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Review

Smart Water Resource Management Using Artificial Intelligence—A Review

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Abstract: Water management is one of the crucial topics discussed in most of the international forums. Water harvesting and recycling are the major requirements to meet the global upcoming demand of the water crisis, which is prevalent. To achieve this, we need more emphasis on water management techniques that are applied across various categories of the applications. Keeping in mind the population density index, there is a dire need to implement intelligent water management mechanisms for effective distribution, conservation and to maintain the water quality standards for various purposes. The prescribed work discusses about few major areas of applications that are required for efficient water management. Those are recent trends in wastewater recycle, water distribution, rainwater harvesting and irrigation management using various Artificial Intelligence (AI) models. The data acquired for these applications are purely unique and also differs by type. Hence, there is a dire need to use a model or algorithm that can be applied to provide solutions across all these applications. Artificial Intelligence (AI) and Deep Learning (DL) techniques along with the Internet of things (IoT) framework can facilitate in designing a smart water management system for sustainable water usage from natural resources. This work surveys various water management techniques and the use of AI/DL along with the IoT network and case studies, sample statistical analysis to develop an efficient water management framework.

Keywords: internet of things (IoT); deep learning (DL); artificial intelligence (AI); water distribution; water quality; waste water management; water conservation

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1. Introduction

Water management involves the tasks of conserving the water resources, harvesting the water, planning the available net water resources, and distributing it very appropriately to the consumers. It also involves setting up of policies and practices to execute the tasks under fragmented controls. The conventional methods and practices were found to be inadequate in executing the tasks effectively. Water management practices need to take full account so as to maintain the water resource sustainable over the long term. Nearly 97% of water is salty and not suited for drinking. The pollution also affects the available water. Several sectors like intensive agriculture [1], wastewater (UN-Water, 2011), mining, industrial production and untreated urban runoff are the major causes of water pollution. Water from various sources needs to be utilized in an efficient manner which lacks in traditional water management methods. The existing methods for water usage are not so cost-effective [2], and there is also a disinclination towards implementing the latest information and communication technologies (ICT). The machine learning algorithms have the potential to expand the learning process in an exponential manner with a specific target. Standard algorithms would not scale exponentially to cover undiscovered patterns in the new data sets. Water management is required in the areas such as agriculture, public supply, industry, mining, generating hydro power, aqua culture and livestock hood. In agriculture, the key challenges are with respect to water access methods, efficient use of water and sustainable practices to conserve and harvest water. In India, industries are the second highest consumers of water as well as one of the highest source of pollutants. The industries take the water from ground water or surface water. The choice of the selection depends upon various factors like ground water availability, surface water availability, cost and demand of the fresh water from the municipal corporation. The demand for the water by the industries/factories/mining keeps growing on par with the increase in urbanization. Simultaneously, there is an increase in wastewater disposal without treating it appropriately into the natural sources, which is again also polluting the unpolluted water. Due to the lack of adequate water management policies, effective monitoring methodologies need to be devised for the industries to maintain a storage treatment plant (STP) and use this treated water for their purpose. Prolonged drought is also a major issue faced by the general public in the metropolitan cities. Managing the water supply during water shortage season is one of the demanding tasks by the officials of the metropolitan water board. This is the challenge that paved the way for the intervention of intelligent techniques. The water distribution infrastructure modelled by the smart algorithms supports efficient distribution of safe and sustainable water supply to the general public. The model built with intelligent techniques would recommend smart appliances which would utilize less water, impose restriction towards the amount of water usage at homes and apply tariffs for water usage. The quality of the water is assessed by three classes of attributes: physical, biological and chemical. Some of the quality indicators (pollutants) of water include chlorophyll, pH, dissolved oxygen, heavy metal contents, chloride and lead. There are a few researchers who use location and elevation of water bodies as inputs into various machine-learning approaches to forecast pollution [3]. The intelligent systems such as IoT, deep learning [4] and machine learning algorithms could be harnessed towards the process like leak management, flow monitoring, overuse, contamination and devising strategies towards acceptable water use (Figure 1). This paper aims to bring to the forefront compelling new opportunities for intelligent techniques intervening to address the major challenges faced in water management.

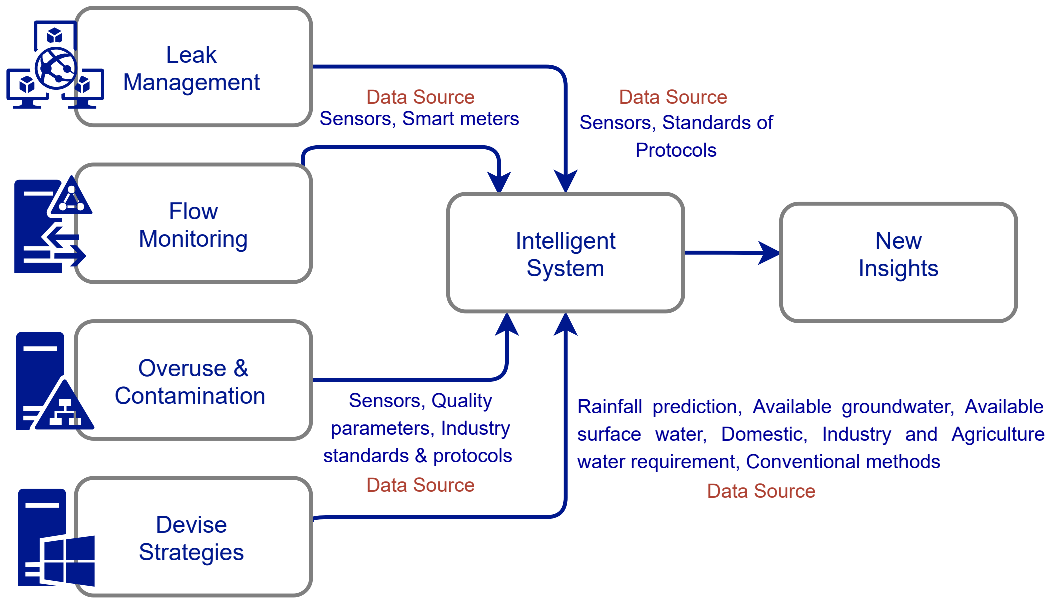

Figure 1. Harnessing intelligent systems for water management.

1.1. Contributions of the Work

- This prescribed work analyzes various water management techniques that provide solution for the harvesting, recycling and conservation of the water resource (Figure 2);

- This work also signifies various water management techniques with detailed analysis and case studies;
- The work uses the contribution of Artificial Intelligence through applications that are supported by the Deep and Machine learning techniques;
- The work also researches various challenges in the deployment of efficient water management system with future directions.

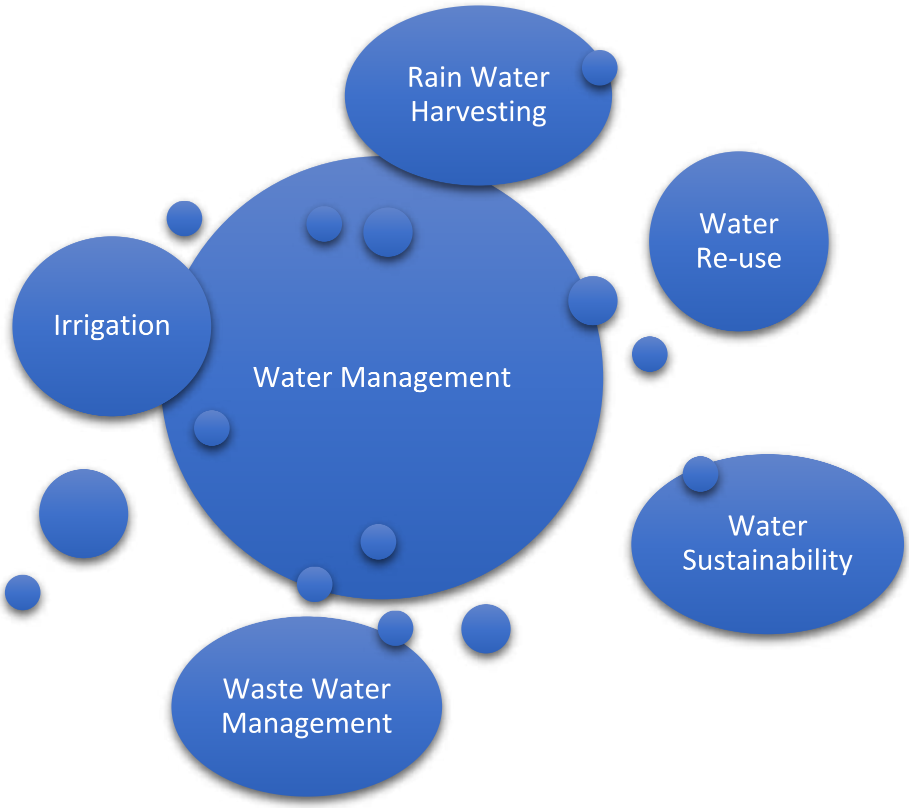

Figure 2. Water management and its parameters.

1.2. Organization of the Work

The organization of rest of the paper is as follows: Section 2 discusses about the background of the water management which includes the techniques and applications using IoT and AI. Section 3 discusses about sample statistical analysis. Section 4 discusses various case studies pertaining to deployment of intelligent techniques in water management. Section 5 highlights the challenges and future directions. Section 6 gives an insight about how this study can be useful for researchers working on deploying smart water management systems. Finally, we conclude by listing AI methods and challenges in water management systems.

2. Background

This section discusses about the existing water management using IoT and AI techniques.

Measuring the water quality is a crucial task for effective water distribution for smart cities. Detecting the pollutants in the water resource is one of the primary tasks to be performed. There are various AI based methods used for treatment of wastewater. Zhao et al. [5] surveyed different AI techniques pertaining to the wastewater treatment process. The authors also discussed the applications of AI used for wastewater management, and the cost and the logistics involved in the entire process. The authors concluded that Artificial Neural Network (ANN) and Federated Learning (FL) were the two major effective AI methods used in the wastewater treatment process. In a similar survey, Malviya et al. [6]

