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REVIEW ARTICLE

A Review of Deep Learning Applications for Sustainable Water Resource Management

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Abstract

Deep learning (DL) techniques and algorithms have the capacity to significantly impact world economies, ecosystems, and communities. DL technologies have been utilized in the development and administration of urban structures. However, there exists a dearth of literature reviewing the present level of these applications and exploring potential directions in which DL can address water challenges. This study aims to review demand projections, leakage detection and localization, drainage defect and blockage, cyber security and wealth surveillance, wastewater recycling and management, water safety prediction, rainfall conversation, and irrigation regulation. The application of DL techniques is currently in its early stages. Most studies have adopted standard networks, simulated information, and experimental or prototype settings to evaluate the efficacy of DL approaches. However, there have been no reported instances of practical adoption. Compared to other reviewed problems, leakage detection is currently being implemented practically in daily operations and handling of water facilities. The major challenges for the practical deployment of DL in water management include algorithmic development, multi-agent platforms, virtual clones, data quality and availability, security, context-aware data analysis, and training efficiency. We validate our study by using several case studies that employ DL for water treatment. Prospective exploration and deployment of DL systems are anticipated to advance water systems toward increased cognition and flexibility. This research aims to encourage further research and development in utilizing DL for feasible water usage and digitalization of the global water sector.

Keywords: Artificial intelligence; Deep learning; Water management; ICT; Sustainability

Introduction

Computer-aided models have become highly important in water management since their initial use for the creation and designing of water-related projects in the Harvard Water Program in 1955 (Reuss, 2003). Over the course of several years, researchers have created physically based models to accurately depict the Water System (WS) at different levels of intricacy. These models are commonly employed to assist in the design, operation, and management of the WS (IWA, 2019). Nevertheless, the progress of physically-based simulations has come to a halt primarily because of the difficulties in comprehending the intricate nature of WSs and their intricate connections with alternative options like natural and climate systems, especially when it comes to accurately representing human perceptions, behaviors, and the subsequent impacts; establishing modeling assumptions, different steps, and layout, as well as checking a significant quantity of model variables, which may lead to similarity issue; limited availability and lack of assurance in data for detailed modeling; substantial computational power needed for virtual reality and optimization; and human assets and expertise needed for model upholding and growth, making it challenging to shift between different systems. Machine learning (ML), a segment of Artificial Intelligence (AI), integrates computers to gain insight from information, instances, and observations without predefined guidelines (Raihan et al., 2024). It is widely acknowledged that such technology has the ability to revolutionize society, economies, and habitats on a global basis (Rahman et al., 2024; Tanchangya et al., 2024a, 2024b). These shifts are occurring in response to urgent concerns such as global warming, wildlife decline, and the COVID-19 pandemic (Butler et al., 2016; Raihan, 2024). ML is anticipated to greatly affect academic studies and activities within the water industry. It will aid in tackling diverse water issues, like resource utilization, access to water, water contamination, floods, and famine. This, in turn, will facilitate achieving the United Nations' sustainable development goals regarding water.

Deep learning (DL), a subtype of ML, is extensively regarded as a major catalyst for the recent advancements in AI. DL commonly employs extensive, multi-layered artificial neural networks (ANNs) to handle substantial unprocessed data sets, hence sometimes referred to as deep networks (Raihan, 2023a). Traditional ML techniques, including multi-layer perceptron (MLP) neural networks, have limitations when it comes to handling raw data and require specialized knowledge in data preprocessing before they can learn. DL is a useful tool for addressing this issue as it facilitates the automatic extraction of features by leveraging numerous stages of illustrations, commencing with basic data, and moving to higher creative degrees (Lecun et al., 2015). Common DL methods comprise Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), Autoencoders, Graph Neural Networks (GNNs), and Deep Reinforcement Learning (DRL). DL technologies have achieved significant achievements in various domains, including image recognition, and have already been implemented in diverse business areas, including medicine and commerce. The water industry is gradually acknowledging the significant potential of DL, as seen by the expanding number of academic publications, case studies, and applications in this field (Shen, 2018). Now is an opportune moment to assess how DL techniques are currently being used in water management and to offer insights into how DL research might advance water engineering and enhance the efficient adoption of these approaches to realistic water issues. Figure 1 presents an overview of the use of deep learning for ecological, environmental, and water resource preservation purposes. The current investigation seeks to offer a thorough assessment of the relevance of DL in the strategic development as well as administration of water systems. It analyzed the advancement of DL research and its application in important water-related issues. We also discussed the areas where more progress in DL research is required to foster the advancement of modern water systems and the digitalization transformation in the field of water. This study examines various intelligent ideas for water governance systems and emphasizes the utilization of DL in different aspects of water handling, including demand forecasting, leakage detection and localization, sewer defect and blockage, cyber security and resource tracking, wastewater recycling and control, water quality prediction, rainwater management, and irrigation h. This study also examines the diverse obstacles in implementing DL and analyzing data, offering significant insights to researchers involved in installing water management systems. An in-depth examination of the different facets of water life cycle management will facilitate the generation of ideas to tackle the current water problem and establish efficient methods for distributing higher-quality water to customers.

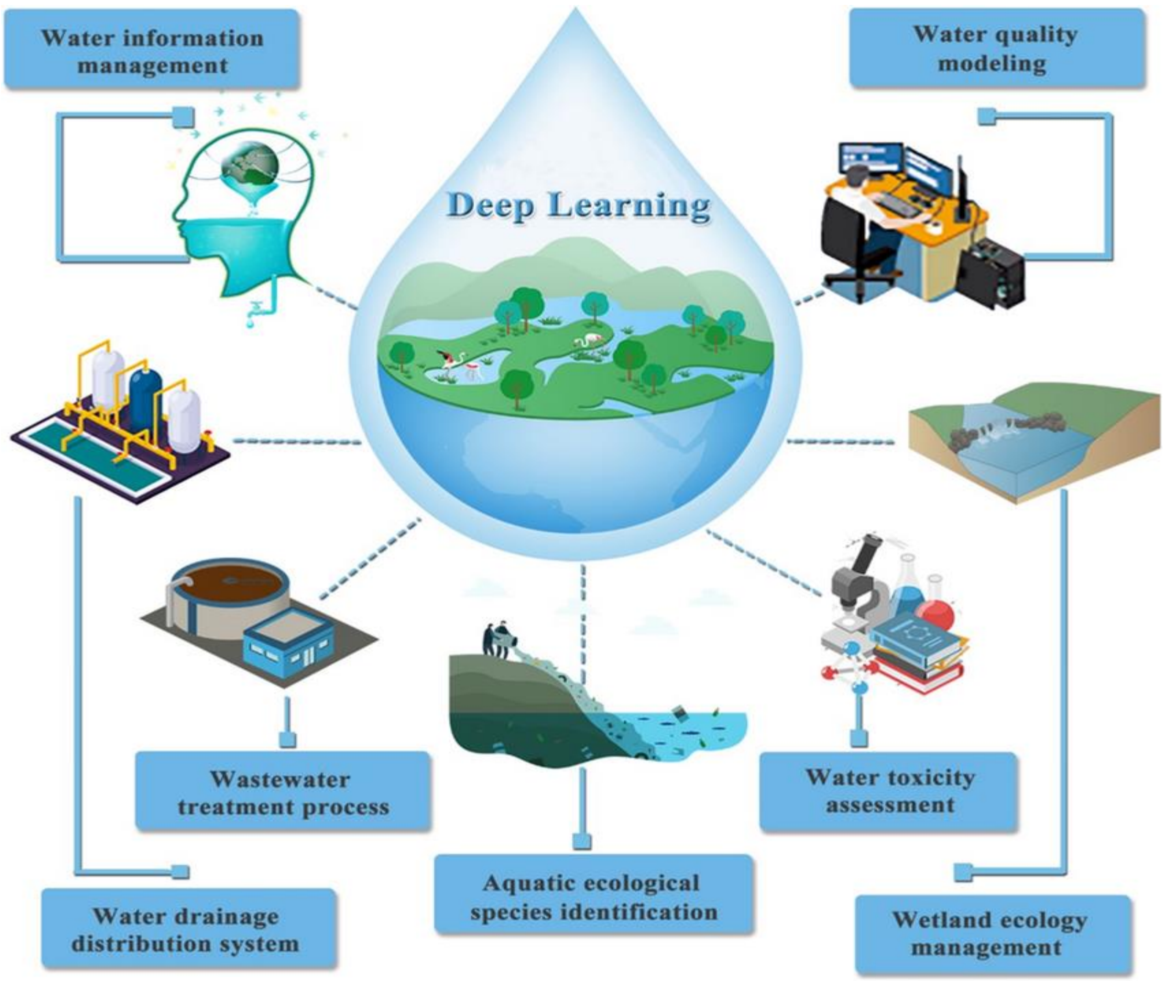

Figure 1. Use of deep learning for ecological, environmental, and water resource preservation purposes (Fu et al., 2024).

