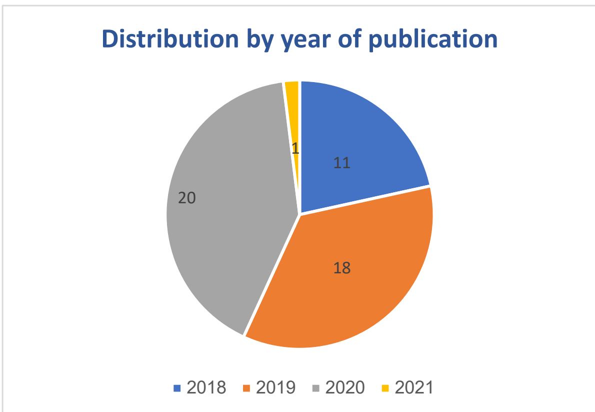

Figure 6. Distribution by year of publication.

Figure 6 illustrates the distribution of the selected articles over the selected period. There is a total of 50 articles, the highest year of publication was the year of 2020 with

20 articles, followed by the year of 2019 with 18 articles, then, the year of 2018 with 11 studies, and lastly the year of 2021 with only one article published in that year.

6. Future Research Directions

6.1. Technology

This section presents the analysis aspect of the Data Acquisition Systems (DAS) that were used to monitor and collect data on water quality in real-time experiments. The three columns in the fourth are used to measure the suitability of DAS, starting with identifying the types of hardware components, i.e., electronic boards, sensors, communication medium, and the technology of data transition to achieve IoT-based implementation. Accordingly, several evaluation criteria are proposed to evaluate the DASs proposed in the literature in terms of cost, complexity, and other criteria [69]. The Evaluation criteria are used with subjective evaluation values to reflect the general aspect of DASs performance and characteristics including physical and software computational based.

This section presents articles that used DAS to collect water quality data. Table 1 lists articles with corresponding evaluation values by the assessment criteria. Design and implementation procedures are examined and reviewed subjectively to analyze the cost-effectiveness of currently available DAS in the literature using the following criteria. (1) Design and Programming: These procedures should be performed when sophisticated devices are integrated into the DAS design. Notably, adding more electronic boards/sensors to a DAS system requires more time to program/interface these devices, i.e., not plug and play. (2) Operation and Maintenance: Routine procedures should be performed on a large DAS to ensure that sophisticated sensors/board components are working properly; if they fail, then replacing them is not economical. (3) Equipment Reliability: If the electronic components of DAS are expensive/sophisticated, then the DAS is mostly reliable; otherwise, using unreliable components is not cost-efficient, i.e., off-the-shelf components have low reliability compared with sophisticated ones. (4) Implementation Cost: This criterion refers to the cost of wiring/adjustment and modification performed on a site location to house DAS components. These modifications increase implementation costs, and DAS which requires a low level of maintenance on the location site must be designed. In the end, cost-efficiency is evaluated subjectively depending on the DAS design layout and provided features. (5) Total Equipment cost: This criterion indicates/describes the level of cost-efficiency of the currently proposed/implemented DAS. For example, if DAS consists of NB-IoT, Wi-Fi, and UAV with 15 or 20 sensors, then the system exhibits a very high cost. All the assessment criteria are subjectively evaluated in five scales (very low, low, medium, high, and very high). (6) DAS Size: This criterion describes the size of the architecture of the proposed DAS in the literature. The assessment value considers the number of electronic elements of DAS. (7) Power Consumption: This criterion estimates the power level required by DAS to fully operate. (8) Latency: This criterion is the time between cause and effect, i.e., the time that elapses when DAS starts measuring the environment until the outcome is delivered to the user. (9) Information Size: This criterion represents the amount of raw data that DAS can collect. (10) Information Diversity: This criterion represents the variety of raw data that DAS can collect. (11) Computational Complexity: This criterion represents the difficulty in processing the amount of collected raw data, i.e., the higher number of boards and sensors can cause this criterion to go high. (12) DAS Complexity Level: This criterion assesses the overall level of complication in the current proposed/implemented DAS in the literature based on the preceding criteria. For example, if the DAS system consists of an Intel board MCU (FPGA), hardware-based computational algorithm, a high number of sensors, and more than one MCU, then the complexity level is very high. DAS complexity increases as the number of components increases. The power consumption of DAS increases following the sophistication of electronic devices and the medium of data transmission. A LoRa technology consumes less power than Wi-Fi, NB-IoT, and ZigBee. NB-IoT consumes very high power compared to Wi-Fi, ZigBee, and LoRa. However, the bit rate of LoRa is limited compared to NB-IoT, ZigBee, and Wi-Fi technologies. Moreover, DAS size affects the power consumption level because increasing the number of layouts and connection cables increases the power consumption level. The power Standalone criterion represents DAS's capability to be powered using solar panels or thermoelectricity sources.

DAS latency criterion represents the entire latency of the DAS system to acquire real-time data from the field of experiment. DAS latency is also related to the technology of data transmission from the experimental site, the number of sensors connected to the MCU board, the number of MCU boards, and cloud-based or gateway-based IoT architecture. Also, using different technologies in one architecture increases the DAS latency, i.e., if ZigBee, NB-IoT, and UAV are in one IoT structure, hence the DAS poses a considerable amount of latency. Hence, the complexity of DAS is related somehow to the DAS latency. Also, the information size of collected raw data increases DAS complexity because additional time is required to process the received amount of data. Information diversity also indicates that DAS needs varied processing/analysis tools to produce raw data.

It can be seen from Table 1 that different electronic boards have been proposed in the literature. The off-the-shelf components (Arduino, Raspberry Pi) were the most used ones in experimental studies. A few other boards from Intel and other manufactured companies are also used. However, these boards are required to be programmed before usage, not like off-the-shelf components. Also, the technology most widely adopted in communication is Wi-Fi, which connects the MCU board to the internet via a wireless connection. This, in turn, needs to be supplied with a power resource and it's a problem for remote locations. LoRa and ZigBee communication technologies are also used with low power consumption. However, Zigbee is used for short-range communication (10–100) m while LoRa is used for WAN to cover (1–5) km in the city and 15 km in the open area. It can be pointed out from this Table that developers did not use Nb-IoT technology in their implementation. This raises a concern about its suitability for IoT applications as it might be related to power consumption, cost, and DAS complexity since this technology requires special operation and maintenance. Wi-Fi technology is also used in connecting the main controller board to the internet gateway. However, this technology consumes a lot of power and only works for a short range despite its availability and cost efficiency. Hence, this technology is not suitable to be deployed in a long-range or wide area.

For the sensor part, the PH sensor is the most used in the literature, followed by turbidity, conductivity, temperature, and O_2 sensors. The chemical characteristics sensors are less used in real-time experiments like Nitrite, Fluoride, Chloride, and Sodium sensors. Some IoT solutions proposed in the literature focus on constructing a cost-efficient architecture, neglecting the reliability and scalability of these architectures. I.e., it's not feasible to connect 15 sensors to a single off-the-shelf MCU board since the data collected needs larger memory to preprocess the collected fetched raw data. Moreover, providing power to the off-the-shelf boards is challenging in its nature since these boards are limited in their hardware and software capabilities. Moreover, no solution offered a data fusion technique to provide a reliable dataset. The literature lacks solutions that provide algorithms that preprocess collected raw data and use manual data cleaning and wrangling, which are time-consuming when it comes to providing reliable and authenticated datasets since the synchronization of these sensors is an issue.