discussed about the major parameters to be measured in wastewater such as Chemical Oxygen Demand (COD), pH levels, Biological Oxygen Demand (BOD), nitrogen, turbidity and sulphur using Genetic Algorithms (GA). The authors also highlighted that the trace of heavy metals and other effluents can be determined by implementing ANN combined with other AI methods which can produce an accuracy of 85–90%. In another work, Nouran et al. [7] highlighted the usage of the adaptive neuro-fuzzy inference system (ANFIS), support vector regression (SVR) and feed forward neural network (FFNN) for determining BOD and COD of the Tabriz wastewater treatment plant (WWTP). The author also implemented the autoregressive integrated moving average (ARIMA) to predict the effluents to differentiate the nonlinear and linear models capability in prediction. The major cause of water pollution is due to the presence of heavy metals such as arsenic, chromium, lead, mercury, etc. This might be due to the industrial effluent or agricultural runoff in surface and groundwater. The use of AI models for heavy metal detection is an onerous process due to the complexity involved in the choice of prediction method, adjusting the variables and optimizing the training process. Bhagat et al. [8] reviewed different AI techniques which might be suitable for heavy metal detection from the water source. The authors also enlist the challenges of each method and possible solutions. Microfiltration is one of the efficient biological wastewater treatment processes. Membrane Bioreactors (MBR) provide an effective way for detection and removal of suspended/organic solids. Kamali et al. [9] analyse the performance of membrane bioreactors by implementing AI techniques. Furthermore, the authors also suggest that the combination of AI prediction algorithms and MBR would be an optimized way for mitigating the pollutants in the water source. In a similar research survey, Viet et al. [10] reviewed the implementation of AI models along with MBR, which is offering a better performance than the existing biological process of wastewater treatment. The presence of organic nitrogen and ammonia adds to the effluent levels of a water source. Manu et al. [11] deployed ANFIS and SVM to examine the accuracy ratio in the mitigation process of Kjeldahl Nitrogen in the treatment of waste water. The input parameters considered for AI modelling and training process were Kjeldahl Nitrogen, total solids (TS), COD, ammonia and pH, which were recorded live from the treatment plant of wastewater in Mangalore on a quarterly basis. The error rate for prediction of Kjeldahl Nitrogen by SVM was better than the ANFIS model and thus the authors concluded by suggesting the usage of SVM, which provides more efficacy in predicting the trace elements. Water evaporation is one of the major parameters for water scarcity especially in tropical regions. Soltani et al. [12] discussed how the surface evaporation impacts water loss by a floating solar system in a wastewater pond using an artificial intelligence algorithm. All independent variables are employed in the simulation as inputs for the neural network, and the dependent variable is the size of the pond. The neural network proved to be best topology for forecasting the level of water that is constructed with 35 neurons in the hidden layer, and it had nine inputs and one output; it achieved a correlation coefficient of 0.999 and a mean square error of 4.64658×10^{20}, according to the results of sensitivity analysis. The most current technique for the destruction and adsorption of a wide spectrum of wastewater pollutants is nanotechnology, particularly green synthesis nanoparticles. XRD, SEM, and EDAX analyses were used to characterise the Green Synthesis nano Zero Valent Iron (GT-nZVI) which is extracted from soft black tea. Mahmoud et al. [13] studied various nonlinear adsorption and kinetic models and are investigated to better understand how organic matter, as represented by COD and BOD, adheres to GT-nZVI. According to the data, GT-nZVI is successful at removing COD and BOD from wastewater, with removal efficiencies of 87.9 and 100% for COD levels of 600 15.0 and 100 11.8 mg/L and 91.3 and 100% for BOD levels of 365 and 60 mg/L, respectively. The amount of effluents deposited in the water source is majorly due to industrial waste being dumped. Organic pollutants including lipids, sugars and starches raise the COD levels over what is acceptable for release into sewage systems. Mahmoud et al. [14] analysed a drop-by-drop approach to successfully synthesise Fe/Cu NPs, and they were then characterised by XRD, SEM, and EDAX analysis. For starting COD concentrations at pH 7, NP dose of 0.6 g/L, 15 min, and 150 rpm, the removal efficiencies ranged from 100 to 69% and between 100 and 800 mg/L.

In the modern era, the use of AI in smart water management system has several implications to improve the water supply and efficient service delivery [15]. Developing AI, DL and ML with IoT technologies are expected to embed intelligent models to overcome complexity and challenges in water management systems [16] and water supply and distribution systems [17]. AI and Machine learning based models are demonstrated in water management applications such as wastewater treatment, water pollution control, smart agriculture, optimize water usage, automate critical water, water quality, water level monitoring, and water based agriculture such as aquaponics and hydroponics [18–20]. Most of the ML models used in water management domain are ANNs [21], ANFISs [22], recurrent neural networks (RNNs) [23], random forest (RF) [24] and support vector regressions (SVR) [25].

Water management in the agriculture sector is playing a vital role for the growth of country economy. Liu et al. [26] built an IoT and a data analytic based intelligent water management system by using the method of time series forecasting. Here, the authors designed two models for performing water management system in an effective manner. The first one is a hardware based ZigBee wireless sensor network monitoring model which is embedded with software acquisition for measuring data in short-distance transmission of the farmland environment, and the second one is an IoT based farmland irrigation model for measuring real-time agricultural water quality. Finally, the author proved that the proposed models produced accurate results by using different parameters. However, the author used only 78 statistical data attributes for measuring quality of water, and this could be enhanced in the future to obtain the result more accurately.

The integration of IoT techniques with the water management system has been rendering a wide range of benefits to reduce the critical challenges in a water supply chain system. In this paper ([27]), the authors studied existing issues that were affected in the rural India water supply management system, and anticipation of it through incorporation of IoT techniques. In addition, the authors explored the water resource mismanagement system in the Indian Government by using different use cases. Finally, the authors provided suitable solutions to mitigate water resource wastage to Government organization by means of formulating the IoT based water management system.

For a well organized city, the water dispersion network for a compact supply of water is essential. The water conveyance framework guarantees that the water has been provided from the distributed network to the households [28]. The water dissemination framework is planned in such a way that, at a negligible expense, the demand is satisfied. Because of urbanization, the water supply demand and the strain to convey them are increasing. This prompts harm and spillages in the current pipelines and furthermore requires extra pipelines to satisfy the need. This paper [29] provides a study on Bentley WATERGEMS software to study the water distribution system in Narangi village, Maharashtra, India. This software helped the users to examine the progression of water in each pipeline, level of the water in each tank, and expansion of water stream speed. However, the authors have a plan to carry forward this work as research to manage the water flow system currently till 2050.

The thought behind smart city is significantly founded on enhancement of expenses, better expectations for everyday comforts, water management system, combination of innovation and quicker exchanges in all fields [30,31]. It consolidates all parts of innovation in changing a confounded framework into a computerized, complex and a less difficult way of life. Here, the authors discussed the benefits of integrating IoT and Artificial Intelligence techniques in prominent needs of people's daily life. Water source utilization plays a vital role of defining the quality of the city. Using these information and communication oriented techniques, it could be achieved to enhance the usage of water in an effective manner. However, the authors did not focus specifically on the water resource; instead, they concentrated on the whole management system improvement with the help of current technologies.

2.1. IoT in Water Management

In agriculture, smart water management for precision irrigation is critical for improving crop production and decreasing expenses while also contributing to the environmental sustainability. Kamienski et al. [32] discusses the Smart Water Management Platform (SWAMP) using IoT in Brazil. SWAMP, which is an IoT platform, builds precision irrigation in agriculture that focuses on different challenges, like information model, complexity, deployment, adaptability, and complexity. Four SWAMP models are used by adaptability to provide enough diversity to understand the specificity and generality levels for several components of software. Several components of wireless technologies and sensor formats must be dealt with. In IoT systems, "one size fits all" is not applicable for precision agriculture that necessitates finding several ways to configure and connect components of software in the deployments based on fog/cloud computing. The authors have identified the necessity of an automated mechanism to deploy the system, given different constraints, infrastructures and requirements. For the metric scalability, significant improvements have to be made by FIWARE [33] to solve the issue scalability in case of scenarios that are extreme. For data storage and distribution in the IoT platform, FIWARE was adopted. The semantic engine framework and context broker are integrated for the metric complexity.

The authors in [34] proposed a system, namely, Smart AgroTech, which is based on the IoT platform for urban farming, with soil moisture, temperature, and humidity considered as very important parameters for farming. This system determines the starting and ending parameters for identifying the condition of the farming land. The Smart AgroTech system concept can be used in a smart city setting to improve irrigation management in farming. Real-time field conditions can be monitored as it is based on IoT, and decisions can be made based on data acquired from parameters such as humidity, soil moisture, and temperature. However, the system has several limitations, such as coverage area of the sensors used in the system, which causes incompetence and data transfer to a web server from the system, which takes a significant amount of time. A comparison of observed data and actual data of soil moisture, temperature and humidity yields an average percentage of the inaccuracy of , 2.51, 2.93 and 1.12, respectively, and presents the concept of feasibility.

Martin et al. [35] discuss smart solutions for the decentralization of water infrastructure using low-cost sensors in their study. A Smart Rain Barrel (SRB) concept for improved rainwater gathering uses low-cost IoT sensors. The SRB is made up of a standard rain barrel that has been enhanced with a a remotely controlled release valve and a water level sensor device. The use of rain barrels with capacities ranging from 200 to 500 liters aids in the retrofitting of infrastructure, that is, existing on a large-scale. Every SRB may be controlled and monitored independently in real time; in addition, the urban water infrastructure can be integrated into the broader management. To avoid system deterioration, large-scale adoption of micro storage can benefit the entire urban water infrastructure.

The potential of the IoT framework for management of water supply in a smart city is exemplified in [36]. Efficient management of a water supply through the use of an IoT application to automate the operation of a motor in each house is discussed. In comparison to earlier smart meters, the technology utilizes a waterproof ultrasonic sensor. It also incorporates cloud-based technology into IoT to make the system scalable.

Peace et al. [37] utilized Internet, sensor technologies to improve irrigation equipment to enable reasonably precise agricultural irrigation control and to efficiently use water for irrigation. In Rwanda, the benefits of efficient water usage from the deployment of IoT technology necessitates overcoming obstacles such as individual farmers' lack of access to equipment, and also lack of irrigation management, improper Internet connectivity and power. The proposed low-cost system will provide control of irrigation automatically based on seasonal and daily needs when the system sensors are working properly. The authors described adopting the low-cost MCP and SARSA for irrigation of rice based on IoT in Rwanda [38].

The authors in [39] proposed a scheme for managing the water for smart cities through big data analytics and IoT using the Supervisory Controller and Data Acquisition (SCADA)

Approach. Big data analysis enables the collection of massive data from IoT sensors deployed in several locations to track the quality, physical status, and use of the devices. The research analyzed systemization and modern storage choices for Big Data and IoT, as well as ways for analyzing and visualizing the data. The study shows that there is a wealth of information on the wastewater and water supply. This means that more technological resources are required to process these data in a timely and cost-effective manner. The benefit of IoT and Big Data is that several models can be built for many segments depending on the information that is available. These models are critical tools for evaluating, running and scheduling current water distribution networks across time. This improves prediction when using an appropriate model. Using big data spectral analysis [40], the authors identified the greatest frequency of water loss cycles. Water distribution entails collecting, storing, analyzing and visualizing IoT sensors and Big data to manage and improve their development processes. The implementation intends to produce better levels of sustainable water supply by proactively controlling water usage to both companies and customers.

Gonçalves et al. [41] proposes an architecture for managing the water independently, which is called a REFlex Water. This system uses declarative business processes, Complex Event Processing (CEP), and IoT to regulate water supply. IoT devices provide low-cost and efficient solutions for controlling distribution of water and also in monitoring the same in real time. Declarative business process languages [42] give the flexibility and rigor needed to design systems with unpredictable behavior. Complex Event Processing (CEP) technology [43] is capable of handling enormous data streams generated by the sensors in IoT; additionally, all rules stated in a declarative business process language may be expressed by CEP languages. REFlex Water is built on FIWARE, which is an open-source platform. A broad set of APIs for the development of smart city applications is provided by REFlex. The authors have also presented a practical use of REFlex Water by using a realistic water distribution system established in a city in Brazil. This scenario is now being applied throughout the Brazilian water supply system.

Nations are working to make agriculture more sustainable by integrating diverse technologies to enhance its operation. The Sustainable Development Goals (SDGs) are addressed via SMART irrigation, which makes use of IoT and sensory systems [44]. IoT and automation are integrated with farming methods to increase the efficiency of the entire process. Irrigation systems are an important factor in the creation of optimum irrigation systems, which could improve the utilization of ongoing research and development efforts aimed at improving the sustainability of operations. According to a study, sensory systems improved farmers' understanding of their crops, reduced environmental consequences, and helped farmers preserve resources. Water scarcity involves a deficit of water, shortage of water and also the water crisis. IoT brings down technology's overall cost, opening up the possibility of managing the irrigation process monitoring system. Real-time monitoring for irrigation activations and precision farming is also facilitated by using wireless sensor networks (WSN).

For all urban systems, groundwater management is crucial. Data must therefore be made available to different decision-makers and stakeholders upon request. In order to gather, analyse and share groundwater data for a variety of purposes, this research work [45] proposes a conceptual framework that has been put into practise. Data gathered continuously from several sources and processed into a common format are made available under controlled access. The four primary components of the system are the Retriever, Collector, API Management Service, and Watchdog. This system's key advantage is that it permits the intake of any spatiotemporal data along with associated meta-data. This system helps with consistency, standardisation and data sharing in the water management sector, allowing stakeholders to focus more on data analysis rather than data retrieval and manipulation. The technology has undergone rigorous testing and has been implemented in numerous connected instances. With this method, the most recent data as well as past records are constantly accessible for immediate inquiries and deeper analysis.