The subsequent paper is organized as follows: Section 2 outlines the employed technique. Portion 3 compares DL to conventional ML and highlights its advancements. Section 4 reviews the utilization of DL in water management, including tasks such as demand projections, leak detection and localization, sewage issue and blockage identification, cyber security and resource observing, wastewater recycling and management, water quality prediction, rainwater management, and irrigation control. Chapter 5 provides case evaluations. Section 6 demonstrates the challenges, open issues, and prospective trajectories. Finally, conclusions are offered in Section 7.

Methodology

The research performed comprehensive scholarly work to examine various articles pertaining to the application of AI in water management. The present study employed the systematic literature review methodology which is considered to be a reliable approach for review analysis (Raihan, 2023b, 2023c, 2023d, 2023e, 2023f; 2023g, 2023h, 2023i). This report of the review was implemented on prominent databases, including Scopus, Web of Science, and Google Scholar. The search parameters for these electronic files encompassed smart water management, DL techniques in water management, intelligent approaches to wastewater management mitigation, and advanced techniques for integrating rainfall retention. The chosen documents were selected based on multiple specifications, including a potential assessment of the project field, focus on potential executions, precision of results derived from DL approaches for various water conservation strategies, openness to model use, and simplicity in the literature.

Furthermore, in order to guarantee the excellence of the documents, we select articles exclusively through peer-reviewed journals. Figure 2 illustrates the inclusion and exclusion criteria considered to select suitable publications. The publications were chosen based on the themes of smart water management, deep learning techniques in water management, innovative approaches to wastewater mitigation, and intelligent methods for rainwater storage optimization. Only documents written in English were incorporated for the review study. Furthermore, only the articles aligned with the research objective were incorporated into this review from the selected source on the topic. Moreover, only articles published from 2020 to 2023 were incorporated in this review.

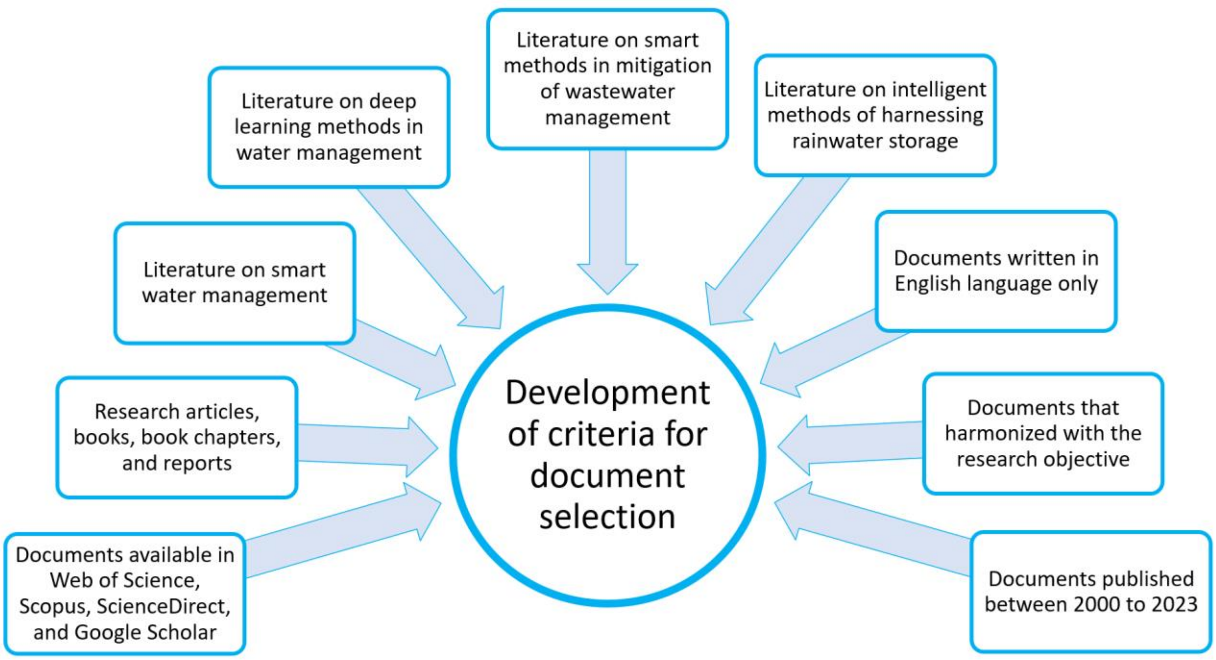

Figure 2. The criteria for the document selection.

Figure 3 delineates the techniques that were applied to the comprehensive analysis in this study. Following the selection of the investigation topic, the procedure proceeded with the identification and collection of pertinent articles, the review and summary of diverse source material, and the creation of written resources for publication appraisal. In the consolidation phase, a wide number of documents were compiled and incorporated into theoretical or experimental inspections, enhancing the final work.

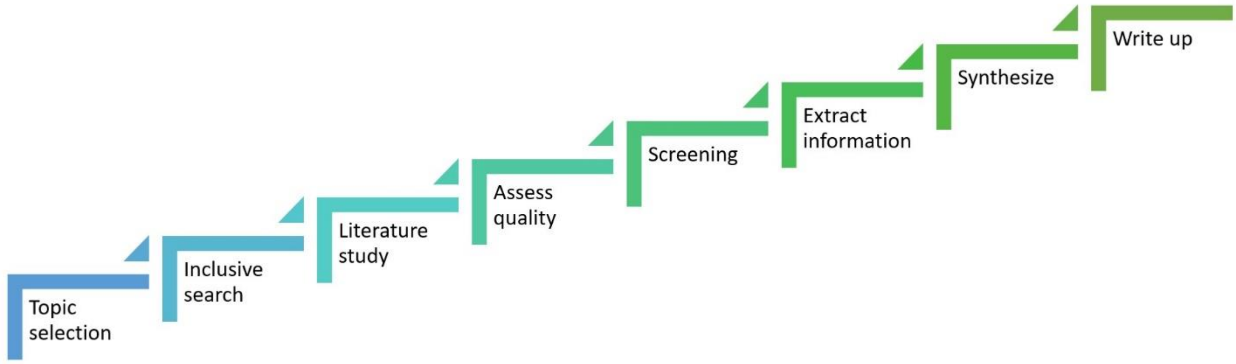

Figure 3. The methodological process taken for the bibliometric analysis.

Advances in Deep learning

Throughout history, AI has had periods of significant progress as well as setbacks. However, in recent times, the advancement and utilization of AI have been primarily driven by DL, which is having a profound impact on numerous industries. DL has made significant advancements in various domains when compared to traditional ML. Firstly, it allows for the automated extraction of characteristics from unprocessed data by employing many stages of representation learning, commencing from the basic information and progressing to improve and higher stages (Lecun et al., 2015). It obviates the need for attribute engineering and specialist skills in order to acquire traits from raw data prior to their input into ML algorithms. Moreover, this enhances the ability to learn by magnifying significant patterns and reducing the impact of unwanted fluctuations in the source data. This is achieved by leveraging the exponential benefits of incorporating numerous hidden layers in deep networks, which allows for the representation of intricate non-linear functions. (Lecun et al., 2015; Shen, 2018).

Furthermore, the widespread use of the modified linear unit activation function, represented by the equation $f(x) = max\ (x, 0)$, and its various modifications, offers multiple benefits: 1) Deep networks can be trained quickly because their derivatives, which are either 1 for positive inputs or 0 for negative inputs, allow for computation savings. Additionally, the use of error terms contributes to this efficiency. 2) The problem of vanishing gradients can be resolved by utilizing elevated slopes and uniformity. 3) The connection of unseen strata in deep networks can produce actual zeroes for negative inputs, resulting in poor depiction. This is a pleasing characteristic in representation instruction. In contrast, the sigmoid activation function will only yield a zero output, achieving a value closest to zero but not a real zero value (Goodfellow et al., 2016). Furthermore, the execution of the random gradient descent algorithms can greatly enhance the efficiency of training dynamic circuits, particularly when dealing with extensive datasets. This method achieves efficiency by randomly selecting a minor portion, known as a mini-batch, taken from the learning sample. It continues till the learning ends, reaching convergence. Various enhancements have been made to the stochastic gradient descent approach, including the highly employed Adam algorithm (Kingma & Ba, 2014), which has become prominent in the field of DL. In addition, the efficiency and effectiveness of network training have been enhanced via various approaches, including novel structures, unattended pre-training, load exchange, reduced models and distilling, and means of regularization (e.g., dropout) (Shen, 2018).

The effectiveness of DL is ultimately dependent on the progress made in machine speeds, specifically graphics processing units (GPUs), as well as the accessibility of extensive datasets. Data parallelization is a frequently employed approach on GPUs to speed up the training of DL models, particularly when using mini-batch training. The technique involves storing a duplicate of the network and training it on a separate set of information on every GPU. The calculated slopes and costs are then transmitted to the same systems (such as the CPU) for consolidations. After aggregation, the updated parameters are sent back to the GPUs for further updates. It can significantly promote the creation of neural networks for extensive databases and enhance the ability of learning. The frameworks of various widely used DL algorithms, such as autoencoders, LSTMs, CNNs, DRL, and GNNs, together with their main characteristics, are depicted in Figure 4, beside the traditional multi-layer perceptron ANN.