The sensors' types might be chosen according to the current sensors' capability to record and sense entities in real-time traffic conditions. The used sensors must assess the quality of water (Ph, temp, Oxygen, etc.), and the status of the monitoring system (active, idle, or sleepy) ensuring a reliable communication architecture. Such metrics might offer a whole picture regarding the pattern of water quality and identifying the critical water quality conditions. Moreover, an approach to selecting a combination of adequate sensors was required to detect and record all features/factors. As a result, more research is required to evaluate the efficiency of sensors in determining water quality. To determine which equipment, whether it be a sensor or a DAS in various circumstances and at various times, best captures water characteristics, a generic framework to define the procedure of selection and benchmarking is required. A trade-off between complexity, cost-efficiency, and scalability criteria should be considered by the framework.

6.2. AI Models

It can be seen from Table 2 that different types of articles proposed in the literature attempt to implement artificial intelligence in the design and process of water quality monitoring. However, these attempts are limited to a total number of proposed models. Different machine learning algorithms were adopted to predict the quality of water with no clear or valid procedure to select the most suitable one.

Since the evaluation of missing data, specifically looking at its impact on the accuracy of data labeling and classification, has not yet been conducted, the treatment technique for missing data is not clear within the literature. There is only one article considered the missing data effect on classification accuracy, others either removed the missing points or did not mention the way of treatment in Table 2 which shows that authors could not discuss the issue of unbalanced data, insufficient data, or data bias as they are well-known issues for classification algorithms. Multi-class categorization is a problematic, widely used approach. The issues with multi-class classifications that are most frequently mentioned are class separability, class overlaps, and imbalances between and within classes. Multi-class categorization might become severely complex as a result of nonlinear patterns that are not visible in the dataset [70,71].

There is also disagreement about how many machine learning algorithms should be used for water quality modeling. Table 2 shows that the majority of the writers either used data collection systems (DAS), or specially created equipment to get their data, proving that there is no freely available, easily usable data.

Data labeling is the process of giving each collected piece of information a name that accurately describes its category. A data pre-processing method for identifying the good quality of water is labeling. In the literature, there have been two basic approaches suggested for labeling datasets. Specifically, manual testing. This method involves doing a normal experiment to gather data on normal water quality patterns by employing manual procedures for data labeling by applying thresholds and rules. The second approach is automated data labeling which can be done using unsupervised machine learning.

Without human intervention, the data is automatically labeled in automated labeling; however, the labeling process is carried out using rules and equations that have been developed for other case scenarios in a separate field with a different objective. Also possible are biases or errors in the expert labeling. However, there is no agreement on the best method to use most effective method (expert labeling or questionnaire, automated, unsupervised machine learning-based, etc.). The right way to label something is also a topic of disagreement. The labeling method has not yet taken unsupervised learning into account. To efficiently label data, it is advised to study the effectiveness of unsupervised learning algorithms. K nearest neighbors is a popular machine learning strategy for this work, although careful tuning is advised, especially when picking the K number.

Although deep learning approaches may need a large number of datasets, they are still recommended. To evaluate whether they can improve recognition models, augmentation pre-processes and other data maximization techniques can be looked at. In addition, more research is needed to determine how imbalanced datasets affect the labeling process and model accuracy. Future research is advised to address missing data handling in the pre-processing stage. It is suggested that an investigation to be conducted on how missing data affects the labeling process and classification accuracy. The optimum machine learning to input the missing data should be chosen using a framework. Finding the sample size is another aspect of future directions. It is necessary to go into further detail on the sample sizes needed for real-time experimental experiments. For small-scale, financially-effective, in-the-moment investigations, knowing the number of observations is a huge advantage.

6.3. Geographical of Real-Time Experiments

It can be seen from Table 3 that the location of experiments is 3 river sites, 2 lake sites, and other sites. 3 sites were used to conduct experiments for water quality monitoring for fish farming. 2 other sites were used to monitor wastewater quality levels. Hence, it can be pointed out that there is no agreement on the site location of the experiment. Each experiment was customized to be fitted within the environment of sense. The result of experimenting is reflecting the living conditions of living species according to the quality level of water, i.e., experimenting with aqua water is different that river, lake, and farming water. Also, the number of sites is different from one experiment to another. Hence, there is no agreement on the number of sites and each DAS used to measure the water quality was customized only to be employed within these sites. No general framework is provided to compare DASs and no generalized design model or architecture that is flexible enough to be deployed in any place. Even though the time of experiments was conducted in a brief period, the experiments were deployed to provide a concept of implementation not only for continuous monitoring which is in the span of 1 or 2 years of monitoring. As this long period can test the real performance of DAS, and collect data in different weather conditions, not just in normal conditions.

Hence, there is no generalized model that can always reflect the quality level of water, in all locations.

6.4. Dataset Issues

The lack of the necessary acceptable experiential data for investigating the characteristics of water quality, which forced researchers to create only experimental models, was one of the unique difficulties they faced. As a result, the slow growth of this field of research remains problematic. Insufficient style representations are produced by outdated data and brief, incomplete periods. The accuracy of the adjustment procedure is impacted by incomplete datasets. It is difficult to develop an exact model to evaluate water quality. Unrecognized characteristics influence water quality. Real-time monitoring has several flaws, and data on water quality aspects have not been sufficiently varied to accurately reflect the pattern of quality water. Biased datasets may be produced when fields are used in water quality investigations. Future studies on water quality monitoring might consider developments in measurement technology and undertake tests in remote locations. Additionally, smartphone sensor apps may offer important opportunities for determining the quality of the water. Future research should also explore how missing data affects how water quality monitoring and testing is categorized and recognized. To gain additional knowledge about evaluating water quality, a full framework that conducts real-time tests in various places, at various times of day, and in various weather situations is suggested.

7. Comparing This Work to Previous Work

This study presents a comprehensive review conducted on various but related research topics concerning water quality monitoring. As far as we know, no survey articles or reviews cover the model regarding water testing and monitoring from the perspective of data sources or provide a thorough analysis related to data collection with the use of electronic devices in real-time fields. The existing literature does not offer extensive knowledge to evaluate the presently suggested/used classification/regression model's performance. In addition, the number of researchers exploring the classification model's functionality, cost efficiency, and complexity are lacking. Choosing the optimum cost-effective/practical DAS was complicated because of the lack of clear criteria concerning performance evaluation. Therefore, this work aims to analyze the literature associated with water quality monitoring models, types of data, and systematically searched related articles. Table 4 shows the differences between the presented study and previous ones.

Table 1. Technology Analysis of Water Quality Monitoring.

