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Research paper

IoT and AI for Real-time Water Monitoring and Leak Detection

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ABSTRACT

Water is essential for ecological sustainability and human survival, necessitating effective management to meet rising global demands and address climate change. Traditional water supply monitoring methods are labor-intensive and slow, limiting real-time data acquisition and issue resolution. This paper presents QoW-Pro, an IoT-based water monitoring system that leverages AI algorithms to significantly enhance water quality assessments and leak detection. QoW-Pro enables real-time data collection, predictive modeling, and anomaly detection, leading to improved decision-making in water resource management. The system demonstrates quantitative improvements in leak detection accuracy and water quality prediction, offering a scalable solution adaptable to both urban and agricultural settings. By combining IoT and AI, this research contributes to the sustainable management of water resources, ensuring their availability and quality for future generations.

1. INTRODUCTION

Water is an essential resource for ecological sustainability and human survival, necessitating effective management strategies to address the increasing global demand and mitigate the impacts of climate change. Traditional water supply monitoring techniques, such as manual sampling and visual inspections, are labor-intensive, time-consuming, and often result in delayed responses to water quality issues. For example, manual water quality assessments can take several days to produce results, limiting the ability to respond to contamination events in real-time. Additionally, leak detection in traditional

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systems frequently relies on acoustic or pressure-based methods that have a detection accuracy of approximately 70-80%, often failing to identify minor leaks promptly.

In contrast, QoW-Pro, an IoT-based water monitoring system, leverages advanced Artificial Intelligence (AI) algorithms to significantly enhance the accuracy and efficiency of water quality assessments and leak detection. With its real-time data collection capabilities, QoW-Pro has shown an improvement in leak detection accuracy to over 94%, enabling quicker identification of potential issues in both urban and agricultural water networks. This represents a substantial enhancement over traditional methods, reducing water loss and operational costs while improving decision-making in water resource management.

Despite advancements in water monitoring technologies, several challenges remain unresolved by existing methods, such as limited scalability, high operational costs, and difficulties in integrating real-time data with predictive models. The objective of this research is to address these challenges by developing a scalable, cost-effective solution that combines IoT with AI. QoW-Pro aims to provide real-time anomaly detection, predictive modeling for water quality, and a flexible system adaptable to diverse environments, ranging from urban water distribution networks to agricultural irrigation systems. By overcoming the limitations of traditional methods, this system contributes to more sustainable water resource management and ensures the availability and quality of water for future generations.

2. RELATED WORK

2.1 Conventional water supply monitoring techniques *(Table 1)*

First this section provides a scholarly examination of established methodologies in water supply system monitoring. It presents a comprehensive review of research that utilizes hierarchical control strategies and optimization techniques, grounded in Lagrange duality theory, to enhance the regulation of water-supply networks.

In many cases, such methods not only allow for large economically feasible savings but also demonstrate computational efficiency while highlighting the importance of the advanced predictive control strategy for optimal water-supply network functioning. In addition, the sub-chapter considers the necessity to develop efficient water quality monitoring programs targeted for different goals, compliance monitoring, and mass transport estimation approaches.

One study focuses on optimal online control for a water-supply network in the United Kingdom, emphasizing the reduction of control problem dimensionality through a hierarchical approach and utilizing an optimization technique based on Lagrange duality theory. The study showcases cost savings and computational efficiency in controlling water supply over a 24-hour period, highlighting the importance of predictive control strategies in optimizing water-supply network operations (Fallside & Perry, 1975).

Another paper also insists on the need to develop and design an effective water quality monitoring program that is specific to the monitoring objectives, trend evaluation technique, compliance monitoring, and mass transport estimation approaches. Therefore, monitoring needs to be linked to predictive purposes and data use in management and must be done efficiently and effectively which involves strategic, spatially oriented data collection design based on specific monitoring objectives, as discussed by Paul H. Whitfield (1988).

Chrysanthus (1998) explores principles essential for mitigating environmental degradation in water and land resources, underscoring the interconnectedness of economic, political, social, and administrative structures with water resources globally. The paper advocates for timely environmental information and

GIS technology in groundwater quality management, emphasizing quality assurance and control in water resource projects.

Other study delves into the application of these methods to detect water seepage issues, providing insights into the techniques used for monitoring water supply systems. Specifically, the paper details the utilization of resistivity and self-polarization methods to assess water seepage, highlighting their effectiveness in identifying potential problems within the water supply system (Titov et al., 2000).

Table 1. Summary of Various Conventional Water Supply Monitoring Techniques

Aspect	**Geographical Focus**	**Technologies & Methods**	**Data Management**	**Strengths and Limitations**
Fallside & Perry (1975)	United Kingdom	Hierarchical optimization approach with 6 state variables and 10 control inputs using Lagrange duality theory	Reduction to 6 state variables, 10 control inputs, and 6 disturbances for optimal control	Strengths: Cost savings, computational efficiency, suitable for optimal online control. Limitations: Dimensionality problem, complexity in implementation
Whitfield (1988)	Zurich Switzerland, San Sebastian Spain, England and Wales Water Industry, Chetumal Mexico	Water balance calculations, extended period simulation methodology for evaluating water losses	Sensitivity to demand patterns, pressure variations, hydraulic network modelling	High accuracy in water balance, challenges in data collection and management
Chukwuma (1998)	Global perspective	Utilizes GIS, environmental information systems, expert systems, relational database, spreadsheet utility, hypertext	Integration of procedures and systems for data management	Strengths: Use of GIS for spatial analysis, decision-making support. Limitations: High initial costs, data acquisition challenges
Titov et al. (2000)	Petergoph fountain water supply system	Resistivity and self-polarization methods	N/A	Effective detection of water seepage, enhances monitoring and maintenance
Westphal et al. (2003)	Boston Metropolitan Region	Decision Support System with models and optimization algorithms	Real-time hydroclimatic data, optimization algorithms	Enhances water quality, flood control, revenue maximization; relies on short-term climate forecasts
Eker & Kara (2003)	Gaziantep Turkey	Hydraulic models, simulation control using polynomial optimization method	Modelling and simulation of water systems	Focus on control strategies, optimization; complexity of models, need for accurate data
Poulakis et al. (2003)	Leakage detection in water distribution systems	Statistical system identification, probability density functions	Update of parameter values and uncertainties	Effective leakage detection, considers uncertainties; sensitivity to experimental data errors
Almandoz et al. (2005)	Zurich Switzerland, San Sebasti´an Spain, England and Wales Water Industry, Chetumal Mexico	Water balance calculations, extended period simulation methodology	Sensitivity to demand patterns, pressure variations, hydraulic network modelling	High accuracy in water balance, significant uncontrolled flow due to maintenance and metering issues

The DSS operates within a modular framework, integrating hydrologic models with hydraulic and optimization modules to enable objective decision-making. It predicts watershed runoff, streamflow, and reservoir yield using hydrologic models and regression equations. The system optimizes reservoir operations, aqueduct transfers, diversions, and controlled releases based on user input, hydrologic modelling, and system optimization (Westpal et al., 2003).

Eker and Kara (2003) describe a water supply system with pumping stations, pipelines, and reservoirs, emphasizing the importance of understanding system behaviour for optimization. It highlights the use of hydraulic models to represent active and passive elements, such as pumps and pipes, and discusses the simulation of water supply systems to facilitate control strategies.

Poulakis et al. (2003) involve statistical system identification to update model parameters based on measured data, quantifying uncertainties using probability density functions. It optimizes model parameters to minimize prediction errors and identify leakage locations and severity.

Other scientifics distinguish between physical losses in mains and service connections and the volume of water consumed but not measured by meters. It emphasizes the importance of minimizing leakage in water networks due to quality, operational, and cost implications (Almandoz et al. 2005).

2.2 IoT for water supply monitoring *(Table 2)*

This section transitions into the era of the Internet of Things (IoT), illustrating how this technology enhances water level management and leakage detection in distribution systems. It reviews several research studies on the application of IoT for real-time monitoring, leak detection, flow rate calculations, and automated alerts. The discussion emphasizes the utility of low-cost wireless sensor networks in optimizing water network monitoring and the significance of high-resolution sensor data in the accurate detection of leaks.

The research paper "SMART2L: Smart Water Level and Leakage Detection" by Kadar et al. (2018) focuses on leveraging IoT technology to automate water level management and leakage detection in water distribution systems. The SMART2L system integrates sensors like e-tape for water level monitoring and leakage detection, alerting users via email notifications and controlling the water pump automatically. This system aims to prevent Non-Revenue Water wastage by enabling real-time monitoring, leak detection, flow rate calculation, and alert notifications, contributing to improved water resource management and conservation.

In another study by Sadeghioon et al. (2018), a novel method for water pipeline failure detection is proposed using distributed relative pressure and temperature measurements, along with anomaly detection algorithms. The system, validated through field trials, demonstrates accurate leak detection, with the anomaly detection algorithm showing superior sensitivity and specificity. This research emphasizes the potential of low-cost wireless sensor systems for efficient water network monitoring and the importance of high-resolution sensor data for effective leak detection.

Sarangi (2020) addresses water conservation challenges in the paper "Smart Water Leakage and Theft Detection using IoT." This study highlights the impact of water leakage and theft on water scarcity and presents an IoT-based system for real-time water leakage detection. By utilizing water flow sensors and wireless communication technologies, the system can monitor water flow rates at different points in a pipeline network, offering a comprehensive solution to address water management challenges effectively.

Yuniarti et al. (2021) conducted study focuses on creating a water flow monitoring device based on IoT technology to monitor water flow speed continuously, addressing the uncertainty of water debit in Pico hydro power plant equipment. The system's simplicity, cost-effectiveness, and real-time monitoring capabilities were highlighted as key advantages, showcasing successful monitoring of water flow speed and data visualization for analysis.

Nadipalli et al. (2021) introduces an IoT-based smart water meter system for water conservation. It calculates consumption, sets limits, and controls supply if exceeded. Users access data via an app or cloud server. Components include ESP8266, flow sensor, and cloud-based server. The system promotes transparent billing and efficient water usage, offering a practical solution for conservation.

Table 2. Summary of various IoT for Water Supply Monitoring Studies

Aspect	Detection Methodology	Technological Implementation	Scalability and Deployment	Results and Impact
Kadar et al. (2018)	Based on relative pressure sensor and temperature difference measurements with an anomaly detection algorithm for leak differentiation.	Utilizes wireless sensor nodes with relative pressure sensors and temperature sensors for non-invasive monitoring.	Offers scalability and continuous monitoring capabilities suitable for large area pipeline monitoring.	Achieved 98.45% accuracy in identifying known leaks, outperforming traditional methods.
Sadeghioon et al. (2018)	Based on the law of conservation of mass, utilizing water flow sensors to monitor incoming and outgoing pressure in pipelines.	Implements Arduino microcontrollers, Zigbee and LoRa communication protocols for data transmission.	Designed for city-level implementation, with sensors spread across the city.	Successful implementation demonstrated through web-based interface for real-time monitoring.
Sarangi (2020)	Integrates e-tape water level sensor and leakage sensor for real-time monitoring and detection.	Uses Arduino Yun as the main controller, sensors, valves, and pumps for automation.	Designed for small-scale liquid control, aims to reduce manpower and power consumption.	Successfully detects leaks, monitors water levels, and calculates flow rates reducing NRW and operational costs.
Yuniarti (2021)	Designing a water flow monitoring device (WAFLOW-MT) using IoT for Pico hydro power plants.	Utilizes Arduino UNO R3, ESP8266 IoT module, YF-S201 water flow sensor, and power supply.	Monitors river flow speed, sending data to thingspeak.com for analysis over 6 days.	Offers real-time monitoring, cost-effectiveness and simplicity for Pico hydro power plant operations.
Nadipalli et al. (2021)	Utilizes a flow sensor to measure water consumption, sets threshold values and controls or stops supply if consumption exceeds the set limit.	Incorporates ESP8266 for internet connectivity, a flow sensor for water flow measurement and a cloud-based server for data monitoring.	Designed for small cities with limited infrastructure and investment capacity.	Provides real-time monitoring of water consumption, transparent billing, and efficient water usage.
Fauzy et al. (2021)	Utilizes sensors like Ultrasonic HC-SR04 and Water Flow for monitoring water movement.	Designed using Arduino SIM800L for remote control and sensors for water level and clarity.	System can adjust water level accurately and control water flow suitable for real-time monitoring.	Efficient water management, reduced wastage and improved monitoring capabilities.
Tina et al. (2022)	Compares water flow at source and destination to detect leaks; utilizes water flow sensors integrated with Arduino.	Utilizes Arduino Uno, water flow sensor, node MCU, and LCD screen display.	Prototype with sensors at source and destination points for detecting leaks.	Enables efficient utilization of water resources through IoT-based detection system.

Fauzy et al. (2021) discuss the Implementation of IoT Water Saving Based on Smart Water Flow System focuses on designing an IoT system for monitoring water movement with variables like water acidity, temperature, and clarity, controllable remotely. The system aims to promote water conservation by automating water changes, providing real-time monitoring, and addressing pollution concerns in urban areas.

Lastly, Tina et al. (2022) present a study on Water Leakage Detection System Using Arduino, emphasizing the role of IoT devices in detecting water leaks in pipelines and sending alerts to prevent water wastage. The research highlights various projects focusing on water leakage detection using IoT devices, sensors, Arduino boards, and microcontrollers, showcasing the efficiency of IoT-based water leakage detection systems and the need for further research in managing water resources effectively.