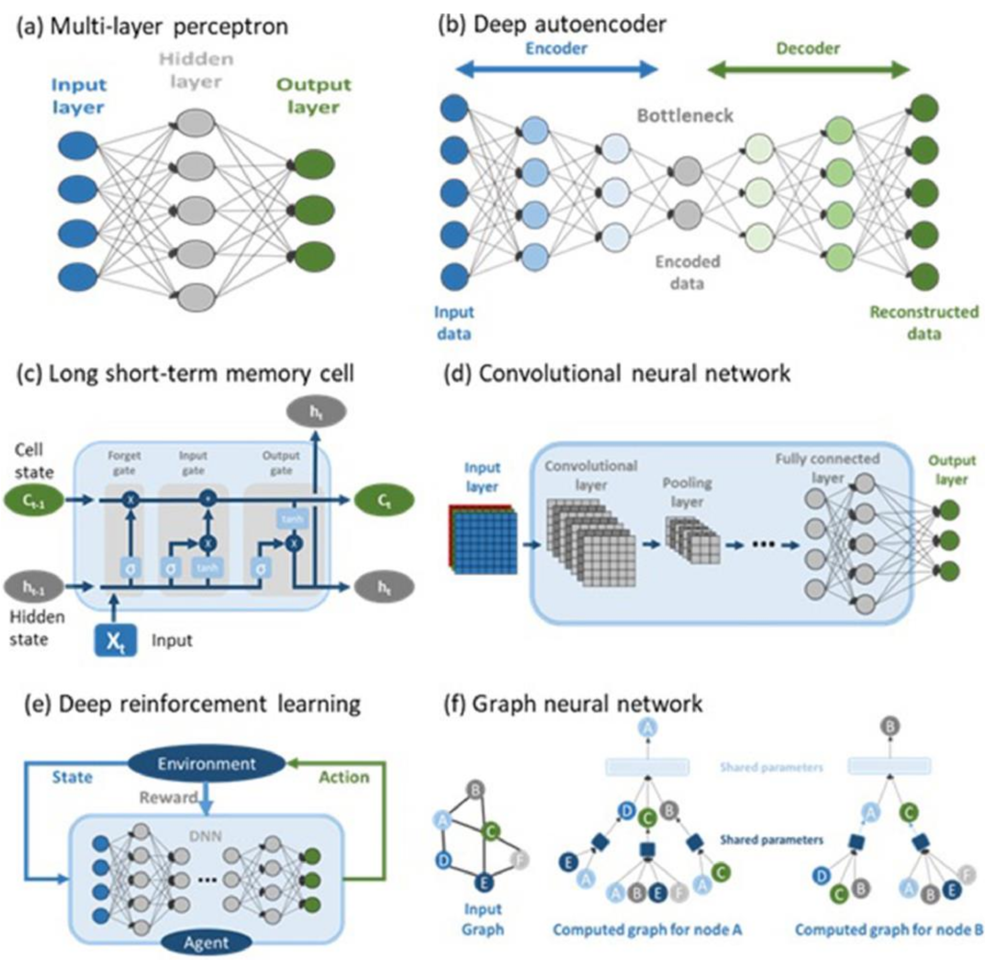

Figure 4. Multi-layer perceived neural systems and current DL algorithms. (a) a fully connected three-layer neural network employs non-linear activation functions like the sigmoid. (b) autoencoders usually consist of two identical aspects: an encoder and a decoder, which are taught to recreate information by transiting a congestion level; hence, deploying an informal learning strategy. (c) LSTM cells, comprising a forget gate, input gate, and output gate, act as the basic parts of LSTM networks, allowing the formation of dependency chains in time series data. (d) CNNs combine pools and convolution to create higher-order traits from input images. (e) Deep Reinforcement Learning (DRL) blends reward instruction with deep computing to educate an agent for the best return via environmental interactions. (f) GNNs for graph-structured data to illustrate various interactions involving communication across graph nodes (Fu et al., 2022).

Deep Learning in Water Management

Demand forecasting

Time series analysis often uses controlled learning to project demand. Thus, LSTM algorithms are typically used to capture temporal patterns in historical data. By extracting traits from previous time-step needs, they may predict hourly or sub-hourly wishes without considering weather or demographics. A GRU-based recurrent neural network (RNN) outperformed typical ML models in accurately and reliably predicting water demand for 15 minutes and 24 hours, according to Guo et al. (2018). Mu et al. (2020) showed that LSTM models can reliably anticipate demand at 15-minute and 1-hour spatial precision. These models were compared to ARIMA, SVM, and random forest models for their ability to handle abrupt demand increases. To predict the normal water consumption behavior at a 1-hour interval in a virtual classroom, LSTMs need several initial training days. Based on past data for the following day, these might estimate demand for pump operations (Kühnert et al., 2021). As smart water meters become increasingly popular, LSTMs can effectively anticipate water usage using consumption data. This allows water utilities to improve resource allocation and efficiency. Figure 5 illustrates a smart water supply in a water distribution system.

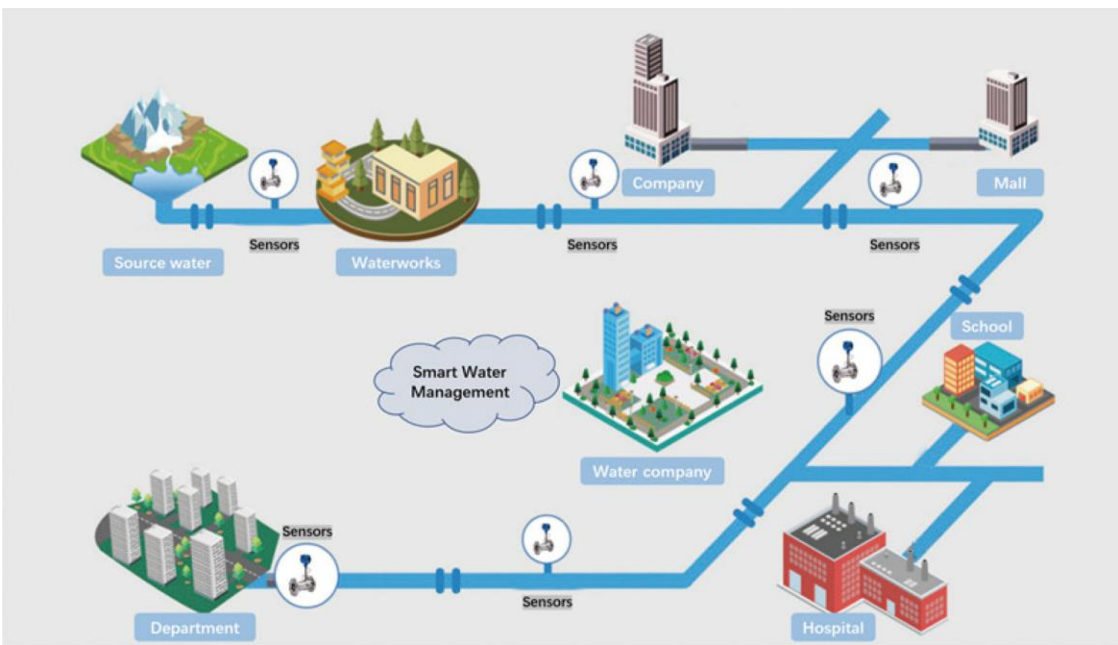

Figure 5. Smart water supply in a water distribution system (Wang et al., 2024).

Nasser et al. (2020) found that the LSTM model outperformed SVMs and random forest models using 10-minute smart meter data for 2-20 Cairo residences. The LSTM model failed to estimate peak demand. Recent research shows that hybrid DL models accurately anticipate daily water demand when climatic and sociological parameters are considered. Du et al. (2021) forecast daily water intake using mixed LSTM. The model prepares initial data with two LSTMs, periodic wavelet transforms, and principal component analysis. One LSTM calculates the initial pattern using a denoised demand series, while another uses consumption leftovers to predict synthetic distortion. The main climatic and vacation features stimulate both systems. Using CNN, Hu et al. (2019) extracted characteristics from five days of historical water usage data and daily maximum temperatures. These features were entered into a simultaneous LSTM algorithm to compute daily water needs.

The blended CNN-LSTM paradigm surpassed LSTM, Bi-LSTM, and CNN in prediction precision. Preliminary processing methods such as time series signal breakdowns may improve attribute extraction and GRU-based model prediction (Hu et al., 2021).

