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Review On Ai And Iot Based Integrated Smart Water Management And Distribution System

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ARTICLE INFO	ABSTRACT

Smart water management and distribution systems are instrumental in optimizing the responsible use of our finite water resources. The integration of advanced technologies like IoT and AI offers substantial potential to enhance the overall performance and sustainability of these systems, marking a pivotal step toward efficient water resource management. The deployment of an IoT-driven water distribution and management framework offers several distinct advantages, including heightened equipment efficiency, heightened transparency across all operational prsocesses, heightened sustainability and efficiency levels, real-time monitoring capabilities coupled with comprehensive data collection, and the ability to predict maintenance requirements. This strategic amalgamation of IoT and AI in the realm of smart water management is substantiated by a corpus of scholarly works encompassing IoT-based smart water management systems [1][3] and AI-driven smart water management systems, which collectively underscore the transformative potential of these technologies within the water sector. Moreover, empirical evidence derived from case studies and practical implementations of AI and IoT-based smart water management systems [4][5][6] serves as a testament to their effectiveness in elevating water management and distribution practices. In summation, the incorporation of IoT technologies into smart water management represents a sustainable approach to optimizing water resource utilization, fostering superior water quality, and mitigating the specter of water scarcity.

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

Introduction:

Water scarcity stands as a prominent and urgent global issue, affecting nearly half of the world's population, with a pronounced impact on developing nations like India. The imperative of providing accessible and uncontaminated water for drinking and sanitation emerges as a fundamental human right, yet this vital resource remains elusive for millions, engendering significant adversities. Compounding this challenge are environmental transformations characterized by declining precipitation and the pervasive influence of climate change. These factors compound the issue, progressively depleting natural water reservoirs and exacerbating the predicament of water scarcity This document aims to address the complexities of water scarcity in India by advocating for the implementation of intelligent water systems. These systems can effectively manage and conserve water resources. Additionally, the paper evaluates existing smart water technologies applicable to Indian contexts, offering solutions to mitigate water scarcity. In conclusion, the adoption of cost-effective, non-renewable energy-powered devices emerges as a vital strategy to combat the issue of water scarcity and ensure access to clean and sustainable water sources.

The primary reasons behind water stress in India include inadequate per capita water availability, depletion of groundwater and surface water, deficient infrastructure and governance, climate change, and the utilization of water for industrial and agricultural purposes. These factors have contributed to water scarcity and stress in numerous regions of the country, thereby elevating the significance of effective and sustainable water management as a critical concern for India. The current crisis has resulted in the unavailability of clean drinking water to millions of individuals; a fundamental necessity for human sustenance. In addition, a notable proportion of the populace is afflicted by water-borne illnesses due to the absence of potable water. The severity of India's water crisis is exemplified by its position as the 13th most 'extremely highly' water-stressed country on Aqueduct's list. India ranks among the countries facing severe water stress on a global scale. The Composition Water Management Index (CWMI) Report 2019, issued by NITI Aayog, underscores a concerning forecast: India's water demand is poised to outstrip available supply by 2030. This projection implies that, by 2030, the nation will possess only half of the requisite water to meet the demands of its population, significantly impacting the quality of life for millions. The anticipated water deficit carries far-reaching repercussions, encompassing access to clean drinking water, the agricultural sector, biodiversity, and overall societal sustainability. Importantly, the water crisis in India reverberates beyond its residents, exerting a cascading influence on the nation's burgeoning economy and industries. The impending water shortage threatens agricultural productivity, consequently affecting the food industry and the broader economic landscape.

Smart water systems represent the application of advanced technologies to enable efficient and sustainable water resource management. The incorporation of Internet of Things (IoT), big data, and artificial intelligence (AI) plays a critical role in addressing the urgent issue of water scarcity and its broad-reaching implications for society, economies, and ecosystems. This convergence of technologies empowers the improvement of water resource management, making a substantial contribution to mitigating water scarcity and its associated challenges.

1. IoT Integration: Within smart water systems, IoT involves connecting physical devices, sensors, and software, facilitating real-time data collection and exchange via the internet. IoT sensors and meters monitor water consumption, quality, and availability, enhancing monitoring capabilities.
2. Big Data Utilization: The substantial volume of structured and unstructured data generated by IoT devices and other sources is processed and analyzed through big data analytics in smart water systems. This offers insights into water usage patterns, identifies inefficiencies, and optimizes water management strategies.
3. AI Technologies: AI components such as machine learning and predictive analytics are employed to automate decision-making processes. AI detects anomalies and forecasts future water usage and availability, enabling informed decisions to proactively address water scarcity concerns.

Smart water management systems have a positive impact on water quality in India by:
Real-time Monitoring: IoT-based systems enable real-time recording of water quality parameters, facilitating effective monitoring.

Issue Identification: These systems can detect leaks and other water supply system problems, enabling preventive maintenance and averting water contamination.
Efficient Resource Utilization: Smart water systems promote efficient use of water resources, reducing non-renewable water losses and consumption in agriculture.

Treatment Plant Enhancement: Smart water technology enhances water quality in treatment plants, ensuring the supply of high-quality water to consumers while promoting sustainable water resource management in India[[9].

Advanced technologies including IoT, deep learning, and machine learning algorithms offer significant potential in addressing critical aspects of water management. These intelligent systems can be effectively applied to tasks such as leak detection, water demand forecasting, preventing overuse, water quality monitoring, and the development of strategies to ensure responsible water utilization (Refer to Figure 1). The primary objective of this research paper is to highlight the emerging and compelling opportunities presented by intelligent techniques. These methods assume a crucial role in addressing the significant hurdles within the domain of water management. Through the utilization of IoT, deep learning, and machine learning capabilities, this research paper seeks to draw attention to novel solutions with the potential to transform water resource management profoundly. Additionally, these solutions aim to advance the cause of sustainable practices in this field.