Residential water supplies are subject to contamination from pipe residues and silt, which causes cloudiness, a terrible taste, and an odor in the water. One of the key elements for determining the quality of water is turbidity, a measurement of water cloudiness. The study [46] suggests a cost efficient system based on a light detecting device to gauge water cloudiness. The three components of the system architecture are the user interface, gateway device and turbidity sensing. A microcontroller with digital outputs can control larger loads. The system will start the process to filter and clean the water once the turbidity level reaches a certain point. In two separate environments which are darkness and ambient light, the voltage output recorded from the developed system versus the total suspended solid (TSS) in a sample of water is graphed and examined. For both the 90° and 180° detector, turbidimeters were installed, and it was discovered that the trends of the projected graph fall as the total suspended solid increases, simulating the trends of a commercial turbidimeter. Using a Thingspeak.io service [47], the data obtained from the board are successfully logged to the cloud. With the foregoing findings taken into account, a design for a real-time, low-cost web-based water quality monitoring system in an IoT environment was suggested.

In a wide variety of ways, water is vital to our everyday routines. Technologies that address water-related issues include adaptive management, remote sensing, global information integration, and others. This research work [48] utilizes Dam Water Management system (IoT-DWM) based on IoT to reduce water wastage. The IoT-DWM also includes many elements, including an IoT network section, a field sensor section, and a dam control section. The data could be monitored by several sensors set in the agriculture farm area, and data will be transmitted to the server. The dam controller obtains the actual data for the specific location and calculates the water demand. The water needs vary based upon the crop planted in that location. When predicting water requirements, the controller takes into account several data points, such as crop kinds in that location, temperature, humidity and wind speed. Utilizing IoT-DWM to simulate water demand results in greater performance, significant water savings and a decrease in water scarcity. A significant quantity of dam water will be saved as a result of the controller's automated adjustment of the flow control lever dependent on the weather. Matlab is utilized for the simulation, and the results reveal that the suggested system is employed for water management systems on a large-scale.

Nandhini et al. [49] developed effective water management and intrusion detection system using IoT. The automatic irrigation system has been utilized to measure soil parameters, including soil moisture, pH, and humidity. The pressure sensor's detected values are displayed on the dashboard. With the aid of a PIR sensor, the intruder detection system is carried out, and birds are deterred from reaching the agriculture field. A communication channel between the farmer and the agricultural field has been created using the GSM module. The farmer gets updated about the current field state by SMS, and via the dashboard, it helps farmers to reduce manpower and time.

To study the supply and demand of tap water in Taiwan, an Intelligent water management (IWM) has been used. The research [50] objective is to enhance the management of water in the country. Leveraging the SCADA technology that uses sensors in an infrastructure that is distributive, the system manages the assets, monitors discharge, assesses quality, and detects leaks of water utility. The authors proposed a prototype for intelligent monitoring of water utility in urban areas through installation of a smart water meter. However, a higher water charge is not the motivating factor for its development. The country has water distribution that is uneven and advanced ICT; hence, it is an ideal region for adapting IoT technology. Smart cities are a growing issue, in which the application and analysis of big data are the key success factors. Three steps are utilised to demonstrate intelligent water management: (1) Selection of a data transmission method; (2) Installing communication equipment and creating a cloud database; and (3) Implementation of value-added applications through big data. Water and energy can be saved by managing the water supply system in a smart way that paves the way for utilization of water resources optimally.

Water is a crucial component of life and for sustainability of living beings. The population of cities is growing quickly in the modern era because more people are migrating from rural to urban regions. Researchers [51] suggest an IoT-based strategy to address the need for monitoring water quality. The data are gathered via sensors and made available in real time through a cloud dashboard. The suggested system uses a variety of sensors, including a water level sensor, a pH sensor, water flow sensor and a water control valve, in addition to a Raspberry Pi that serves as the system's prominent controller. A microcontroller examines the sensor data before sending it to the cloud using a wireless communication module. Providing good quality water to every home, business and other establishment with an appropriate quantity are the advantages of this system, which can be used in smart city implementation.

2.2. Usage of IoT and Artificial Intelligence for Effective Water Management

In [52], the authors have adopted Long Short-Term Memory (LSTM) embedded with an ensemble deep learning model and a Convolutional Neural Network (CNN) to simulate water quality and water levels in South Korea's Nakdong river basin. The water quality parameters considered were organic carbon, phosphorous and nitrogen contents. The CNN produced an acceptable NSE value of 0.933, and the water levels are high in the rainy season and low in other seasons. LSTM produced a value of 0.75, which is in the "very good performance" range. Furthermore, the authors applied this technique to simulate the quality parameters such as dissolved oxygen, chlorophyll, fecal bacteria and algae.

In [53], the authors have deployed an IoT based model to simulate the water level and water quality. In this system, the LV-MAXSONAR-EZ1 sensor is used to monitor the water quality, DS18B20, SKU SEN0219 is used to monitor CO_2, temperature and KE SEN0189 sensor is used for turbidity. The proposed model is deployed on the E1-SoC FPGA Development Kit. The performance output parameters such as turbidity, CO_2 and temperature were monitored. However, this model has not specified the pH levels.

In [54], the authors developed a hydro informatics integration platform (IHIP) based on a machine learning model, which is used for online flood forecasting and inundation in regional flood depth. The proposed model disseminates alarms of flash floods and inundation in regional threats' areas. The system contains five modules such as data access, servicer, functional subsystem, data integration and end-user application. The Google Maps were fused with a proposed model to enhance the advance decision on predication of floods and alerts to the communities.

In [55], the authors have proposed an ensemble AI based system which includes SVR, ANFIS, Multivariate Linear Regression (MLR), Group Method of Data Handling (GMDH) and ANN for foreseeing the infiltrated water irrigation system. The proposed Firefly Algorithm (FA) optimizer model uses the input parameters such as advance time at the end of the furrow (AT), inflow rate (IQ), furrow length (FL), infiltration opportunity time (IT) and cross-sectional area of inflow (CI). The proposed system performance was evaluated based on the correlation coefficient (R2), root mean square (RMSE), the mean absolute error (MAE), index of agreement (IA) and the Nash–Sutcliffe efficiency index (NSE). Firefly Algorithm optimizer models improved the accuracy of RMSE by 1%, 4%, 5%, and 47% in the GMDH, MLPNN, ANFIS and SVR, respectively.

In [56], the authors have introduced automatic water quality prediction model based on a framework consisting of PIC micro controller, sensors, monitoring server system and base station. The proposed model uses the parameters such as temperature, turbidity and pH for analysing the water quality. The Global System for Mobile Communications (GSM) monitoring was used to collect the data from the base stations. The GSM system sends alert signals via Short Message Service (SMS) to the management centre when water quality is not present as the expected level. However, the proposed model is limited to measure the water quality and not focused on other significant challenges like leakage of water and water supply interruption.

In [57], the authors have developed a smart IoT system which consist of various sensors for water flow, water supply valve, pH and raspberry core controller. The proposed model controls/monitors the water storage system by deploying a web interface. The web interface ensures the uniform water supply management to all water supply points. However, this model is expensive to be deployed in the real time water supply system with various characteristics.

In [58], the authors have proposed an intelligent model to anticipate risk in water supply management systems-based Complex Event Processing (CEP) technology. This model also allows for controlling the device remotely for real-time water supply. However, it does not provide the scalability and flexibility in a real-time scenario. In a similar work [41], the authors presented ensemble model-based CEP, declarative processes and smart IoT to develop an efficient, flexible and powerful model for water management supply in the Brazilian municipality. This model uses the REFlex water model to demonstrate the context of water supply. The REFlex was implemented by using a FIWARE platform which contains powerful API's to develop the smart IoT based water supply management systems.

In [59], the authors deployed WaterWise platform to manage and analyse the data collected from the smart IoT system. The proposed platform supports various tasks including online water leakage detection, pipe leaks, water demand and hydraulic water prediction and water quality measurement. The developed platform is used to represent smart water supply management. However, this model does not support dynamic anticipation in the occurrence of any issues in the water management.

In [60], the authors developed a layered model that contains an application layer, information communication layer and device perception layer. This model focuses on developing effective water supply management system to automatize the water management for domestic usage. The first layer stores the information about water such as quality, leakage of water and amount of water consumed for various connection points. The second layer is used to acquire the data, and the third layer is the sensor networks, which are used to detect the leakage. In a similar work [61], the authors have implemented an IoT based solution for automatic water pipe leakage detection. The proposed model contains several IoT devices and cloud services for efficient detection of pipe leakage. This model finds the amount of water leakage and wastage by the leakage by deploying sensors in strategic locations.

In [62], the authors proposed integrated deep learning automatic detection models with U-net and CNN. The main aim of the proposed system is to find the temporal resolution and high spatial imagery system that map center pivot irrigation systems. The proposed system uses high spatial resolution Palnetscope satellite images on the modified U-net system. U-Net uses TensorFlow library and Google cloud platform for training the images. The parameters produced out of the proposed models are recall 88% and precision 99%. However, this model takes 24 h for training and segmentation.

In [63], the authors presented a model for monitoring and controlling a remote water distribution system in a smart city by deploying a WaterWise digital water solution. The proposed model consists of several phases ranging from acquiring the data and application management. In the first phase, the data are collected through the sensors and are sent to the next layer. In order to achieve the sending and receiving of the data, MOSCA, Eclipse Ponte is used. The second phase is responsible for data integration which includes third party data like weather information. Apache Flink is used to analyse the complex data and detect the real time events. Cassandra and PostgreSQL are used to store the data. Apache Spark stack is used to improve the water management.

This research work [64] was performed as part of a joint work with the Company of Production and Management of Water in Tunisia. The integration of AI and IoT technologies allowed for an increase in productivity by reducing wasteful consumption and enhancing users' access to information that is current and accurate. This work focuses on the Smart City paradigms, Industry 4.0 and proposes a novel method to track and monitor water consumption by making use of an optical character recognition (OCR) device, along with an artificial intelligence algorithm combined with the YoLo 4 machine learning model. The training was performed on 10% for validation, test on 20% of the images and 70% of the images. The purpose of this effort is to produce outcomes that are optimised as they are being displayed in real time. The proposed algorithms yield a recognition rate of around 98% when applied to the data.

AI can anticipate agricultural energy output and environmental implications due to its ease of use, adaptability, and utilisation of historical data to predict future energy usage patterns under limits. This research work [65] predicts paddy production energy output and environmental impact in Iran using ANNs and ANFIS. On-farm paddies, emissions are a hotspot for global warming, acidification and eutrophication. In farm fertiliser, emissions also pollute water. Compost is a recommended organic fertiliser. Compost avoids leaching into groundwater or streams. Compost microorganisms can bind heavy metals in soil, preventing leaching into water. The best energy prediction model is 12-6-8-1 ANN. The forecasted output energy was determined using a hybrid learning approach, with R ranging between 0.860 to 0.997 for environmental implications. Results obtained prove that multi-level ANFIS is a beneficial technique determining the energy output on a large scale and to calculate efficiently the environmental indices of agricultural production.

There has been a significant role in forecasting suspended sediment yield (SSY) in water resource management and design. Many intricate mechanisms make precise sediment prediction extremely challenging using traditional models. Ref. [66] was carried out in the Godavari River Basin, India which is a highly generalized, completely automated, robust and accurate AI model to anticipate SSY. An artificial intelligence model well suited for SSY prediction is the genetic algorithm (GA) combined with an ANN (GA-ANN). The parameters of the ANN are streamlined all at once with the help of the GA. Daily water discharge and water level are used to train the GA-ANN and to determine the SSY at Polavaram, which is in the downstream section of the river. Analysis was performed between the GA-ANN model, the multiple linear regression (MLR) model and the sediment rating curve (SRC) model to see how well each model performed. The GA-ANN has the least biased (0.020) and maximum correlation coefficient (0.927) values of all the compared models. The root means that the square error is the lowest (0.053). Compared to more conventional models, the GA-ANN model provided better prediction of SSY.