Leakage detection and localization

Classification and prediction-based DL leak detection techniques exist. Models recognize normal and pathological events using labeled data and pressure, flow, auditory, and vibration inputs. One drawback of this strategy is the strain of acquiring and classifying a lot of data. Hydraulic models can manufacture artificial training data (Javadiha et al., 2019). Forecast-oriented techniques use DL models to predict system states like pressure and flow. Using a threshold, it classifies disparities between expected and observed event values. CNNs are the main DL leak detection and localization method in literature. CNNs are trained to classify events as normal or abnormal using labeled data in most research. The article describes several prediction-based DL algorithms. Wang et al. (2020) predicted water consumption using LSTM. This method performed well in detection precision, actual positive rate, and false positive rate. This study will focus on CNN classification based on pressure/stream data, sound/vibration data, and input formats. Pressure data is used to create CNNs to find leaks at numerous sites. Six CNN models were trained using pressure data from Fang et al. (2019). They manually categorized leakage events using Water Distribution System (WDS) statistics from a laboratory platform. Top performers CNN model used 21 and 8 pressure sensors to achieve 97.33% and 92.11% accuracy. From 96.43% for one leak to 91.56% for three, accuracy decreased. Due to the large number of sensors used (8 to 21 for a 400-meter network), which is not practical for real-world networks, accuracy is great. Zhou et al. (2019b) advised using hydraulic models to create pressure data with several leaks for training. Hydraulic models generated synthetic data before this. However, those data were generated under typical conditions with little or no leakage. Zhou et al. (2019b) developed a completely linear DenseNet to effectively identify WDS leakage characteristics and localize pipe leaks. They detected 200 leak occurrences per pipe and showed that the program can precisely locate pipe breaches. Javadiha et al. (2019) trained CNNs with simulated leaking data, while Fan et al. (2021) trained autoencoders. However, they created pressure residual maps by removing sensor pressure data from hydraulic network model pressure estimates. These maps were then converted into 2D images to train CNNs to find leaks. Pressure residual maps analyze all probable leak locations, although hydraulic modeling uncertainties may affect their accuracy. Synthetic data for leakage location (Javadiha et al., 2019; Zhou et al., 2019b) and detection (Fan et al., 2021) considered unknown hydraulic models, such as random demands and leak sizes. CNNs (Nam et al., 2021) or autoencoders (Cody et al., 2020) can assess pipe pressure variations and cracks' acoustic and vibration data. Elasticity waves across the pipe create these signals. These models characterize events as normal or aberrant. Kang et al. (2018) trained and tested a one-dimensional CNN on 1580 normal and 660 aberrant signal pairs from accelerometer sensors in a Seoul water distribution system (WDS). They used a support vector machine to identify feature types and denoising and a bandpass filter to improve detection accuracy. Shukla and Piratla (2020) used a CNN derived from a pre-trained AlexNet architecture to detect PVC pipe leaks in scalogram images without preprocessing. Using experimental pipeline testbed data, they accurately determined leak diameters and places. A 2D CNN-based autoencoder helped Cody et al. (2020) detect leaks in acoustic data spectrograms with 97.2% accuracy. Jiao et al. (2021) used CCTV footage and an autoencoder to detect pipeline irregularities, expanding its use in water system surveillance when elastic waves flow through pipes.

CNN input data format has been extensively studied due to its high link with recognition and identification precision. Javadiha et al. (2019) and M. Zhou et al. (2019a) investigated leak identification and localization using two-dimensional pictures from one-dimensional pressure data. CNNs are ideal for turning audio signals into two-dimensional pictures, so Cody et al. (2020) studied this. This process may lose data and raise computational expenses (Zhou et al., 2021). Kang et al. (2018), Fang et al. (2019), and Zhou et al. (2021) used 1D CNNs to directly evaluate 1D time series signals for leak diagnosis by extracting features from vibration and pressure signals. Before inputting raw data into a 1D CNN, Rahimi et al. (2020) used FFT, wavelet transformations, and time-domain characteristics to efficiently identify leaks in plastic and composite water tanks. Guo et al. (2021) created a time-frequency CNN to collect leaking spectrograms at various resolutions. Spatial clustering with CNNs to discover leakage zones and transfer learning with pre-trained models like AlexNet are two methods CNNs use to find leaks. Satellite images and CNN models have also been used to detect leaks. These approaches cannot monitor in real-time and often cause false alerts due to satellite photo resolution (Shukla & Piratla, 2020). Figure 6 illustrates the architectural diagram of the intelligent sound-assisted water leak detection system.

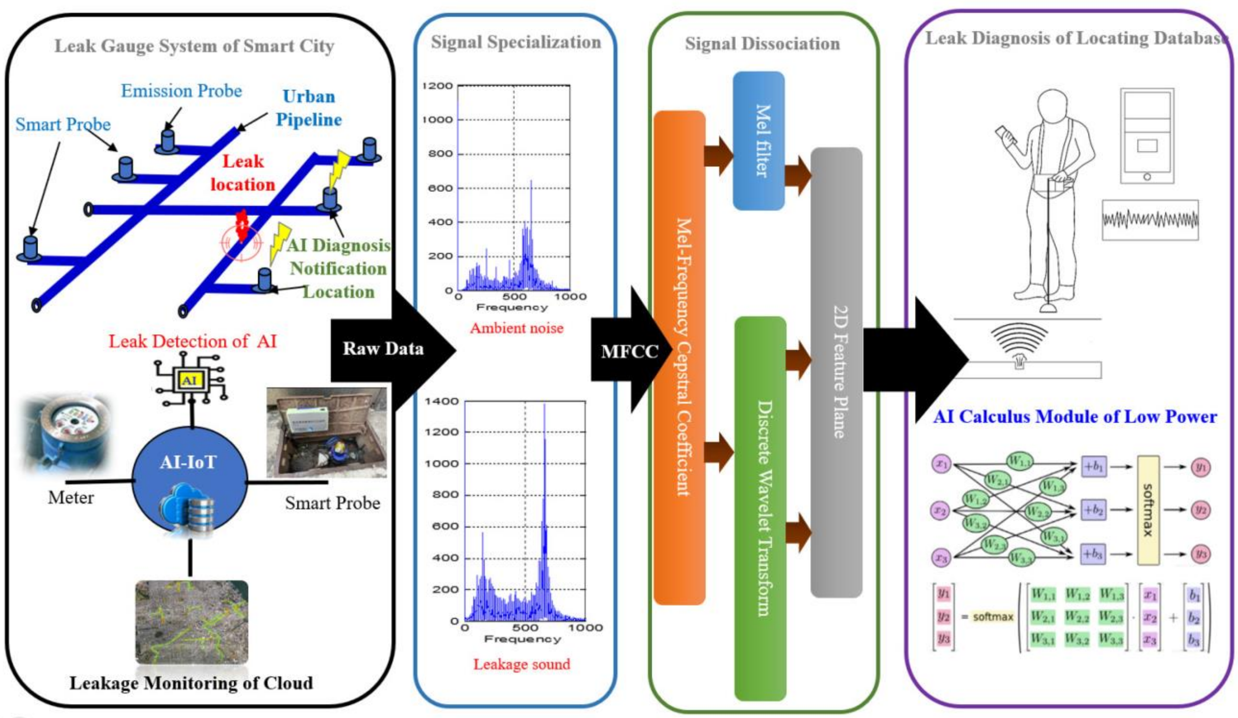

Figure 6. Leakage detection and localization system by using a deep learning approach (Tsai et al., 2022).

Sewer defect and blockage

CCTV videos are used by expert inspectors to inspect sewers inside. This procedure is laborious and time-consuming. CNNs are becoming useful for automatic sewer flaw detection. Their performance in these pieces has been particularly impressive: 1) CCTV image categorization by defects 2) Object identification: identifying defects and their locations; 3) Semantic segmentation: labeling defect-related pixels. Figure 7 presents the architecture of detecting sewer defects and blockage by using a deep learning approach.

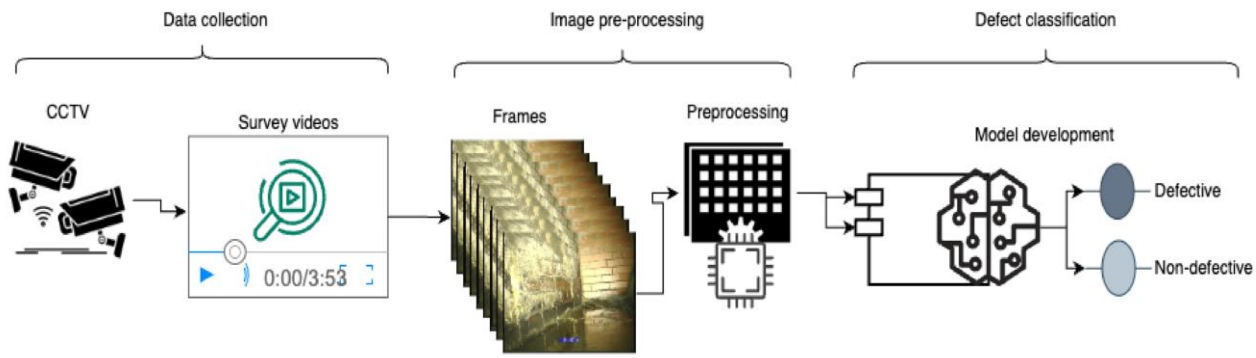

Figure 7. Detecting sewer defects and blockage by using a deep learning approach (Yusuf et al., 2024).