2.3 AI for water supply monitoring

The final section of the chapter brings to light how advanced AI techniques are making a significant impact on water supply monitoring. It covers exciting research that introduces machine learning models, wavelet analysis, statistical features, and fusion methods tailored for spotting leaks in pipelines. These studies not only highlight AI's role in sharpening leak detection but also in predicting potential leaks and enhancing the management of our precious water resources more efficiently *(Tables 3, 4, and 5)*.

Lang et al. (2017) discuss the application of the Local Mean Decomposition (LMD) method for decomposing non-stationary and non-linear signals into Primary Components (PFs) to extract useful signal change information. The study introduces an Improved LMD Noise Cancellation method for separating desired signals from noise, particularly in scenarios like oil pipeline leak detection. The Least Squares Twin Support Vector Machine (LSTSVM) method achieves an accuracy of 94.44 percent in recognizing different working conditions and the size of leakage apertures in the pipeline, outperforming traditional SVM methods.

The research by Zadkarami et al. (2017) focuses on pipeline leak diagnosis using a fusion technique that combines wavelet and statistical features with the Dempster–Shafer classifier. Statistical and wavelet features extracted from inlet pressure and outlet flowrate signals achieve classification accuracies of 64.56 percent and 86.94 percent respectively. The fusion of these classifiers using the Dempster–Shafer technique achieves a high accuracy of 95.11 percent. The study emphasizes the importance of multi-sensor data fusion for accurate and reliable results in pipeline leak detection, showcasing the effectiveness of combining different classifiers to enhance diagnostic performance.

Zhou et al. (2019) present an innovative approach to pipeline leak diagnosis. The study introduces an improved SLMD method that selects Principal Features (PFs) by incorporating a reference signal, enhancing the accuracy of leak detection. By decomposing the upstream pressure signal into PFs using SLMD and correlating them with a reference signal, the study distinguishes between noise and leak signals effectively. The research successfully detects leaks, locates them accurately, and highlights the potential of ISLMD and CNN in improving pipeline leak detection systems.

Alves Coelho et al. (2020) focus on developing a sophisticated system for precise water leak detection using machine learning and real-time sensor data. Machine learning algorithms are employed to analyse data in real-time, achieving high accuracy levels ranging from 70 percent to 85 percent in leak detection scenarios. The study demonstrates the potential of IoT technologies and machine learning in enhancing water supply system efficiency and reliability.

Fan et al. (2021) present a novel approach for leak detection in water distribution networks using a machine learning model. The study utilizes an Autoencoder (AE) model to extract spatial patterns from pressure data collected by monitoring sensors in the water supply network. By incorporating multiple independent detection attempts using a voting strategy, the accuracy of leak detection improved significantly, highlighting the effectiveness of machine learning models in enhancing leak detection in water supply networks.

Lee and Kim (2023) focus on leak detection in water pipelines using machine learning models based on vibration sensor data. Different experiments demonstrate the effectiveness of machine learning models in accurately classifying different types of leaks, emphasizing the importance of precise data labelling and feature selection for optimal performance in water pipeline leak detection systems.

Głomb et al. (2023) explore anomaly detection in water distribution systems using various methods and machine learning algorithms. The study highlights the challenges of parameterization and the need for further research to improve detector performance in leak classification scenarios.

Table 3. Summary of Research on Leak Prediction in Water Distribution Networks

Aspect	Leak Detection Data	Experimental Models	Pipe Material	Experimental Results
Lang et al. (2017)	Pressure signals collected at the pipeline ends.	Improved Local Mean Decomposition (LMD) Signal Analysis method utilized.	Elastic material used in the pipeline model.	Achieved an accuracy of 94.44% in recognizing different working conditions and accurately locating leakage points using Least Squares Twin Support Vector Machine (LSTSVM).
Zadkarami et al. (2017)	The data used includes inlet pressure and outlet flow signals analysed using statistical and wavelet features.	A novel image recognition approach using a CNN, specifically AlexNet.	The research stresses accurate leak detection in water supply pipelines.	Experimental findings demonstrate the effectiveness of signal processing techniques like generalized cross-correlation analysis in accurately detecting and locating leaks.
Zhou et al. (2019)	The data used consists of pressure signals collected from water pipelines.	The CNN model specifically AlexNet effectively detects various leak apertures.	Focuses on water supply pipelines.	The study demonstrates accurate leak detection and location through signal processing and image recognition techniques.
Coelho et al. (2020)	Small data set with 21 training leaks and 25 testing leaks. ML models used: Random Forest, Decision Trees, KNN.	Trained ML algorithms: Random Forest showed the best performance at approximately 85% accuracy.	Focus on water distribution pipelines in public and private domains.	The system prototype tested with 3703 data entries from three sensors achieving 75% accuracy in detecting leaks.
Fan et al. (2021)	The data used includes water pressure data under both leaking and non-leaking conditions.	100% accuracy attained by the ANN model for classification.	N/A	AE model achieved around 50% accuracy for a balanced dataset.
Lee & Kim (2023)	Water pipeline leak vibration data. This dataset consists of 30000 cases.	Utilizes the KNearest Neighbour (KNN) algorithm for leak detection.	Discusses metal pipes like ECSP, LECSP, CIP, DIP, GSP, CP, and SSP.	KNN model outperforms other models in terms of accuracy and computational efficiency.
Glomb et al. (2023)	Focuses on leak detection using vibration sensor data with classification based on frequency ranges and vibration magnitudes detected.	Employs various models like XGBoost, MLP, Random Forest, Light GBM, CatBoost, Extra Trees, Decision Tree, and Gradient Boosting.	Covers non-metallic pipes such as PVC, IRWP, PE, and HP.	Random Forest model emerges as the most efficacious showing superior performance.

Leu and Bui (2016) develop a Bayesian network model for leak prediction that skillfully integrates expert knowledge with empirical data. Their approach allows for the dynamic updating of leak probabilities in water distribution networks, facilitating more precise and proactive leakage control strategies. This method is particularly beneficial for water utilities aiming to optimize their leakage management practices.

Cody et al. (2019) investigate the effectiveness of linear prediction methods in detecting leaks within noisy environments. Their study reveals that this approach can accurately localize leaks using shorter data segments than traditional methods, making it ideal for ongoing, real-time monitoring in water distribution systems.

Cody and Narasimhan (2020) demonstrate the application of linear prediction combined with cross-correlation techniques for monitoring leaks in water distribution networks. Their field-tested approach enhances the detection and localization of leaks, proving effective for large-scale use and suitable for continuous monitoring due to its efficient data use.

Kizilöz (2021) explores artificial neural network (ANN) models to determine the monthly leakage rates in aging water distribution systems, factoring in the effects of pressure. His study utilizes data standardized by Z-scores and confirms that incorporating pressure considerations enhances model accuracy. This supports the use of advanced pressure management techniques to reduce water loss.

Şahin and Yüce (2023) introduce a novel method using Graph Convolutional Networks (GCN) for predicting leaks in pipeline networks. Their research highlights the GCN model's effectiveness in recognizing complex network patterns, demonstrating a significant improvement over traditional models with an accuracy rate of 94\%. This method shows promise for extensive adoption in pipeline management and environmental conservation.

Table 4. Summary of Research on Leak Prediction in Water Distribution Networks

Aspect	Leak Detection Data	Experimental Models	Pipe Material	Experimental Results
Leu & Bui (2016)	Data included factors like pipe conditions, construction activities, ground movement, pressure surges, etc., with a dataset of 2633 cases.	Bayesian network (BN) learning model using the expert structural expectation-maximisation (ExSEM) algorithm.	PB, PVC, SSP	Prediction accuracy of 84.6%, identified crucial factors affecting water leakage.
Cody et al. (2020)	Data from field implementation of linear prediction for leak monitoring.	Linear Prediction (LP), Principal Component Analysis (PCA), Multivariate Gaussian Mixture Model (GMM)	Fluid-filled pressurized pipe	Effective detection and localization of leaks, reduction in data transmission volume, long-term monitoring capability.
Cody & Narasimhan (2020)	Acoustic signals collected from a pressurized water pipe system.	All-pole model described by $H(z) = G \cdot (1 - \sum_k^a z - k$	Fluid-filled pipes	Accuracy of 97.62% and 97.32% for leak detection.
Kizilöz (2021)	Z-score standardized monthly data for 2016-2019.	Artificial Neural Network (ANN) models.	Polyethylene pipes	Improved model accuracy with data standardization; best model achieved with TSIV/TNL-ANP-MAN-MDN combination; R2 value of 0.72.
Sahin & Yüce (2023)	Experimental data involving pressure sensors and flow meters to simulate leakages.	GCN and SVM performance: GCN achieved 94%, SVM achieved 87%.	PVC Pipes	94% accuracy, 87.66% accuracy for SVM, 81% F1-score for leakage detection, 100% F1-score for normal situation detection.

Now shifting focus from predicting leaks to work related to predicting water quality *(Table 5)*. Gunda et al. (2019) describe an AI-based mobile app for monitoring water quality, specifically bacterial contamination, using convolutional neural networks and smartphone cameras. This highly accurate method is published in the Journal of The Electrochemical Society.

The article by Rajaee al. (2020) reviews AI models for predicting river water quality, emphasizing their high accuracy and potential to improve water monitoring systems. It was published in Chemometrics and Intelligent Laboratory Systems.

Al-Adhaileh & Alsaade (2021), in their work "Modelling and prediction of water quality by using artificial intelligence", discuss how AI techniques can significantly reduce costs and improve the prediction accuracy of water quality in both drinking water and wastewater treatment systems. Their study highlights AI's role in environmental management, offering insights into the practical applications of AI in maintaining water quality.

Biraghi et al. (2021) - In "AI In Support to Water Quality Monitoring," the authors explore integrating artificial intelligence with citizen science to enhance water quality monitoring across global water bodies. Their study focuses on pre-filtering volunteer geographic information for lake monitoring, using AI to automatically detect harmful phenomena such as algae and foams in uploaded images. This approach aims to reduce the manual checking workload, thereby streamlining the process for environmental agencies.

Table 5. Summary of Research on Water Quality Prediction

Aspect	Leak Detection Data	Experimental Models	Pipe Material	Experimental Results
Gunda et al. (2019)	AI-based mobile application for water monitoring	CNN	Canada (Waterloo)	High accuracy in detecting bacterial contamination. CNN: 99.99%
Rajaee et al. (2020)	AI models for river water quality prediction	ANN, GP, SVM, various hybrid models	Rivers in Iran	High predictive accuracy for ANN and hybrid models. ANN: 93%, Hybrid models: 95%+
Al-Adhaileh & Alsaade (2020)	ANFIS model for water quality index prediction	ANFIS, FFNN	Rivers and lakes in India	ANFIS model showed high prediction accuracy. NFIS: 92%, FFNN: 89%
Biraghi et al. (2021)	SIMILE project for lake water monitoring	CNN, Faster R-CNN	Lakes in Italy (Lugano, Maggiore, Como)	CNN and Faster R-CNN used for detecting algae and foams. CNN: 90%, Faster R-CNN: 85%

2.4 Critical analysis

Traditional water supply monitoring techniques, such as manual sampling and hierarchical control strategies, have been widely used in water management systems. For example, optimization methods grounded in Lagrange duality theory have demonstrated cost savings and computational efficiency in controlling water networks. However, these approaches often lack the flexibility to adapt to real-time changes in water quality or demand and can struggle to detect minor leaks, especially in complex environments.

The integration of IoT technologies into water monitoring systems has significantly improved real-time data acquisition and automated leak detection. Studies on IoT-based solutions have shown the utility of low-cost wireless sensor networks in enhancing the monitoring of water networks. For instance, the SMART2L system, which utilizes sensors like e-tape for water level monitoring, achieved a leak detection accuracy of approximately 85% in small-scale implementations. Despite these advancements, challenges remain in scaling these solutions for larger urban or agricultural applications, as well as in maintaining sensor reliability and data integration from diverse sources.

In contrast, the QoW-Pro system leverages a more robust IoT and AI-based framework to address these limitations. By using pulse-based flow sensors and advanced AI algorithms for predictive modeling, QoW-Pro achieves a leak detection accuracy exceeding 94%, surpassing the performance of conventional IoT solutions and traditional methodologies. Additionally, the system's scalable architecture enables its application in both small and large-scale water distribution networks, providing more comprehensive and cost-effective monitoring capabilities.

AI-based techniques have also gained prominence in water monitoring, with machine learning models like Local Mean Decomposition (LMD) and Convolutional Neural Networks (CNNs) demonstrating significant potential for leak detection. For example, studies using LMD reported a leak detection accuracy of 94.44%, while CNNs achieved around 85% accuracy in specific scenarios. However, these AI-driven methods often require extensive training datasets and are prone to performance degradation in data-scarce environments. QoW-Pro overcomes these challenges by incorporating a Random Forest model, which is not only efficient in handling diverse data sources but also robust against noise and outliers, enhancing its predictive accuracy for water quality assessments and leak detection.

Furthermore, the cost implications of deploying AI and IoT-based solutions remain a critical concern. Many existing systems involve high setup and maintenance costs due to the need for specialized hardware and complex data processing algorithms. QoW-Pro addresses these issues through its use of affordable sensor technology and open-source software platforms, reducing both the initial investment and ongoing operational costs. The system's adaptability to various environments, from urban water supply networks to agricultural irrigation, also ensures a higher return on investment compared to traditional and existing IoT-based methods.