Due to high water leak and contamination rates, water pipe deterioration modelling has been a popular topic for two decades. Since there is a time lag between failure occurrence and repercussions, failure processes are difficult to diagnose. In the last two decades, AI techniques have gained popularity for predicting and assessing water distribution network deterioration. Literature lacks a rigorous analysis of water infrastructure modelling using AI and ML. This article [67] attempts to fill information gaps and overcome restrictions. This study makes two contributions. First, a systematic strategy for conducting a comprehensive literature review is described. AI-based deterioration modelling for urban water systems is reviewed, including approaches, contributions, drawbacks, comparisons and critiques. Second, new research directions and problems are identified to help build a vibrant agenda for the water pipe deterioration.

Water is important for socio-economic development and healthy environments today. Water resources that are efficient and effective at lowering poverty and advancing equity. In order to meet all competing demands, including on-site and groundwater, the conventional water system management raises water flows. Climatic changes will exacerbate water resource management difficulties by increasing uncertainty. The future of civilisation depends on the management of sustainable water resources. Hydraulic limitations, stochastic dynamics and nonlinear effects make ecological water planning difficult. Ref. [68] proposes Adaptive Intelligent Dynamic Water Resource Planning (AIDWRP) for sustainable urban water environments. A sort of AI used to simulate sustainable water development is adaptive intelligence. Data-driven decision-making and water efficiency are increased when numerical AI techniques are combined with human intellectual abilities. The Markov Decision Process (MDP) is used in the AIDWRP to optimise environmental planning and management methods for dynamic water resource management with annual consumption and released locational limits. As a result, the local economy is made to operate more effectively while the supply and demand for water resources are eased.

Ref. [69] investigates how AI might contribute to sustainability. One of the biggest concerns right now is sustainable development. Sustainability and development are mutually exclusive. The current initiatives to address the global crisis through individual activities have less of an impact than anticipated. Underutilized is the potential of currently existing technology, particularly artificial intelligence. Eco-innovation initiatives mostly centre on intelligent mobility, efficient energy and water use, and trash recycling, but they fail to take into account the need for behavioral and cognitive evolution. The IT market is changing as a result of ideas such as smart, intelligent, innovative, green and wise cities, which were developed to support existing technologies. The majority of services include data processing using statistical and optimization techniques. This article shows how using AI approaches and techniques along with good reasoning could help come up with ways to solve the Planet Crisis.

Ref. [70] deployed the Omni IoT system, which is a smart cage culture management system, an artificial intelligence feeding system and underwater image analysis. The Omni IoT system consists of a cloud system, sensors, autogiros, ROVs, an underwater and waterproof platform, and a communications system which allows for the rapid collection of massive amounts of data on fish and feeding in a cage environment. Administrators can use big data to keep an eye on the environment and the fish's food intake. In the framework of AI computation, massive amounts of data can also be used to examine images of marine life and AI feeding system modules. The non-intrusive, real-time photo analysis and up-to-date creature status that underwater image processing technology offers can be very helpful to aquaculture firms. The AI's feeding schedule is based on the volume of splashes made by competing for fish. Based on the results, the authors highlight that the amount of wasted food was cut in half after AI was added to the automatic feeding system. Cage culture can be encouraged and professional aquaculture can be performed with the help of the suggested AIoT culture technology.

For environmental monitoring, exploration, and defense, the Internet of Underwater Things (IoUT) has gained popularity in the past decade. Traditional IoUT systems use ML to ensure reliability, efficiency, and timeliness. This study [71] shows how important privacy and security are for mission-critical IoUT frameworks. Federated learning (FL) is a secure, decentralized machine learning system that will assist with IoUT difficulties. This study describes FL's applicability in IoUT, its problems, unresolved topics, and future research directions. FL approaches in an IoUT setting are beneficial for the reasons indicated: Device/Network Configuration, Data Transmission, Unreliable Channel Condition, System Heterogeneity, Privacy and Real-time Generation of labels.

In [72], the authors have developed an IoT based sustainable irrigation water management for agricultural fields and gardens without human intervention. The proposed system supports efficient water supply management by saving the water waste along with other natural resources. This model uses real-time data to manage the water supply to gardens. The results show that the proposed model save up to 26–30 percent of water using the IoT network by analysing the parameters such as soil moisture levels, temperature and humidity. Some of the significant research works are tabulated in Table 1.

Table 1. Summary of the existing works.

References	Method	Advantages	Disadvantages	Outcomes
[73]	ANN- Artificial Neural Networks RNN- Recurrent Neural Networks Bi-LSTM- Bidirectional long short-term memory LSTM- Long short-term memory GRU- Gated Recurrent Unit	Effective and efficient model for stream flow	Low accuracy Further to help experts, mangers and officials	Correlation Coefficient (CC): 0.85% Mean Absolute Error (MAE): 13.4% Root Mean Square Error (RMSE): 21.16% Nash–Sutcliffe Efficiency Coefficient (NS): 0.65
[52]	Hybrid model Convolutional Neural Network (CNN) Long Short-Term Memory (LSTM)	CNN for predicting the water level LSTM for monitoring the water quality Considered three water quality parameters such as, Total Nitrogen (TN), Total Organic Carbon (TOC), and Total Phosphorus (TP)	Used limited data set Not concentrated on parameters like chlorophyll, algae, dissolved oxygen, and fecal bacteria	NS: 0.75 MSE: 0.055 TOC: 0.832 TN: 0.987 TP: 0.899
[62]	U-Net, Tensor Flow Libraries CNN	The proposed method determines the center pivot irrigation systems efficiently	The proposed model is deployed on short area and consumes more time	Accuracy: 99% Precision: 99% Recall: 88%
[74]	SVM (Support Vector Machine) SVR (Support Vector Regression) Radial Basis Function Kernel Random Forest Regression	Proposed IoT smart system for automating the agriculture industry	It does not support dynamic systems Limited Data set Low Accuracy	Accuracy: 81.6%
[75]	Deep learning neural network models Belief Rule Based Model (BRDM)	low power consumption, low-cost and high detection accuracy	It works for only small area Not considered parameters such as Dissolved Solid, Dissolved Oxygen Chemical Oxygen Demand	Temperature: 46.19 celsius Ph Value: 4.28

Table 1. *Cont.*

References	Method	Advantages	Disadvantages	Outcomes
[76]	Deep Neural Networks (DNNs) Feed-Forward Deep Neural Networks (FF-DNNs) RMSprop optimization algorithm	Proposed real-time water quality and monitoring model	Used limited data set Need to improve the accuracy	NSE: 0.89 MSE: 0.52
[77]	SVM, Long-Short Term Memory (LSTM)	Efficient water quality monitor for aquaculture and fisheries	Implemented on limited data set Not dynamic systems Simple LSTM Deployed	RMSE: 4.197
[78]	K-Nearest Neighbour (KNN) SVM	Proposed automated water quality monitoring system	Uses different sensors such as pH, temperature, turbidity, and conductivity	Accuracy: 94%
[79]	Principal Component Analysis (PCA) Random forest	Efficient for Urban Water Management	Limited data set Quality Parameters not considered	MAE: 0.046 RMSE: 0.061

2.3. Applications of IoT and DL in Various Aspects in Water Management

2.3.1. Recent Trends in Waste Water Recycle and Management by Deep Learning

Prediction of real-time water treatment parameters is a challenging task. The prescribed work [80] provides a data-driven approach for prediction of the treatment process of municipal wastewater by means of anaerobic membrane bioreactors (AnMBRs). They operated two such AnMBRs for about one year under six metrics pertaining to the experimental setup, like temperature of the reactor, environment, COD, flux and eight metrics related to the wastewater treatment evaluation such as effluent COD, pH, COD removal efficiency, biogas composition/production rate and oxidation-reduction potential. A few deep learning structures were deployed to analyse and produce the input/output evaluation parameters. The statistical study revealed a strong correlation between the deep learning analysis and the actual measurements performed on AnMBR. The densely connected convolution neural networks' (CNN) ability to predict outcomes with an accuracy rate of up to 97.44 percent and, more significantly, their ability to complete a single calculation in less than one second, both of which point to improved performance for AnMBR treatment prediction using deep learning techniques.

Wastewater treatment facilities (WWTP) are made to get rid of contaminants and lessen environmental pollution brought on by human activity. However, in fact, these facilities produce a lot of sludge and emit a lot of greenhouse gases, necessitating additional optimization [81]. This research [82] demonstrates how to simultaneously optimise the dissolved oxygen and chemical dosage in a wastewater treatment plant (WWTP) using the unique technique known as multi-agent deep reinforcement learning (MADRL). From a life-cycle perspective, the incentive function was created to achieve sustainable optimization. The results show that optimization based life cycle assessment (LCA) has lower environmental impacts compared to a baseline scenario as cost, energy and greenhouse gas consumption reduced to 0.890 CNY/m^3—ww, 0.530 kWh/m^3—ww, 2.491 kg CO_2-eq/m^3—ww, respectively. Compared to the LCA-driven plan, the cost-oriented strategy performs comparably overall, but at the expense of environmental advantages. It is important to note that the effect factor should be taken into account while retrofitting WWTPs based on resources. The main indicators of this work demand a substantial amount of data, which requires further investigation.

One major reason why facilities fail is the buildup of fat, oil, and grease (FOG) in the sumps of the waste water pumping stations [83]. Individual particles from floating soils can build up into thick, rigid FOG layers because floating soils are not always transferred to the pump suction inlets. The main problem in addressing the mitigation process is the lack of data pertinent to the FOG layer. This work [84] uses an automated system based on cameras to observe the dynamics of the FOG layer in the water pumping stations with high frequency and across long time frames (months). A deep learning computer vision model with FOG layer dynamics and other hydraulic processes is used in the pump sump to analyse optical imagery. Additionally, the system has the capability to process camera images, enabling the transfer of compressed processed information when used in remote places. This capability might be very helpful for the monitoring of hydro-ecological measurements. At the waste water pumping station in the Dutch municipality of Rotterdam, a six-month, two-minute instance data set was gathered for the study. This system manages the water pumping station and makes it possible to gather standardised high-frequency data on the dynamics of the FOG layer for a thorough explanation of the FOG build-up and transit process. The camera-based detection system provided root-mean square error of just 0.11 and Nash–Sutcliffe efficiency of 0.901. Thus, the various works on the waste water treatment process enhance the recycle performance eliminate pollutants by reducing the emission of gases, cost and energy.

This section also addressed FOG layer optimization which would also improve the performance of the waste water recycle plants.

Context aware data acquisition and quality of data are the major challenges of this application. Because of the sedimentation of polluting factors like Fat, Oil and Gas. These are context aware data, which need to be carefully measured. In addition, increase in the sedimentation levels increase the attributes under measurement.

2.3.2. Recent Deep Learning Models for Water Quality Prediction

Various DL and ML models provide mechanisms for determining the quality of the water used for diversified purposes. This section deals with various applications, infrastructures and models for determining the quality of the water that is to be used for various purposes. The increasing water pollution around the world is an endangering factor for the water quality. Measuring these pollutants with Machine Learning and Auto-ML models are possible with the current applications. However, they require sound mathematical background and modelling. Hence, deep learning models are more preferred for the measurement of water quality, since the parameters involved with water quality measurements are mostly time-series data. Recent research [85] on Deep Learning focuses on a technique called "Bi-LSTM". This model works with time-series data and hence is useful for the periodic evaluation of the water quality. This work is done with monthly data collection of quality report for about six years in Yamuna River, New Delhi (2013–2019). The Bi-LSTM model not only focuses on training but also focuses mainly on missing value imputation. This estimation is very important for minimizing the errors in the measurement. The first step of the Bi-LSTM involves determining how to impute missing values. The second phase involves creating feature maps from the input data. The third phase involves training. The fourth phase involves providing an optimum loss function that minimises learning errors. The experimental analysis is made on BOD and COD levels. COD levels provide the MSE, RMSE, MAE, and MAPE results as, 0.015, 0.117, 0.115, and 20.32, respectively, for the Palla region. BOD analysis shows that the MSE, RMSE, MAE, and MAPE values as 0.107, 0.108, 0.124, and 18.22, respectively. The proposed model exceeds all other models in terms of the best predicting accuracy with the lowest error rates, according to a comparison analysis. The usage of smart sensors in water quality measurements provides next-level solutions for water quality measurement applications. Recent research [86] uses smart sensors for collecting the water quality parameters. Then, the missing values and outliers are removed in the sensor data with the data cleaning process. Later, features are extracted to provide learning with G-SMOTE technique. This model employs hyper parameter tuning technique with a multi class model of deep learning with an MDLNN neural network. This model provides the incremental learning of the unseen data. The model provides the validation loss of 0.0415% and accuracy of 99.34%. Recent research [87] proposes that the usage of auto deep learning techniques for determination of the water quality gives better results. Auto Deep Learning (Auto DL) is one of the most recent and promising technologies. This technology involves simple interpretation and model creation possibly with a minimal amount of coding. The time of execution is also less when compared with the conventional deep learning techniques. The accuracy of the binary data measurements in conventional models for deep learning is more than 1.8 percent of the Auto-DL model, and the accuracy is about 1 percent more than the Auto-DL model in case of the multi class data models. The accuracy of the conventional DL model is around 98–99 percent, and, for the Auto DL model, it is around 96–98 percent. However, it provides ease in finding the appropriate DL model automatically and reduces the time complexity in arriving such models in real time. Thus, the Auto-DL provides more flexibility in practical application of the problem in real time.