Image classification

Kumar et al. (2018) trained binary classification CNNs to detect specific problems. To save training time, Meijer et al. (2019) constructed a single CNN to classify frames by defect. Gutiérrez-Mondragón et al. (2020) used CNN to detect sewage issues and pipe obstructions. Famous CNNs were analyzed for sewer issues by experts. The hierarchical classification system employed by Xie et al. (2019) distinguished between normal and defective pipes and subsequently categorized defective ones. Li et al. (2019) used ResNet18 in a hierarchical architecture with residual learning from He et al. (2016). Chen et al. (2018) used SqueezeNet for its improved extraction. Chen et al. (2019) improved a binary identification CNN with a cost-sensitive activation layer and Cost-Mean Loss. Kumar et al. (2020a) showed CNN weights and changes using class activation mapping. Finally, Moradi et al. (2020) used CNNs to locate problems in sewer frames by distance.

Object detection

Previous investigations have categorized and localized frame faults. Classification algorithms struggle with several defect kinds in a single image, although object detection models help. CNN-based approaches are divided into region-based (two-stage) and one-stage detection. R-CNN was faster for Cheng and Wang (2018), although Zhang et al. (2018) used VGG-16. Instead, Yin et al. (2020) used YOLOv3, a one-stage network, for real-time sewer problem detection. Kumar et al. (2020b) found that YOLOv3 is faster and better for onsite detection, but faster R-CNN is more accurate for offsite evaluation. Wang et al. (2021a) used quicker R-CNN to track flaws and count defects in successive video frames.

Semantic segmentation

Image semantic segmentation models can label each pixel of a recognized object. Kunzel et al. (2018) employed a two-stream CNN, the Full-Resolution Residual Network (FRRN), to automatically detect and categorize sewer pipe failures and structural issues. CNN processed unrolled and stitched CCTV footage. Pan et al. (2020) improved CNN-based U-Net sewage problem segmentation by integrating feature reuse and attention blocks. Wang and Cheng (2020) used DilaSeg, a deep CNN with dilated convolution, and a dense conditional random field-based RNN. DilaSeg extracts feature maps, whereas CRF-based RNN resolves local ambiguities. Wang et al. (2021b) also suggested studying semantic segmentation data to analyze sewer conditions and operational and maintenance difficulties.

Cyber security and asset monitoring

The U.S. Department of Homeland Security has designated water and wastewater infrastructure as a key cyberattack target in the 16 essential infrastructure sectors, citing various cybersecurity issues. This sector was the third most targeted in 2015 after industry and energy, with 25 cybersecurity incidents (Hassanzadeh et al., 2020). Thus, practical and scholarly attention to water infrastructure protection has grown. DL methods including LSTM, autoencoders, and GNNs have enhanced high-dimensional intrusion detection. Inoue et al. (2017) trained an LSTM model with water treatment plant normal operation data and tested it with 36 attack scenarios. Taormina et al. (2018) found that autoencoders outperformed XGBoost and LightGBM in 14 water distribution system attack scenarios. Evasion attacks against deep autoencoder-based detectors were examined by Erba et al. (2020). Deng and Hooi (2021) found that an attention-based GNN detects water treatment system cyberattacks better than baseline models. Tsiami and Makropoulos (2021) showed that convolutional GNNs may detect water distribution system assaults using SCADA data linkages. Urban Water Systems (UWS) research is needed to reduce threats from water infrastructure digitization and AI. UWS cybersecurity best practices must be developed, and DL techniques like LSTM, autoencoders, and GNNs can improve security and identify threats. Erba et al. (2020) applied adversarial machine learning to detection systems, however, Taormina et al. (2018) suggest testing on real-world cyber-attack situations. Deep learning can be used to monitor water assets as a soft sensor or surrogate model in addition to anomaly identification. Lack of sensors or cyber system breakdowns makes water system measurements inaccessible. Soft sensing uses secondary measurements to forecast missing primary data. The researchers trained 2D CNN and LSTM models using one-minute operational data from 100 sensors at a water treatment facility over a year. Researchers used several linear regressions to merge these models. Lower root mean square errors showed that the combined technique predicted better than CNN and LSTM models (Cao et al., 2018). Especially when the 100 sensors are offline, an ensemble model can forecast flow and water level. In wastewater treatment facilities (WWTP), LSTM models accurately predict key variables (Cheng et al., 2020). A multi-layer perceptron with layered restricted Boltzmann machines (Wu & Rahman, 2017). Based on a limited collection of nodal pressure data, we rebuilt pressures at all nodes using a GNN with K-localized spectrum filtering. This method had an average relative error of less than 5% on three benchmark networks with a 5% observation ratio. Hajgató et al. (2021) conducted it. This shows that GNNs can be used as soft sensors or alternative models to assess network pressure. Belghaddar et al. (2021) used GNNs to fill voids in wastewater network pipe dimensions, materials, and system statuses. CNN was used to monitor time fluctuations of the Fat-Oil-Grease layer and other hydraulic processes in a wastewater pump sump (Moreno-Rodenas et al., 2021). It predicts pump sump failure.

Wastewater recycling and management

Forecasting real-time water treatment parameters is difficult. Data is used to estimate the precaution process in municipal wastewater through anaerobic membrane bioreactors by Li et al. (2022a). They tested two AnMBRs for a year, evaluating reactor temperature, COD, flux, effluent COD, pH, and other wastewater treatment variables. They analyzed these parameters using multiple deep learning (DL) architectures, and a CNN predicted outcomes with 97.44% accuracy. The CNN was also calculated in under a second, improving the AnMBR treatment result prediction. WWTPs reduce pollution and ecosystem damage. They produce a lot of sludge and GHG, necessitating additional optimization (Badeti et al., 2021). MADRL was used to optimize WWTP dissolved oxygen and chemical dosing by Moreno-Rodenas et al. (2021). Optimizing their life-cycle assessment (LCA) lowered ecological impacts including costs, energy consumption, and GHG relative to a

baseline scenario. The LCA-driven strategy surpassed a cost-oriented method in environmental benefits, underscoring the relevance of impact elements when retrofitting WWTPs, which need substantial data analysis.
FOG in wastewater pumping stations causes infrastructure failure (Nieuwenhuis et al., 2018). If suspended soils are not effectively transported to pump suction inlets, large clusters of particles can create thick, hard FOG layers. The lack of FOG layer data is the biggest mitigation challenge. Chen et al. (2021) monitored water pumping station FOG layers with an automated camera system. The system recorded data often for months. The pump sump uses a novel computer vision model that analyzes optical images using DL techniques to account for FOG layer dynamics and other hydraulic phenomena. Additionally, this gadget monitors the water pump station and provides standardized high-frequency FOG layer data. This data is crucial for understanding FOG buildup and movement. The camera-based identification method had a 0.11 root-mean-square error and 0.901 Nash-Sutcliffe efficiency. Several wastewater treatment experiments improve recycling efficiency and eliminate pollutants by lowering fuel emissions, expenses, and energy use. Figure 8 illustrates an innovative wastewater treatment system.

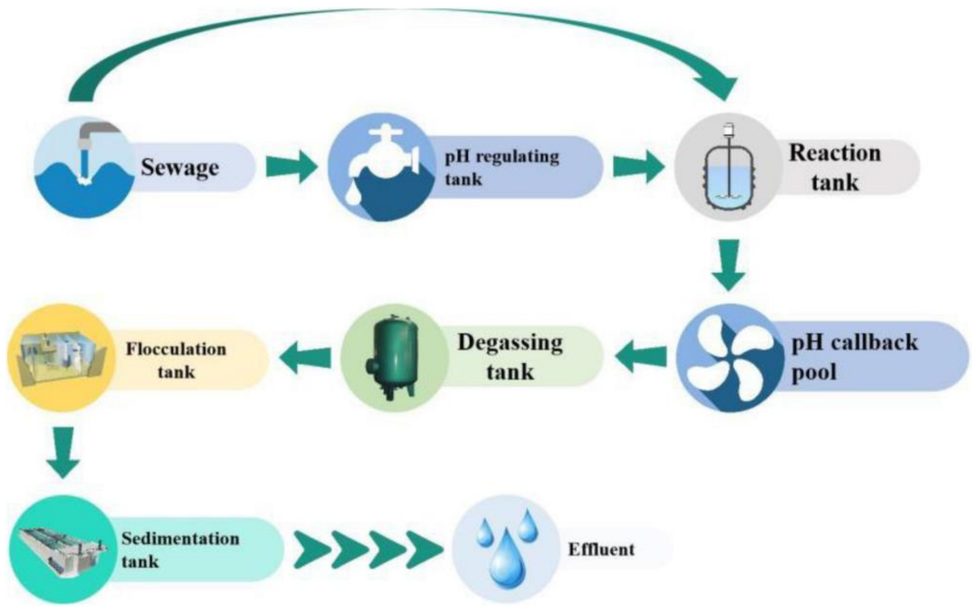

Figure 8. An innovative wastewater treatment system (Lin et al., 2022).