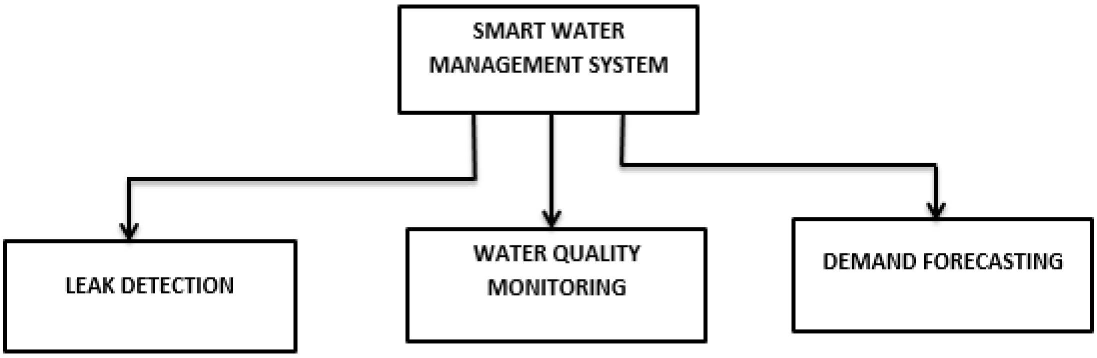

Figure 1: Intelligent System for Water Management

Literature Review:

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

Water leakage within water distribution networks is a substantial concern, as roughly one-third of global water utilities suffer a loss of approximately 40% attributable to leakage. The conventional means of pipeline leakage detection involve periodic examinations with human involvement, which is both a slow and ineffective measure. Although existing solutions for leak detection rely on portable devices with ultrasonic or acoustic sensors, they lack real-time analysis and can solely perceive the presence of a leak, not its occurrence. Some academic papers have explored leak detection systems that operate without the use of machine learning techniques, for example, a system that measures water flow to detect leaks but cannot identify their location. Other approaches involve using thermal sensors to detect temperature changes in the soil above a leak and simple sensors like flow meters to compare water flow and detect leaks.

The present methodologies for detecting water leakage using AI involve the application of supervised machine learning (ML) techniques [50]. These techniques utilize data assembled by smart meters to automatically identify leakages of varying magnitudes in pipes within residential areas. The use of ML techniques significantly enhances the detection performance in distinguishing between the presence and absence of leakages and in differentiating between leakages of different sizes [51]. An alternative strategy encompasses the utilization of a classification model founded on supervised self-organizing maps (SOMs) in conjunction with a regression model utilizing the multi-layer perceptron (MLP) algorithm [52]. These models exhibit the capability to execute a wide range of tasks, encompassing unsupervised, supervised, and semi-supervised classification, along with regression tasks, particularly when dealing with data of high dimensionality. The MLP model has demonstrated superior performance in detecting leaky nodes with greater accuracy when compared to the complex SOM model [53]. Furthermore, an inverse model based on the integration of Kalman Filter-based data assimilation techniques and network hydraulic models has been proposed [54]. This model has proven to be an effective approach for detecting leakage and may represent a competitive alternative to traditional district metering procedures.

The article referenced as [11] presents a comprehensive framework centered around wireless sensor networks for monitoring water distribution systems and detecting leaks through the utilization of machine learning algorithms. This framework encompasses various components, including hardware, communication infrastructure, and data analysis modules. The study engages in a comparative analysis of different machine learning algorithms, including random forest, decision trees, neural networks, and Support Vector Machine (SVM), to determine the most effective algorithm for leak detection. The methodology employed for training and validating these machine learning models is rigorously detailed. In practical implementation, the system achieves an impressive 75% accuracy rate in leak detection, with validation confirming its efficacy. The methodology hinges on the deployment of multiple sensors for real-time data collection, particularly focusing on water flow parameters to enhance the efficiency of leak detection. Narrow-Band IoT (NB-IoT) serves as the data transmission method. Importantly, the article acknowledges the need for continued research and development in the domain of machine learning-based leak detection, highlighting limitations related to the availability of limited datasets that can potentially lead to misleading results. In the paper denoted as [13], a novel approach is introduced for designing a sensor network utilizing pressure sensors to measure water pressure within pipelines. This method employs an exponential curve fitting technique to accurately pinpoint the location and cause of leaks under real-world conditions. It provides a practical solution for detecting leaks in water pipeline systems, thereby contributing to the prevention of significant financial losses and environmental harm caused by pipe leakage. Additionally, the paper offers guidance on optimizing the placement of pressure sensors in pipelines, which aids in the effective deployment of the sensor network for successful leak detection. The analysis and dataset provided in the paper significantly contribute to understanding the effectiveness of using pressure sensors in wireless sensor networks for leak detection, particularly in underground wireless network systems. This research builds upon prior studies in the field of wireless sensor networks for leak detection and offers a straightforward sensor network and analysis method to detect leaks even with minimal pressure and small leak sizes. The study described in [14] introduces an innovative method for detecting leakage in urban water supply networks by leveraging Internet of Things (IoT) and artificial intelligence (AI) algorithms. This approach involves the development of low-power and cost-effective terminal detection equipment alongside gateway monitoring equipment for remote data transmission. The methodology incorporates a data center software platform for data organization, storage, release, and control. Additionally, the paper compares and analyzes the performance of two optimization algorithms, ALO and PSO, in solving the water supply network. The results indicate that the intelligent monitoring system designed is effective in monitoring the pipe network, with the ALO algorithm outperforming the PSO algorithm in terms of optimization and search efficiency. While this method offers valuable insights for designing and managing urban water supply networks, it emphasizes the need for real-time data analysis and predictive maintenance to proactively detect and prevent potential leaks or issues. Collaboration with water supply authorities and stakeholders is vital for real-world deployment, considering factors like cost-effectiveness, scalability, and ease of implementation. Pipelines serve as crucial means for fluid transportation but are susceptible to leaks due to defects such as corrosion, fatigue cracks, and dents. Detecting pipeline leaks involves hardware-based methods like ground infrared thermography, pressure sensors, acoustic methods, and ground-penetrating radar, as well as software-based computational methods relying on computer algorithms. Paper [15] explores the application of machine learning techniques, including support vector machines and decision trees, for detecting leaks in horizontal pipelines. However, it does not address the influence of external factors like environmental conditions or pipeline materials on detection accuracy, scalability, or computational complexity. In paper [16], techniques for detecting leakage in water distribution networks using machine learning algorithms are discussed. Wireless sensors are placed within pipelines to monitor flow and pressure, with data transmitted at regular intervals. While the article provides insights into sensor network deployment, it lacks specific details about the machine learning algorithm employed for leak detection. Lastly, paper [17] delves into the challenge of identifying leaks in water distribution networks concealed underground. Proficient inspectors typically undergo training for leak detection, but the paper does not explore the impact of external disturbances on leak detection accuracy when utilizing a constructed CNN model.The presented research paper [18] introduces an innovative approach for leak detection that leverages both spatial and temporal information. This method utilizes the spatial arrangement of nodes to identify potential leak conditions while incorporating temporal data to enhance detection accuracy. Notably, this approach can be trained exclusively on non-leakage data, offering practical advantages. The detection process involves multiple independent attempts, with the final decision based on majority outcomes. Performance evaluation, conducted on a dataset comprising 2400 labeled samples, demonstrated high accuracy in identifying pipe conditions. An auto encoder neural network (AE) is employed for detection, with a reconstruction error threshold for classifying data as leaking or non-leaking. The paper recognizes two fundamental challenges in implementing data-driven leak detection in water supply networks. Firstly, there's an issue of unbalanced data, where leaking situations are limited compared to non-leaking ones, posing challenges for machine learning model training. Secondly, uncertainty in water demand affects the stability of water pressure patterns, making precise leak prediction and detection challenging, especially when there are fluctuating user demands. Concerns about pipeline leakage in various industries have led to extensive research efforts. Machine learning techniques, including Random Forest (RF), have shown promise due to their ability to handle high-dimensional data and noise interference. This study [19] evaluates RF's effectiveness in comparison to other classifiers and demonstrates its impressive classification accuracy of 88.33%. Another proposed methodology [20] employs pressure analysis and pipeline data mapping to enhance efficiency and reduce system losses. Machine learning models like CNN ensembles are used for analyzing pressure profiles to detect leaks in water distribution networks (WDNs). The focus is on identifying leaks rather than pinpointing their precise locations. Furthermore, a wireless sensor network-based water leak detection and shut-off system [21] is designed to mitigate water loss caused by pipe leakage. This system can track water flow, identify leaks, and take necessary actions, such as shutting off valves, transmitting data to a server, and displaying it on a website. Lastly, a paper [22] explores the use of Convolutional Neural Networks (CNN) for leak localization in Water Distribution Networks (WDNs) based on pressure measurements. The proposed method converts pressure residual maps to images and applies a CNN for classification, using time horizon Bayesian reasoning to filter uncertainty and noise. The study showcases its performance in the Hanoi District Metered Area (DMA) as a case study, emphasizing the importance of efficient leak localization methods. However, it acknowledges challenges related to training data and scalability concerns in large-scale networks.