A major challenge in determining the water quality is the variation of pollutants in water due to the sudden occurrences of flood, heavy rains, mixture of drainage water, industrial wastage and sewage water. This affects the various attributes under measurement by changing them abruptly. These sudden changes may reduce the quality of data and measurement. If the change is experienced during the training, it also affects the training efficiency.

2.3.3. Recent Trends of Deep Learning on Rainwater Management

Prediction of rainfall plays a vital role in water harvesting and management. The rainwater is the primary source for agriculture as well as for the drinking water for the general public. The prediction of rainfall becomes necessary and interesting for everyone around the world. This prediction is also very important for government agencies, since they use power plants during the rainy seasons through hydraulic converters, once the dams are getting filled up with rainwater. The prescribed work [88] focuses on rainfall data provided by the metrological department in Andhra Pradesh, India which was recorded over a year. The features are divided using splitting to form both the training as well as the testing data. This system is built around two ML models and one DL model. The ML models were the Linear Regression model and SVM, and the DL model was CNN. Finally, when tested for accuracy, the neural network had 77.17% followed by Linear model with 48.8% and by the SVM 32.5%. These findings show that, even in an irregular data set like rainfall data, the deep learning algorithms perform the prediction much better than the machine learning algorithms with increased accuracy and seems to be better suited for this purpose.

Most rainwater collection systems are not designed for maximum water conservation. It is challenging to obtain approval for such systems, but it is also crucial to construct such shared rainwater harvesting storage facilities in metropolitan neighbourhoods. Due to the complexity of the system's viability, numerous manual inspections are required [89]. Due to the complexity of the system's viability, numerous manual inspections are required. The suggested work [90] supports this process by combining computer vision-based solutions that automate the entire process by implementing rooftop picture segmentation, depth estimation, rainfall forecast and optimal tank placement using machine learning and deep learning algorithms. A rolling forecasting model based on seasonal autoregressive moving averages (SARIMA) is used to predict rainfall. The Canny edge technique and contour mapping are added to the mask R-CNN segmentation model to compute the rooftop catchment volume. Thus, the system can predict the break-even point for the compound metrics and offer the installation's viability.

The rain water harvesting and measurement are time-series data, thus it subjected to the time series analysis. These data are aggregated over a long period of time for analysis. Since it involves a large volume of data, adequate training is required for the deep learning models. Variation in climatic conditions would affect the measuring attributes, thus challenge the quality of data.

2.3.4. Recent Trends in Irrigation Control Using Deep Learning

Excessive usage of groundwater for the agricultural purpose endangers the water usage of other applications around the world. It also threatens the potable access of water around the world [91]. The soil texture classes are diversified in order to identify the irrigation requirements of them. Deep learning models play a vital role in bringing up this classification process with practical solutions. This sophisticated classification of the soil texture using various architectures and neural networks. The suggested study [92] deploys a proximate sensing system that uses a colour camera in conjunction with a deep learning and computer vision smart irrigation system to determine the water requirements of three classes of soil texture under various lighting circumstances. An imaging system is also deployed to reduce the workload of image training using the deep convolutional neural networks. Five deep learning architectures are used in this study to identify classes of water texture. They are AlexNet, Google Net, Res Net, VGG16 and Squeeze net. The best of all the models is AlexNet which outperforms all other networks with F1 score of 0.9973. The fastest detection is provided by Google Net and ResNet, processing in 16.92 ms. The results of this study demonstrate that deep learning models have enormous promise for predicting the producing field's irrigation needs under various conditions.

Understanding how the irrigation control system works on a wide scale and how quickly it reacts to different stresses is necessary for effective water management. Ref. [93] deploys a deep learning model that classifies the irrigation control systems in a regional scale using the remote sensing imagery. The task at hand deploys a U-Net Architecture with the use of Resnet-34 after experimenting with various model topologies, hyperparameters, class weights and picture sizes. They applied transfer learning here to improve the training efficiency and the performance of the model. This model is applied on a large scale across urban and background areas with four irrigation systems. The National Agricultural imaging programme of the US Department of Agriculture provides 8600 very high quality photos labelled with ground-truth observations. An efficient performance in segmentation process was achieved by the model with the different classes on validation data (72–86%), training data (85–94%) and test data (70–86%). Because the deep learning approach is transferable to other places worldwide, the model is flexible. This study provides fresh insights into the effects of transfer learning, unbalanced training data and the effectiveness of different model topologies for segmenting several irrigation types.

DL models not only determine the basic factors of irrigation but also helps in measuring special quantifiers like surface flow velocity, through the ripples produced in the water. To monitor the surface of huge rivers, a UAV Velocity measurement system [94] based on the optical flow method and the YOLOV5 deep learning algorithm has been built. Using the monocular range, this technique estimates the true velocity and transforms the pixel distance to the actual distance. The river-loop irrigation area of Inner Mongolia saw the successful application of this technique in the Yongji canal. The procedure produced high-quality photos, and the measurements and results were in agreement. The decision-making process in irrigation and agricultural systems depends on evaporation, a key process in the worldwide hydrological cycle. The most crucial step in this technique is the precise determination of the parameter pan evaporation Ep. Ref. [95] uses a hybrid LSTM model embedded with the Component Analysis to predict Ep in regions in Queensland, Australia using feature selection. They had time series evaluation on daily-scale data set (31 August 2002 to 22 September 2022). The results obtained in this work contain Root Means square error <20% with the highest Kling–Gupta efficiency >87%. With an enhanced feature selection procedure, an accurate estimation of Ep and future utility in the prediction of daily value of Ep, the model outperformed its rivals, including standalone DL, hidden layer neural networks and decision-tree based models. Thus, evaporation measurement also becomes an important measure to manage and control the irrigation process.

Irrigation control is generally completed by a set of sensors and actuators. They are randomly dropped on the soil, which later get connected with each other and establishes communication. There are chances of node failure, and the quality of data being aggregated from different sensors is reduced. The challenge of dimensionality reduction in the learning process occurs, which also effects the data quality. These sensors can be manipulated by an attacker in the absence of cyber security mechanisms. The attackers may gain access to the agricultural area by intercepting these sensors. The sensors also provide real-time data, so such large data sets would be involved with the training process.

This survey involves various applications such as recent trends in wastewater recycling, water quality measurement, rainwater management and irrigation control. This survey analyses the waster water recycling, quality measurement and rainwater harvesting with almost equal proportionality (27–28%). The irrigation control which is comprised of both machine and deep learning techniques is analyzed around 18% in this survey. This is due to the real-time data analysis and multi-sensor data environments. The distribution density of the analysis of the applications is represented in Figure 3.

The various Artificial Intelligence techniques surveyed in this proposed work are presented in the below mentioned graph (Figure 4). This chart distribution shows that the water management applications preferably use the deep learning techniques such as CNN or LSTM (Long Short Term Memory). The reason behind this is that, in most of the situations, the training data for a water based application are generally images. The training of a system with various features relevant to an image data and building a model for evaluation is a time-consuming and complex process. These processes can be handled by deep learning techniques with a desired power of GPU (Graphical Processing Units) and software. Various application with significant parameters are listed in Table 2

Table 2. Summary of applications and relevant techniques.

		Application				Technical Aspect								
Ref.	**Description**	**Waste Water Recycle and Management**	**Rain Water Management**	**Irrigation Control**	**Water quality Measurement**	**CNN**	**Auto DL**	**LCA**	**SVM**	**LR**	**ARIMA**	**Visual DL**	**LSTM**	**MDLNN**
[80]	Application of CNN on anaerobic membrane bioreactors (AnMBRs).	✓				✓								
[82]	Application of multi-agent deep enforcement learning (MADRL) with LCA optimization in waste water treatment plants	✓						✓						
[83]	FOG estimation on waste water pumping stations	✓										✓		
[90]	Seasonal auto regressive moving average (SARIMA) with R-CNN enhanced with canny edge algorithm with contour mapping		✓			✓					✓			
[92]	Smart irrigation system based on computer vision and deep learning. Alex Net, Google Net, Res Net, VGG16 and Squeeze net are the deep learning applications used.			✓								✓		
[93]	Irrigation segmentation using U-Net and Resnet-34 applications.			✓								✓		
[94]	UAV Velocity measurement system and YOLOV5 algorithm in deep learning with a hybrid Long Short-Term Memory (LSTM) model employed to monitor the Ep.			✓								✓	✓	
[85]	Bi-LSTM with COD and BOD analysis.				✓								✓	
[86]	IoT based G-SMOTE technique with MDLNN				✓									✓
[87]	Application of AutoDL in quality measurement				✓		✓							

Figure 3. Various applications analyzed for the water management techniques.

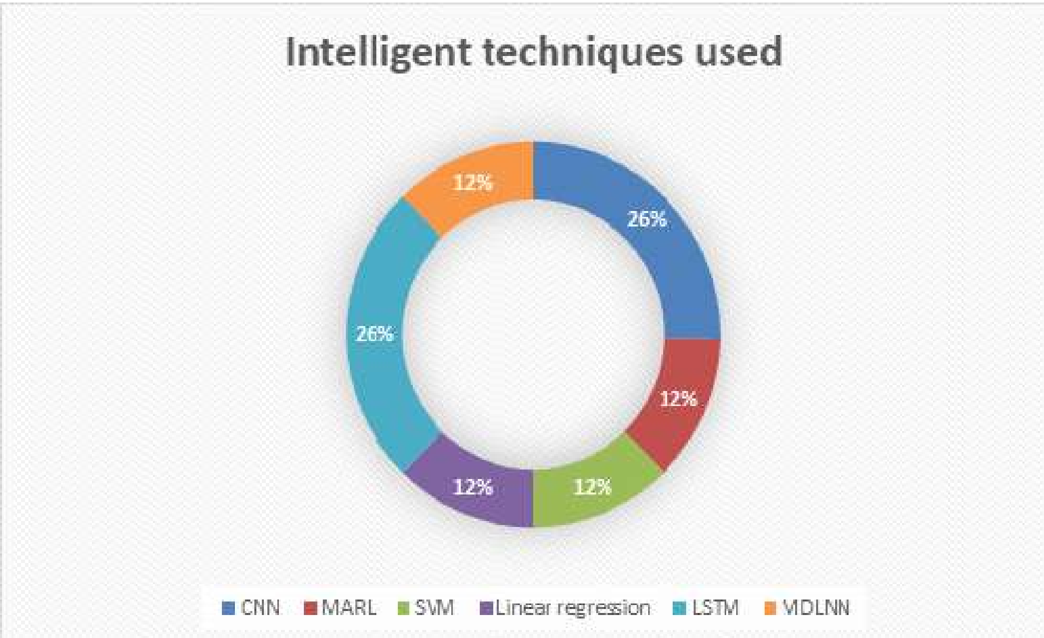

Figure 4. Various artificial intelligent techniques analyzed for the water management.