Ref.	Main Board	Medium of Communication between Sensors and MCU (GSM/GPRS/Cable)	Number of Sensors	Ph Sensor	Conductivity Sensor	Turbidity Sensor	Ammonia Sensor	Flow Rate Sensor	Ultrasonic Sensor	Humidity and/or Temperature Sensor	Total Dissolved Solid Sensor	O2 Sensor	Calcium and Chloride Sensor	Water Level Sensor	Co2 Sensor	ORP Sensor	Chemical Oxygen Demand	Oil Content/Pressure Sensor	GPS Sensor	Nitrite Sensor	Fluoride Sensor	Chloride Sensor	Sodium Sensor	Cadmium/Chromium Sensor	Copper Sensor	Zinc Sensor	Nickel Sensor	Lead Sensor	Color/Odour/Taste Sensor	Soil Moisture/Pesticides/Arsenic Sensor	Number of Electronic MCU Boards	Design and Programming	O/P	Equipment Reliability	Implementation Cost	Total Equipment Cost	DAS Size	Power Consumption	Power Stand Alone	DAS Latency	Information Size	Information Diversity	Computational Complexity	DAS Complexity
[16]	UAV	LoRaWAN + Cloud	8	×	×	×	×			×		×					×	×													1	VH	VH	H	VH	VH	VH	VH	No	H	VB	H	H	VH
[4]	MCU + Zigbee	Zigbee + IoT	4	×						×	×				×																2	M	M	L	H	M	M	M	No	M	M	L	M	H
[39]	ARM microprocessor + Zigbee	Zigbee + IoT	3	×		×			×																						2	L	L	L	L	L	M	M	No	M	L	L	M	H
[40]	Waspmote + Zigbee + Cloud	Zigbee + IoT	7	×		×				×		×	×	×	×																1	H	L	H	H	H	M	H	No	M	H	H	H	H
[30]	Arduino	Offline	3	×		×		×																							1	VL	M	L	L	M	S	L	No	L	L	L	L	M
[72]	LoRa node and Rx64M MCU	Offline	3	×						×	×																				1	L	L	L	L	L	VL	L	No	L	L	L	VL	L
[32]	Arduino ATmega + Sensors	Zigbee	6	×	×	×				×		×				×															1	M	H	L	M	L	B	M	No	H	M	M	M	M
[67]	Sensor(I2C) + ESP8266 MCU + IoT	I2C/WiFI	1																										×		1	VL	VL	VL	L	L	VL	VL	No	VL	VL	VL	VL	VL
[73]	Arduino + (TX/RX)	offline	4	×	×	×		×																							1	H	M	L	L	L	M	L	No	M	L	M	L	M
[37]	Special Design+ Wireless	4G	3	×		×					×																				1	VH	H	H	VH	H	VB	H	No	M	L	L	L	VH

Table 1. *Cont.*

Ref.	Main Board	Medium of Communication between Sensors and MCU (GSM/GPRS/Cable)	Number of Sensors	Ph Sensor	Conductivity Sensor	Turbidity Sensor	Ammonia Sensor	Flow Rate Sensor	Ultrasonic Sensor	Humidity and/or Temperature Sensor	Total Dissolved Solid Sensor	O2 Sensor	Calcium and Chloride Sensor	Water Level Sensor	Co2 Sensor	ORP Sensor	Chemical Oxygen Demand	Oil Content/Pressure Sensor	GPS Sensor	Nitrite Sensor	Fluoride Sensor	Chloride Sensor	Sodium Sensor	Cadmium/Chromium Sensor	Copper Sensor	Zinc Sensor	Nickel Sensor	Lead Sensor	Color/Odour/Taste Sensor	Soil Moisture/Pesticides/Arsenic Sensor	Number of Electronic MCU Boards	Design and Programming	O/P	Equipment Reliability	Implementation Cost	Total Equipment Cost	DAS Size	Power Consumption	Power Stand Alone	DAS Latency	Information Size	Information Diversity	Computational Complexity	DAS Complexity
[58]	RF LoRa + IoT	WiFi/2G/3G	4	×						×		×				×															1	VH	H	M	H	H	B	H	No	M	M	M	L	H
[59]	Raspberry pi + Sensors	WiFi	5	×		×				×				×	×																1	M	L	L	M	M	M	H	No	M	M	H	M	M
[41]	Sensor + Arduino + RPI + 4G + UAV	4G	4	×	×	×				×		×																			2	VH	VH	VH	VH	VH	B	H	No	H	H	M	M	VH
[60]	Arduini + NB-IoT	GSM	3	×						×		×																			1	VH	VH	M	VH	M	VB	H	No	M	L	L	L	H
[54]	Intel Edison + Zigbee to sensors + Wifi to server	WiFI	3	×						×		×																			1	H	H	L	M	M	S	VH	Yes	H	M	L	L	H
[61]	Arduino + ESP8266	WiFi	5	×		×		×		×									×												1	H	L	M	H	M	B	H	No	L	M	M	M	H
[62]	NB-IoT	4G	7	×			×			×	×	×		×	×																1	H	H	M	H	H	B	H	No	M	M	M	M	H
[55]	P89V51RD2 MCU + Zigbee + Sensor	Zigbee	4	×						×		×		×																	1	M	L	L	L	L	M	L	No	M	M	M	L	M
[49]	ESP8266 + (cable) Sensors	WiFI	4	×						×				×	×																1	L	L	L	L	L	L	H	No	L	S	M	M	L

Table 1. *Cont.*

Ref.	Main Board	Medium of Communication between Sensors and MCU (GSM/GPRS/Cable)	Number of Sensors	Ph Sensor	Conductivity Sensor	Turbidity Sensor	Ammonia Sensor	Flow Rate Sensor	Ultrasonic Sensor	Humidity and/or Temperature Sensor	Total Dissolved Solid Sensor	O2 Sensor	Calcium and Chloride Sensor	Water Level Sensor	Co2 Sensor	ORP Sensor	Chemical Oxygen Demand	Oil Content/Pressure Sensor	GPS Sensor	Nitrite Sensor	Fluoride Sensor	Chloride Sensor	Sodium Sensor	Cadmium/Chromium Sensor	Copper Sensor	Zinc Sensor	Nickel Sensor	Lead Sensor	Color/Odour/Taste Sensor	Soil Moisture/Pesticides/Arsenic Sensor	Number of Electronic MCU Boards	Design and Programming	O/P	Equipment Reliability	Implementation Cost	Total Equipment Cost	DAS Size	Power Consumption	Power Stand Alone	DAS Latency	Information Size	Information Diversity	Computational Complexity	DAS Complexity
[56]	Arduino + Xbee + Sensors	Zigbee	2	×						×																					2	H	M	L	M	M	B	M	No	VH	VS	VL	VL	H
[63]	NodeMCU ESP8266 + Wifi	Wifi	4	×	×	×		×																							1	VL	VL	L	L	L	VS	H	No	M	M	M	L	M
[42]	Pic16f877a + Sensors	offline	2	×					×																						1	L	L	VL	VL	L	S	L	No	VL	S	L	L	L
[45]	Arduino + ARTIK cloud	WiFi	5	×		×		×	×	×																					1	L	L	L	L	M	S	H	No	VL	M	M	L	M
[43]	Sensors(cable) +Arduino+ Raspberry Pi	WiFI/GSM	4	×	×	×																								×	2	H	H	L	L	M	M	H	No	H	M	M	M	H
[13]	RaspberryPi+ loRaWAN	2G/3G	4	×	×				×		×																				1	H	H	M	H	H	M	M	No	M	M	M	L	H
[51]	Raspberry Pi ZeroW + SimCom(Sim800)	GSM/GPRS	1																	×											2	H	H	H	H	H	B	M	No	M	VS	VL	VL	H
[44]	Arduino + Ethernet	Ethernet	15	×	×	×		×										×		×	×	×		×				×	××	××	1	H	H	M	M	H	B	H	No	H	M	VH	H	H
[64]	RaspberryPi + Sensors	Simple internet connection	4	×						××	×																				1	L	L	VL	L	L	M	M	No	L	S	L	L	M