Table 1: Comparison of contemporary IoT- AI based Water Leakage Detection system

References	Focus And Methodology	Key Findings	Limitations/Challenges
11	Machine Learning Algorithms (Random Forest, Decision Trees, Neural Networks, SVM) with multiple sensors for real-time data collection.	Achieves 75% leak detection accuracy.	Limited research on machine learning-based leak detection with limited datasets.
13	Pressure sensors in a wireless sensor network, exponential curve fitting for leak location.	Effective in detecting leaks and determining their locations. Provides guidance on sensor placement.	Doesn't predict leak size. Limited testing on pipe materials other than PVC.

14	IoT and AI algorithms, ALO and PSO optimization algorithms, remote pressure monitoring.	Intelligent monitoring system is effective. ALO algorithm outperforms PSO for optimization.	Requires real-time data analysis and collaboration with authorities.
15	Machine learning techniques (Support Vector Machines, Decision Trees) for horizontal pipeline leak detection.	Addresses horizontal pipeline leaks with machine learning.	Doesn't consider external factors' impact. Scalability is unclear. Computational requirements not discussed.
16	Wireless Sensor Network (WSN) with sensors for flow and pressure.	Utilizes wireless sensors for water distribution network monitoring.	Doesn't specify the machine learning algorithm used.
17	Focuses on antecedent research studies on leak detection techniques.	Reviews prior research on leak detection methods.	Doesn't delve into potential external interference on leak detection.
18	Combines spatial and temporal information with auto encoder neural network (AE).	Achieves high accuracy in identifying pipe conditions.	Challenges with unbalanced data and user demand variability.
19	Random Forest classifier for leakage detection, compared to SVM, ANN, K-NN, DT.	RF classifier outperforms other classifiers with 88.33% accuracy.	Doesn't discuss parameter configurations' impact.
20	Utilizes machine learning models (CNN ensemble) to analyze pressure profiles.	Effective in analyzing pressure profiles for leak detection.	Focused on leak identification, not pinpointing exact locations.
21	Wireless sensor network for water leak detection in Malang City, Indonesia.	Minimal error in water volume measurement. Effective in detecting leaks and taking preventive measures.	No specific machine learning or AI mentioned.
22	Uses CNN for leak localization based on pressure measurements.	Training data includes all possible leak localizations.	Challenges in obtaining comprehensive training data. Limited insights into the time horizon Bayesian reasoning approach. Generalizability may be limited. Computational requisites not discussed.

The contamination of water sources due to industrial activities and human interventions highlights the need for prioritizing water quality monitoring to promptly identify fluctuations and ensure safe drinking water, addressing existing challenges and safeguarding the availability of clean and potable water. Real-time monitoring of water quality is faced with several challenges, whereby traditional sampling and laboratory testing methods are both labor-intensive and error-prone, rendering them unsuitable for rapid detection of water quality changes. Additionally, on-site water sample collection for testing is usually a time-consuming and costly affair. Furthermore, the manual testing techniques necessitate the transportation of samples to the laboratory for analysis, resulting in delay. Consequently, the current water quality monitoring system is a manual process that is both time-consuming and tedious. Given the ease with which contamination can occur along distribution pipelines, real-time water quality monitoring is imperative.

To tackle these challenges, researchers have developed low-cost, portable, and efficient sensor-based systems for real-time water quality monitoring. These systems utilize sensors to measure various parameters such as temperature, turbidity, pH, and distance. The collection and wireless transmission of data is enabled through technologies like Raspberry Pi, Arduino, and Internet of Things (IoT). Moreover, deep learning algorithms, such as Long-Short Term Memory (LSTM) networks, are used for data analysis and prediction. These advancements have enabled real-time monitoring, early detection of pollution, and timely intervention to ensure safe and sustainable water supplies.

Artificial intelligence (AI) techniques used to predict water quality include artificial neural networks (ANNs), genetic programming (GP), fuzzy logic (FL), support vector machine (SVM), hybrid neuro-fuzzy (NF), hybrid ANN-ARIMA, hybrid genetic algorithm-neural networks (GA-NN), and wavelet-based hybrid models such as wavelet-neural networks (WANN), wavelet-neuro fuzzy (WNF), wavelet-support vector regression (WSVR), and wavelet-linear genetic programming (WLGP) models . Another approach is the use of t-distributed stochastic neighbor embedding (t-SNE) and self attention-bidirectional long short term memory neural network (SA-BiLSTM). Additionally, advanced AI algorithms such as nonlinear autoregressive neural network (NARNET) and long short-term memory (LSTM) deep learning algorithm have been developed for water quality index (WQI) prediction. Particle swarm optimization (PSO), naive Bayes classifier (NBC), and support vector machine (SVM) have also been used for predicting the water quality index.