3. Case Studies

Real-time applications/projects on intelligent water management systems.

3.1. Using Artificial Intelligence for Smart Water Management Systems

The deployment of ICT has been emerged in every domain. Intelligent data analysis can render an efficient water management for improvising the water distribution and to curtail the cost. Artificial Intelligent (AI) techniques can be deployed for effective decision-making for the usage of water for various purposes. The combination of ICT with AI would facilitate achieving the Sustainable Development Goals [15] for water management and sanitization. The use of AI in water management also would help in solving the water scarcity keeping in mind the population density and to formulate policies in reducing the water leakage.

3.2. Smart Water Management—Case Study Report

Korea Water Resources Corporation made a joint venture with the International Water Resources Association (IWRA) for implementing a smart water management system. This system uses ICT for rendering real-time water data to IWRA for intelligently resolving water issues globally. The smart water management system also provides solutions for monitoring water quality, efficient irrigation, leak detection and intelligent water management during floods using AI mechanisms. The system [96] consists of IoT devices, GIS monitoring engines and real time satellite data. The system is also trained by AI to provide automated services during various events which help in efficient decision making.

3.3. Grid Intelligence Water Case Study

Applying modern technologies for water management is a challenging task. During the water crisis, water distribution for various sectors involves usage of huge resources. There is a dire need to deploy efficient and accurate water metering systems in the city. Verizon Grid Wide Intelligent Water solutions [97] provided a smart water metering system deployed in cloud for small cities in the southeastern U.S. This system contains water meter sensors for managing and monitoring the water usage, and the IoT gateway provides secure multi-point communication. The water leaks and the abnormal water usage are completed using Machine Learning analysis.

3.4. Smart Water Management: The Way to (Artificially) Intelligent Water Management

Most of the countries developed a Smart Water Management system (SWM) which contained various policies and technologies for dynamic water management for the new age. A summarized report written by Nickum et al. [98] highlights the various SWMs in different countries. Mexico, Korea and France developed a smart flood monitoring system which uses the IoT network and AI for prediction analysis. A Mexican project named "PUMAGUA" contained data monitors for improving water quality and reducing the overall water consumption based on an intelligent water resource network. Researchers in South Korea developed an intelligent SWM called a Hydro Intelligent Toolkit which uses the parameters such as hydrological data, rainfall forecasting, flood analysis and groundwater levels. These parameters are calculated from data analysis from the intelligent IoT network.

3.5. Smart Water Management towards Future Water Sustainable Networks

The purpose of the case study [99] is to investigate and construct smart water grids in Portugal. The water sector has faced significant challenges in recent years to improvise efficiency and to render sustainable performance (e.g., social, technical and environmental). Through effective smart water planning and management, the use of smart technology contributes to the future of water-smart cities as well as to the energy nexus. As a result of technological improvements, smart cities cut expenses, enhance service quality, and maximise system performance. In this case study, the use of monitoring and water loss control technologies enabled a high level of efficiency, especially in terms of minimizing water losses and, as a result, cutting associated costs. The implementation of these techniques resulted in a shift in the category of the most efficient cities, moving it from 20th to 5th place globally. The analysis reveals that the water sector has a tremendous potential for technically and economically viable micro-hydropower projects, which could significantly improve energy efficiency and lower CO_2 emissions. In a twelve-year timeframe, the case study reveals significant savings of 57 GWh and 100 Mm^3. These cost savings enabled a 47,385 t CO_2-eq reduction in CO_2 emissions. There is also a forecast for energy production in Portugal.

3.6. Moving towards Sustainable and Resilient Smart Water Management

In today's world, water has become a valuable 'asset', requiring proactive management. The major aim of Smart Water Management (SWM) [100] is to use strategies to manage water effectively. Adopting SWM as a growth strategy and engine will aid in achieving water sustainability and resilience in underdeveloped nations. The considerable potential for smart water technologies has been demonstrated in this work. Utilizing the advantages of connecting water users, water facilities, sensors, and systems with intelligent data analysis is gradually conceivable. Benefits include greater performance, increased flexibility, and cost savings and operational efficiencies. Addressing global issues, including climate change, population expansion, fast urbanisation, natural disasters and environmental degradation, will heavily rely on SWM. The water business is undergoing significant structural changes, necessitating new work practises, technical expertise and water management regulations. All of this indicates that the water sector has a promising future, as a new water paradigm is being built that makes use of SWM.

4. Challenges, Open Issues and Future Directions

The major challenges pertaining to deep learning in water management is broadly classified into few major categories

4.1. Data Quality and Availability in Deep Learning Based Water Management Systems

Deep learning networks use a huge volume of data for training an intelligent system that classifies huge test data or real-time data acquired from the sensors or images used in the water management and conservation systems. The data requirement is also a major area of concern. The restrictions are there for acquiring data from scientific and commercial industries since they are highly sensitive for the area of application and can be exploited with the competitive advantages. Certain data pertaining to government organisations are critical which can hardly be acquired for the research and development due to the legal and political restrictions. Data are also restricted because of the demographic constraints. When there is a huge demand for the real-time big data for training the deep learning models, the concern regarding the quality of the same arises in parallel. When a huge amount of data is acquired for training, the quality of each piece of the data is hard to analyse and evaluate. Hence, the trained model cannot be claimed to be a model that is built with quality data. There are chances in case the pre-processing is not completed properly; there could also be outliers or noisy data that may build the trained system as error prone.

4.2. Security in Deep-Learning Based Water Management Systems

Deep learning networks use a huge amount of data for training the water management systems; data that are used are open-source or may be handled by different people around the research or business. The changes in the input data reflect the behaviour of the system. This is the interest of the potential attackers to compromise the system. For example, because of the competitive advantage, an irrigation control system can be misled to dispense excessive water by an attacker that may compromise the whole agricultural yield. The purpose of embedding the AI based deep learning model for the water management, smart-agriculture or smart-farming will be in vain if the final system is compromised with attacks. Thus, like the smart systems, these deep learning based water management systems must be incorporated with cyber security policies and integrity of data access.

4.3. Context Aware Data Analysis in Deep-Learning Based Water Management Systems

The deep learning speaks more about architecture or a model, but it does not speak about an algorithm in reality. The algorithms in deed need revisions as the systems evolve to the next generation. The amount of re-training required for a deep-learning network will never be sufficient if the model goes with a major technical revision. For example, we can deploy smart sensors for determining the water quality, with few parameters under study. In the future, if this system is enhanced, we need to re-train the deep neural networks that govern the smart sensors for new parameters introduced. This indeed is very difficult to enhance and also unpredictable. For smart or IoT based systems which work with real-time data, this re-training is highly complex to perform. This challenge is mainly due to the nature of non-context aware behaviour of the neural networks and the unpredictable nature of the post training behaviour.

4.4. Training Efficiency

The real-time systems work with deep neural networks, basically getting updated for the change of the algorithms that were previously deployed. However, due to the unpredictable nature of this deep learning network, the revised algorithms does not guarantee the accuracy or the optimization that was previously achieved by an existing algorithm under the same environment. The change of the sensors may also influence the change of the neurons in neural networks that may result in the change of the behaviour of the whole model, which was previously deployed. Thus, the efficiency of training is very critical for the deep neural networks to deliver optimal performance with a required level of accuracy even if the system in total undergoes a major revision.

The futuristic systems would be automated, built across AI based smart technologies. These systems are required to be built with context-awareness for the successful roll-out of these technologies as commercial and technical solutions. These systems would be requiring high data quality standards and exhaustive training with quality. The technically and commercially viable systems should withstand all the above-mentioned challenges in real-time environments.

5. Findings

This work has surveyed about closer to 90 papers connected with AI in water management. The papers were taken from digital resources such as IEEE, Springer, Elsivier, MDPI, Nature, Taylor and Francis, Chemical Engineering journal. The search criteria for these digital resources were smart water management, AI methods in water management, smart methods in mitigation of wastewater management and intelligent methods of harnessing rainwater storage. The selected papers were chosen due to various parameters such as feasibility analysis on the application domain, focus on the future implementations, accuracy of the results obtained by the AI methods for different water management methods, clarity on model deployment and clarity on the write-up.

Advantages of Artificial Intelligence in the Water Management Process

The advantages of the various AI technologies are listed below. They are the primary source of the inspirations for implementing the same in the prescribed work [16]:

- Feature extraction and dimensionality reduction of the huge attributes;
- Finding the solution to a complex problem through parallel processing capabilities;
- Prediction of the target variables with a desired level of accuracy;
- Working with multiple data points in certain applications;
- Algorithms like RNN is useful for time-series prediction and analysis;
- Algorithms like DNN offers faster prediction and training;
- ANN is used for faster prediction, high arbitrary function and works with multi-dimensional datasets.

This study focuses on surveying different intelligent water management mechanisms and highlights the applications of AI in various areas of the water management such as water quality, wastewater treatment process, recycling, effective water distribution and rain water harvesting. This study also discusses the various challenges in AI deployment and data analysis, thus providing valuable insights into the researchers while deploying the water management systems in smart cities. The extensive study in the various aspects of water life cycle management would render brainstorming an ideation process for addressing the current issue of the water crisis and to implement effective mechanisms to distribute the better water quality to the consumers.

6. Conclusions

The emerging technologies for water harvesting, management and recycling provide positive reinforcement to the processes of the global water preservation and conservation. The support of artificial intelligence techniques such as machine and deep learning provide the road map for the future conservation of the water resources. With that approach, the proposed study provides various insights regarding water management applications that are built around the latest deep neural network models with their significance and their relevance towards the different water management processes. This study also discusses various challenges and opportunities regarding implementation of the deep neural networks for the water management process such as the data quality and availability in deep learning based water management systems, security in deep-learning based water management systems, context aware data analysis in deep-learning based water management systems and the training efficiency. Thus, the proposed study provides future directions for the upcoming research activities with the insight about the challenges and open issues of implementing water management with deep neural networks.