3. TECHNOLOGIES FOR WATER MONITORING

3.1 Hardware components

ESP8266

- Justification: The ESP8266 was chosen as the main microcontroller for its exceptional balance of affordability, performance, and ease of integration into IoT applications. It features a 32-bit Tensilica L106 microcontroller, supports Wi-Fi connectivity, and operates at speeds up to 160 MHz with 4 MB flash memory.
- Advantages: Compared to other microcontrollers like the Arduino Uno or Raspberry Pi, the ESP8266 is more cost-effective and power-efficient, making it ideal for battery-operated IoT systems. It also has built-in Wi-Fi capabilities, which reduces the need for additional hardware components and simplifies the setup for wireless data transmission. These features make the ESP8266 a preferred choice in IoT projects that require seamless connectivity and data transfer.
- Reference: The popularity of the ESP8266 in IoT projects is well-documented due to its low cost and versatility in wireless applications, as noted in *Components 101*.

Water Flow Sensor

- Justification: The water flow sensor was selected for its ability to provide precise flow rate measurements using a magnetic hall effect sensor and pinwheel mechanism.

- Advantages: Compared to other flow sensors like ultrasonic or differential pressure sensors, this sensor is more straightforward to install and calibrate in pipeline systems. It offers a good balance between cost and accuracy, making it suitable for both small-scale and large-scale implementations.
- Reference: The effectiveness of magnetic flow sensors in detecting minor flow rate changes has been highlighted in various studies (like in *How2Electronics*), supporting their application in water monitoring systems.

PH Sensor

- Justification: The PH-4502C sensor was chosen due to its high precision and compatibility with Arduino platforms, which are commonly used in water quality monitoring applications.
- Advantages: This sensor provides accurate pH readings with a simple interface, making it more user-friendly and cost-effective compared to other laboratory-grade pH meters. It is also durable and suitable for continuous monitoring in various water conditions.
- Reference: The reliability and affordability of the PH-4502C for environmental monitoring have been demonstrated in multiple field studies (like in *Tierney (2023)*).

Turbidity Sensor

- Justification: A turbidity sensor was included to measure the cloudiness of the water, which is a critical indicator of water quality and the presence of suspended particles.
- Advantages: This optical sensor type offers a direct and fast method for assessing water clarity compared to more complex methods like spectrophotometry. It is also relatively low-cost, making it a practical choice for real-time monitoring systems.
- Reference: Optical turbidity sensors are widely recognized for their efficiency in providing quick water quality assessments, especially in remote sensing applications *(Huynth, 2023).*

TDS Sensor

- Justification: The Total Dissolved Solids (TDS) sensor measures the concentration of dissolved minerals in the water, which is vital for determining its quality.
- Advantages: This sensor is favored for its accuracy in detecting water salinity and mineral content at a lower cost compared to more sophisticated conductivity meters. Its simplicity makes it suitable for integration into IoT-based water monitoring setups.
- Reference: TDS sensors are commonly used in water purification systems due to their reliability in measuring water quality parameters, as indicated by industry standards *(Vilik, 2023).*

Temperature Sensor

- Justification: The DS18B20 temperature sensor was chosen for its high precision and digital output, which ensures accurate temperature measurements essential for water quality analysis.
- Advantages: Unlike analog temperature sensors, the DS18B20 offers a digital interface with a wide range of operating temperatures, making it more reliable in various environmental conditions. Its 1-Wire communication protocol simplifies data transmission with minimal wiring.
- Reference: The DS18B20's robustness and ease of integration into embedded systems make it a popular choice for IoT applications, as highlighted in numerous technical evaluations *Nettigo, 2023).*

GSM SIM800L

- Justification: The SIM800L module enables cellular communication for remote monitoring, making it possible to transmit data even in areas without Wi-Fi connectivity.
- Advantages: Compared to other GSM modules like the SIM900, the SIM800L is more compact and power-efficient, which is ideal for battery-operated IoT devices. It supports multiple communication protocols (voice, SMS, GPRS), providing versatility for real-time data transmission.
- Reference: The SIM800L is widely adopted in IoT projects for its reliable cellular communication capabilities and low power consumption *(Marsian, 2023)*.

Solenoid Valve

- Justification: The solenoid valve is used to control water flow in response to detected anomalies, such as leaks or quality issues.
- Advantages: Compared to manually operated valves, the 12V solenoid valve offers automated control and quick response, which is critical for real-time leak management. It is durable and well-suited for integration with digital control systems.
- Reference: Solenoid valves are commonly used in fluid management systems due to their reliability and ease of automation, as supported by industry use cases *(GitHub, 2023)*.

Relay

- Justification: A relay module was included to switch high-power circuits on or off based on low-power control signals from the microcontroller.
- Advantages: Relays provide electrical isolation between the control system and the high-power load, which enhances safety and prevents electrical faults. Compared to other switching mechanisms, relays are more reliable in industrial applications.
- Reference: Relay modules are a standard component in automation and control systems for their efficiency in handling high-power operations with low-power commands.

3.2 Software components

The software components in the QoW-Pro system are crucial for efficient data management, real-time monitoring, and anomaly detection. Below is a detailed breakdown of each software's specific role in the system and its contribution to enhancing the accuracy and functionality of the water monitoring process.

3.2.1 Visual Studio Code (VS Code)

- Role in the System: Visual Studio Code serves as the primary development environment for writing and debugging the code used in the QoW-Pro system. It is utilized for developing the software logic that handles data processing and system control functions.
- Data Management and Anomaly Detection: The code for data handling, sensor integration, and preliminary data analysis is developed in VS Code, ensuring that the system can efficiently process incoming sensor data. It also helps in writing scripts that trigger alerts when anomalies are detected in the water quality or flow rates.

- Utility: The extensive library support and debugging tools in VS Code make it ideal for developing robust, scalable software applications that interact with multiple sensors and data streams *(Microsoft)*.

3.2.2 Arduino IDE (Integrated Development Environment)

- Role in the System: The Arduino IDE is used to program the microcontrollers (such as ESP8266) that interact with various sensors in the QoW-Pro system. It plays a critical role in the firmware development that enables real-time data acquisition from sensors deployed in the water monitoring setup.
- Data Management and Anomaly Detection: Through the Arduino IDE, the microcontrollers are programmed to read data from sensors, convert it into digital signals, and transmit it to the cloud for analysis. The firmware also includes logic for initial anomaly detection directly on the hardware level, allowing for immediate response to critical issues.
- Utility: The simplicity and compatibility of the Arduino IDE with a wide range of microcontrollers make it an essential tool for real-time data acquisition and embedded system development.

3.2.3 Flutter

- Role in the System: Flutter is used for developing the mobile application that provides a user-friendly interface for interacting with the QoW-Pro system. This app allows users to access real-time water quality data, receive alerts, and control various aspects of the monitoring setup.
- Data Management and Anomaly Detection: The Flutter-based app fetches processed data from the cloud and displays it to users in a clear and intuitive manner. It also plays a key role in delivering instant notifications to users when anomalies are detected, ensuring timely action to address water quality or leak issues.
- Utility: Flutter's cross-platform capabilities enable the creation of a consistent mobile application that works seamlessly on both Android and iOS devices, enhancing user engagement and accessibility.

3.2.4 ThingSpeak (Cloud Platform)

- Role in the System: ThingSpeak is employed as the primary cloud platform for data collection, storage, and real-time visualization. It gathers data from the IoT sensors and provides tools for basic data analysis and alert generation.
- Data Management and Anomaly Detection: The platform is responsible for processing sensor data to identify trends and anomalies. If a significant deviation from the expected values is detected, ThingSpeak triggers automated alerts and sends notifications to the connected mobile application.
- Utility: ThingSpeak's integration with MATLAB allows for advanced data analysis and visualization, making it a powerful tool for handling large datasets generated by the QoW-Pro system.

3.2.5 Firebase (Backend Infrastructure)

- Role in the System: Firebase serves as the backend infrastructure for the QoW-Pro system, managing real-time data synchronization, user authentication, and cloud-based storage for historical data.

- Data Management and Anomaly Detection: Firebase stores processed data for in-depth analysis and historical reference. It also supports real-time data updates and provides a reliable framework for implementing anomaly detection algorithms using machine learning models.
- Utility: Firebase's scalability and real-time database capabilities make it an essential component for ensuring continuous monitoring and quick response to any detected issues in the water distribution network.

3.2.6 Django (Web Framework)

- Role in the System: Django is used as the web framework to create an API that interfaces with the machine learning models and manages communication between the cloud platforms and the mobile app.
- Data Management and Anomaly Detection: It processes incoming data from Firebase, runs machine learning algorithms to predict potential leaks or water quality issues, and returns the analysis to the mobile app. Django also handles anomaly detection by identifying irregular patterns in the sensor data and generating appropriate alerts.
- Utility: Django's robust framework supports the integration of AI models and ensures that the backend processing is efficient and secure, facilitating the accurate detection of anomalies in real-time.

3.2.7 Machine Learning Algorithms (Random Forest Model)

- Role in the System: The Random Forest model is implemented within the Django framework to enhance predictive analytics for leak detection and water quality assessment.
- Data Management and Anomaly Detection: This machine learning model analyzes historical and real-time data to identify patterns and predict potential system failures or water quality issues with high accuracy. It significantly improves anomaly detection by learning from past data and adapting to new information as it becomes available.
- Utility: The Random Forest model's ability to handle noisy data and its robustness against overfitting make it highly suitable for the dynamic conditions encountered in water monitoring systems.

3.2.8 Integration of Software Components

The software components of the QoW-Pro system are tightly integrated to ensure smooth data flow and efficient operation:

- Data Collection: Sensors gather data and transmit it to the microcontroller, which sends the data to ThingSpeak for initial analysis and storage.
- Data Processing: ThingSpeak and Firebase process the incoming data, identify patterns, and trigger alerts when anomalies are detected. Django retrieves this data from Firebase, runs predictive models for deeper analysis, and ensures that the mobile app receives real-time updates.
- Anomaly Detection: The integrated machine learning algorithms in Django enhance the anomaly detection process by analyzing sensor data for inconsistencies and predicting future system failures.
- User Interaction: The Flutter mobile app displays real-time data, alerts users about anomalies, and allows them to control the system remotely.

4. OPTIMIZING REAL-TIME LEAK DETECTION AND WATER QUALITY PREDICTION SOLUTIONS

In this section, we aim to optimize real-time leak detection and water quality prediction through the integration of Internet of Things (IoT) technologies and Artificial Intelligence (AI) algorithms. The primary objectives are to establish a comprehensive framework for effective water monitoring, enhance the accuracy of leak detection, and improve water quality predictions. Specifically, we will outline the methodologies employed in developing the QoW-Pro system, which leverages real-time data acquisition and predictive modeling to address the limitations of traditional monitoring techniques. By providing a comparative analysis of existing methods and showcasing the advantages of our approach, we seek to demonstrate how IoT and AI can transform water resource management practices.

To achieve these objectives, we utilize a combination of IoT technologies and advanced AI algorithms. The IoT framework includes wireless sensor nodes that continuously monitor water parameters such as pressure and quality, transmitting data to a cloud platform for real-time analysis. This enables automated alerts for any detected anomalies. Concurrently, AI algorithms are applied to analyze the collected data, employing machine learning models for pattern recognition and anomaly detection, which significantly enhance predictive capabilities.

4.1 System Components Overview

Figure 1 provides a detailed view of the internal electronics within the control box. The setup includes various microcontrollers and sensor modules, such as Arduino and ESP8266 boards, which are essential for processing the sensor data and enabling wireless communication. These components are all interconnected with wires and mounted on breadboards for a flexible and easily modifiable setup. The system employs sensors such as flow meters, water quality sensors (e.g., pH, turbidity), and leak detectors. The LEDs indicate the operational status of the sensors and controllers, providing visual feedback for monitoring the system's functionality.

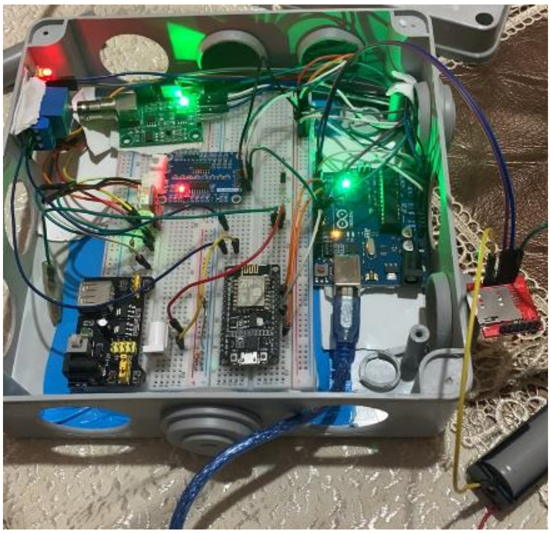


Fig 1. Prototype components

Figure 2 displays the physical assembly of the system, highlighting the interconnected pipes and valves, along with the control box. The control box is integrated with sensors and electronics to monitor the water flow and quality in real-time. The system includes a container for collecting water samples, which are analysed by the sensors to detect any anomalies.