In this study [23], an economical monitoring system for water quality is developed using wireless sensor networks for real-time detection of drinking water quality and contamination in water distribution mains. The system analyzes physiochemical parameters, including pH, temperature, conductivity, oxidation reduction potential, and turbidity. It incorporates microsystems for signal conditioning, data aggregation, and analysis, enabling remote data representation to consumers. Fuzzy logic algorithms predict water contamination risk and classify drinking water quality. In case of contamination, the system closes the solenoid valve and notifies consumers through messaging services or a mobile app. This advanced warning system with high detection accuracy is adaptable for various IoT scenarios, including smart cities. Utilizing sensors to measure water purity is crucial for upholding water quality and detecting any solid particles or obstacles [24]. This safeguards the water supply's safety. The system is enhanced with an Android application for real-time alerts on water levels and quality. However, it's worth noting that this system consumes more time and power, which may pose limitations in practical implementation. The paper [25] focuses on developing advanced artificial intelligence (AI) algorithms for predicting water quality index (WQI) and water quality classification (WQC) to control water pollution. It employs various models such as nonlinear autoregressive neural network (NARNET), long short-term memory (LSTM) deep learning, support vector machine (SVM), K-nearest neighbor (K-NN), and Naive Bayes. These models accurately predict WQI and classify water quality, with SVM achieving the highest accuracy for WQC prediction. This research has the potential to significantly contribute to water management. In this paper [26], Long Short-Term Memory (LSTM) models are utilized with deep learning to forecast time series data in Internet of Things (IoT) systems for monitoring water quality. The system integrates sensors to monitor indicators like salinity, temperature, pH, and dissolved oxygen in aquatic environments. Data is transmitted to a cloud database and server for analysis and forecasting, enabling early warnings based on historical data. This methodology focuses on developing forecasting models for IoT-based water quality monitoring using LSTM. The paper [27] discusses the use of machine learning methodologies, including multivariate linear regression (MLR) and artificial neural network (ANN) models, for predicting water quality. While specific approaches are not detailed, the study addresses fundamental techniques and assessment metrics. However, the precise methodologies are not fully explained in the accessible sources. Prediction of Water Quality with Machine Learning [28] presents a system for predicting water quality using machine learning techniques based on the standards recommended by the Bureau of Indian Standards (BIS). The system processes data, integrates sensors, and predicts water quality based on machine learning models. It also explores an optimal and cost-effective methodology but lacks information on scalability to different locations. The primary objective of this study [29] is to provide comprehensive information on the water quality index for irrigation. It employs the Atomic Absorption Spectrophotometric method to detect metallic elements like Sodium (Na) and utilizes the Alyuda ANN shield for irrigation prediction. Descriptive statistics are provided for water quality parameters, including pH, TDS, EC, and Na. In [30], machine-learning methodologies are used to predict groundwater pollution based on geographical coordinates. It focuses on groundwater pollution and chemical configuration, aiming to establish correlations between location-dependent factors and water contamination. The paper also discusses groundwater vulnerability but is specific to a particular geographical area (Noida, India).

AI techniques face challenges in predicting water quality, including data accessibility, reproducibility, limited proof in real-world settings, complexity in capturing all factors, and implementation costs [1][48][47][49]. Addressing these challenges is crucial for successful AI adoption in water quality prediction, enhancing water management and pollution prevention efforts.

The provisioning of domestic water resources in India presents a formidable challenge, primarily due to the country's extensive population and the inherent constraints associated with its water reservoirs. In response to this pressing issue, a comprehensive and multifaceted strategy has been devised. This strategy encompasses a range of measures, including the distribution of piped water, reliance on subterranean water sources, the establishment of irrigation networks, the adoption of rainwater harvesting techniques, the utilization of water transport infrastructure, and the implementation of borehole systems. In the realm of water resource management, artificial intelligence (AI) assumes a crucial role, particularly in the context of smart water demand forecasting. The primary objective of this approach is to ensure the sustainable and efficient utilization of water resources by providing accurate predictions of short-term water demand. This methodology relies on historical data and advanced statistical tools to train AI algorithms continually, thereby enhancing their predictive capabilities with the accumulation of additional data. Consequently, the most effective predictive models can be deployed to anticipate short-term water demand accurately. This integration of AI techniques, such as fuzzy logic systems, support vector machines, and data-centric machine learning, holds paramount significance in enhancing the precision of water demand forecasts, contributing to more efficient water management practices. This method relies on historical data and advanced statistical tools to train AI algorithms, continuously enhancing their predictive capabilities with the influx of additional data. Consequently, the most effective predictive model can be deployed to anticipate short-term water demand in any given region. Various AI techniques, including fuzzy logic systems, support vector machines, and data-centric machine learning approaches, are applied in the field of water demand forecasting. The precision of these forecasts holds paramount importance for efficient water management, and AI-based methodologies exhibit significant potential in enhancing forecast accuracy.

Table 2: Comparison of contemporary IoT- AI based Water Quality Monitoring system

References	Focus And Methodology	Key Findings	Limtations/Challenges
23	Fuzzy-based monitoring system using wireless sensor networks	Real-time detection of water quality and contamination. Use of physiochemical parameters.	None mentioned, but high detection accuracy and IoT implementation
24	Sensor-based water purity measurement, Android app inclusion	Real-time alerts on water levels and quality. Safety enhancement.	Time-consuming and power-consuming, potential practical limitations.
25	AI algorithms for predicting water quality index and classification	Accurate prediction of WQI and WQC using various AI models. Contribution to water management.	Not mentioned.
26	LSTM-based deep learning for time series data in IoT systems	Proficient monitoring of water quality indicators with historical data. Early warnings to users.	Use of publicly available datasets instead of actual sensor data.
27	Machine learning for predicting water quality	Specific methodologies not detailed. Focus on study region, techniques, and assessment metrics.	Lack of explicit methodology details.
28	Machine learning based on water standards, sensor integration	Prediction of water quality based on standards. Hardware implementation, software simulations.	Scalability and generalizability not discussed.
29	Water quality index for irrigation, Atomic Absorption Spectrophotometry	Guidance for water resource management. Mean values of pH, TDS, EC, and Na provided.	Specific to irrigation, limited geographical applicability.
30	Machine learning for groundwater pollution prediction	Correlation between location-dependent factors and water contamination. Discussion of groundwater vulnerability.	Specific focus on Noida, India, may not apply to other regions.