Table 1. *Cont.*

Ref.	Main Board	Medium of Communication between Sensors and MCU (GSM/GPRS/Cable)	Number of Sensors	Ph Sensor	Conductivity Sensor	Turbidity Sensor	Ammonia Sensor	Flow Rate Sensor	Ultrasonic Sensor	Humidity and/or Temperature Sensor	Total Dissolved Solid Sensor	O2 Sensor	Calcium and Chloride Sensor	Water Level Sensor	Co2 Sensor	ORP Sensor	Chemical Oxygen Demand	Oil Content/Pressure Sensor	GPS Sensor	Nitrite Sensor	Fluoride Sensor	Chloride Sensor	Sodium Sensor	Cadmium/Chromium Sensor	Copper Sensor	Zinc Sensor	Nickel Sensor	Lead Sensor	Color/Odour/Taste Sensor	Soil Moisture/Pesticides/Arsenic Sensor	Number of Electronic MCU Boards	Design and Programming	O/P	Equipment Reliability	Implementation Cost	Total Equipment Cost	DAS Size	Power Consumption	Power Stand Alone	DAS Latency	Information Size	Information Diversity	Computational Complexity	DAS Complexity
[57]	Smart Water Sensors + RF 900 MHZ	WiFI to cloud	8	×	×					×														×	×	×	×	×			1	H	H	H	H	H	VB	VH	No	L	B	M	M	M
[19]	Arduino + RF ID+ ZigBee	Zigbee (sensors-Node) + RFID (among Nodes)	3	×						×		×																			1	H	H	L	H	M	M	H	Yes	H	S	L	L	H
[47]	MCU + GSM	GSM	3	×						×		×																			1	L	L	M	L	L	S	L	No	M	S	L	M	L
[46]	Arduino + Sensors	GPRS	3	×				×																					×		1	L	L	L	L	H	L	H	No	M	S	L	L	M
[17]	Arduino + Wifi + Sensors	(Wifi) ESP8266	4	×		×			×	×																					2	M	M	L	L	L	M	H	No	L	M	L	L	H
[52]	Arduino Atmel ATmega2560 + Wifi + Sensors	Wi-FiESP8266	10	×		×				×	×	×				×				×	×	×	×								1	H	H	L	H	M	B	VH	No	H	B	H	H	H
[65]	Raspberrypi + Wi-FI	Wi-Fi	4	×					×			×		×																	1	L	L	L	L	M	M	H	No	M	S	M	L	M
[38]	Arduino + Sensor	Wifi	2			×				×																					1	L	VL	L	L	L	L	H	No	L	S	L	L	L
[31]	Arduino + Wifi + Sensor	Wifi (Node MCU V3 ESP8266 Development Board CH340)	4	×	×					×		×																			1	L	L	VL	M	M	S	H	Yes	M	S	M	L	M

Table 1. *Cont.*

Ref.	Main Board	Medium of Communication between Sensors and MCU (GSM/GPRS/Cable)	Number of Sensors	Ph Sensor	Conductivity Sensor	Turbidity Sensor	Ammonia Sensor	Flow Rate Sensor	Ultrasonic Sensor	Humidity and/or Temperature Sensor	Total Dissolved Solid Sensor	O2 Sensor	Calcium and Chloride Sensor	Water Level Sensor	Co2 Sensor	ORP Sensor	Chemical Oxygen Demand	Oil Content/Pressure Sensor	GPS Sensor	Nitrite Sensor	Fluoride Sensor	Chloride Sensor	Sodium Sensor	Cadmium/Chromium Sensor	Copper Sensor	Zinc Sensor	Nickel Sensor	Lead Sensor	Color/Odour/Taste Sensor	Soil Moisture/Pesticides/Arsenic Sensor	Number of Electronic MCU Boards	Design and Programming	O/P	Equipment Reliability	Implementation Cost	Total Equipment Cost	DAS Size	Power Consumption	Power Stand Alone	DAS Latency	Information Size	Information Diversity	Computational Complexity	DAS Complexity
[66]	Arduino + Sensors	Offline	3	×		×					×																				1	L	L	L	L	M	S	L	No	VL	VS	L	L	L
[2]	DAS + IoT	Wifi	5		×	×				×		×				×															1	VH	VH	H	VH	VH	VB	H	Yes	M	B	M	M	H
[5]	Intel Galilo + Wifi	Wifi	1			×																									1	H	H	M	M	M	M	H	No	L	S	VL	L	M
[53]	Raspberry Pi + Wifi	WiFi	1							×																					1	H	L	L	L	M	S	H	No	L	S	VL	VL	M
[41]	Total			35	11	20	2	7	6	26	8	15	1	6	5	4	1	2	1	3	2	2	1	2	1	1	1	2	5	3														

VH: very High, H: High, M: medium, L: Low, VL: Very Low, VS: very small, S: Small, B: Big, VB: Very Big.

Table 2. AI Experimental Analysis.

Ref	Machine Learning Name	Classification or Regression (C/R)?	Labeling Method (Manual Automatic)	Feature Extraction Method (Manual, automated)	Data Source (Collected by Authors or Not	Number of Features	Data Size	Data Duration (Time)	Pre-Processing Required? (Y/N)	Number Metrics Used in Evaluation
[29]	K means	clustering	auto	NA	NA	NA	NA	NA	NA	NA
[7]	-LOF -model tree	classification and regression	auto	Auto	Authors	pH, temperature, electrical conductivity, turbidity, and dissolved oxygen	S (instantaneous)	Instantaneous	Y	Mean and correlation, MAE
[30]	RF + Fuzzy Logic	Regression	Manual	Manual	Authors	Turbidity, flow rate, and pH	M	NA	NA	Accuracy, MSE, RMSE
[33]	LSTM deep neural network	Regression	Manual	Auto	Authors	Temperature, pH, DO, conductivity, Turbidity, CODMn, NH3–N,	B	1 January 2016–30 June 2018	Y linear imputation model (missing data treatment)	MSE
[32]	Fuzzy logic	Classification	Manual	NA	Authors	Turbidity, Oxidation Reduction Potential, Temperature, pH, and Electrical Conductivity.	S instantaneous	Instantaneous	NA	NA
[14]	LSTM deep neural network	Regression	Manual	Auto	Other Authors	salinity, temperature, pH, and dissolved oxygen	B	NA	Y (remove missing value)	Root mean squared error (RMSE)
[13]	Linear Regression Algorithm	Regression	Manual	Manual	Authors	PH, conductivity, Salinity, water level	S	NA	NA	recharge rate and consumption rate.
[34]	LSTM deep neural network	Regression	Auto	Algorithm	Other Authors	1–3 Training Hidden Layers	B	1 January 2010 till 31 March 2018	No	MAPE, ACC, MASE
[31]	Decision Tree Algorithm	Classification	Manual	Manual	Authors	O2, pH, Temp, Ammonia NH3, Salinity	S	NA	NA	Correlation, (R) Mean, MAE

MAPE: Mean Absolute Perception Error, MASE: Mean Absolute Scaled Error.