Water quality prediction

Different DL and ML models analyze water quality for different uses. This section discusses applications, infrastructures, and methods for assessing water quality for various purposes. Figure 9 presents the application of DL in different water systems. Water quality is threatened by worldwide water contamination. These applications measure pollutants using ML and auto-ML models. However, math skills and model-making are required. Since water quality assessments require time-series data, DL models are best for measuring it. Khullar and Singh (2022) say DL concentrates on "Bi-LSTM." Monthly data for the Yamuna River quality report in New Delhi was collected from 2013 to 2019. Bi-LSTM prioritizes training and missed-value imputation. This estimate is essential for accurate measurement. Finding the best missing value-filling method is the first step of the Bi-LSTM. The second phase creates input-based feature maps. Training is the third stage. The fourth phase optimizes the loss function to reduce learning errors. The experiment measures BOD and COD. Palla COD values are MSE = 0.015, RMSE = 0.117, MAE = 0.115, and MAPE = 20.32. Values from BOD analysis: MSE

= 0.107, RMSE = 0.108, MAE = 0.124, MAPE = 18.22. Compared to other methods, the proposed one is more reliable and has fewer errors. Smart sensors improve water quality monitoring applications. Nemade and Shah (2022) collected water quality data with smart sensors. Next, they clean sensor data to remove missing values and outliers. The G-SMOTE method extracts traits for learning. This model optimizes a multi-class DL model utilizing an MDLNN neural network and hyperparameter tuning. Step-by-step learning from new data is made easier with this paradigm. The model's identification loss is 0.0415% and precision is 99.34%.

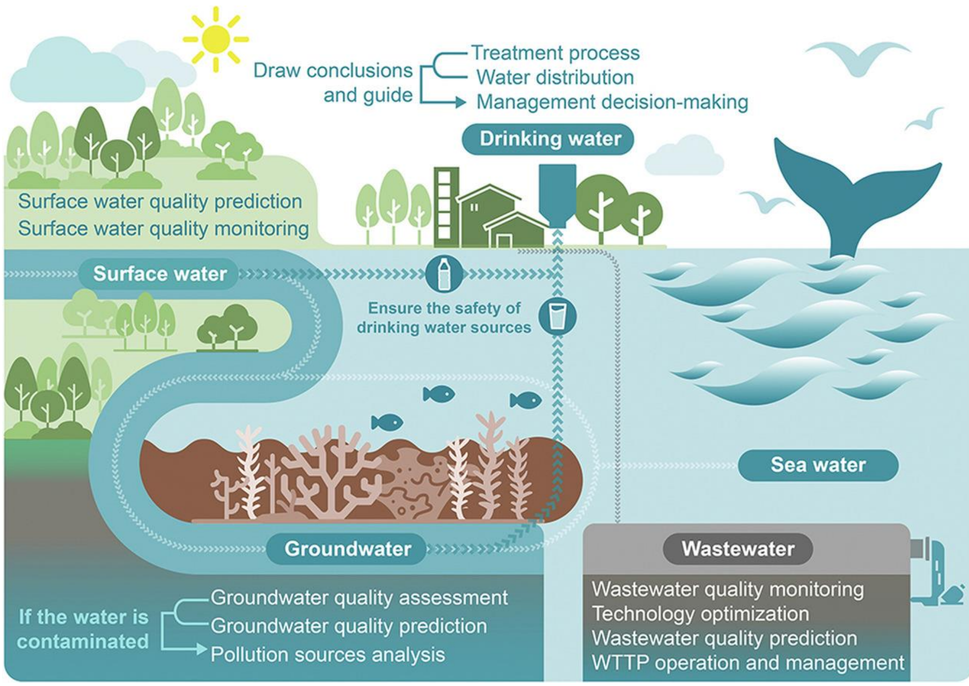

Figure 9. Application of deep learning in different water systems (Zhu et al., 2022).

Prasad et al. (2022) suggested that automated DL algorithms improve water quality evaluation. Auto DL is a promising new technology. involves evaluating and building models with little or no coding. The execution time is shorter than typical DL algorithms. The Auto-DL model is 1 percent less efficient than standard DL models in binary data measurements, which are above 1.8 percent accurate. In multi-class data models, contemporary models are around 1% more accurate than Auto-DL. Standard DL achieves 98-99% accuracy, whereas Auto DL achieves 96-98%. It helps choose the right DL model automatically and reduces the time needed to get them in real-time. Thus, Auto-DL allows for more real-time problem implementation flexibility.

Rainwater management

Water collection and management require accurate precipitation forecasts. Rainwater is the main agricultural and domestic water supply. Predicting precipitation is important and fascinating worldwide. This forecast is crucial for governments that use hydraulic converter power plants to generate energy from rainwater reservoirs during the rainy season. Bhattacharyya et al. (2021) examined Andhra Pradesh meteorological service rainfall data for one year. The partitioning technique splits features into training and testing datasets. Two ML and one DL models make up this system. CNN was utilized for DL linear regression and SVM for machine learning. The neural network had 77.17% accuracy, the linear model 48.8%, and the SVM 32.5% throughout testing. DL algorithms outperform ML in rainfall data predicting, especially with irregular data patterns. Deep learning algorithms seem more suitable for this because of their precision. Water conservation is not optimum in most rainwater gathering systems. Creating communal rainwater harvesting storage facilities in cities is crucial, but obtaining approval may be difficult. The system's viability is complex, requiring many human evaluations (Lani et al., 2018). Complex system viability requires multiple manual assessments. Gaurav et al. (2021) automate the entire procedure with computer vision. They use ML and DL algorithms for image ceiling division, thickness computation, precipitation forecasting, and tank positioning. Rainfall projections are made using SARIMA continuous modeling. The Mask R-CNN separation technique used Canny edge recognition and shape mapping to estimate the rooftop reservoir. Thus, the system can predict the mix's metrics break even and analyze installation feasibility.

Irrigation control

Water for other worldwide uses is threatened by excessive groundwater extraction for agriculture. It also threatens the world's drinkable water supplies (Ding et al., 2021). Various soil textures are classified to determine irrigation needs. DL models are essential for effective categorization. This complex soil texture classification uses neural networks and frameworks. Kurtulmuş et al. (2022) assessed the water needs of three soil textures under different lighting situations using a proximal sensing system with a color camera, DL, and computer vision. To simplify image training, they created an imaging system using deep convolutional neural networks. This study classifies water textures using five deep-learning architectures. AlexNet, GoogleNet, ResNet, VGG16, and SqueezeNet are neural networks. AlexNet is the best model with an F1 score of 0.9973. With 16.92 ms processing time, Google Net and ResNet identify the fastest. They show that DL algorithms significantly predicted agricultural region irrigation needs under diverse scenarios. Effective water management requires understanding the operational dynamics of large-scale irrigation handling and its rapid response to varied pressures. Raei et al. (2022) claim to have constructed a regional irrigation control system classification DL model utilizing remote sensing photos. A U-Net architecture is being integrated with ResNet-34. This was achieved by testing model topologies, hyperparameters, class weights, and picture sizes. Transfer learning improved model training efficiency and performance. This method is used in urban and rural regions with four irrigation systems. The US Department of Agriculture's National Agricultural Imaging Program provides 8,600 high-quality images with exact ground-truth observations. The model's data segmentation accuracy was 72%–86% for validation, 85%–94% for training, and 70%–86% for testing. Global transferability gives the DL approach versatility. This work reveals how transfer learning, imbalanced training datasets, and varied model architectures can discriminate irrigation kinds. Li et al. (2022b) created a UAV velocity measurement system for large rivers. The optical flow approach and YOLOV5 DL algorithm use the monocular range to accurately measure velocity and transform pixel distance into the actual distance in this system. In the Yongji Canal, Inner Mongolia's river-loop irrigation region successfully adopted the method. The procedure yielded high-quality photographs and consistent measurements. Jayasinghe et al. (2022) predicted Ep across Queensland, Australia, using feature selection and a hybrid LSTM model with component Analysis. Time series analysis was used to evaluate daily data from August 31, 2002, to September 22, 2022. This study shows a Root Mean Square Error below 20% and a Kling-Gupta efficiency above 87%. The model calculated and predicted daily Ep values more accurately than standalone DL hidden layer neural networks and decision-tree-based models using an upgraded feature selection technique. Managing and adjusting irrigation requires monitoring evaporation.