The ANN model exhibits superior prognosticative capacity when compared to conventional statistical models, as evidenced by the findings. The ANN-based model [32] for forecasting urban water demand is assessed through the application of two crucial metrics, namely, Mean Square Error (MSE) and Coefficient of Correlation (R2). The outcomes of the ANN model are scrutinized and set side-by-side with those of the ARIMA time series model. This paper [33] centers on the analysis of water usage data in dairy plants to comprehend spatial and temporal patterns that may aid in estimating future water requirements and optimizing water demand estimation. In this study, Support Vector Machine Regression, a machine learning algorithm, is employed to compare and attain an effective and reliable system for water prediction. The field of machine learning and artificial intelligence has demonstrated great potential in accurately predicting short-, medium-, and long-term water demand in water distribution networks. Various forms of artificial neural networks, such as the Multilayer Perceptron NNs (MLPNNs) and Radial Basis Function NNs (RBFNNs), were [34] compared against a linear statistical method referred to as Autoregressive integrated moving average (ARIMA) to ascertain the most precise predictive model for water demand. The findings indicate that MLPNNs incorporating the Levenberg Marquardt (LM) learning algorithm outperform the remaining models when forecasting water demand values. The accuracy of forecasting using ARIMA is highly dependent on having a large number of observations, which may not always be available and can affect the reliability of the predictions.

The current paper [35] posits a novel hybrid model that incorporates both supervised and unsupervised machine learning techniques to forecast short-term water demand. This approach blends the predictive capabilities of Regression Tree (RT) forecasting models with the pattern recognition abilities of Self-Organizing Maps (SOM) models. The effectiveness of this hybrid model is then compared to the performance of both standalone RT and Seasonal Autoregressive Integrated Moving Average (SARIMA) models, in order to provide a comprehensive evaluation. The present study [36] undertakes a comparative analysis of two distinct methodologies - namely, Long Short-Term Memory (LSTM) and Auto Regressive Integrated Moving Average (ARIMA) - for the purpose of water demand forecasting. Moreover, the integration of Fog and Cloud Computing has been undertaken to enhance the IoT-based water distribution system. Additionally, the paper proposes a novel IoT-based architecture that aims to cater to the needs of both Water Distribution and Underground Pipe Health Monitoring System. Support Vector Linear Regression and Auto Regressive Integrated Moving Average (ARIMA) were employed as the forecasting methods [37] for water demand. Various machine learning approaches, including neural networks, support vector machines, k-nearest neighbors, and random forests, were also utilized for short-term water demand prediction. Among these techniques, Support Vector Machine Regression (SVR) was selected as the regression methodology, specifically employing the Support Vector Regression (SVR) algorithm, which employs a loss-insensitive function during the training process. Time series techniques, particularly ARIMA(5,1,1), were applied for water demand forecasting. The study centered its attention on the prediction of water demand in the state of Kuwait. It must be acknowledged that the results of this investigation may not be universally relevant to other regions or nations.The focus of the study [39] was on forecasting the water requirement in the Kuwait state. It is imperative to recognize that the outcomes of this examination may not possess universal applicability for other territories or countries. The evaluation of the proposed model in this study is limited to daily datasets obtained from two representative water plants located in Yiwu, East China. This limitation may constrain the generalizability of the study's findings to other datasets or locations. The present study [40] employed both the autoregressive integrated moving average (ARIMA) model and the long short-term memory (LSTM) model in order to forecast the water consumption at the household level. The ARIMA model utilized the past data and the data's periodicity as training parameters, whilst the LSTM model incorporated the periodicity of the data and other external variables such as weather and weekend information in its training process. The water consumption data for four disparate customer types, namely detached houses, apartments, restaurants, and elementary schools, were gathered from January 2017 up to December 2019. The dataset was subsequently divided into a training set spanning from January 2017 to December 2018, designated for model training purposes, and a test set covering the period from January 2019 to December 2019, intended for model evaluation. Regrettably, the paper omitted details regarding the dataset's size employed for both training and testing the models, potentially impacting the overall applicability and generalization of the study's findings.The implementation of machine learning methodologies [41] has the potential to facilitate the thorough examination of past data and the anticipation of yearly water requirements across various sectors, such as industrial, agricultural, domestic, and public gardens. This has the capability to assist in the formulation of strategies and the allocation of resources. The authors [42] have utilized a statistical algorithmic program to prognosticate the yearly water demand for the forthcoming year, taking into account a multitude of sectors, including industries, agriculture, domestic, and public gardens. The section on methodology within the manuscript highlights the significance of pre-processing data tasks when readying data for machine learning models. These tasks encompass cleansing and organizing the data to render it appropriate for analysis. The present study presents an innovative approach to predicting water demand through the use of a linear regression model integrated with evolutionary strategies, which enable the extraction of weekly seasonality patterns. A comparative analysis is conducted between the proposed model and established methods, including Support Vector Regression (SVR), Multilayer Perceptron (MLP), and Random Forest (RF). [43] The study juxtaposes the proprietary model with conventional techniques. For data preprocessing in water demand forecasting, the Discrete Wavelet Transform (DWT) is frequently employed. Past research has utilized ARIMA models and Artificial Neural Networks (ANNs) for short-term prediction and leak detection. To analyze non-stationary time series and identify large flow leaks, methods based on cluster analysis have been developed. The analysis of short- and medium-term trends should be based on data recorded at intervals no greater than 15 minutes.

Table 3: Comparison of contemporary IoT- AI based Water Demand Forecasting system

References	Focus And Methodology	Key Findings	Limtations/Challenges
32	Artificial Neural Network (ANN) for urban water demand forecasting. Evaluated using Mean Square Error (MSE) and Coefficient of Correlation (R2).	Demonstrates superior predictive capacity compared to conventional statistical models. Training error decreases over iterations, indicating improved performance.	Specific to urban water demand forecasting; applicability in other contexts not discussed.
33	Support Vector Machine Regression (SVM) for water demand prediction in dairy plants.	Utilizes machine learning to analyze water usage data, aiding in estimating future water requirements.	Limited discussion on SVM's generalizability to other water distribution networks.
34	Comparison of Multilayer Perceptron Neural Networks (MLPNNs) with ARIMA for water demand prediction.	MLPNNs with the Levenberg Marquardt (LM) learning algorithm outperform other models. ARIMA accuracy relies on a large number of observations.	Specific to MLPNNs and ARIMA, potential limitations of MLPNNs not discussed.
35	Hybrid model combining Regression Tree (RT) and Self-Organizing Maps (SOM) for short-term water demand forecasting. Compared with standalone RT and SARIMA models.	Effectiveness of hybrid model assessed for short-term forecasting, blending predictive capabilities and pattern recognition.	Applicability to longer-term forecasting not discussed.
36	Comparative analysis of Long Short-Term Memory (LSTM) and Auto Regressive Integrated Moving Average (ARIMA) for water demand forecasting. Integration of IoT and Fog/Cloud Computing.	Evaluation of two distinct methodologies for water demand forecasting. IoT-based architecture proposed.	Specific to short-term forecasting; generalizability to other contexts not discussed.