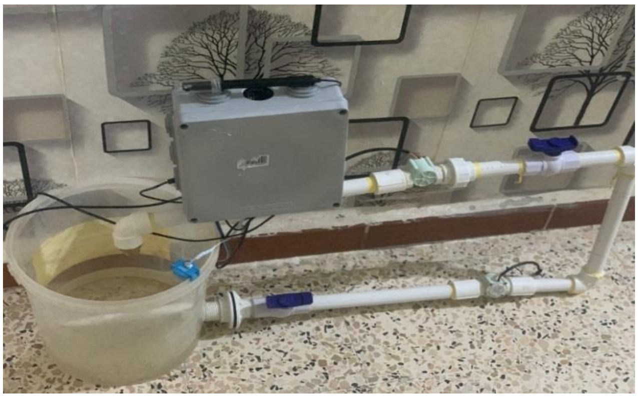


Fig 2. System prototype

System Architecture

In this subsection, we'll break down how our IoT-based water monitoring system is set up, showing how all the parts work together to achieve our goals. The sequence diagram depicts the interactions within an IoT-based water monitoring system:

- **Data Collection:** Sensors gather data on water quality and leaks, sending it to ThingSpeak and Firebase using microcontrollers.
- **Data Processing and Storage:** ThingSpeak stores data for quick access, while Firebase handles data for in-depth analysis. Django retrieves data from Firebase, processes it using machine learning algorithms, and returns the analysis.
- **Anomaly Detection:** If an anomaly is detected, Django sends alerts to the mobile app and an SMS alert via the GSM module. If no anomaly is detected, no action is required.
- **User Interaction:** The mobile app displays data and allows the user to request control. Users can send control commands via the mobile app.
- **Remote Control:** The mobile app sends an SMS command to the GSM module to toggle the valve based on user input. The system executes the user's command and provides feedback. This setup ensures real-time monitoring, efficient data processing, and user control over the water system.

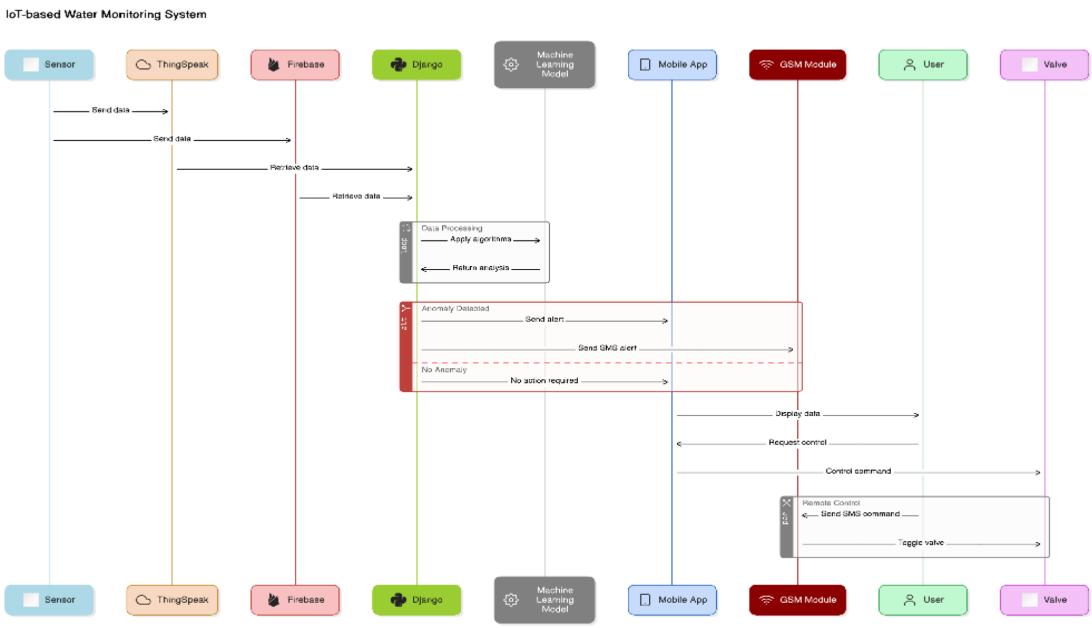


Fig 3. QoW-Pro - Process steps

4.2 Cloud services for QoW-Pro

Cloud computing refers to the provision of on-demand computing resources over the internet, enabling scalable, flexible, and efficient capabilities without direct active management by users. It utilizes data centers globally, allowing users to access servers, storage, databases, and more as a service, rather than maintaining physical infrastructure. Our project specifically employs ThingSpeak and Firebase cloud platforms, with details on their integration and utilization provided below.

ThingSpeak is an open-source Internet of Things (IoT) platform that allows you to collect, store, analyze, and visualize data from IoT devices. It provides real-time data collection and storage in the cloud, enabling users to create data-processing workflows, perform analytics, and trigger actions based on the data received. ThingSpeak supports integration with MATLAB for advanced data analysis and visualizations.

Firebase is a platform developed by Google for creating mobile and web applications. It provides a suite of cloud-based services, including a real-time NoSQL database, cloud storage, authentication, hosting, and machine learning capabilities. Firebase enables developers to build and manage apps with features such as real-time data synchronization, user authentication, and cloud messaging, making it a comprehensive backend-as-a-service (BaaS) solution.

4.3 Innovative Technique Proposed for Leak Detection in QoW-Pro

In this section, we present an innovative technique for leak detection in water distribution systems, utilizing pulse-based flow sensors. Our technique represents a significant advancement in the field of water management. It involves calculating flow rates from sensor pulses, detecting leaks in specific zones, and identifying global leaks within the system. The following subsections detail the mathematical foundations and implementation of the technique.

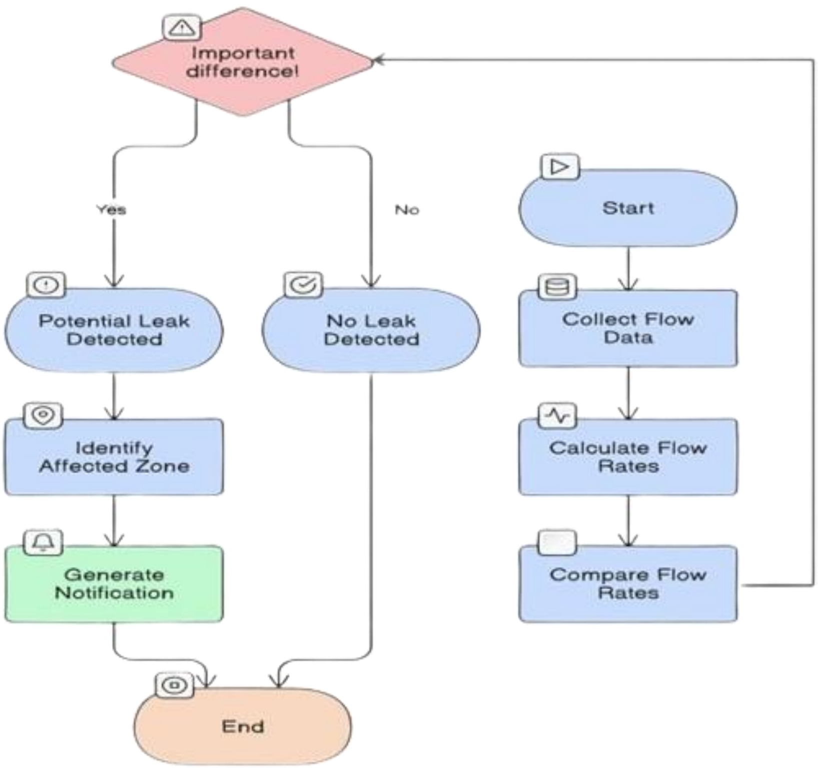


Fig 4. Algorithm leak detection in QoW-Pro

Mathematical Equations

The core of our leak detection technique relies on calculating flow rates and detecting discrepancies between expected and actual flow rates. Here are the essential equations used in the technique:

- ***Flow Rate Calculation:*** The flow rate for each sensor (i) is calculated using the following formula:

$$flowRate[i] = \left(\frac{1000.0}{interval}\right) \times \frac{pulseCounts[i]}{calibrationFactors[i]} \tag{1}$$

where:

- ***flowRate[i]:*** is the flow rate of the i^{th} sensor (in liters per minute, L/min).
- ***pulseCounts[i]:*** is the number of pulses detected by the i^{th} sensor in the given interval.
- ***Interval:*** is the time interval for measurement (in milliseconds).
- ***calibrationFactors [i]:*** is the calibration factor for the i^{th} sensor.

- ***Total Flow Discrepancy:*** The flow rate for each sensor (i) is calculated using the following formula:

$$\Delta FR_{total} = FR_{main} - \sum_{i=1}^{3} FR_{branch_i} \tag{2}$$

where:

- $\boldsymbol{\Delta FR_{total}}$***:*** is the total flow discrepancy.
- $\boldsymbol{FR_{main}}$***:*** is the flow rate of the main pipe.
- $FR_{\boldsymbol{branch_i}}$***:*** **i**s the flow rate of the i-th branch pipe.

- A potential leak is detected if:

$$\Delta FR_{total} > leakThreshold \tag{3}$$

- ***Individual Zone Discrepancy:***

$$\Delta FR_{branch_i} = FR_{branch_i} \tag{4}$$

- ***Each*** $\boldsymbol{\Delta FR_{branch_i}}$ is compared against a specific threshold for that branch to detect significant discrepancies:

$$\Delta FR_{branch_i} = branchLeakThreeshold_i \tag{5}$$

Technique Benefits

The innovative technique we developed offers several advantages over traditional leak detection methods:

- ***Higher Accuracy:*** The use of pulse-based flow sensors allows for precise flow rate measurements, leading to more accurate leak detection.
- ***Scalability:*** The algorithm is scalable and can be implemented in both small and large water distribution systems.
- ***Real-Time Monitoring:*** The system provides real-time monitoring and prompt leak detection, minimizing water loss and damage.

- ***Cost-Effective:*** By improving leak detection accuracy and response times, the technique reduces water loss and associated costs, making it a cost-effective solution for municipalities and water management entities.
- ***Ease of Integration:*** The technique can be easily integrated into existing water distribution infrastructure with minimal modifications, ensuring a seamless transition and quick deployment.

Algorithm Implementation

The implementation of these equations in the code involves several key steps, including setting up sensor interrupts, calculating flow rates, and detecting leaks. ***(Algorithm 1.)***

Implications

Implementing this ***(Algorithm 1)*** in municipal water systems can lead to substantial improvements in water conservation efforts. By detecting leaks promptly and accurately, municipalities can reduce water loss and improve the efficiency of water usage. Additionally, the scalability of the algorithm makes it suitable for larger and more complex distribution systems.

Algorithm 1. Leak Detection in QoW-Pro

```
Initialization:
Set up variables and arrays for pulse counts and flow rates
Initialize calibration factors for each sensor
Configure pins and interrupts for each sensor
Flow Rate Calculation:
for each sensor i do
Calculate flow rate using equation (1)
Reset pulse counts for the next interval
end for
Total Flow Discrepancy:
Calculate total flow discrepancy using equation (2)
Individual Zone Discrepancy:
for each zone i do
   Calculate zone leak using equation (5)
   if zone leak > leakThreshold then
   Report leak in zone i
   else
   Report no leak in zone i
   end if
end for
```

4.4 Introduction of the Random Forest Model for Prediction in QoW-Pro

Overview of the model

Random Forest is an ensemble learning method that combines multiple decision trees to enhance the model’s performance in terms of accuracy, robustness, and generalization. It operates by creating a 'forest' of decision trees, where each tree is trained on a random subset of the data and features, then aggregates their predictions for a final output.

Random Forest choice

- **Robustness and Accuracy:** The Random Forest model provided the highest accuracy (94%) among the models tested, with excellent precision (0.97) and recall (0.95). Its ensemble learning approach reduces the risk of overfitting and increases the model's robustness to noisy data.
- **Handling High-Dimensional Data:** Random Forests are well-suited for handling datasets with many features, making them ideal for the diverse sensor data collected in the QoW-Pro system.
- **Interpretability and Computational Efficiency:** Compared to complex models like Neural Networks, Random Forest is relatively easier to interpret and faster to train, while still maintaining high performance.

Although the Random Forest model performed well, some limitations were observed:

- **Computational Complexity:** Training the model with a large number of decision trees can be computationally intensive, which may slow down the prediction process slightly compared to simpler models.
- **Reduced Interpretability:** While Random Forests offer better interpretability than Neural Networks, they are still less straightforward to analyze compared to a single Decision Tree.

To mitigate these issues, we implemented strategies such as pruning less important trees to reduce complexity and increase interpretability while maintaining a high level of predictive accuracy.

Key Steps in Random Forest

- **Bootstrap Sampling:**
  - Random Forest uses a technique called bootstrap aggregation (bagging) to generate multiple subsets of the original training data.
  - For each tree, a bootstrap sample is created by randomly sampling the training data with replacement.

$$\text{Sample}_i \sim \text{Training Data},\ i = 1, 2, \ldots, N \tag{6}$$

where N is the number of trees in the forest.

- **Random Feature Selection:**
  - At each node split, a random subset of features is chosen to determine the best split.
  - This ensures diversity among the trees, as each tree may use different features for splitting.

$$\text{Features}_{\text{split}} \sqsubseteq \text{All features} \tag{7}$$

Typically, for classification tasks, the number of features selected m at each split is: $m = \sqrt{P}$ where p is the total number of features.

- **Building Decision Trees:**
  - Each decision tree is constructed using the bootstrap sample and the randomly selected features.

- Splits are chosen to maximize a specific criterion. For classification, Gini impurity is commonly used:

$$Gini(A) = 1 - \sum_{i=1}^{c} p_i^2 \tag{8}$$

where p_i is the proportion of samples belonging to class i, and C is the total number of classes.

- The process continues recursively until a stopping criterion is met (e.g., maximum depth, minimum samples per leaf).