Table 3. Location Analysis of Real-Time Experiments.

Ref.	Site Type (River, Sea, Lake, Farm, Etc.)	Number of Sites	Experiment Time (Day, Nigh)	Experiment Condition (Normal, Hazardous Weather)	Duration of Experiment (Min)	Experiment Purpose (Online Monitoring (Continuous Feed, Off-Line Data Collection)	Comments
[16]	River	5 sites	day	normal	10 min with Drones	Data collection	
[29]	Rural Areas					Data collection and analysis	No experiment
[7]	Fish Farms	2 nodes	Day and night		from 16 September 2018, to 15 October 2018, were acquired daily at time points of 6:00, 9:00, 16:00, and 22:00.	Analysis and forecasting	

Table 3. *Cont.*

Ref.	Site Type (River, Sea, Lake, Farm, Etc.)	Number of Sites	Experiment Time (Day, Nigh)	Experiment Condition (Normal, Hazardous Weather)	Duration of Experiment (Min)	Experiment Purpose (Online Monitoring (Continuous Feed, Off-Line Data Collection)	Comments
[33]	River	3 locations			At a fixed time daily from 1 January 2016 to 30 June 2018 with a total of 917 sets	Analysis and forecasting	
[36]							Secondary data used for analysis
[14]						Forecasting water quality	Secondary data used for analysis
[37]							Secondary data used for analysis
[54]	River	1 location					No info (pilot test)
[61]	Lake	16 sites	Afternoon	Normal	5 min for each site	Data acquisition	
[55]	Fishpond	4 nodes, 2 locations			24–30 January 2019. With a 6 feet depth	Data acquisition	
[49]					Send data every 5 s	Continuous feeding	No proper info
[50]							No info (no full paper to check)
[51]	Wastewater	8 devices in 4 sites			2 daily readings during March 2019 and eight samples were compared on the following days 1, 4, 8, 12, 14, 18, 20, and 22.	Data acquisition	
[57]	Wastewater Industry	14 stations			April 2018	Data acquisition and analysis	
[19]	Crab Pond				sampled 10 times in the period of approximately 10.30 am on the 26 June 2019	Data acquisition	
[47]	Lake						No info
[46]	Water Pumping Station				Send data every 5 s	Report generation	
[17]		10 samples					No further info
[52]	Water Station	5 stations			24 h for 10 days. stored in the database every 10 min.	Continuous monitoring	
[65]	Aqua Tanks						No info
[34]						Forecasting water demand	Secondary data used
[66]	River						No proper info
[2]	Bristol Floating Harbour	3 sites			6 cm deep and Data transfer every 15 min	Continuous monitoring	
[5]	Water Tank						No info
[53]	Fish Pond	2 nodes			Every 1 min		(proof of concept testing only)

Table 4. Comparing Review Articles.

Ref	Year	Topics	Architecture	Taxonomy	AI Models Analysis	DAS and Sensors Analysis	DAS Evaluation
[18]	2018	Energy Efficiency for WSN	WSN only	No	No	No	No
This Review	2022	Energy; Sensor and DAS integration	Any Architecture	Yes	Yes	Yes	Yes

7.1. DAS Availability

Real-time data are important for advancement in this field of study. Modelling and understanding can benefit from additional data. The lack of scalable, affordable, and reliable data collection technology is the biggest obstacle to the availability of datasets. Particularly for long-term experiments or short-term research involving large sites and numerous data-gathering nodes, the creation and construction of DAS are pricy. Consequently, providing a low-cost, dependable, accurate, and easy-to-implement solution is a significant advancement in the research. Water quality prediction methods using online sensors in real-time circumstances are needed to give better water quality evaluation strategies.

Additionally, sensor manufacturers and system designers ought to think about creating more adaptable systems that can quickly integrate a variety of sensors without the requirement for soft interfacing techniques between the sensor and the main board of the data-gathering system. This process can make DAS less difficult and make the researcher more inclined to use electronic equipment for more real-time investigations. Additionally, designers and producers should take into account the level of dependability of the data-gathering system, as having a cost-effective system does not always entail integrating cheap and unreliable sensors. For instance, as they offer greater protection and system dependability, power protection circuits and reverse polarity protection circuits can be incorporated into the design of a low-cost microcontroller board [71].

7.2. Selecting the Best Machine Learning Technique

In terms of evaluation, benchmarking, and choosing the best machine learning-based model, this section discusses the difficulties and issues with those models. Benchmarking is the process of contrasting a recently created model with current models using comparable circumstances and traits. One of the techniques used in the evaluation and benchmarking is to look at how well water quality assessment models perform concerning actual water parameters. When creating new machine learning-based models, several aspects must be taken into consideration, including a low error rate, high reliability, minimal complexity, and high accuracy. However, actual performance will be affected if one of these requirements is met but not the others. These elements need to be carefully examined to highlight performance in real-world applications. Future research should look into any conflicts or trade-offs between these criteria or measurements, and a clear, dependable mechanism should be devised to address this potential conflict. The following evaluation criteria for machine learning-based models must be considered during the benchmarking and testing processes to test and compare the effectiveness of the developed machine learning-based water quality assessment models: accuracy, precision, true positive rate, false-positive rate, true-negative rate, F-measure, training time, area under the curve, and error rate. The primary question to be answered by the research is whether the developed machine learning-based water assessment models include all of the benchmarking and evaluation criteria during development. Also worth investigating is how developed models manage benchmarking and assessment [69,70].

7.3. Assessment Method of DAS

To address the difficulties of the present and potential solutions in further research, this section presents some highlights on specific areas. Future study needs to take into consideration the choice of the best DAS that can be incorporated into a certain design. To make considerable progress in this area of research, it is critical to take the cost and complexity of DAS into account. However, choosing a DAS should not be based solely on one design factor and disregarding other ones. Table 1 lists the subjective evaluation scores for the characteristics that, in the eyes of researchers, best represent the DAS as a system. The evaluation criteria conflict with one another and must be traded off, it can be said. Whether the research is conducted at a small site (within a 1-km radius) or on a big scale, this trade-off has an impact on both (more than a 1 km radius). All assessment criteria should be considered during the DAS evaluation process for a more accurate and thorough DAS assessment. The criteria can be assigned a significant value using various weighting techniques to include a degree of precision in the assessment process. To gain a better understanding of the advantages and disadvantages of any suggested DAS, it is useful to compare (benchmark) several DAS. The selection process can be viewed as a complex challenge that incorporates numerous qualities and various DAS that are documented in the literature to choose the best available DAS [69,70]. There is no clear and valid method for selecting this type of assessment procedure. Hence, providing a systematic procedure for DAS selection would be a huge leap for research and industrial communities [74].

8. Limitations

Although the database sources used for the presented investigation were extensive and trustworthy, identification was nevertheless challenging. Additionally, the increased development in this area had an adverse effect on the review's timing. Studies conducted at particular period on such a crucial topic does not always accurately reflect the influence or application. However, the data only reflects the reaction of the research community to the subject.