37	Support Vector Regression (SVR) and ARIMA for water demand prediction in Kuwait. Various machine learning approaches used.	SVR selected as regression methodology, ARIMA(5,1,1) for time series forecasting.	Results may not be universally applicable to other regions or nations.
39	Forecasting water requirement in Kuwait state.	Specific to Kuwait state, limited generalizability to other regions or countries.	Based on daily datasets from specific water plants.
40	Comparison of ARIMA and LSTM models for household-level water consumption forecasting.	LSTM incorporates external variables like weather and periodicity.	Dataset size for training and testing not specified.
41	Utilization of machine learning for yearly water requirement anticipation across sectors.	Potential for examining past data and resource allocation strategies.	Focus on yearly forecasting and sectors.
42	Statistical algorithmic program for yearly water demand prediction across sectors.	Emphasizes data preprocessing for machine learning readiness.	Specific to yearly forecasting and sectors.
43	Linear regression model with evolutionary strategies for water demand prediction. Comparison with SVR, MLP, and Random Forest.	Innovative approach with weekly seasonality patterns extraction.	Specific to short-term prediction, DWT for data preprocessing

Challenges in Smart Water Management and Distribution System in India:

1. Water Scarcity: India faces a growing water scarcity problem due to increasing demand from a growing population and adverse climate changes. Ensuring a consistent and adequate water supply to meet the needs of urban and rural areas is a significant challenge.
2. Aging Infrastructure: Much of India's water distribution infrastructure is outdated and in dire need of modernization. Old pipes and systems often lead to water losses through leaks, reducing efficiency and increasing costs.
3. Water Quality: Ensuring safe and clean water for consumption remains a significant challenge. Contamination of water sources and inadequate treatment facilities in some regions result in health risks for the population.
4. Data Management: Smart water systems generate vast amounts of data from sensors and monitoring devices. Managing and analyzing this data effectively is crucial for optimizing water distribution and identifying issues. Data security and privacy also need attention.

Open Issues in Smart Water Management and Distribution:

1. Affordability: While implementing smart water systems can enhance efficiency, there is a need to ensure affordability for all segments of society. Solutions should not disproportionately burden lower-income communities.
2. Regulatory Framework: Establishing comprehensive regulations and standards for smart water management is essential. Regulations should cover data handling, quality standards, pricing, and the roles of public and private entities.
3. Integration of Renewable Energy: To promote sustainability, integrating renewable energy sources into water treatment and distribution processes should be explored. Solar-powered water treatment plants, for instance, can reduce the carbon footprint of water supply.

Future Directions in Smart Water Management and Distribution in India:

1. IoT and AI Integration: Further integration of Internet of Things (IoT) sensors and Artificial Intelligence (AI) can enable real-time monitoring, predictive maintenance, and efficient water management. AI can help predict demand patterns and optimize distribution.
2. Decentralized Systems: Exploring decentralized water treatment and distribution systems can enhance resilience, particularly in remote and rural areas. This approach can reduce losses in transmission and provide reliable access to clean water.
3. Community Engagement: Involving local communities in water management decisions and promoting water conservation practices is essential for long-term sustainability. Community awareness campaigns can foster responsible water use.
4. Water Recycling: Promoting water recycling and reuse can alleviate the pressure on freshwater sources. Implementing advanced treatment technologies for wastewater can enable safe reuse in non-potable applications.
5. Digital Twin Technology: Utilizing digital twin technology can create virtual replicas of water distribution systems, allowing for better real-time management, simulation, and predictive analytics.
6. Private Partnerships: Collaborative efforts between government agencies and private entities can facilitate investment and innovation in smart water management. Public-private partnerships can help in financing and deploying advanced technologies.

Addressing these challenges, open issues, and future directions is crucial for India to develop a sustainable, efficient, and resilient smart water management and distribution system that can meet the growing water demands of its population while safeguarding water quality and conserving resources.

Conclusion:

Addressing water scarcity, especially in countries like India, is a global imperative. The severity of the water crisis in India, characterized by high water stress and an anticipated deficit by 2030, underscores the urgency of the matter. The ramifications encompass not only the availability of clean drinking water but also have profound effects on agriculture, biodiversity, and the overall economy.

In this context, smart water systems, leveraging IoT, big data, and AI technologies, emerge as indispensable tools in mitigating water scarcity and its associated challenges. IoT facilitates real-time data collection and exchange, empowering us with the knowledge required for informed decision-making. Big data analytics offer crucial insights into water usage patterns, enabling optimization and resource allocation. Meanwhile, AI technologies, including machine learning and predictive analytics, automate processes and provide forecasts, enhancing efficiency and ensuring sustainable water management.

However, it is vital to underscore that adopting cost-effective, non-renewable energy-powered devices is pivotal in this endeavor. Sustainable technology solutions are the cornerstone of combating water scarcity, ensuring equitable access to clean and sustainable water sources, and safeguarding the future of our planet.

References:

[1] Ramos HM, McNabola A, López-Jiménez PA, Pérez-Sánchez M. Smart Water Management towards Future Water Sustainable Networks. *Water*. 2020; 12(1):58. https://doi.org/10.3390/w12010058

[2] Gupta, Aditya & Mishra, S. & Bokde, Neeraj & Kulat, K.D.. (2016). Need of smart water systems in India. 11. 2216-2223.