Case Studies

Artificial Intelligence (AI) for smart water management systems

In all sectors, ICT usage has increased. Advanced data analytics optimizes water delivery and reduces costs. Several industries can use AI to improve water use decisions. ICT and AI would help accomplish the Sustainable Development Goals for water management and sanitation (Jenny et al., 2020). AI may efficiently manage water limits by evaluating population density and enforcing leakage regulations.

Smart water management—a case study of Korea

The Water Resources Corporation and IWRA are developing an advanced water management system. This strategy uses ICT to quickly offer real-time water data to the IWRA to address global water issues. The advanced water management system tracks water, optimizes irrigation, detects leaks, and uses AI algorithms to mitigate floods. Krishnan et al. (2022) combined IoT detectors, GIS observing engines, and satellite data. AI enhances the system by automating services in many situations, improving decision-making.

Grid intelligence water case study

Integrating current water management technologies is difficult. Water distribution across sectors during the water crisis takes enormous resources. Citywide water metering must be accurate and effective. Verizon released Grid Wide Intelligent Water Solutions in 2018 as a cloud-based smart water metering system for southeastern US communities. Water meter sensors monitor and control water usage, while the IoT gateway allows secure, efficient communication across multiple locations. Water leaks and abnormal water consumption are detected and fixed using machine learning.

Smart water management

Most regions use Smart Water Management (SWM) to efficiently manage modern water resources by integrating policies and technologies. Nickum et al. (2020) detailed national solid waste management methods in a concise report. Mexico, Korea, and France developed a smart flood-handling method using IoT and AI for predictive analysis. The Mexican "PUMAGUA" effort used sophisticated water resource networks and data monitors to improve water quality and reduce use. South Korean experts created the Hydro Intelligent Toolkit program. This toolset provides advanced water management solutions using hydrological data, precipitation forecasts, flood assessments, and groundwater measures. The intelligent IoT network analyzes data to measure.

Smart water management towards future water sustainable networks

Ramos et al. (2019) examined and improved modern Portuguese water distribution pipes. The water business has faced many challenges in the previous decade in achieving efficiency and ethics, including interpersonal, scientific, and ecological aspects. Intelligent technology helps water-smart cities and the energy nexus develop through effective water planning and management. Smart city technology improves service quality, cost, and system performance. This analysis shows that monitoring and water loss control systems maximize efficiency by reducing water losses and costs. These efforts raised the global ranking of the most efficient cities from 20th to 5th. The analysis shows that the water industry has technological and economic possibilities for microhydropower projects. These projects can improve power conversation and reduce CO_2 emissions. The case study shows 12-year savings of 57 GWh and 100 Mm^3. Cost savings reduced CO_2 equivalent emissions by 47,385 metric tons.

Challenges, Open Issues and Future Directions

The primary obstacles associated with DL in water management can be roughly categorized into several key groups, as depicted in Figure 10. The major challenges for the practical deployment of DL in water management include algorithmic development, multi-agent platforms, virtual clones, data quality and availability, security, context-aware data analysis, and training efficiency.

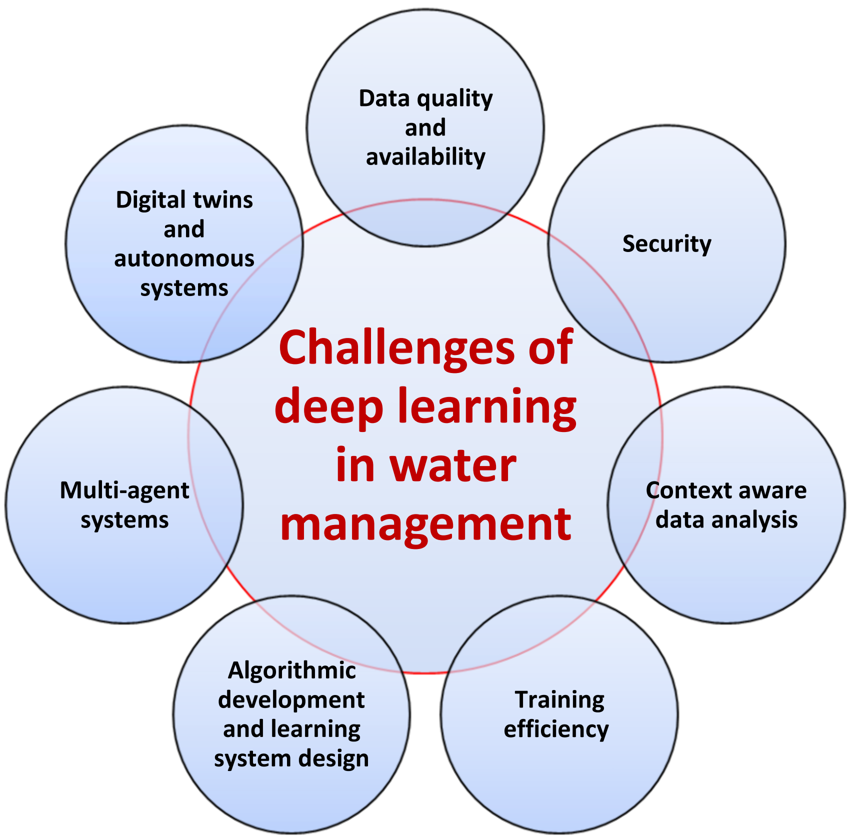

Figure 10. Major obstacles of DL application in water resource management.

Data quality and availability

DL networks leverage substantial datasets to train an intelligent system that classifies large test data or real-time info coming from sensors or images used in water management and safety systems. We establish restrictions to govern the procurement of data from scientific and commercial enterprises, given their significant sensitivity and potential exploitation for gaining competitive advantages. Legal and political limitations greatly complicate the acquisition of essential data from government organizations for research and development. Data is constrained by demographic limitations. When there is a substantial need for extensive real-time data to train the DL algorithm, apprehensions regarding its quality simultaneously emerge. Acquiring a large volume of data for training makes it hard to assess the quality of individual data elements. Therefore, we cannot claim that the trained model is based on high-quality data. Inadequate pre-processing may lead to difficulties such as outliers or noisy data, increasing the trained system's vulnerability to errors.To address challenges related to data quality and availability in the application of deep learning to water resource management, it needs to employ strategies such as: augmenting data collection via advanced sensors and IoT devices, applying data imputation techniques to address gaps, integrating domain knowledge into model architecture, utilizing data augmentation to expand sample size, and investigating hybrid models that merge deep learning with physics-based methodologies to enhance accuracy and robustness, particularly in scenarios of limited or unreliable data. To address data limitations in real-world DL applications for water management, essential strategies encompass: augmenting data collection via sophisticated sensor technology, applying data imputation techniques to address gaps, utilizing semi-supervised or unsupervised learning approaches in the absence of labeled data, harnessing transfer learning to adapt models across diverse water systems, and integrating domain expertise to develop more resilient and pertinent models; all while addressing the specific challenges of data quality, spatiotemporal variability, and restricted accessibility in water management systems.

Security

DL networks utilize a substantial volume of data to train water management systems. This data is either open-source or may be managed by various individuals within the inquiry or commercial domain. The modifications in the input data are indicative of the actions and responses of the framework. Moreover, probable predators have a vested interest in compromising the algorithm. For instance, an irrigation governance system can be manipulated by an attacker to distribute an excessive amount of water, perhaps jeopardizing the entire agricultural output due to the competitive advantage it provides. If the last structure is penetrated by attacks, the aim of integrating the AI-based DL model for water management and modern agriculture will be rendered futile. Therefore, similar to intelligent systems, it is essential to integrate cyber security regulations and ensure the integrity of data access in these water management systems based on DL.

To address security challenges in deep learning applications for water resource management, essential strategies encompass: implementing stringent data protection protocols, ensuring model transparency and interpretability, mitigating data privacy issues, establishing secure infrastructure, conducting regular threat assessments, and integrating feedback mechanisms for ongoing system enhancement, all while taking into account the specific context of the water management system and applicable local regulations. Recent examples of deep learning applications addressing security concerns in water management encompass: employing computer vision to identify leaks and anomalies in pipelines via CCTV footage, detecting potential cyberattacks on water distribution networks through the analysis of traffic patterns, predicting water quality concerns by scrutinizing sensor data, and forecasting extreme weather phenomena such as floods to proactively mitigate water security risks; all utilizing deep learning algorithms to analyze extensive datasets and discern patterns that may signify a security threat.

Context-aware data analysis

DL primarily focuses on the design and structure of a model or architecture rather than the specific method used. The algorithms indeed require updates when the systems go to the next generation. If a deep-learning network undergoes a significant technical upgrade, the quantity of retraining needed will always be inadequate. As an illustration, we can implement intelligent sensors to assess the water quality, focusing on a limited number of characteristics. If this system is improved in the future, it will be necessary to retrain the deep neural networks that control the smart sensors with new parameters. Undoubtedly, this task is highly challenging to improve and also characterized by its lack of predictability. Retraining for intelligent or IoT systems that operate with real-time data is exceedingly intricate. The fundamental challenge arises from the non-context-aware behavior of neural networks and the unknown side of their activity after training.