9. Conclusions

This article conducted a comprehensive evaluation of the prior research on techniques for evaluating the quality of water in real-time experiments. To simplify the analysis of the articles and glean important insights, a taxonomy for the literature was used to organize the articles according to similarities and potential trends. The investigation of the factors that sustain scholars' interest in this field of study led to several significant discoveries and key findings that were presented. Other elements, such as difficulties and issues, were also emphasized and shown. Additionally, ideas for recommendations were discussed for various entities to further advance this research area. To provide key insights, two sorts of analyses—methodological and substantive—are given. The reviewers looked over the development articles they had surveyed and conducted further analyses. The analysis of prior literature about development articles was real-time based experiments, which are more accurate but necessitate specialized electronic designs and a significant expense that cannot be dismissed which hampers advancement in this research area. The research is still sparse when it comes to model representation employing real-time, on-site datasets and intelligent (machine learning) techniques. To effectively duplicate the pattern style and unique electronic design features, this approach needs a sizable dataset. Additionally, artificial intelligence-based algorithms have overfitting issues and need specialized hardware/tools to analyze the datasets. The type of deployed DAS and the dataset's availability, dependability, and completeness have the biggest impacts on the accuracy of water assessment models.

It is important to consider the multiple attributes of the problem of choosing a DAS that meets the needed design. There is a lack of generalized DAS frameworks in the literature that can always measure water quality and under many circumstances. The topics mentioned for future research paths on intelligent automation of water quality assessment contain useful information. This thorough assessment of the literature concludes that there is no single model at this juncture that can accurately measure the features of water over a range of locations, periods, and types of sites. The review summarises a literature study and identifies research gaps, providing crucial information for researchers.

Author Contributions: Conceptualization, A.H.A., M.T. and B.B.Z.; methodology, A.A., S.S. and A.B.I.; validation, A.R.I.; investigation, C.Z.Z. and S.G.; writing—review and editing C.Z.Z., O.S.A., A.S.A. and S.G. formal analysis, I.Y.Y.A. and C.F.S.; original draft preparation, N.H.H. and H.H.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research is funded by the Ministry of Higher Education Malaysia under the Research Excellence Consortium Grant Scheme (KKP) or KPM-Special Grant RMK-10 (JPT(BPKI)1000/016/018/25(54) or KKP Vot. No. K343)/UPSI 2021-0033-106-10.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

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

References

1. Vikesland, P.J. Nanosensors for water quality monitoring. *Nat. Nanotechnol.* **2018**, *13*, 651–660. [CrossRef] [PubMed]
2. Chen, Y.; Han, D. Water quality monitoring in smart city: A pilot project. *Autom. Constr.* **2018**, *89*, 307–316. [CrossRef]
3. Ighalo, J.O.; Adeniyi, A.G. Mitigation of Diclofenac pollution in aqueous media by adsorption. *ChemBioEng Rev.* **2020**, *7*, 50–64. [CrossRef]
4. Gehlot, A.; Singh, R.; Samkaria, R.; Choudhury, S.; De, A. Kamlesh, Air quality and water quality monitoring using XBee and internet of things. *Int. J. Eng. Technol.* **2018**, *7*, 24–27. [CrossRef]
5. Ibrahim, S.N.; Asnawi, A.; Abdul Malik, N.; Mohd Azmin, N.; Jusoh, A.; Mohd Isa, F. Web based Water Turbidity Monitoring and Automated Filtration System: IoT Application in Water Management. *Int. J. Electr. Comput. Eng.* **2018**, *8*, 2503–2511. [CrossRef]
6. Ighalo, J.O.; Adeniyi, A.G.; Marques, G. Internet of things for water quality monitoring and assessment: A comprehensive review. In *Artificial Intelligence for Sustainable Development: Theory, Practice and Future Applications*; Springer: Cham, Switzerland, 2021; pp. 245–259.
7. Gao, G.; Xiao, K.; Chen, M. An intelligent IoT-based control and traceability system to forecast and maintain water quality in freshwater fish farms. *Comput. Electron. Agric.* **2019**, *166*, 105013. [CrossRef]
8. Kanoun, O.; Lazarević-Pašti, T.; Pašti, I.; Nasraoui, S.; Talbi, M.; Brahem, A.; Adiraju, A.; Sheremet, E.; Rodriguez, R.D.; Ben Ali, M. A review of nanocomposite-modified electrochemical sensors for water quality monitoring. *Sensors* **2021**, *21*, 4131. [CrossRef] [PubMed]
9. Chen, Y.; Song, L.; Liu, Y.; Yang, L.; Li, D. A review of the artificial neural network models for water quality prediction. *Appl. Sci.* **2020**, *10*, 5776. [CrossRef]
10. Liu, Q. Intelligent water quality monitoring system based on multi-sensor data fusion technology. *Int. J. Ambient. Comput. Intell. IJACI* **2021**, *12*, 43–63. [CrossRef]
11. El-Tohamy, W.S.; Azab, Y.A.; Abdel-Aziz, N. Evaluation of the Water Quality of Damietta Harbor: Using the Zooplankton Diversity and the Traditional Water Quality Parameters. *Int. J. Ocean. Oceanogr.* **2019**, *13*, 229–246.
12. Das, B.; Jain, P. Real-time water quality monitoring system using Internet of Things. In Proceedings of the 2017 International Conference on Computer, Communications and Electronics (Comptelix 2017), Jaipur, India, 1–2 July 2017; pp. 78–82.
13. Lalithadevi, B.; Yadav, A.; Pandey, A.; Adhikari, M. Iot based wsn ground water monitoring system with cloud-based monitoring as a service (maas) and prediction using machine learning. *Int. J. Innov. Technol. Explor. Eng. Regul. Issue* **2019**, *9*, 816–821.
14. Thai-Nghe, N.; Thanh-Hai, N.; Chi Ngon, N. Deep learning approach for forecasting water quality in IoT systems. *Int. J. Adv. Comput. Sci. Appl.* **2020**, *11*, 686–693. [CrossRef]
15. Nadu, T. An Underground Pipeline Water Quality Monitoring Using Iot Devices. *Eur. J. Mol. Clin. Med.* **2020**, *7*, 2046–2054.
16. Elijah, O.; Rahman, T.A.; Leow, C.; Yeen, H.; Sarijari, M.; Aris, A.; Salleh, J.; Chua, T. A concept paper on smart river monitoring system for sustainability in river. *Int. J. Integr. Eng.* **2018**, *10*, 130–139. [CrossRef]
17. Pasika, S.; Gandla, S.T. Smart water quality monitoring system with cost-effective using IoT. *Heliyon* **2020**, *6*, e04096. [CrossRef]
18. Olatinwo, S.O.; Joubert, T.-H. Energy efficient solutions in wireless sensor systems for water quality monitoring: A review. *IEEE Sens. J.* **2018**, *19*, 1596–1625. [CrossRef]
19. Boonsong, W.; ISMAIL, W.; Shinohara, N.; Nameh, S.M.I.S.; Alifah, S.; Hafiz, K.; Kamaludin, T.A. Real-time water quality monitoring of aquaculture pond using wireless sensor network and internet of things. *J. Theor. Appl. Inf. Technol.* **2020**, *98*.
20. Oztemel, E.; Gursev, S. Literature review of Industry 4.0 and related technologies. *J. Intell. Manuf.* **2020**, *31*, 127–182. [CrossRef]