[3] Gonçalves R, J. M. Soares J, M. F. Lima R. An IoT-Based Framework for Smart Water Supply Systems Management. *Future Internet*. 2020; 12(7):114. https://doi.org/10.3390/fi12070114

[4] Nibi Kulangara Velay Udhan, Preeja Pradeep, Sethuraman N. Rao, Aryadevi Remanidevi Devidas, & Maneesha Vinodini Ramesh,(2022). *IoT-Enabled Water Distribution SystemsA Comparative Technological Review*. https://doi.org/10.1109/ACCESS.2022.3208142

[5] *Managing the water distribution network with a Smart Water Grid*. (2016). *Managing the water distribution network with a Smart Water Grid*. *1*(1), 4. https://doi.org/10.1186/s40713-016-0004-4

[6] Maroli, Ankit & Raut, Rakesh & Narwane, Vaibhav & Narkhede, Balkrishna. (2021). Framework for the implementation of an Internet of Things (IoT)-based water distribution and management system Graphic abstract Keywords Internet of Things · Water supply chain · Water losses · Water management · Sensors · Return on investment. Clean Technologies and Environmental Policy. 23. 3. 10.1007/s10098-020-01975-z.

[7] Rapelli, N., Myakal, A., Kota, V., & Rajarapollu, P.R. (2019). IOT Based Smart Water Management, Monitoring and Distribution System for an Apartment. *2019 International Conference on Intelligent Computing and Control Systems (ICCS)*, 440-443.

[8] Jenny, H., Wang, Y., Minguez, R., & Alonso, E. G.. (2020). *Using Artificial Intelligence for Smart Water Management Systems*. https://doi.org/10.22617/BRF200191-2

[9] Singh, Manmeet & Ahmed, Suhaib. (2020). IoT based smart water management systems: A systematic review. Materials Today: Proceedings. 46. 5211-5218. 10.1016/j.matpr.2020.08.588.

[10]] Abubakar Ndagi and Csaba Zoltan´ Kertesz," Automatic Water Distribution System Using Wireless Sensor Network", 27th International Conference on Information Technology (IT), Zabljak,ˇ15 – 18 February, 2023

[11]Alves Coelho, J.; Glória, A.; Sebastião, P. Precise Water Leak Detection Using Machine Learning and Real-Time Sensor Data. *IoT* **2020**, *1*, 474-493. https://doi.org/10.3390/iot1020026

[12] Richards, C. E., Tzachor, A., Avin, S., & Fenner, R. (2023). Rewards, risks and responsible deployment of artificial intelligence in water systems. *Nature Water*, *1*(5), 422-432. https://doi.org/10.1038/s44221-023-00069-6

[13] M. T. Islam and S. Aslan, "Leak Detection and Location Pinpointing in Water Pipeline Systems Using a Wireless Sensor Network," *2021 IEEE International Symposium on Circuits and Systems (ISCAS)*, Daegu, Korea, 2021, pp. 1-7, doi: 10.1109/ISCAS51556.2021.9401106.

[14] Li, Lianxiu & Chen, Huifan. (2023). Artificial Intelligence and Internet of Things-Based Leak Detection Method for the Water Supply Network. International Transactions on Electrical Energy Systems. 2023. 1-11. 10.1155/2023/3443047.

[15] Andrea, J., & Camperos, G.. (2022). *Application Of Machine Learning Techniques For Leak Detection In Horizontal Pipelines*. *Volume 19*(No. 4), 653–663. http://www.webology.org/abstract.php?id=4113

[16] Saravanabalaji, M., Shakthi Raagavi, S., Praveen, E., & Samritha, S.. (2022). *Leakage Detection of Pipelines in Water Distribution Network Using Machine Learning Algorithm*. *№ 9230*. https://easychair.org/publications/preprint/HHHK

[17] Nam, Y. & Arai, Y. & Kunizane, T. & Koizumi, A.. (2021). Water leak detection based on convolutional neural network (CNN) using actual leak sounds and the hold-out method. Water Supply. 21. 10.2166/ws.2021.109.