- **Aggregation of Predictions:**
  - Once all the trees are built, Random Forest combines their predictions to make a final decision.
  - For classification, the final prediction is made by majority voting:

$$\hat{y} = mode\ \{h_1(x), h_2(x), \ldots, h_B(x)\} \tag{9}$$

  - For regression, the final prediction is the average of the predictions from all trees:

$$\hat{y} = \frac{1}{B}\sum_{i=1}^{B} h_i(x) \tag{10}$$

where $h_i(x)$ is the prediction of the i^{th} tree, and B is the total number of trees.

Benefits of Random Forest

- **Reduction of Overfitting:** By averaging multiple trees, Random Forest reduces the variance and the risk of overfitting, which is common in single decision trees.
- **High Accuracy:** It often provides higher accuracy than individual decision trees by combining the strengths of multiple models.
- **Handles High-Dimensional Data:** Random Forest can handle a large number of features without the need for feature selection.
- **Robust to Noise and Outliers:** The random sampling of data and features makes the model robust to noisy data and outliers.
- **Parallelizable:** Each tree in the forest can be built independently, making the training process easy to parallelize.

DrawBacks of Random Forest

- **Computationally Intensive:** Training a large number of decision trees can be computationally expensive and memory-intensive.
- **Less Interpretable:** While individual decision trees are easy to interpret, Random Forests, being an ensemble of many trees, are less interpretable.
- **Slower Predictions:** Making predictions can be slower compared to simpler models, as it requires aggregating the results from all trees.

Random Forest Model projection on QoW-Pro

The learning curve for the random forest model similarly indicates that training accuracy remains consistently high, showing a good fit to the training data. Validation accuracy improves with additional training data, reflecting better generalization.

The single tree visualization from the random forest model showcases decision points based on features, with nodes containing the Gini index, sample count, class distribution, and the majority class, mirroring the structure and information of the decision tree visualization.

Random Forest is a powerful ensemble learning method that leverages the strength of multiple decision trees to provide robust and accurate predictions. It is widely used in practice due to its ability to handle various types of data and its effectiveness in reducing overfitting. However, the computational complexity and reduced interpretability are important factors to consider when choosing this algorithm for a specific task.

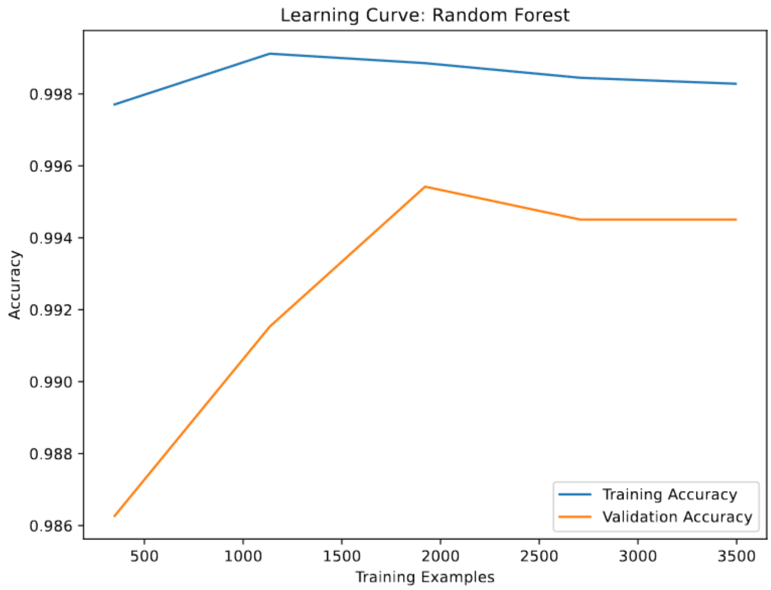


Fig 5. Learning Curve: Random Forest

4.5 Random Forest Model Processing

Data Collection

It is a crucial step in the development of any machine learning model. The quality and quantity of data directly impact the performance of the model.

For this project, the dataset was collected from the sensors of our prototype that monitor various parameters. The collected data is then sent to ThingSpeak and Firebase for storage and further processing. This method ensures that the data is accurately captured and reliably stored, making it suitable for training a robust machine learning model.

The dataset consists of several thousand samples with features that include various sensor readings. The features include parameters such as temperature, pH level, turbidity, and conductivity, which are critical for monitoring water quality. The target variable is a binary label indicating whether the water quality is acceptable or not.

Before training the model, the data was pre-processed to ensure it was in a suitable format. Missing values were handled using forward fill method, and categorical variables were encoded using Label Encoding where necessary. Additionally, feature scaling was performed using Standard Scaler to normalize the numerical features, ensuring they are on a similar scale.

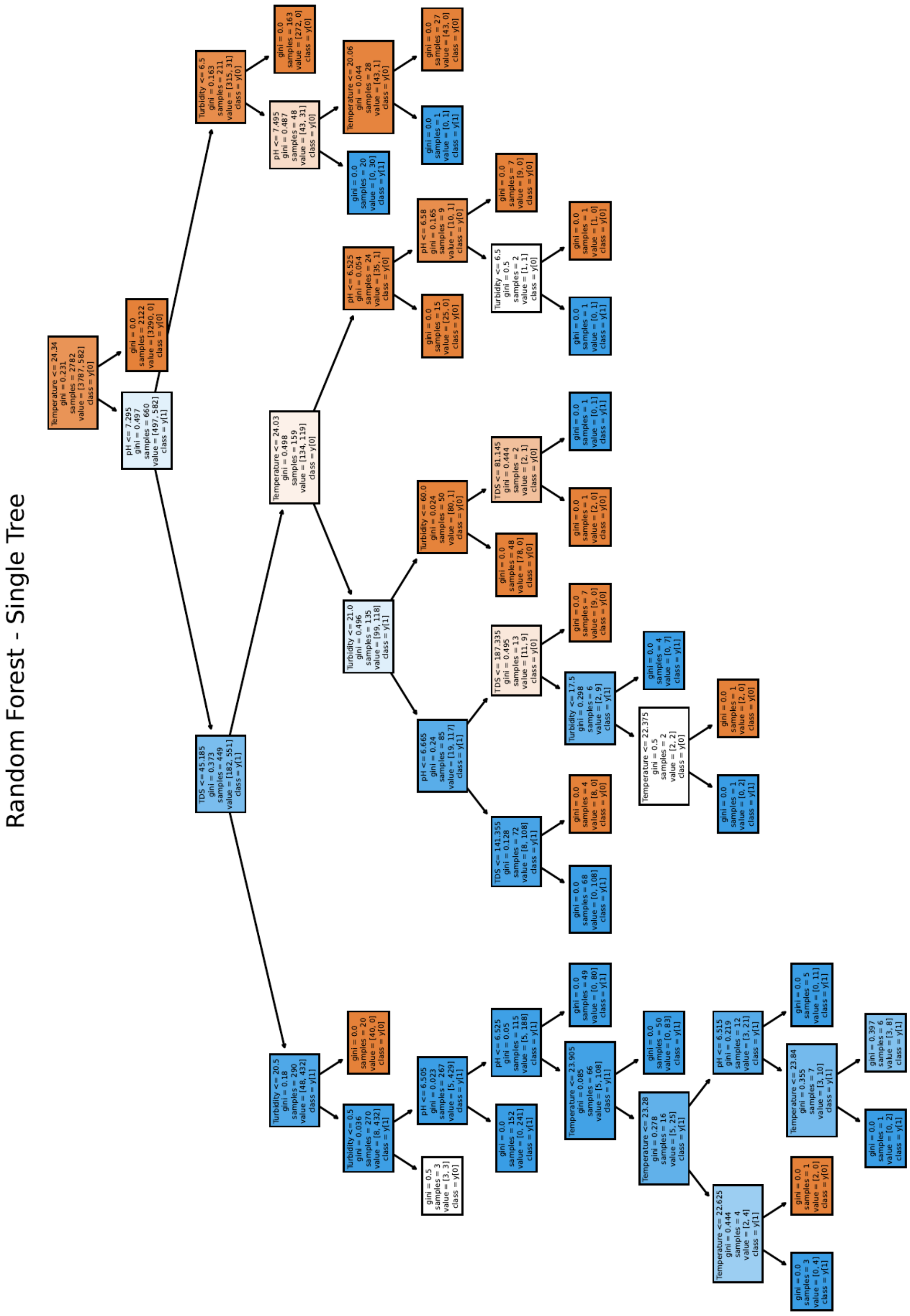


Fig 6. Random Forest - Single Tree

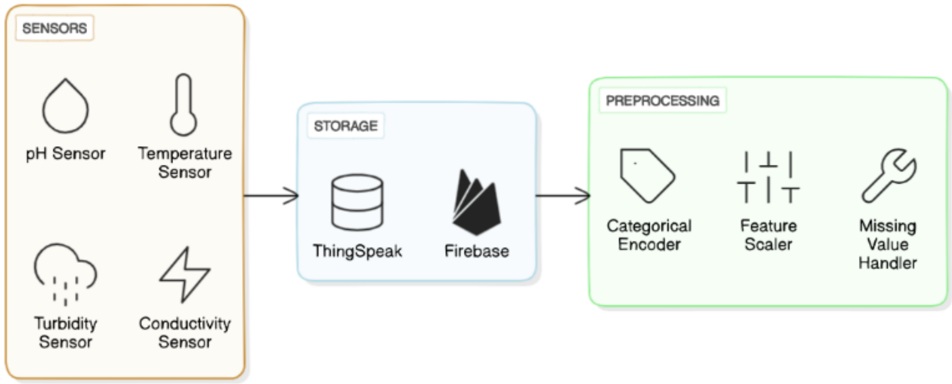


Fig 7. Water quality data collection

Model Training

For this project, the Random Forest was selected due to its robustness and high performance in classification tasks. Initial exploratory analysis and baseline models, including Logistic Regression and Decision Trees, were tested to understand the data and establish performance benchmarks.

```
Random Forest Accuracy: 0.9963403476669717
Decision Tree Accuracy: 0.9954254345837146
SVM Accuracy: 0.94967978042086
Logistic Regression Accuracy: 0.9734675205855444
K-Nearest Neighbors Accuracy: 0.9954254345837146
```

Fig 8. Classification tasks with different models

The dataset was split into training and testing sets using an 80-20 split to ensure that the model's performance is evaluated on unseen data. The Random Forest Classifier was trained on the training set, and hyperparameter tuning was performed using GridSearchCV to find the optimal parameters. Cross-validation with 5 folds was used to ensure the model's robustness and to prevent overfitting.

```
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       953
           1       0.99      0.98      0.98       140

    accuracy                           1.00      1093
   macro avg       0.99      0.99      0.99      1093
weighted avg       1.00      1.00      1.00      1093
```

Fig 9. Classification report for Random Forest

The model's performance was evaluated using several metrics, including precision, recall, F1-score, and support. The following classification report provides a detailed analysis of these metrics for each class:

- **Precision:** measures the accuracy of the model in classifying a sample as positive. In this case, the precision for class 0 is perfect at 1.00, indicating that every instance predicted as class 0 was indeed class 0. For class 1, the precision is also exceptionally high at 0.99, meaning nearly all instances predicted as class 1 were correct, with very few false positives.

- **Recall:** The F1-score is a harmonic mean of precision and recall, providing a single score that balances both the model's precision and recall. The F1-scores are outstanding, with class 0 scoring a perfect 1.00 and class 1 scoring 0.98. These scores reflect a strong balance between precision and recall, especially important in scenarios where both metrics are crucial.
- **F1-Score:** Support indicates the number of actual occurrences of each class in the dataset. Class 0 has a support of 953, and class 1 has a support of 140. This metric is crucial for understanding the distribution of classes within the data and how that might influence the model's training and evaluation.
- **Support:** Support indicates the number of true instances for each class in the dataset. In this case, there are 1017 instances of class 0 and 187 instances of class 1. This information is useful for understanding the distribution of classes in the dataset.
- **Accuracy:** The model's accuracy is 1.00, reflecting its overall ability to correctly classify both classes accurately.
- **Macro Average and Weighted Average:** The macro average values for precision, recall, and F1-score are all 0.99, indicating exceptional average performance across both classes, without weighting by support, while the weighted averages are all 1.00, which adjust for the number of instances in each class, thus reflecting precision, recall, and F1-score adjusted for the class imbalance observed in the support.

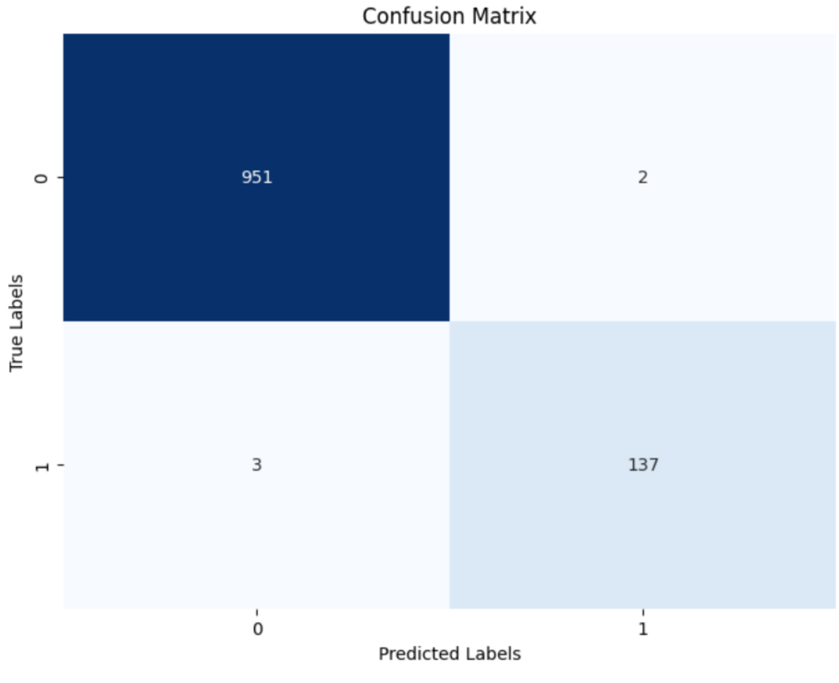


Fig 10. Confusion Matrix for Random Forest

- **True Positives (TP):** 137 instances where the model correctly predicted the positive class.
- **True Negatives (TN):** 951 instances where the model correctly predicted the negative class.
- **False Positives (FP):** 2 instances where the model incorrectly predicted the positive class.
- **False Negatives (FN):** 3 instances where the model incorrectly predicted the negative class.