To address challenges in context-aware data analysis within deep learning applications for water resource management, it needs to adopt strategies such as integrating spatial and temporal features, employing hybrid models that merge physics-based and data-driven methodologies, utilizing data preprocessing techniques to manage missing values and inconsistencies, and developing context-aware architectures that adapt to fluctuating environmental conditions, all while ensuring meticulous data collection, quality control, and the consideration of pertinent contextual factors such as meteorological patterns, land use, and water quality metrics.

Training efficiency

DL networks in real-time systems undergo constant modification to accommodate changes in previously implemented methods. Nonetheless, owing to the erratic characteristics of this DL structure, the modified algorithm cannot assure the same level of accuracy or optimization as the previous method under equivalent situations. The replacement of sensors may affect neuronal remodeling in neural systems, potentially altering the behavior of the entire present framework. The effectiveness of training is crucial for deep neural networks to achieve optimal performance with the necessary accuracy, even after a significant system modification.

To address training efficiency challenges in deep learning applications for water resource management, essential strategies encompass: optimizing data collection and preprocessing, selecting suitable deep learning architectures according to data characteristics, employing transfer learning, applying methods to diminish computational complexity, integrating physics-based knowledge into models, and emphasizing data augmentation to enhance limited datasets; all while accounting for the specific context and constraints of the water resource management issue at hand.

Algorithmic development and learning system design

The creation of deep learning models presents a considerable challenge in formulating an algorithm tailored to a particular issue. Addressing this obstacle is essential for enabling the implementation of these models in practical water issues. When we clearly articulate the real-world water issue and delineate the training data, such as time series or image data, we can easily identify specific methodologies like supervised or unsupervised learning, regression, or classification. Nonetheless, choosing a suitable technique can be difficult due to the plethora of available DL algorithms. After selecting the algorithm, the subsequent challenge is to build its architecture to enhance performance. Prior to training a CNN with data, it is essential to define numerous parameters, including the input data type (1D or 2D), the number of convolutional layers, and the dimensions of the filters. Manual procedures often formulate and evaluate the network architecture—a procedure that can be arduous and susceptible to errors. Nevertheless, the implementation of optimization techniques can resolve this problem, referred to as the neural architecture search (NAS) issue. NAS, a specialized field within automated machine learning, focuses on enhancing the deployment of machine learning for practical issues. The process encompasses a complete workflow, starting with the initial raw data and concluding with the installation of the finalized model. Prior studies have demonstrated that NAS methodologies surpass manually crafted network architectures in several applications, particularly in computer vision. However, only a few studies focus on the development of CNNs for algal categorization in river catchments, limiting the application of NAS in water administration. Additionally, it is crucial to explore the capabilities of NAS in developing a mixed network, such as CNN+LSTM, to address intricate water-related issues. DL facilitates the creation of a unified model to address intricate issues and promote comprehensive learning. Typically, these problems encompass a sequence of tasks that conventional learning methods address. To surmount challenges in algorithmic development and learning system design for deep learning applications in water resource management, it needs to prioritize resolving data quality issues, selecting suitable architectures such as LSTMs for time-series data, integrating domain knowledge into feature engineering, formulating robust validation strategies, ensuring model explainability, and mitigating computational constraints through optimization techniques and cloud computing.

Multi-agent systems

A system with several agents comprises multiple intelligent humans that engage within a shared setting to pursue either cooperative or adversarial objectives. An agent is a software entity, robotic system, or individual. Each agent generally possesses unique views of the surroundings, conduct, and goals. Each agent substantially engages with other agents through its actions or modifications to the communal environment. The agents may exhibit collaboration, competition, or a combination of both. Multi-agent systems can efficiently oversee the dynamic interactions among various components of the UWS system and the surrounding environment. These interactions become increasingly significant as the system grows more complicated and uncertain. River basins and hydrological systems extensively use agent-based models to analyze the collective behaviors of multiple agents and formulate land and water management strategies (Yang et al., 2009). Nonetheless, the Underwater System (UWS) limits the implementation of multi-agent systems, primarily emphasizing agent design and the resolution of technological obstacles. The independent choices on ideal strategy and operational issues require the deployment of cooperative multi-agent systems. When you combine different agents with advanced deep reinforcement learning technology, you can make an autonomous choice framework that can make the best decisions in real-time and adjust to a changing environment. An illustration is the formulation of a multi-agent deep reinforcement learning methodology to simultaneously optimize dissolved oxygen (DO) levels and reagent dosages in WWTP. This framework can supervise the functioning of storage vessels and Sustainable Drainage Systems (SuDS) within the sewage system, regulate water containers and pumps in the water distribution network, or orchestrate several drones during flood emergency operations. The system ingredients, defined as multiple people, may collaborate to attain the defined objectives. In the domain of pump operations, we can develop a specialized agent to oversee pumps in a designated section of the water network, providing optimal pressure to satisfy increased demand. An auxiliary agent can be devised to control pumps in a neighboring section of the water line in order to maintain low pressure and reduce leakage. To achieve competing strategic goals in the water system, the two operators must engage and skillfully maneuver under dynamic conditions. The implementation of multi-agent systems facilitates the creation of a decentralized, very effective underwater wireless sensor system (UWS). Furthermore, representatives from numerous groups, including owners, planners for cities, and water customers, have the ability to negotiate to safeguard their respective interests in the development and administration of water systems. To address the challenges of implementing deep learning in multi-agent systems for water resource management, essential strategies encompass: meticulously designing agent interactions, regulating information sharing, employing suitable reinforcement learning methodologies, formulating robust reward functions, integrating domain expertise, and ensuring scalability for intricate water systems; all while accounting for the distinctive attributes of the water resource environment and the varied stakeholders involved.

Digital twins and autonomous systems

The concept of digital twins has generated considerable interest and progress in the water sector. While there are some similarities between a digital twin and a classical model, a digital twin typically integrates with the real world. IBM defines digital as a virtual embodiment of a physical system across its full lifecycle, employing real-time data to enhance understanding, learning, and reasoning. While the precise construction of a digital twin remains a topic of debate, we typically anticipate it to possess the following fundamental characteristics: We integrate the employed mathematical models with the real water system they depict, which may be based on physical principles, machine learning, or a combination of both. Real-time info coming from connected sensors combines these models to accurately depict the recent condition of the physical structure. They have the ability to analyze hypothetical events and provide forecasts regarding future conditions. Moreover, it may leverage design, maintenance, and operational ideas gained by digital twins to establish a connection between the digital twin and the physical system. Moreover, it can consistently update the digital twin with data from the actual environment and use it in rapid calculations to enhance system competence and amenities. The advent of modern twins will significantly influence our engagement with, oversight of, and regulation of physical systems. The integration of machine learning in the expansion of digital twins within the water sector is markedly insufficient. In our expertise, all recorded cases of digital twins have depended on physically based simulations, but a limited number have employed machine learning to enhance the efficacy of hydraulic models, such as forecasting pump speeds or assessing their impact on WWTPs. The DL algorithms discussed in Section 3 can significantly impact digital twins, facilitating autonomous operation by automating tasks. ML is a fruitful innovation that can enhance our knowledge of mechanical structures and offer closure to optimize their performances. The progression of AI can deliver a more profound comprehension of the mechanisms within a system. Physics-informed ML is a burgeoning investigation domain that leverages system data to develop ML models that are more accurate and flexible. Hydrology and water quality have effectively used this methodology, and it has the potential to create digital twins for urban water systems. To address challenges in deploying deep learning applications in digital twins and autonomous systems for water resource management, it needs to prioritize data quality, model complexity, real-time feedback loops, infrastructure compatibility, robust data pipelines, and the ethical and societal implications while utilizing advanced methodologies such as transfer learning, explainable AI, and federated learning to improve model performance and reliability.

Conclusions

The world's efforts to protect and conserve water are positively impacted by technological advancements like water consumption forecasting, leak detection and localization, sewage problem and blockage identification, cyber security and resource evaluation, wastewater recycling and administration, water safety estimation, rainwater management, and irrigation oversight. The application of AI technologies, particularly deep learning, provides a strategic framework for the prospective preservation of water supplies. The suggested research delivers significant thoughts into the adoption of deep neural network models in water management. It underscores the importance and relevance of these models in diverse water management practices. This paper investigates the obstacles and potential related to the execution of deep neural networks in water management. These encompass algorithmic development, multi-agent operations, digital twins, data quality and accessibility, security, context-aware data analysis, and training efficacy. Consequently, the proposed study provides direction for forthcoming research initiatives by emphasizing challenges and outstanding issues in water management through deep neural networks. Stakeholders in the water management sector aiming to incorporate

DL technologies should identify pertinent use cases, establish a robust data foundation, collaborate with data scientists and specialists, initiate pilot projects with a limited scope, prioritize data quality and accessibility, ensure stakeholder engagement, and cultivate a culture of continuous learning and adaptation to maximize the potential of DL in water management systems.

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