21. Moparthi, N.R.; Mukesh, C.; Sagar, P.V. Water quality monitoring system using IoT. In Proceedings of the 2018 4th International Conference on Advances in Electrical, Electronics, Information, Communication and Bio-Informatics (AEEICB 2018), Chennai, India, 27–28 February 2018; pp. 1–5.
22. Manavalan, E.; Jayakrishna, K. A review of Internet of Things (IoT) embedded sustainable supply chain for industry 4.0 requirements. *Comput. Ind. Eng.* **2019**, *127*, 925–953. [CrossRef]
23. Haque, H.; Labeeb, K.; Riha, R.B.; Khan, M.N.R. IoT based water quality monitoring system by using Zigbee protocol. In Proceedings of the 2021 International Conference on Emerging Smart Computing and Informatics (ESCI), Pune, India, 5–7 March 2021; pp. 619–622.
24. Poor, P.J.; Pessagno, K.L.; Paul, R.W. Exploring the hedonic value of ambient water quality: A local watershed-based study. *Ecol. Econ.* **2007**, *60*, 797–806. [CrossRef]
25. Muehlenbachs, L.; Spiller, E.; Timmins, C. The housing market impacts of shale gas development. *Am. Econ. Rev.* **2015**, *105*, 3633–3659. [CrossRef]
26. Nair, S.; de la Vara, J.L.; Sabetzadeh, M.; Briand, L. An extended systematic literature review on provision of evidence for safety certification. *Inf. Softw. Technol.* **2014**, *56*, 689–717. [CrossRef]
27. Oviedo-Trespalacios, O.; Truelove, V.; Watson, B.; Hinton, J.A. The impact of road advertising signs on driver behaviour and implications for road safety: A critical systematic review. *Transp. Res. Part A Policy Pract.* **2019**, *122*, 85–98. [CrossRef]
28. Martín-delosReyes, L.M.; Jiménez-Mejías, E.; Martínez-Ruiz, V.; Moreno-Roldán, E.; Molina-Soberanes, D.; Lardelli-Claret, P. Efficacy of training with driving simulators in improving safety in young novice or learner drivers: A systematic review. *Transp. Res. Part F Traffic Psychol. Behav.* **2019**, *62*, 58–65. [CrossRef]
29. Vergina, S.A.; Kayalvizhi, S.; Bhavadharini, R.; Kalpana Devi, S. A real time water quality monitoring using machine learning algorithm. *Eur. J. Mol. Clin. Med.* **2020**, *7*, 2035–2041.
30. Loyola, L.G.; Lacatan, L.L. Water Quality Evaluation System for Prawn (*Penaeus monodon*) Using IoT Device and Decision Tree Algorithm. *J. Crit. Rev.* **2020**, *7*, 983–988.
31. Priya, S.K.; Shenbagalakshmi, G.; Revathi, T. Architecture of smart sensors for real time drinking water quality and contamination detection in water distributed mains. *Sci. Technol.* **2019**, *22*, 202–214.
32. Liu, P.; Wang, J.; Sangaiah, A.K.; Xie, Y.; Yin, X. Analysis and prediction of water quality using LSTM deep neural networks in IoT environment. *Sustainability* **2019**, *11*, 2058. [CrossRef]
33. Narayanan, L.K.; Sankaranarayanan, S.; Rodrigues, J.J.; Kozlov, S. Water demand forecasting using deep learning in IoT enabled water distribution network. *Int. J. Comput. Commun. Control.* **2020**, *15*, 3977. [CrossRef]
34. Olatinwo, S.O.; Joubert, T.-H. Energy efficiency maximization in a wireless powered IoT sensor network for water quality monitoring. *Comput. Netw.* **2020**, *176*, 107237. [CrossRef]
35. Nie, X.; Fan, T.; Wang, B.; Li, Z.; Shankar, A.; Manickam, A. Big data analytics and IoT in operation safety management in under water management. *Comput. Commun.* **2020**, *154*, 188–196. [CrossRef]
36. Zhang, J.; Sheng, Y.; Chen, W.; Lin, H.; Sun, G.; Guo, P. Design and analysis of a water quality monitoring data service platform. *CMC Comput. Mater. Contin.* **2021**, *66*, 389–405. [CrossRef]
37. Miry, A.H.; Aramice, G.A. Water monitoring and analytic based ThingSpeak. *Int. J. Electr. Comput. Eng.* **2020**, *10*, 3588. [CrossRef]
38. Bhagavan, K.; Krishna, R.V.; Gangadhar, A.C.L.; Arun, M. An efficient method in real time for water quality monitoring using internet of things. *Int. J. Eng. Technol.* **2018**, *7*, 170–173. [CrossRef]
39. Amit Ganatra, N.D. An IoT Based Real Time Smart Water Quality Monitoring and Controlling System using Waspmote and ZigBee Module. *Int. J. Adv. Sci. Technol.* **2020**, *29*, 1147–1151.
40. Esakki, B.; Ganesan, S.; Mathiyazhagan, S.; Ramasubramanian, K.; Gnanasekaran, B.; Son, B.; Park, S.W.; Choi, J.S. Design of amphibious vehicle for unmanned mission in water quality monitoring using internet of things. *Sensors* **2018**, *18*, 3318. [CrossRef]
41. Ramya, A.; Rohini, R.; Ravi, S. Iot based smart monitoring system for fish farming. *Int. J. Eng. Adv. Technol.* **2019**, *8*, 420–424.
42. Babu Loganathan, G.; Mohan, E.; Siva Kumar, R. IoT based water and soil quality monitoring system. *Int. J. Mech. Eng. Technol. IJMET* **2019**, *10*, 537–541.
43. Bojja, P.; Kumari, P.; Preetha, P.; Raga, S.N.P.; Akhila, P. Portable drinking water quality measurement system for implementation of smart villages. *Int. J. Recent Technol. Eng.* **2019**, *7*, 764–767.
44. Kamidi, P.; Sabbi, V.; Sanniti, R. IoT based smart water quality monitoring and prediction system. *Int. J. Eng. Adv. Technol.* **2019**, *8*, 484–489.
45. Saravanan, K.; Anusuya, E.; Kumar, R.; Son, L.H. Real-time water quality monitoring using Internet of Things in SCADA. *Environ. Monit. Assess.* **2018**, *190*, 556. [CrossRef] [PubMed]
46. Dasgupta, S.; Zambare, M.; Kulkarni, N.; Shaligram, A. Real-time water quality monitoring system analysis of Pashan lake, Maharashtra, India. *Int. J. Eng. Adv. Technol. IJEAT* **2019**, *8*, 1166–1171. [CrossRef]
47. Mirzavand, R.; Honari, M.M.; Laribi, B.; Khorshidi, B.; Sadrzadeh, M.; Mousavi, P. An unpowered sensor node for real-time water quality assessment (humic acid detection). *Electronics* **2018**, *7*, 231. [CrossRef]
48. Spandana, K.; Rao, V.S. Internet of things (Iot) based smart water quality monitoring system. *Int. J. Eng. Technol.* **2018**, *7*, 259–262. [CrossRef]
49. Narayanan, L.K.; Sankaranarayanan, S.; Rodrigues, J.J.; Lorenz, P. Multi-agent-based modeling for underground pipe health and water quality monitoring for supplying quality water. *Int. J. Intell. Inf. Technol. IJIIT* **2020**, *16*, 52–79. [CrossRef]