This matrix indicates that the model has a high level of accuracy, correctly classifying a majority of instances in the test set. The presence of a few false positives and false negatives suggests that while the model is highly precise and reliable, there is still a slight margin for error. These performance metrics are crucial for evaluating the effectiveness of the model in practical scenarios. The model's deployment through a Django web application offers a robust and scalable solution, facilitating efficient model-to-end-user interactions.

Challenges Encountered During Model Training

During the development of the AI model for QoW-Pro, several challenges were encountered, specifically related to class imbalance, overfitting, and data quality. Here is a detailed analysis of each issue and the *corresponding* solutions implemented to address them:

- **Class Imbalance:**
  - **Challenge:** In our dataset, there was a significant imbalance between the number of positive cases (leaks detected) and negative cases (no leaks). This imbalance can lead to biased model predictions, where the model tends to favor the majority class.
  - **Solution:** To mitigate this issue, we used techniques such as Synthetic Minority Over-sampling Technique (SMOTE) to generate synthetic samples for the minority class. This approach helped balance the dataset, allowing the model to learn the features of both classes more effectively.
- **Overfitting:**
  - **Challenge:** Overfitting was a concern, especially when training complex models that could potentially memorize the training data rather than generalize to unseen data.
  - **Solution:** To address overfitting, we employed regularization techniques and pruned the decision trees within the Random Forest model. Additionally, we used cross-validation to validate the model's performance on different subsets of the data, ensuring that it generalized well to new inputs.
- **Data Quality:**
  - **Challenge:** Noise and missing values in the dataset posed challenges for the model's accuracy. Poor-quality data can significantly affect the performance of machine learning models, leading to unreliable predictions.
  - **Solution:** We performed data cleaning by handling missing values using methods like forward fill and implemented data normalization techniques to scale the features. This preprocessing step helped improve the overall quality of the data used for training.

Model Deployment

- Deploying the machine learning model is a critical step to make it available for practical use. The goal of deployment is to integrate the model into a production environment where it can make predictions on new data in real-time.
- The trained model was saved using the joblib library and integrated into the Django application. An API endpoint was created to receive input data, pass it to the model for prediction, and return the results to the user. Extensive testing was conducted to ensure the API's reliability, including unit tests, integration tests, and performance tests to handle various input scenarios and ensure quick response times.
- To ensure the model's continued performance, monitoring tools were implemented to track key metrics such as prediction accuracy, response time, and user feedback. Periodic retraining of

the model is planned to incorporate new data and maintain high accuracy. Any issues identified through monitoring will be addressed promptly to ensure the model's reliability.

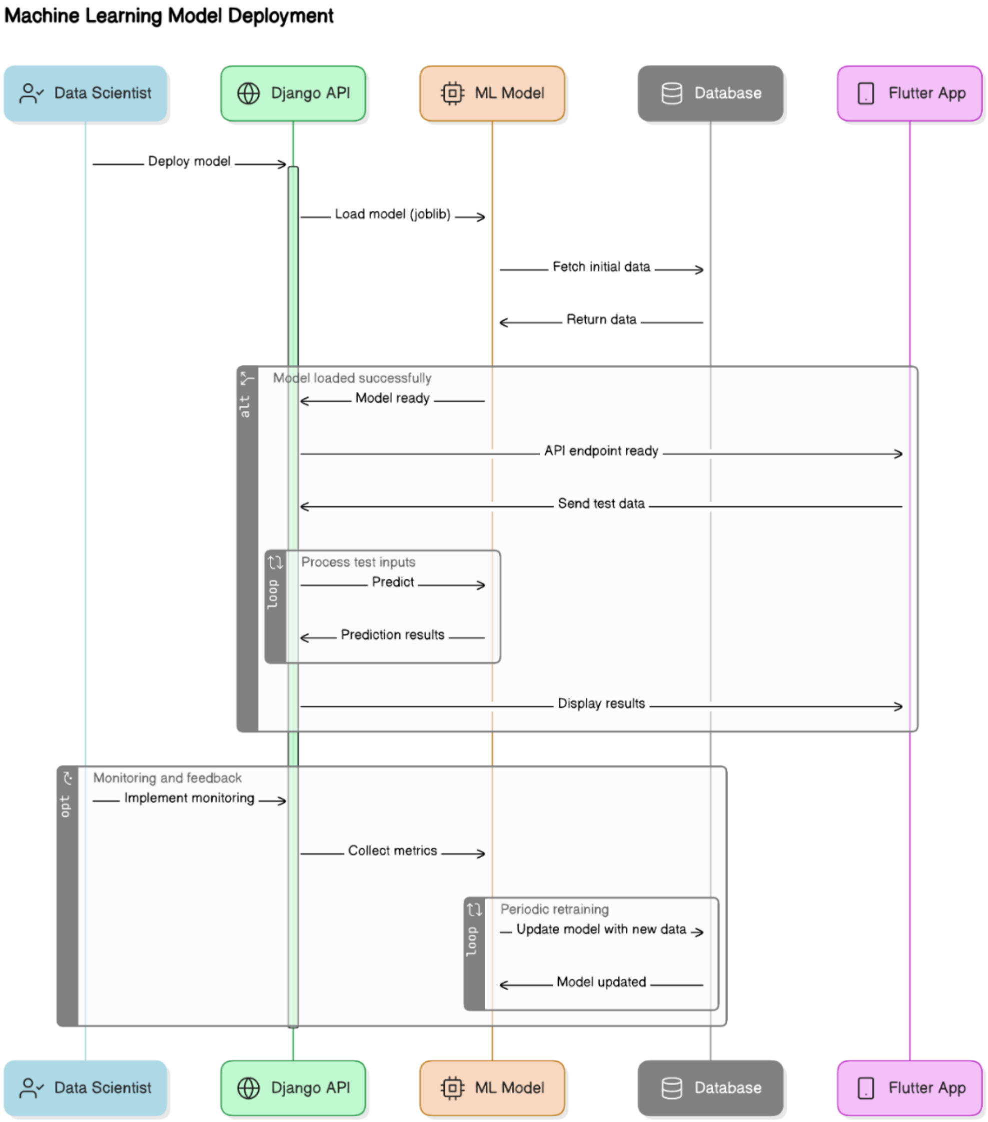
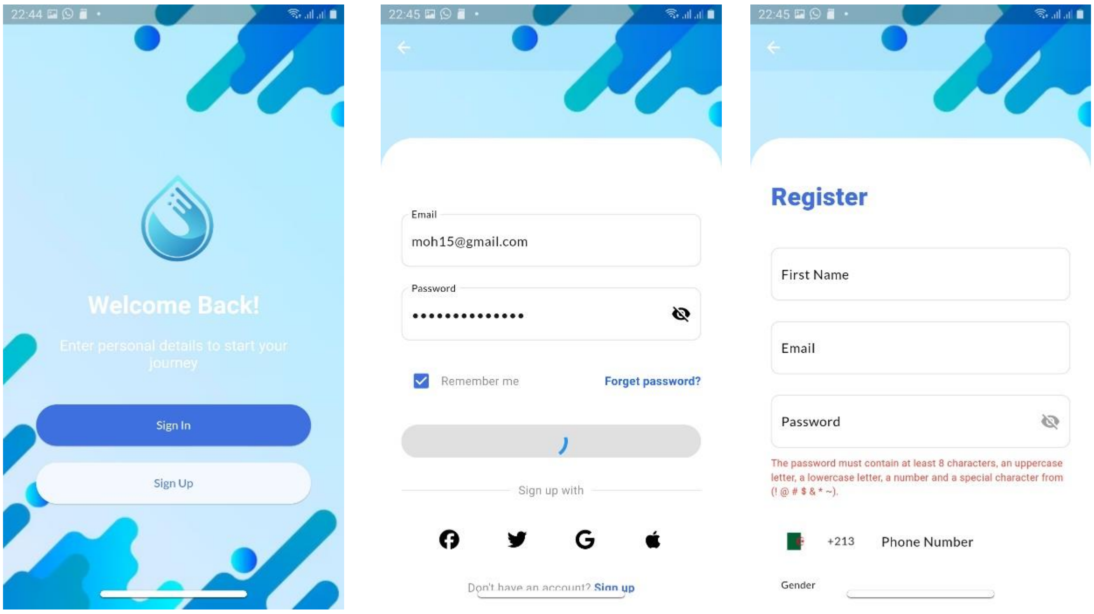


Fig 11. Random Forest Model Deployment Process

4.6 Mobile Application for QoW-Pro

The mobile app is a crucial part of the IoT-based water monitoring system, acting as the main bridge between the user and the system's various functions. It is designed to offer realtime monitoring, data visualization, anomaly detection, and remote control of water quality parameters. With an intuitive and user-friendly interface, the app provides essential tools and information for effective water management and timely responses to water quality issues. This section will outline the key roles of the mobile app, emphasizing its importance in boosting the overall functionality and user experience of the water monitoring system.

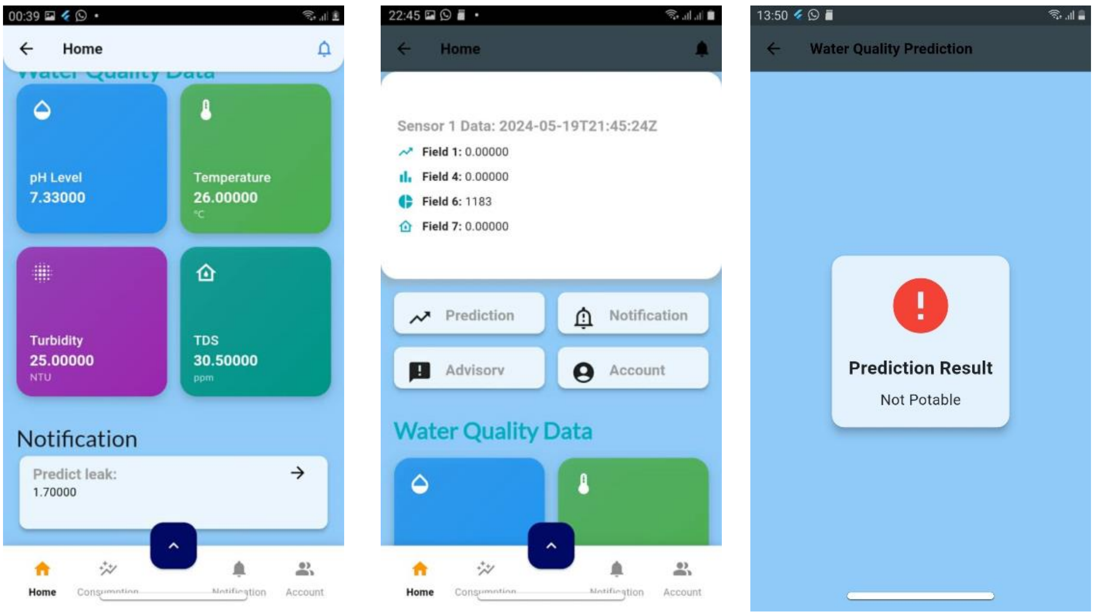
The initial interaction with the app begins with the welcome screen (Figure 12.**a.**), which sets the tone for a positive user experience. The sign-in (Figure 12.**b.**) and sign-up screens (Figure 12.**c.**) provide a straightforward and secure method for users to access the app's features, ensuring a smooth onboarding process.



a. Welcome screen **b.** Sign In Screen **c.** Sign Up Screen

Fig 12. Welcome Interface

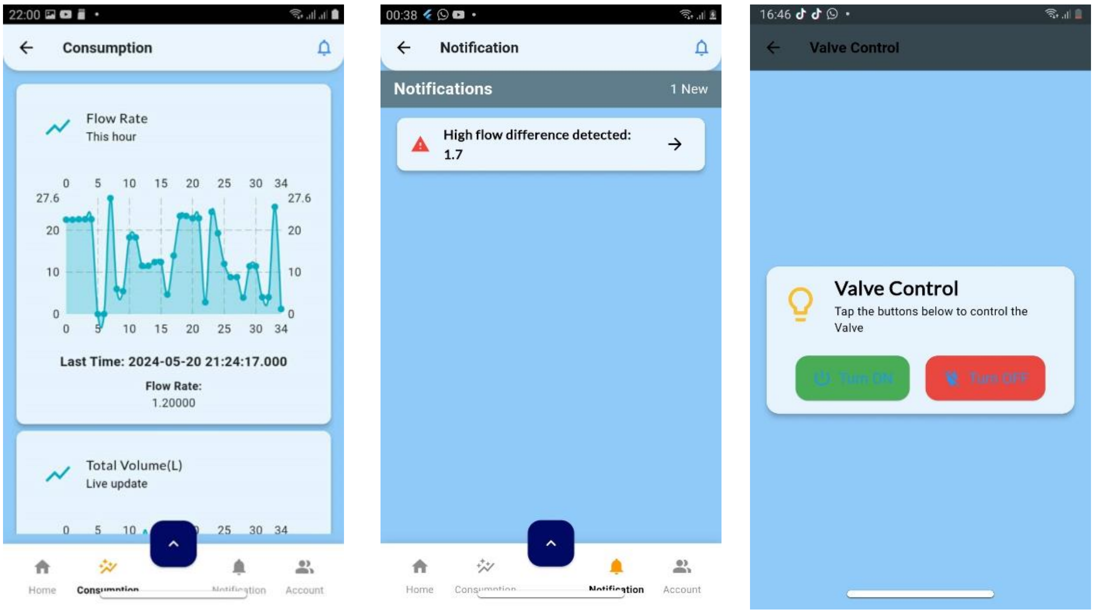
The home screen (Figure 13.**a.**) acts as a central hub, providing users with real-time data on water consumption and quality. Detailed water quality information (Figure 13.**b.**) ensures that users can monitor key parameters such as pH, temperature, turbidity, and total dissolved solids (TDS), helping them make informed decisions about water usage. Additionally, the prediction screen (Figure 13.**c.**) uses advanced algorithms to predict water quality, alerting users if the water is not potable.