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References

1. Berthet, A.; Vincent, A.; Fleury, P. Water quality issues and agriculture: An international review of innovative policy schemes. *Land Use Policy* **2021**, *109*, 105654. [CrossRef]
2. Koech, R.; Langat, P. Improving irrigation water use efficiency: A review of advances, challenges and opportunities in the Australian context. *Water* **2018**, *10*, 1771. [CrossRef]
3. Banerjee, K.; Bali, V.; Nawaz, N.; Bali, S.; Mathur, S.; Mishra, R.K.; Rani, S. A Machine-Learning Approach for Prediction of Water Contamination Using Latitude, Longitude, and Elevation. *Water* **2022**, *14*, 728. [CrossRef]
4. Ray, P.; Kaluri, R.; Reddy, T.; Lakshmanna, K. Contemporary Developments and Technologies in Deep Learning–Based IoT. In *Deep Learning for Internet of Things Infrastructure*; CRC Press: Boca Raton, FL, USA, 2021; pp. 61–82.
5. Zhao, L.; Dai, T.; Qiao, Z.; Sun, P.; Hao, J.; Yang, Y. Application of artificial intelligence to wastewater treatment: A bibliometric analysis and systematic review of technology, economy, management, and wastewater reuse. *Process Saf. Environ. Prot.* **2020**, *133*, 169–182. [CrossRef]
6. Malviya, A.; Jaspal, D. Artificial intelligence as an upcoming technology in wastewater treatment: A comprehensive review. *Environ. Technol. Rev.* **2021**, *10*, 177–187. [CrossRef]
7. Nourani, V.; Asghari, P.; Sharghi, E. Artificial intelligence based ensemble modeling of wastewater treatment plant using jittered data. *J. Clean. Prod.* **2021**, *291*, 125772. [CrossRef]
8. Bhagat, S.K.; Tung, T.M.; Yaseen, Z.M. Development of artificial intelligence for modeling wastewater heavy metal removal: State of the art, application assessment and possible future research. *J. Clean. Prod.* **2020**, *250*, 119473. [CrossRef]
9. Kamali, M.; Appels, L.; Yu, X.; Aminabhavi, T.M.; Dewil, R. Artificial intelligence as a sustainable tool in wastewater treatment using membrane bioreactors. *Chem. Eng. J.* **2021**, *417*, 128070. [CrossRef]
10. Viet, N.D.; Jang, D.; Yoon, Y.; Jang, A. Enhancement of membrane system performance using artificial intelligence technologies for sustainable water and wastewater treatment: A critical review. *Crit. Rev. Environ. Sci. Technol.* **2022**, *52*, 3689–3719. [CrossRef]
11. Manu, D.; Thalla, A.K. Artificial intelligence models for predicting the performance of biological wastewater treatment plant in the removal of Kjeldahl Nitrogen from wastewater. *Appl. Water Sci.* **2017**, *7*, 3783–3791. [CrossRef]
12. Soltani, S.R.K.; Mostafaeipour, A.; Almutairi, K.; Dehshiri, S.J.H.; Dehshiri, S.S.H.; Techato, K. Predicting effect of floating photovoltaic power plant on water loss through surface evaporation for wastewater pond using artificial intelligence: A case study. *Sustain. Energy Technol. Assess.* **2022**, *50*, 101849.
13. Mahmoud, A.S.; Farag, R.S.; Elshfai, M.M. Reduction of organic matter from municipal wastewater at low cost using green synthesis nano iron extracted from black tea: Artificial intelligence with regression analysis. *Egypt. J. Pet.* **2020**, *29*, 9–20. [CrossRef]
14. Mahmoud, M.; Mahmoud, A.S. Wastewater treatment using nano bimetallic iron/copper, adsorption isotherm, kinetic studies, and artificial intelligence neural networks. *Emergent Mater.* **2021**, *4*, 1455–1463. [CrossRef]
15. Jenny, H.; Alonso, E.G.; Wang, Y.; Minguez, R. *Using Artificial Intelligence for Smart Water Management Systems*; Asian Development Bank: Mandaluyong, Philippines, 2020.
16. Alam, G.; Ihsanullah, I.; Naushad, M.; Sillanpää, M. Applications of artificial intelligence in water treatment for optimization and automation of adsorption processes: Recent advances and prospects. *Chem. Eng. J.* **2022**, *427*, 130011. [CrossRef]

17. Nasser, A.A.; Rashad, M.Z.; Hussein, S.E. A two-layer water demand prediction system in urban areas based on micro-services and LSTM neural networks. *IEEE Access* **2020**, *8*, 147647–147661. [CrossRef]
18. Lowe, M.; Qin, R.; Mao, X. A review on machine learning, artificial intelligence, and smart technology in water treatment and monitoring. *Water* **2022**, *14*, 1384. [CrossRef]
19. Akhund, T.M.; Ullah, N.; Newaz, N.T.; Zaman, Z.; Sultana, A.; Barros, A.; Whaiduzzaman, M. Iot-based low-cost automated irrigation system for smart farming. In *Intelligent Sustainable Systems*; Springer: Berlin/Heidelberg, Germany, 2022; pp. 83–91.
20. Jain, H.; Buch, M.; Babu, P. Water management system using machine learning. In *Data Engineering and Intelligent Computing*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 481–492.
21. Gaya, M.; Zango, M.; Yusuf, L.; Mustapha, M.; Muhammad, B.; Sani, A.; Tijjani, A.; Wahab, N.; Khairi, M. Estimation of turbidity in water treatment plant using Hammerstein-Wiener and neural network technique. *Indones. J. Electr. Eng. Comput. Sci.* **2017**, *5*, 666–672. [CrossRef]
22. Okoji, C.N.; Okoji, A.I.; Ibrahim, M.S.; Obinna, O. Comparative analysis of adaptive neuro-fuzzy inference system (ANFIS) and RSRM models to predict DBP (trihalomethanes) levels in the water treatment plant. *Arab. J. Chem.* **2022**, *15*, 103794. [CrossRef]
23. Zanfei, A.; Brentan, B.M.; Menapace, A.; Righetti, M.; Herrera, M. Graph convolutional recurrent neural networks for water demand forecasting. *Water Resour. Res.* **2022**, *58*, e2022WR032299. [CrossRef]
24. Phasinam, K.; Kassanuk, T.; Shinde, P.P.; Thakar, C.M.; Sharma, D.K.; Mohiddin, M.; Rahmani, A.W. Application of IoT and cloud computing in automation of agriculture irrigation. *J. Food Qual.* **2022**, *2022*. [CrossRef]
25. Roshni, T.; Mirzania, E.; Hasanpour Kashani, M.; Bui, Q.A.T.; Shamshirband, S. Hybrid support vector regression models with algorithm of innovative gunner for the simulation of groundwater level. *Acta Geophys.* **2022**, *70*, 1885–1898. [CrossRef]
26. Liu, H. Agricultural water management based on the Internet of Things and data analysis. *Acta Agric. Scand. Sect. B Soil Plant Sci.* **2022**, *72*, 300–311. [CrossRef]
27. Maroli, A.A.; Narwane, V.S.; Raut, R.D.; Narkhede, B.E. Framework for the implementation of an Internet of Things (IoT)-based water distribution and management system. *Clean Technol. Environ. Policy* **2021**, *23*, 271–283. [CrossRef]
28. Radhakrishnan, V.; Wu, W. IoT technology for smart water system. 2018 IEEE 20th International Conference on High Performance Computing and Communications; IEEE 16th International Conference on Smart City. In Proceedings of the IEEE 4th International Conference on Data Science and Systems (HPCC/SmartCity/DSS), Exeter, UK, 28–30 June 2018; pp. 1491–1496.
29. Mohseni, U.; Pathan, A.I.; Agnihotri, P.; Patidar, N.; Zareer, S.A.; Saran, V.; Rana, V. Design and Analysis of Water Distribution Network Using Watergems–A Case Study of Narangi Village. In Proceedings of the International Conference on Intelligent Computing & Optimization, Shenzhen, China, 12–15 August 2021; Springer: Berlin/Heidelberg, Germany, 2021; pp. 695–706.
30. Navarathna, P.J.; Malagi, V.P. Artificial intelligence in smart city analysis. In Proceedings of the 2018 International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India, 13–14 December 2018; pp. 44–47.
31. Mishra, K.N.; Chakraborty, C. A novel approach toward enhancing the quality of life in smart cities using clouds and IoT-based technologies. In *Digital Twin Technologies and Smart Cities*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 19–35.
32. Kamienski, C.; Soininen, J.P.; Taumberger, M.; Dantas, R.; Toscano, A.; Salmon Cinotti, T.; Filev Maia, R.; Torre Neto, A. Smart Water Management Platform: IoT-Based Precision Irrigation for Agriculture. *Sensors* **2019**, *19*, 276. [CrossRef]
33. López-Riquelme, J.; Pavón-Pulido, N.; Navarro-Hellín, H.; Soto-Valles, F.; Torres-Sánchez, R. A software architecture based on FIWARE cloud for Precision Agriculture. *Agric. Water Manag.* **2017**, *183*, 123–135. [CrossRef]
34. Podder, A.K.; Bukhari, A.A.; Islam, S.; Mia, S.; Mohammed, M.A.; Kumar, N.M.; Cengiz, K.; Abdulkareem, K.H. IoT based smart agrotech system for verification of Urban farming parameters. *Microprocess. Microsyst.* **2021**, *82*, 104025. [CrossRef]
35. Oberascher, M.; Kinzel, C.; Kastlunger, U.; Kleidorfer, M.; Zingerle, C.; Rauch, W.; Sitzenfrei, R. Integrated urban water management with micro storages developed as an IoT-based solution—The smart rain barrel. *Environ. Model. Softw.* **2021**, *139*, 105028. [CrossRef]
36. Gautam, G.; Sharma, G.; Magar, B.T.; Shrestha, B.; Cho, S.; Seo, C. Usage of IoT Framework in Water Supply Management for Smart City in Nepal. *Appl. Sci.* **2021**, *11*, 5662. [CrossRef]
37. Bamurigire, P.; Vodacek, A.; Valko, A.; Rutabayiro Ngoga, S. Simulation of Internet of Things Water Management for Efficient Rice Irrigation in Rwanda. *Agriculture* **2020**, *10*, 431. [CrossRef]
38. Bamurigire, P.; Vodacek, A.; Jayavel, K.; Ngoga, S.R. A Decision-making Module for Fertilization and Irrigation Control System in Rice Farming Using Markov Chain Process and SARSA Algorithms. In Proceedings of the 2021 The 11th International Workshop on Computer Science and Engineering (WCSE 2021), Shanghai, China, 19–21 June 2021; pp. 367–372.
39. 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]
40. Kamilaris, A.; Kartakoullis, A.; Prenafeta-Boldú, F.X. A review on the practice of big data analysis in agriculture. *Comput. Electron. Agric.* **2017**, *143*, 23–37. [CrossRef]
41. Gonçalves, R.; Soares, J.J.M.; Lima, R.M.F. An IoT-Based Framework for Smart Water Supply Systems Management. *Future Internet* **2020**, *12*, 114. [CrossRef]
42. Goedertier, S.; Vanthienen, J.; Caron, F. Declarative business process modelling: Principles and modelling languages. *Enterp. Inf. Syst.* **2015**, *9*, 161–185. [CrossRef]