50. Martínez, R.; Vela, N.; El Aatik, A.; Murray, E.; Roche, P.; Navarro, J.M. On the use of an IoT integrated system for water quality monitoring and management in wastewater treatment plants. *Water* **2020**, *12*, 1096. [CrossRef]
51. Ramadhan, A.; Ali, A.; Kareem, H. Smart water-quality monitoring system based on enabled real-time internet of things. *J. Eng. Sci. Technol.* **2020**, *15*, 3514–3527.
52. Saparudin, F.; Chee, T.; Ab Ghafar, A.; Majid, H.; Katiran, N. Wireless water quality monitoring system for high density aquaculture application. *Indones. J. Electr. Eng. Comput. Sci.* **2019**, *13*, 507–513. [CrossRef]
53. Shareef, Z.; Reddy, S. Design, development and analysis of an IoT-based framework for monitoring aquaculture farms. *Int. J. Mob. Netw. Des. Innov.* **2019**, *9*, 183–191. [CrossRef]
54. Dasig, D.D., Jr. Implementing Zigbee-based Wireless Sensor Network in the Design of Water Quality Monitoring System. *Int. J. Recent Technol. Eng.* **2019**, *8*, 6174–6179.
55. Rahmadya, B.; Zaini, Z.; Muharam, M. Iot: A mobile application and multi-hop communication in wireless sensor network for water monitoring. *Int. J. Interact. Mob. Technol.* **2020**, *14*, 288–296. [CrossRef]
56. Lin, Y.-P.; Mukhtar, H.; Huang, K.-T.; Petway, J.R.; Lin, C.-M.; Chou, C.-F.; Liao, S.-W. Real-time identification of irrigation water pollution sources and pathways with a wireless sensor network and blockchain framework. *Sensors* **2020**, *20*, 3634. [CrossRef]
57. Danh, L.V.Q.; Dung, D.V.M.; Danh, T.H.; Ngon, N.C. Design and deployment of an IoT-based water quality monitoring system for aquaculture in Mekong Delta. *Int. J. Mech. Eng. Robot. Res.* **2020**, *9*, 1170–1175. [CrossRef]
58. Kumar, M.J.V.; Samalla, K. Design and development of water quality monitoring system in IoT. *Int. J. Recent Technol. Eng. IJRTE* **2019**, *7*, 527–533.
59. Huan, J.; Li, H.; Wu, F.; Cao, W. Design of water quality monitoring system for aquaculture ponds based on NB-IoT. *Aquac. Eng.* **2020**, *90*, 102088. [CrossRef]
60. Ab Aziz, M.A.; Abas, M.F.; Bashri, M.K.A.A.; Saad, N.M.; Ariff, M. Evaluating IoT based passive water catchment monitoring system data acquisition and analysis. *Bull. Electr. Eng. Inform.* **2019**, *8*, 1373–1382. [CrossRef]
61. Lin, Y.-B.; Tseng, H.-C. FishTalk: An IoT-based mini aquarium system. *IEEE Access* **2019**, *7*, 35457–35469. [CrossRef]
62. Kalpana, D.; Venkatesulu, S. Iot Based Public Watering System With Quality Measurement. *Eur. J. Mol. Clin. Med.* **2020**, *7*, 2360–2366.
63. Amareshwar, E.; Jahan, S. Raspberry pi based water quality monitoring and flood alerting system using IoT. *Int. J. Innov. Technol. Explor. Eng.* **2019**, *8*, 237–240.
64. Angani, A.; Lee, J.C.; Shin, K.J. Vertical recycling aquatic system for internet-of-things-based smart fish farm. *Sens. Mater.* **2019**, *31*, 3987–3998. [CrossRef]
65. Pantjawati, A.B.; Purnomo, R.; Mulyanti, B.; Fenjano, L.; Pawinanto, R.; Nandiyanto, A.B.D. Water quality monitoring in Citarum River (Indonesia) using IoT (internet of thing). *J. Eng. Sci. Technol.* **2020**, *15*, 3661–3672.
66. Oommen, A.K.; Saji, A.; Joseph, S.; Kuriakose, B.P. Automated Water Quality Monitoring System for Aquaponics. *Int. Res. J. Eng. Technol.* **2019**, *7832*, 7832–7841.
67. Di Luccio, D.; Riccio, A.; Galletti, A.; Laccetti, G.; Lapegna, M.; Marcellino, L.; Kosta, S.; Montella, R. Coastal marine data crowdsourcing using the Internet of Floating Things: Improving the results of a water quality model. *IEEE Access* **2020**, *8*, 101209–101223. [CrossRef]
68. Wang, Y.; Rajib, S.S.M.; Collins, C.; Grieve, B. Low-cost turbidity sensor for low-power wireless monitoring of fresh-water courses. *IEEE Sens. J.* **2018**, *18*, 4689–4696. [CrossRef]
69. Talal, M.; Ramli, K.N.; Zaidan, A.A.; Zaidan, B.B.; Jumaa, F. Review on car-following sensor based and data-generation mapping for safety and traffic management and road map toward ITS. *Veh. Commun.* **2020**, *25*, 100280. [CrossRef]
70. Abdulwahid, S.N.; Mahmoud, M.A.; Zaidan, B.B.; Alamoodi, A.H.; Garfan, S.; Talal, M.; Zaidan, A.A. A comprehensive review on the behaviour of motorcyclists: Motivations, issues, challenges, substantial analysis and recommendations. *Int. J. Environ. Res. Public Health* **2022**, *19*, 3552. [CrossRef]
71. Zaidan, R.; Alamoodi, A.; Zaidan, B.; Zaidan, A.; Albahri, O.; Talal, M.; Garfan, S.; Sulaiman, S.; Mohammed, A.; Kareem, Z. Comprehensive driver behaviour review: Taxonomy, issues and challenges, motivations and research direction towards achieving a smart transportation environment. *Eng. Appl. Artif. Intell.* **2022**, *111*, 104745. [CrossRef]
72. Fathoni, H.; Miao, H.-Y.; Chen, C.-Y.; Yang, C.-T. A Monitoring System of Water Quality Tunghai Lake Using LoRaWAN. In Proceedings of the 2020 International Conference on Pervasive Artificial Intelligence (ICPAI), Taipei, Taiwan, 3–5 December 2020; pp. 281–283.
73. Sithole, M.P.P.; Nwulu, N.I.; Dogo, E.M. Dataset for a wireless sensor network based drinking-water quality monitoring and notification system. *Data Brief* **2019**, *27*, 104813. [CrossRef]
74. Mahmoud, U.S.; Albahri, A.S.; AlSattar, H.A.; Zaidan, A.A.; Talal, M.; Mohammed, R.T.; Albahri, O.S.; Zaidan, B.B.; Alamoodi, A.H.; Qahtan, S. DAS benchmarking methodology based on FWZIC II and FDOSM II to support industrial community characteristics in the design and implementation of advanced driver assistance systems in vehicles. *J. Ambient. Intell. Humaniz. Comput.* **2022**, 1–28. [CrossRef]