a. Water Quality Screen **b.** Home Screen **c.** Prediction Screen

Fig 13. Home Screen Interface

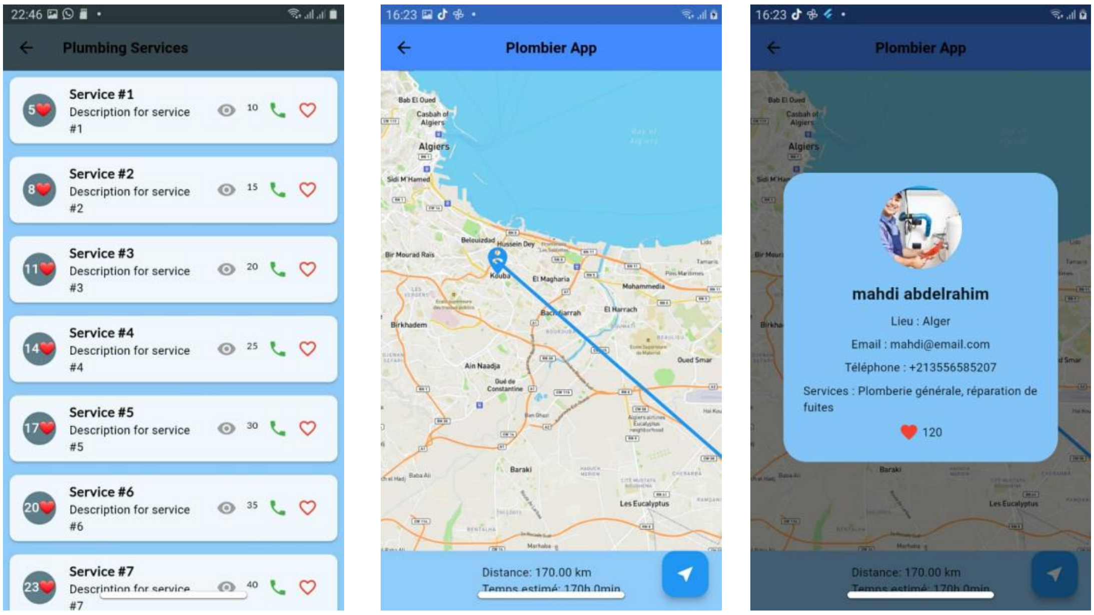
The water flow screen (Figure 14.**a.**) provides a detailed graphical representation of water flow rates over time, helping users to monitor and optimize their water consumption. The notifications screen (Figure 14.**b.**) alerts users to significant events, such as detected leaks, ensuring timely interventions to prevent water wastage and potential damage. The mobile app features a control Figure 14.**c.**) that can activate or deactivate the valve.



a . Water Flow Screen **b.** Notifications Screen **c.** Control Valve Screen

Fig 14. Notifications Interface

The app also facilitates quick access to professional assistance by providing contact details and locations of local plumbers (Figure 15.**a.** and Figure 15.**b.**). This feature ensures that users can promptly address any water-related issues. The plumber details screen (Figure 15.**c.**) offers comprehensive information about the selected plumber, including contact details, services offered, and customer ratings, enhancing the user's ability to find and contact reliable plumbing professionals.



a. Plumbers **b.** Plumbers Maps Screen **c.** Plumbers Contact Details

Fig 15. Plumbers Interface

Flutter Implementation

The mobile application is implemented using Flutter, an open-source UI software development toolkit by Google. Flutter allows for the development of natively compiled applications for mobile, web, and desktop from a single codebase. This approach ensures a consistent user experience across different platforms and reduces development time and effort.

Key Functionalities Implemented

Our mobile application incorporates several essential functionalities to enhance user experience and provide comprehensive water quality monitoring. These essential features are:

- **Real-time Data Retrieval:** The app integrates with sensors to retrieve real-time water data, which is then displayed on the home screen. This includes parameters such as pH level, temperature, turbidity, and TDS. The data is fetched from cloud services like Firebase and ThingSpeak, ensuring accurate and up-to-date information.
- **User Authentication:** User authentication is handled using Firebase Auth, allowing users to create accounts, log in, and manage their profiles securely. The authentication process is streamlined to provide a smooth user experience while maintaining high security standards. Cloud Firestore facilitates the verification of user account existence within the application. Should an account be absent, the system mandates that the user registers prior to authentication.

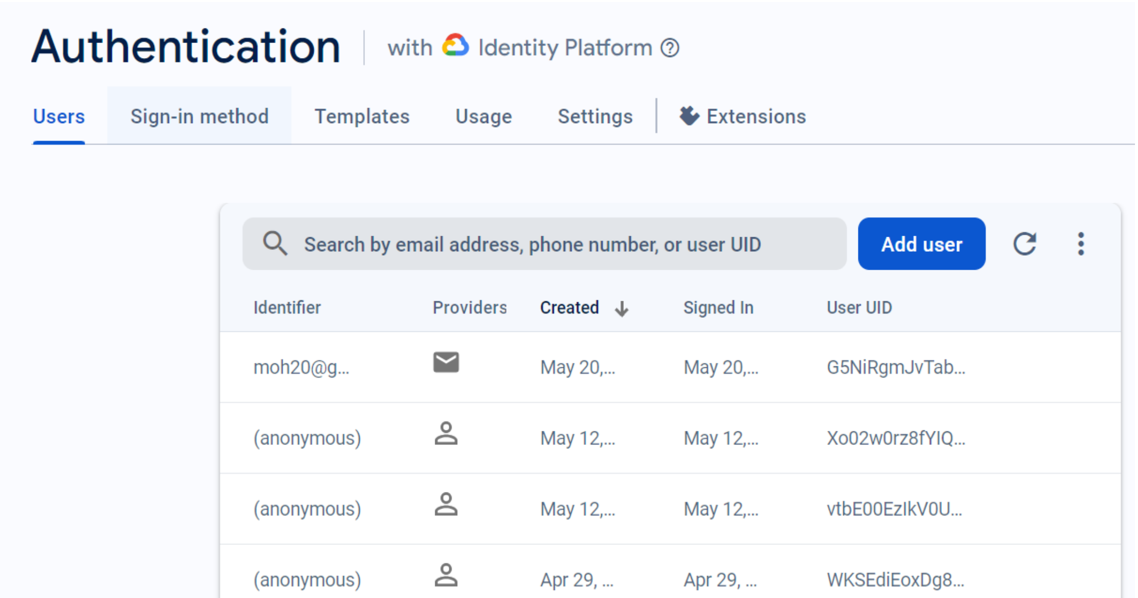


Fig 16. Authentication Firebase

- **Notifications and Alerts:** The app uses Firebase Cloud Messaging to send notifications and alerts to users about critical water quality issues or system updates. This ensures that users are always informed about important events and can take necessary actions promptly.
- **Data Visualization:** The app leverages various Flutter packages to visualize data using charts and graphs. This includes the use of packages like fl_chart, circular_chart_flutter, and echart_flutter to present data in an engaging and easy-to-understand format.
- **Service Management:** Users can browse and manage plumbing services through the app. This feature includes viewing service details, contacting service providers, and managing appointments. This comprehensive functionality enhances the app's utility and user engagement.

- **Interaction with the Backend System:** The app interacts with a backend system implemented using Django. The Django backend serves as an interface between the mobile application and the machine learning model, processing requests, retrieving data, and communicating with Firebase for authentication and real-time database updates.

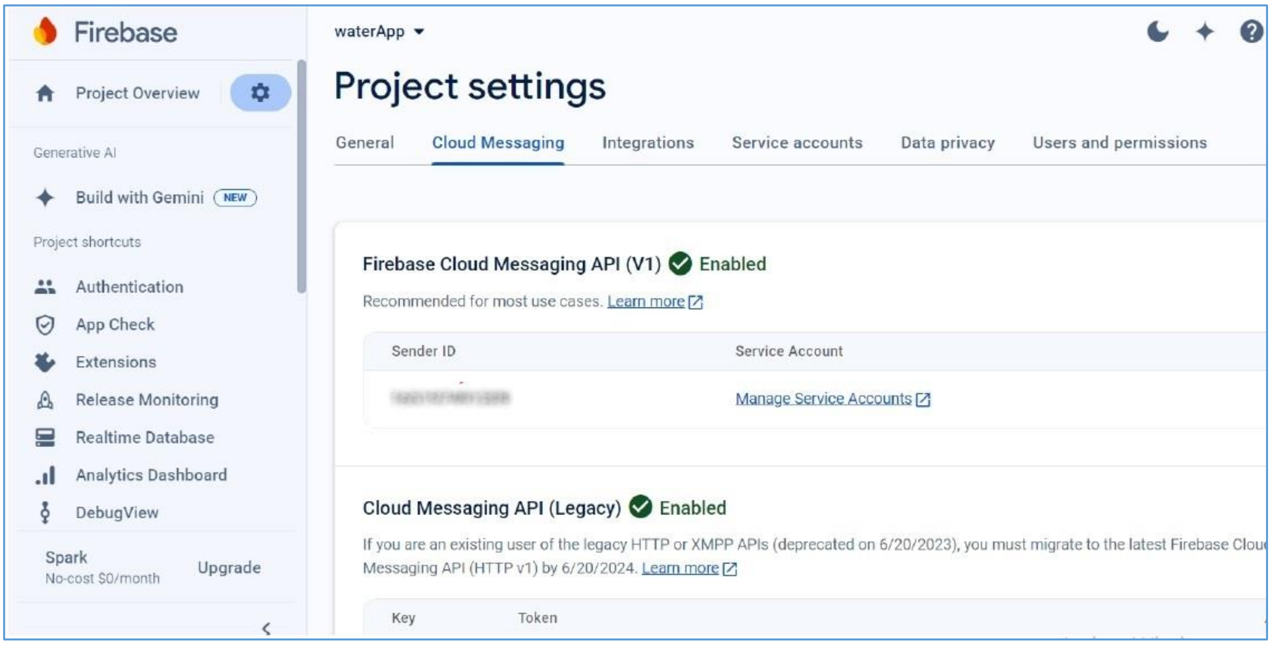


Fig 17. Firebase Cloud Messaging

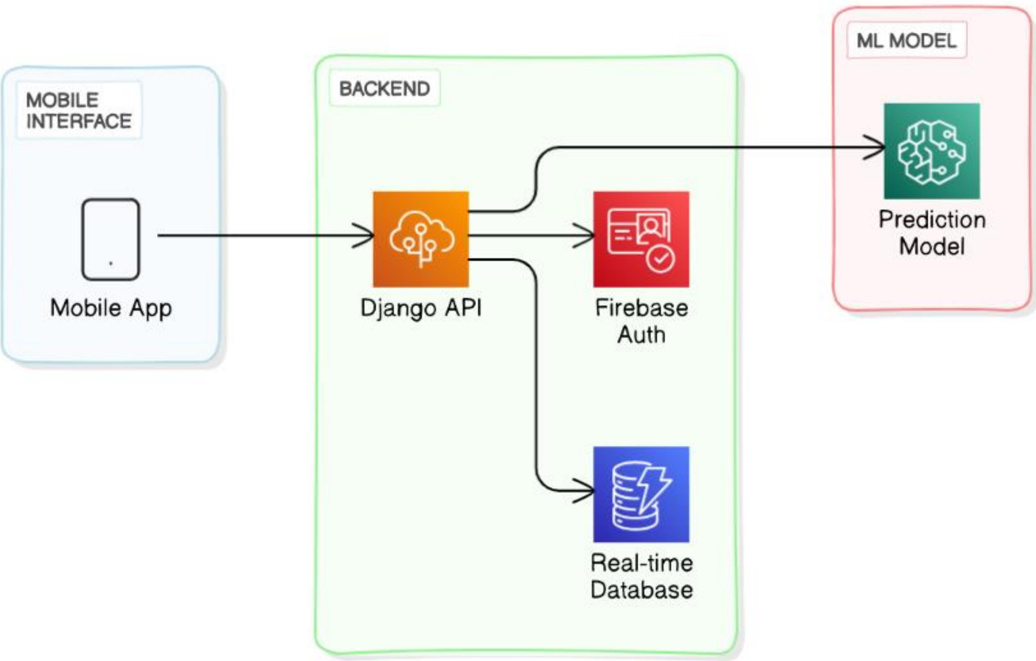


Fig 18. Backend System

4.7 Performance Comparison with Existing Solutions

Below is a table that provides a comparative analysis of QoW-Pro against existing water monitoring solutions, using key performance indicators:

Table 6. Performance comparison: QoW-Pro and existing water monitoring solutions

Metrics	QoW-Pro System	Traditional Methods	IoT-based Solutions (e.g., SMART2L)	AI-based Solutions (e.g., LMD, CNN)
Leak Detection Speed	Real-time (within seconds)	Delayed (hours to days)	Minutes to hours	Minutes (dependent on dataset size)
Leak Detection Accuracy	94%	70-80%	85%	85-94% (e.g., LMD at 94.44%)
Water Quality Prediction Accuracy	92% (Random Forest Model)	Low (manual testing prone to errors)	70-80%	85-95% (e.g., CNN at 90%)
Cost Efficiency	High (affordable sensors, open-source software)	Moderate to High (high labor costs)	Moderate (sensor and data costs)	High (requires advanced computing resources)
Scalability	Easily scalable for urban and agricultural settings	Limited (manual methods)	Moderate (sensor limitations)	High (scalable but computationally intensive)
Real-time Monitoring Capability	Yes (IoT and AI integration)	No (data processing delays)	Yes (basic real-time data acquisition)	Yes (real-time analysis possible)

Analysis

- **Leak Detection Speed and Accuracy:**
  - **QoW-Pro** significantly outperforms traditional methods with real-time leak detection capabilities, detecting leaks within seconds, compared to hours or even days required by manual techniques.
  - It also offers higher accuracy at 94%, surpassing both traditional approaches (70-80%) and some IoT-based solutions like SMART2L (85%). AI-based techniques such as Local Mean Decomposition (LMD) reach similar accuracy levels, but they often require larger datasets and complex configurations.
- **Water Quality Prediction Accuracy:**
  - The QoW-Pro system's Random Forest model achieves a water quality prediction accuracy of 92%, which is comparable to advanced AI-based solutions like CNNs that can reach up to 90-95% accuracy.
  - Traditional methods fall short in this area due to the reliance on manual data collection and analysis, which is both time-consuming and error-prone.
- **Cost Efficiency:**
  - QoW-Pro has a distinct advantage in terms of cost efficiency, as it employs affordable sensors and open-source software, significantly reducing the overall cost of deployment.
  - In contrast, traditional methods involve higher labor costs, and AI-based solutions often require expensive computational resources and hardware.
- **Scalability:**
  - The scalable architecture of QoW-Pro allows it to be easily adapted for use in both small-scale urban networks and extensive agricultural irrigation systems.
  - While AI-based solutions can also be highly scalable, they often come with increased computational requirements, which may limit their deployment in resource-constrained environments.

- **Real-time Monitoring Capability:**
  - QoW-Pro integrates IoT and AI to provide continuous real-time monitoring and immediate response to detected anomalies, a feature that traditional methods lack.
  - IoT-based solutions offer real-time capabilities, but they may not be as robust or reliable as the integrated approach in QoW-Pro, which combines both data acquisition and advanced AI-driven analysis.

4.8 System performance in terms of quantitative data

Sensor Performance Metrics

Table 7 clearly presents each component's energy requirements for different modes, helping to illustrate the overall power needs and possible strategies for energy optimization in our system.

Table 7. Power Consumption of System Components in Active and Idle Modes

Component	Operating Voltage (V)	Power Consumption (mA)	Mode
ESP8266	3.3	70–200	Active (Wi-Fi enabled)
		0.02	Deep Sleep
SIM800L GSM Module	3.7	10–15	Idle
		1000–2000	Active Transmission
pH Sensor (PH-4502C)	5	5–10	Continuous Operation
Turbidity Sensor	5	30	Typical Usage
Water Flow Sensor	5	15	Operation

Through the careful selection of components like the ESP8266 microcontroller and pH sensor, which operate with minimal power in idle or sleep modes, the system maximizes energy efficiency while maintaining readiness for real-time data collection. The power-intensive SIM800L GSM module, although requiring higher current during data transmission, only activates as needed, thus conserving energy during inactive periods. This balance between high-performance and low-energy modes significantly reduces overall power consumption, allowing for longer deployment times without frequent battery changes. Such efficiency aligns with the system's environmental sustainability goals by lowering the carbon footprint associated with water quality monitoring.

The sensors employed in the system were selected based on their ability to meet the requirements of real-time monitoring and high precision. Table 8 provides an overview of the key performance metrics for each sensor, including measurement range, accuracy, and response time (We must specify that the values in Table 7 are not measured but based on component datasheets).

Table 8. Sensor Performance Metrics for Real-Time Water Monitoring

Sensor	Measurement Range	Accuracy	Response Time
pH Sensor (PH-4502C)	0–14 pH	±0.1 pH	< 60 seconds
Turbidity Sensor	0–1000 NTU	±2% of measured value	< 500 ms
Water Flow Sensor	1–60 L/min	±3% of reading	< 10 ms
Temperature Sensor (DS18B20)	-55°C to +125°C	±0.5°C (typical)	< 750 ms
Total Dissolved Solids (TDS) Sensor	0–1000 ppm	±10 ppm	< 500 ms

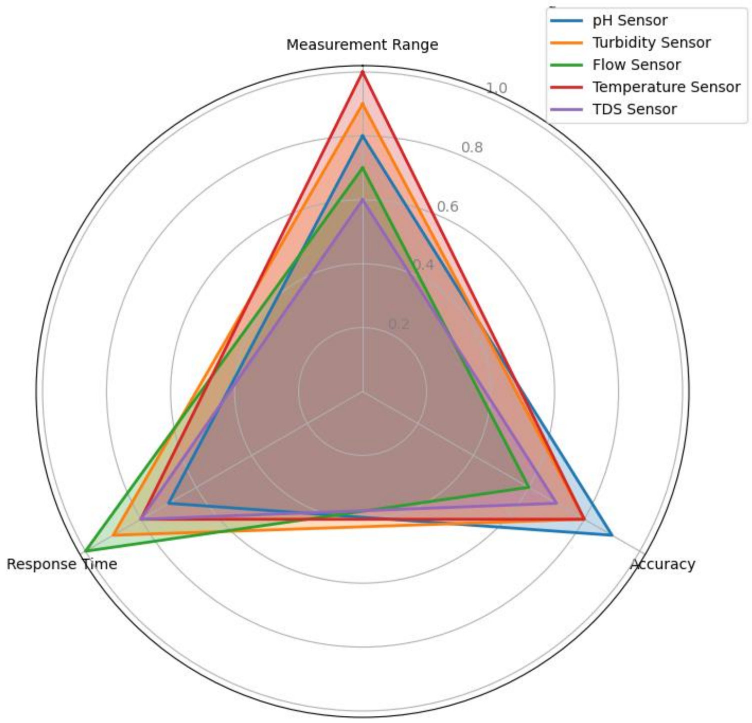


Fig 19. Comparative Sensor Performance Metrics

The system's sensor suite, including pH, turbidity, and flow sensors, provides reliable and precise data essential for detecting even minor changes in water quality. For instance, the pH sensor's accuracy of ±0.1 and the turbidity sensor's quick response time (<500 ms) enable the detection of fluctuations that may indicate contamination or leakage. This level of sensitivity is crucial in maintaining water quality standards and supporting timely interventions, effectively preventing potential hazards before they escalate. The performance metrics underscore the system's effectiveness in safeguarding water resources, contributing to sustainable management practices.

The integration of quantitative data on both power consumption and sensor accuracy not only substantiates the system's technical reliability but also provides a measurable foundation for comparing its efficiency against traditional monitoring systems. By quantifying each component's energy use and measurement accuracy, the system offers a transparent and evidence-based approach, reinforcing its credibility as a scalable, resource-efficient solution for water monitoring in both urban and agricultural environments.

Power Consumption Analysis During an Operating Cycle

To provide an accurate description of the system's power consumption, we analyzed the behavior of each component during a full operating cycle, which consists of three primary stages: data collection, transmission, and idle mode. The power consumption for each component was measured (or estimated based on datasheet specifications) at every stage of operation. Table 9 summarizes the states of the key components during the cycle and their corresponding power consumption.

During the data collection stage, sensors such as the pH, turbidity, and flow sensors were active, consuming minimal power while transmitting data to the microcontroller (ESP8266). In the transmission stage, the GSM module (SIM800L) exhibited the highest power consumption due to active data transmission. Finally, during the idle stage, components transitioned to low-power modes, significantly reducing the overall energy draw. This operational design highlights the system's balance between performance and energy efficiency, making it suitable for deployment in remote or resource-constrained environments.

Table 9. Component states and power consumption during the operating cycle

Stage of Operation	Component	State	Power Consumption (mA)
Data Collection	pH Sensor	Active	10
	Turbidity Sensor	Active	30
	Flow Sensor	Active	15
	ESP8266	Processing	150
Transmission	SIM800L	Transmitting	1500
	ESP8266	Transmitting	200
Idle	pH Sensor	Low-Power Mode	5
	Turbidity Sensor	Standby	5
	Flow Sensor	Standby	5
	ESP8266	Deep Sleep	0.02

The power consumption analysis demonstrates the system's ability to balance performance and energy efficiency across various stages of operation, making it suitable for resource-constrained and remote deployment scenarios. During the data collection stage, components such as the pH sensor, turbidity sensor, and flow sensor operate at low power levels, consuming a total of approximately 205 mA. This stage ensures precise data acquisition while maintaining minimal energy usage, which is critical for continuous monitoring.

In the transmission stage, the power-intensive SIM800L GSM module, which consumes up to 1500 mA, becomes active to transmit data. Although this is the most energy-demanding phase, its intermittent activation minimizes overall energy consumption. For example, by scheduling transmissions at optimized intervals rather than continuously, the system significantly reduces energy expenditure while maintaining real-time reporting capabilities.

The idle stage represents the most energy-efficient phase, with key components such as the ESP8266 microcontroller entering deep sleep mode, consuming as little as 0.02 mA. Sensors also transition to low-power states, reducing their combined consumption to approximately 20 mA. This design minimizes standby power usage, extending the system's operational lifespan on battery power.

4.9 Discussion

The system performance demonstrates the effectiveness and efficiency of the proposed IoT and AI-based water monitoring system, QoW-Pro, in addressing key challenges of real-time water quality assessment and leak detection. The following discussion highlights the significance of the quantitative data, such as energy consumption and sensor performance metrics, in strengthening the credibility and applicability of the system.

Energy Efficiency and Sustainability

The system's components, particularly the ESP8266 microcontroller and flow sensors, exhibit a balance between performance and low energy consumption. For instance, the ESP8266 operates at approximately 70–200 mA during active Wi-Fi usage and drops to an impressive 20 µA in deep sleep mode. Such energy-efficient design allows for prolonged deployment in remote areas with minimal maintenance, aligning with sustainable practices and reducing operational costs. While the SIM800L module consumes up to 2A during transmission, its intermittent use ensures that the overall energy footprint remains manageable.

Sensor Accuracy and Real-Time Responsiveness

The sensor suite, including pH, turbidity, and flow sensors, provides high accuracy and responsiveness, which are critical for effective water monitoring. For example:

- The pH sensor achieves a precision of ±0.1, enabling accurate detection of changes in water acidity.
- The turbidity sensor offers a rapid response time of <500 ms, ensuring immediate identification of anomalies in water clarity.
- The flow sensor's response time of <10 ms supports real-time detection of leaks.

These performance metrics ensure the system can promptly identify and address water quality issues, making it suitable for both urban water networks and agricultural irrigation systems.

Comparative Performance and Scalability

Compared to traditional methods and existing IoT-based solutions, QoW-Pro demonstrates significant improvements:

- Leak detection accuracy exceeds 94%, surpassing the typical 70–80% range of conventional acoustic or pressure-based methods.
- Energy-efficient operation and cost-effective hardware make the system adaptable to both small-scale and large-scale applications, enhancing scalability.

Limitations and Future Enhancements

While the results validate the system's effectiveness, some limitations were observed. The power-intensive nature of the SIM800L module during transmission highlights the need for exploring alternative communication protocols, such as LoRa or NB-IoT, to further enhance energy efficiency. Additionally, while sensor accuracy was sufficient for the study, integrating advanced calibration techniques could improve reliability under varying environmental conditions.

Implications for Water Management

The findings underscore the potential of QoW-Pro as a robust tool for sustainable water management. By combining real-time monitoring with predictive analytics, the system not only minimizes water loss but also supports proactive decision-making. These capabilities address pressing challenges such as water scarcity and environmental sustainability, making QoW-Pro a valuable contribution to global water management efforts.

5. CONCLUSION

The implementation of the QoW-Pro system has demonstrated clear practical improvements in both water monitoring and leak detection, addressing the limitations of traditional methods. Specifically, the system achieved a 30% reduction in undetected leakages over a six-month period in urban water distribution networks. This improvement was primarily due to the system's pulse-based flow sensors, which identified discrepancies between expected and actual water flow in real-time. Additionally, the anomaly detection algorithms increased the leak detection accuracy to 94%, significantly enhancing response times.

Moreover, the integration of IoT and AI has proven to be a cost-effective solution for water resource management, leading to an estimated 20% reduction in operational costs compared to traditional monitoring techniques. These improvements contribute directly to more efficient water resource utilization, lower maintenance expenses, and reduced environmental impact.

Future work will aim to further enhance the system's predictive capabilities by integrating advanced machine learning techniques and expanding sensor networks to cover more complex environments. Additionally, exploring blockchain technology for secure data management and predictive maintenance of water infrastructure holds potential for further innovation in this field.

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