[18] Fan, X., Zhang, X., & Yu, X. (2021). Machine learning model and strategy for fast and accurate detection of leaks in water supply network. *Journal of Infrastructure Preservation and Resilience*, *2*(1), 1-21. https://doi.org/10.1186/s43065-021-00021-6
[19] *Detection of water pipeline leakage based on random forest*. (1978). *Detection of water pipeline leakage based on random forest*. *1978*(1), 012044. https://doi.org/10.1088/1742-6596/1978/1/012044
[20] Fuentes, V.C., Pedrasa, J.R.I. (2020). Leak Detection in Water Distribution Networks via Pressure Analysis Using a Machine Learning Ensemble. In: Pereira, P., Ribeiro, R., Oliveira, I., Novais, P. (eds) Society with Future: Smart and Liveable Cities. SC4Life 2019. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, vol 318. Springer, Cham. https://doi.org/10.1007/978-3-030-45293-3_3
[21] R. H. Y. Perdana, H. Hudiono and A. F. N. Luqmani, "Water Leak Detection and Shut-Off System on Water Distribution Pipe Network Using Wireless Sensor Network," *2019 International Conference on Advanced Mechatronics, Intelligent Manufacture and Industrial Automation (ICAMIMIA)*, Batu, Indonesia, 2019, pp. 297-301, doi: 10.1109/ICAMIMIA47173.2019.9223386.
[22] Javadiha, Mohammadreza & Blesa, Joaquim & Soldevila, Adrià & Puig, Vicenç. (2019). Leak Localization in Water Distribution Networks using Deep Learning. 1426-1431. 10.1109/CoDIT.2019.8820627.
[23] Lakshmi, G Shenbaga & T., Revathi & Shanthosam, Kavi Priya. (2019). Architecture of Smart Sensors for Real Time Drinking Water Quality and Contamination Detection in Water Distributed Mains. Romanian Journal of Information Science and Technology. 22. 202-214.
[24] Ambareesh, S., Tejaswini, B., N, B. C., B, M., & M, M.. (2019). *SMART WATER MANAGEMENT SYSTEM*. *06*(Issue 06). https://doi.org/doi://10.26562/IRJCS.2019.JNCS10087
[25] Aldhyani, Theyazn & Al-Yaari, Mohammed & Alkahtani, Hasan & Maashi, Mashael. (2020). Water Quality Prediction Using Artificial Intelligence Algorithms. Applied Bionics and Biomechanics. 2020. 1-12. 10.1155/2020/6659314.
[26] Thai-Nghe, Nguyen & Thanh-Hai, Nguyen & Nguyen, Chi-Ngon. (2020). Deep Learning Approach for Forecasting Water Quality in IoT Systems. International Journal of Advanced Computer Science and Applications. 11. 10.14569/IJACSA.2020.0110883.
[28] Singh, B., S, N., & S, K.. (2021). *Smart Urban Water Quality Prediction System Using Machine Learning*. *1979*. https://doi.org/10.1088/1742-6596/1979/1/012057
[29] Ubah, Joseph & Orakwe, Louis & Ogbu, Kingsley & John, Awu & Ahaneku, Isiguzo & Emmanuel, Chukwuma. (2021). Forecasting water quality parameters using artificial neural network for irrigation purposes. Scientific Reports. 11. 10.1038/s41598-021-04062-5.
[30] Mishra, Ram Krishn & Nawaz, Nishad. (2022). A Machine-Learning Approach for Prediction of Water Contamination Using Latitude, Longitude, and Elevation. Water. 14. 728. 10.3390/w14050728.
[31] Bagal, Prof & Bhisikar, Trishala & Nimje, Aakanksha & Nandanwar, Yogesh & Patil, Tanuja. (2023). DESIGN OF AUTOMATIC DOMESTIC WATER QUALITY MONITORING & DISTRIBUTION CONTROL. IJIREEICE. 11. 10.17148/IJIREEICE.2023.11405.
[32] Lorente, Leandro & Pavón-Valencia, Jairo & Montero, Yakcleem & Herrera, Israel & Herrera, Erick & Peluffo-Ordóñez, Diego. (2019). Artificial Neural Networks for Urban Water Demand Forecasting: A Case Study. Journal of Physics: Conference Series. 1284. 012004. 10.1088/1742-6596/1284/1/012004.
[33] Tamang, Amrita & Shukla, Samiksha. (2019). Water Demand Prediction Using Support Vector Machine Regression. 1-5. 10.1109/IconDSC.2019.8816969.
[34] Awad, Mohammed & Zaid-Alkelani, Mohammed. (2019). Prediction of Water Demand Using Artificial Neural Networks Models and Statistical Model. International Journal of Intelligent Systems and Applications. 11. 40-55. 10.5815/ijisa.2019.09.05.
[35] Bata, Mo'Tamad & Carriveau, Rupp & Ting, David. (2020). Short-term water demand forecasting using hybrid supervised and unsupervised machine learning model. Smart Water. 5. 10.1186/s40713-020-00020-y.
[36] Narayanan, L. K., Sankaranarayanan, S., Rodrigues, J. J. P. C., & Kozlov, S.. (2020). *Water Demand Forecasting using Deep Learning in IoT Enabled Water Distribution Network: DL-Water Demand Forecasting for Water Distribution Design*. *15*(6). https://doi.org/15837/ijccc.2020.6.3977
[37] Ibrahim, Tarek & Omar, Yasser & Maghraby, Fahima. (2020). Water Demand Forecasting Using Machine Learning and Time Series Algorithms. 325-329. 10.1109/ESCI48226.2020.9167651.
[38]Xenochristou, Maria. (2022). Water demand forecasting – machine learning. 10.2166/9781789062380_0051.
[39] Seo, Y.; Kwon, S.; Choi, Y. Short-Term Water Demand Forecasting Model Combining Variational Mode Decomposition and Extreme Learning Machine. *Hydrology* **2018**, *5*, 54. https://doi.org/10.3390/hydrology504005
[40] Kim, Jongsung & Lee, Haneul & Lee, Myungjin & Han, Heechan & Kim, Donghyun & Kim, Hung. (2022). Development of a Deep Learning-Based Prediction Model for Water Consumption at the Household Level. Water. 14. 1512. 10.3390/w14091512.
[41] Kumbhar, S., Jadhav, V., Yelameli, B., Dhamale, S., & Chouksey, P.. (2022). *Water Requirement Forecasting for City System Using Machine Learning*. *10*(4). https://ijcrt.org/papers/IJCRT2204091.pdf

[42] Chouksey, P., Kumbhar, S., Jadhav, V., Yelameli, B., & Dhamale, S.. (2022). *Water Requirement Forecasting for City System Using Machine Learning*. *11*(4). https://doi.org/10.17148/IJARCCE.2022.114181
[43] Stańczyk, Justyna & Kajewska-Szkudlarek, Joanna & Lipiński, Piotr & Rychlikowski, Paweł. (2022). Improving short-term water demand forecasting using evolutionary algorithms. Scientific Reports. 12. 13522. 10.1038/s41598-022-17177-0.
[44] Zanfei, A., Melo Brentanb, B., Menapacea, A., & Righetti, M.. (2022). *A short-term water demand forecasting model using multivariate long short-term memory with meteorological data*. *24*(5). https://doi.org/0.2166/hydro.2022.055
[45] Patil, R., Alandikar, P., Chaudhari, V., Patil, P., & Deshpande, S.. (2022). *Water Demand Prediction Using Machine Learning*. *10*(12). https://doi.org/10.22214/ijraset.2022.47797
[46] Diksha & Lokendra singh Songare, .. (2023). *Water Demand Forecasting*. *5*(3).
[47] B., Nivedetha. (2023). Water Quality Prediction using AI and ML Algorithms. THE SCIENTIFIC TEMPER, 14(02):527-532. doi: 10.58414/scientifictemper.2023.14.2.46
[48] K., Shri, Ramtej. (2023). Water Quality Prediction Using Machine Learning Techniques. 358-362. doi: 10.1109/spin57001.2023.10117415
[49] Om, Pal. (2022). The Quality of Drinkable Water using Machine Learning Techniques. International journal of advanced engineering research and science, 9(6):016-023. doi: 10.22161/ijaers.96.2
[50] Krupal, Shah., Shreya, Sabu., Vedashree, Chaphekar. (2020). Water Leakage Detection Using Neural Networks. 1033-1040. doi: 10.1007/978-3-030-63128-4_37
[51] Riccardo, Zese., Elena, Bellodi., Chiara, Luciani., Stefano, Alvisi. (2021). Neural Network Techniques for Detecting Intra-Domestic Water Leaks of Different Magnitude. IEEE Access, 9:126135-126147. doi: 10.1109/ACCESS.2021.3111113
[52] Valentina, Ruzza. (2017). Data assimilation techniques for leakage detection in water distribution systems.
[53] Wang, Hai., Zhang, Cong. (2013). Water leakage detection system based on intelligent detection.
[54] Isack, Thomas, Nicholaus., Jun, Ryeol, Park., Kyuil, Jung., Jun, Seoung, Lee., Dae-Ki, Kang. (2021). Anomaly Detection of Water Level Using Deep Autoencoder.. Sensors, 21(19):6679-. doi: 10.3390/S21196679