43. Flouris, I.; Giatrakos, N.; Deligiannakis, A.; Garofalakis, M.; Kamp, M.; Mock, M. Issues in complex event processing: Status and prospects in the big data era. *J. Syst. Softw.* **2017**, *127*, 217–236. [CrossRef]
44. Obaideen, K.; Yousef, B.A.; AlMallahi, M.N.; Tan, Y.C.; Mahmoud, M.; Jaber, H.; Ramadan, M. An Overview of Smart Irrigation Systems Using IoT. *Energy Nexus* **2022**, *7*, 100124. [CrossRef]
45. Senožetnik, M.; Herga, Z.; Šubic, T.; Bradeško, L.; Kenda, K.; Klemen, K.; Pergar, P.; Mladenić, D. IoT Middleware for Water Management. *Proceedings* **2018**, *2*, 696. [CrossRef]
46. 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*, 2088–8708. [CrossRef]
47. Vijayakumar, J. Turmeric Farm Monitoring System using Wireless Sensor Network with ESP32 Module. In Proceedings of the 2021 Smart Technologies, Communication and Robotics (STCR), Sathyamangalam, India, 9–10 October 2021; pp. 1–5.
48. Chellaswamy, C.; Nisha, J.; Sivakumar, K.; Kaviya, R. An IoT based dam water management system for agriculture. In Proceedings of the 2018 International Conference on Recent Trends in Electrical, Control and Communication (RTECC), Johor, Malaysia, 20–22 March 2018; pp. 51–56.
49. Nandhini, R.; Poovizhi, S.; Jose, P.; Ranjitha, R.; Anila, S. Arduino based smart irrigation system using IoT. In Proceedings of the 3rd National Conference on Intelligent Information and Computing Technologies (IICT '17), Paris, France, 16–17 March 2017; pp. 1–5.
50. Li, E.Y.; Wang, W.H.; Hsu, Y.S. Adopting IoT technology to optimize intelligent water management. In Proceedings of the International Conference on Electronic Business (ICEB), Dubai, United Arab Emirates, 4–8 December 2017; pp. 38–46.
51. Shevale, R.; Karad, S.; Merchant, M.; Kardile, A.; Mishra, V. IOT based real time water monitoring system for smart city. *Int. J. Innov. Res. Technol.* **2018**, *3*, 246–251.
52. Baek, S.S.; Pyo, J.; Chun, J.A. Prediction of water level and water quality using a CNN-LSTM combined deep learning approach. *Water* **2020**, *12*, 3399. [CrossRef]
53. Jan, F.; Min-Allah, N.; Düştegör, D. IoT Based Smart Water Quality Monitoring: Recent Techniques, Trends and Challenges for Domestic Applications. *Water* **2021**, *13*, 1729. [CrossRef]
54. Chang, L.C.; Chang, F.J.; Yang, S.N.; Kao, I.F.; Ku, Y.Y.; Kuo, C.L.; Amin, I.M.Z.b.M. Building an intelligent hydroinformatics integration platform for regional flood inundation warning systems. *Water* **2019**, *11*, 9. [CrossRef]
55. Sayari, S.; Mahdavi-Meymand, A.; Zounemat-Kermani, M. Irrigation water infiltration modeling using machine learning. *Comput. Electron. Agric.* **2021**, *180*, 105921. [CrossRef]
56. Jadhav, S.B.; Pingle, N.S. Automatic Measurement and Reporting System of Water Quality Based On GSM. *Imp. J. Interdiscip. Res* **2016**, *2*, 657–662.
57. Shah, J. An internet of things based model for smart water distribution with quality monitoring. *Int. J. Innov. Res. Sci. Eng. Technol* **2017**, *6*, 3446–3451.
58. Yang, L.I.U.; Lei, Z.B.; Wu, K.H.; Hua, C.A.I.; Xuan, L.I.; Zhao, X.Y.; Tang, Z.M. Edge-centric Computing for Smart Water Supply: Management and Service. *Destech Trans. Mater. Sci. Eng.* **2016**, *1*, 1–8.
59. Allen, M.; Preis, A.; Iqbal, M.; Whittle, A.J. Water distribution system monitoring and decision support using a wireless sensor network. In Proceedings of the 2013 14th ACIS International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing, Honolulu, HI, USA, 1–3 July 2013; pp. 641–646.
60. Marjani, M.; Nasaruddin, F.; Gani, A.; Karim, A.; Hashem, I.A.T.; Siddiqa, A.; Yaqoob, I. Big IoT data analytics: Architecture, opportunities, and open research challenges. *IEEE Access* **2017**, *5*, 5247–5261.
61. Wu, Y.; Kim, K.; Henry, M.F.; Youcef-Toumi, K. Design of a leak sensor for operating water pipe systems. In Proceedings of the 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Vancouver, BC, Canada, 24–28 September 2017; pp. 6075–6082.
62. Saraiva, M.; Protas, É.; Salgado, M.; Souza, C. Automatic mapping of center pivot irrigation systems from satellite images using deep learning. *Remote Sens.* **2020**, *12*, 558. [CrossRef]
63. Figueiredo, I.; Esteves, P.; Cabrita, P. Water wise—A digital water solution for smart cities and water management entities. *Procedia Comput. Sci.* **2021**, *181*, 897–904. [CrossRef]
64. Ktari, J.; Frikha, T.; Hamdi, M.; Elmannai, H.; Hmam, H. Lightweight AI Framework for Industry 4.0 Case Study: Water Meter Recognition. *Big Data Cogn. Comput.* **2022**, *6*, 72. [CrossRef]
65. Nabavi-Pelesaraei, A.; Rafiee, S.; Mohtasebi, S.S.; Hosseinzadeh-Bandbafha, H.; Wing Chau, K. Integration of artificial intelligence methods and life cycle assessment to predict energy output and environmental impacts of paddy production. *Sci. Total Environ.* **2018**, *631–632*, 1279–1294. [CrossRef]
66. Yadav, A.; Joshi, D.; Kumar, V.; Mohapatra, H.; Iwendi, C.; Gadekallu, T.R. Capability and Robustness of Novel Hybridized Artificial Intelligence Technique for Sediment Yield Modeling in Godavari River, India. *Water* **2022**, *14*, 1917. [CrossRef]
67. Dawood, T.; Elwakil, E.; Novoa, H.M.; Delgado, J.F.G. Artificial intelligence for the modeling of water pipes deterioration mechanisms. *Autom. Constr.* **2020**, *120*, 103398. [CrossRef]
68. Xiang, X.; Li, Q.; Khan, S.; Khalaf, O.I. Urban water resource management for sustainable environment planning using artificial intelligence techniques. *Environ. Impact Assess. Rev.* **2021**, *86*, 106515. [CrossRef]
69. Mercier-Laurent, E. Can Artificial Intelligence Effectively Support Sustainable Development? In *IFIP International Workshop on Artificial Intelligence for Knowledge Management*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 144–159.

70. Chang, C.C.; Wang, J.H.; Wu, J.L.; Hsieh, Y.Z.; Wu, T.D.; Cheng, S.C.; Chang, C.C.; Juang, J.G.; Liou, C.H.; Hsu, T.H.; et al. Applying artificial intelligence (AI) techniques to implement a practical smart cage aquaculture management system. *J. Med Biol. Eng.* **2021**, *41*, 652–658. [CrossRef]
71. Victor, N.C.R.; Alazab, M.; Bhattacharya, S.; Magnusson, S.; Maddikunta, P.K.R.; Ramana, K.; Gadekallu, T.R. Federated Learning for IoUT: Concepts, Applications, Challenges and Opportunities. *arXiv* **2022**, arXiv:2207.13976.
72. Glória, A.; Dionisio, C.; Simões, G.; Cardoso, J.; Sebastião, P. Water management for sustainable irrigation systems using internet-of-things. *Sensors* **2020**, *20*, 1402. [CrossRef]
73. Apaydin, H.; Feizi, H.; Sattari, M.T.; Colak, M.S.; Shamshirband, S.; Chau, K.W. Comparative analysis of recurrent neural network architectures for reservoir inflow forecasting. *Water* **2020**, *12*, 1500. [CrossRef]
74. Vij, A.; Vijendra, S.; Jain, A.; Bajaj, S.; Bassi, A.; Sharma, A. IoT and machine learning approaches for automation of farm irrigation system. *Procedia Comput. Sci.* **2020**, *167*, 1250–1257. [CrossRef]
75. Chowdury, M.S.U.; Emran, T.B.; Ghosh, S.; Pathak, A.; Alam, M.M.; Absar, N.; Andersson, K.; Hossain, M.S. IoT based real-time river water quality monitoring system. *Procedia Comput. Sci.* **2019**, *155*, 161–168. [CrossRef]
76. Karamoutsou, L.; Psilovikos, A. Deep Learning in Water Resources Management: The Case Study of Kastoria Lake in Greece. *Water* **2021**, *13*, 3364. [CrossRef]
77. 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]
78. AlZubi, A.A. IoT based Automated Water Pollution Treatment using Machine Learning classifiers. *Environ. Technol.* **2022**, 1–18. [CrossRef] [PubMed]
79. Gao, X.; Zeng, W.; Shen, Y.; Guo, Z.; Yang, J.; Cheng, X.; Hua, Q.; Yu, K. Integrated Deep Neural Networks-Based Complex System for Urban Water Management. *Complexity* **2020**, *2020*, 8848324. [CrossRef]
80. Li, G.; Ji, J.; Ni, J.; Wang, S.; Guo, Y.; Hu, Y.; Liu, S.; Huang, S.F.; Li, Y.Y. Application of deep learning for predicting the treatment performance of real municipal wastewater based on one-year operation of two anaerobic mem-brane bioreactors. *Sci. Total Environ.* **2022**, *813*, 151920. [CrossRef]
81. Badeti, U.; Pathak, N.K.; Volpin, F.; Dorji, U.; Freguia, S.; Shon, H.K.; Phuntsho, S. Impact of source-separation of urine on effluent quality, energy consumption and greenhouse gas emissions of a decentralized wastewater treatment plant. *Process Saf. Environ. Prot.* **2021**, *150*, 298–304. [CrossRef]
82. Moreno-Rodenas, A.M.; Duinmeijer, A.; Clemens, F.H. Deep-learning based monitoring of FOG layer dynamics in wastewater pumping stations. *Water Res.* **2021**, *202*, 117482. [CrossRef]
83. Nieuwenhuis, E.; Post, J.; Duinmeijer, A.; Langeveld, J.; Clemens, F. Statistical modelling of Fat, Oil and Grease (FOG) deposits in wastewater pump sumps. *Water Res.* **2018**, *135*, 155–167. [CrossRef]
84. Chen, K.; Wang, H.; Valverde-Pérez, B.; Zhai, S.; Vezzaro, L.; Wang, A. Optimal control towards sustainable wastewater treatment plants based on multi-agent reinforcement learning. *Chemosphere* **2021**, *279*, 130498. [CrossRef]
85. Khullar, S.; Singh, N. Water quality assessment of a river using deep learning Bi-LSTM methodology: Forecasting and validation. *Environ. Sci. Pollut. Res.* **2022**, *29*, 12875–12889. [CrossRef]
86. Nemade, B.; Shah, D. An efficient IoT based prediction system for classification of water using novel adaptive incremental learning framework. *J. King Saud-Univ.-Comput. Inf. Sci.* **2022**, *34*, 5121–5131. [CrossRef]
87. Prasad, D.V.V.; Venkataramana, L.Y.; Kumar, P.S.; Prasannamedha, G.; Harshana, S.; Srividya, S.J.; Harrinei, K.; Indraganti, S. Analysis and prediction of water quality using deep learning and auto deep learning techniques. *Sci. Total. Environ.* **2022**, *821*, 153311. [CrossRef]
88. Bhattacharyya, D.; Swathi, K.; Rao, N.T.; Ku-mari, N.M.J. Long term prediction of rainfall in Andhra Pradesh with Deep learning. *J. Med Pharm. Allied Sci.* **2021**, *10*, 3132–3137 [CrossRef]
89. Hafizi Md Lani, N.; Yusop, Z.; Syafiuddin, A. A review of rainwater harvesting in Malaysia: Prospects and challenges. *Water* **2018**, *10*, 506. [CrossRef]
90. Gaurav, V.; Vinod, V.; Singh, S.K.; Sharma, T.; Pradyumna, K.; Choudhary, S. RainRoof: Automated Shared Rainwater Harvesting Prediction. In *Sustainable Communication Networks and Application*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 105–122.
91. Ding, L.; Yang, Q.; Yang, Y.; Ma, H.; Martin, J.D. Potential risk assessment of groundwater to address the agricultural and domestic challenges in Ordos Basin. *Environ. Geochem. Health* **2021**, *43*, 717–732. [CrossRef]
92. Kurtulmuş, E.; Arslan, B.; Kurtulmuş, F. Deep learning for proximal soil sensor development towards smart irri-gation. *Expert Syst. Appl.* **2022**, *198*, 116812. [CrossRef]
93. Raei, E.; Asanjan, A.A.; Nikoo, M.R.; Sadegh, M.; Pourshahabi, S.; Adamowski, J.F. A deep learning image segmentation model for agricultural irrigation system classification. *Comput. Electron. Agric.* **2022**, *198*, 106977. [CrossRef]
94. Li, S.; Liu, H.; Wang, S.; Zhou, Y.; Zhou, B.; Han, Y. Study on flow distribution of irrigation canal system based on image velocimetry. *Comput. Electron. Agric.* **2022**, *195*, 106828. [CrossRef]
95. Jayasinghe, W.L.P.; Deo, R.C.; Ghahramani, A.; Ghimire, S.; Raj, N. Development and evaluation of hybrid deep learning long short-term memory network model for pan evaporation estimation trained with satellite and ground-based data. *J. Hydrol.* **2022**, *607*, 127534. [CrossRef]
96. Rocher, V. *Smart Water Management—Case Study Report*; K-Water: Deajeon, Korea, 2018.

97. Grid Intelligence Water Case Study. 2018. Available online: https://www.verizon.com/business/resources/articles/grid-intelligence-water-case-study/ (accessed on 5 September 2022).
98. Nickum, J.E.; Kuisma, S.; Bjornlund, H.; Stephan, R.M. Smart Water Management: The way to (artificially) intelligent water management, or just another pretty name? *Water Int.* **2020**, *45*, 515–519. [CrossRef]
99. Ramos, H.M.; McNabola, A.; López-Jiménez, P.A.; Pérez-Sánchez, M. Smart Water Management towards Future Water Sustainable Networks. *Water* **2020**, *12*, 58. [CrossRef]
100. Mutchek, M.; Williams, E. Moving towards sustainable and resilient smart water grids. *Challenges* **2014**, *5*, 123–137. [CrossRef]