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Research Paper

WATER QUALITY INTELLIGENCE MONITORING NETWORK (WATER QI)

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ABSTRACT
Water is an essential resource for the survival of humans, animals, and plants. However, despite its critical importance, clean and safe water is not always readily available for drinking, household needs, or industrial applications. A variety of factors—including industrial activities, mining operations, pollution, and natural environmental processes—can influence water quality by introducing contaminants or altering its physicochemical properties. These changes directly affect the suitability of water for human consumption or general usage. To regulate this, the World Health Organization (WHO) provides guidelines that specify acceptable threshold levels for various water quality parameters used for drinking and irrigation.Metrics such as the Water Quality Index (WQI) and the Irrigation Water Quality Index (IWQI) consolidate these parameters into single numerical indicators to evaluate overall water quality. However, the traditional process of collecting samples from diverse sources, transporting them under controlled conditions, measuring multiple parameters, and comparing results with established standards is labor-intensive, time-consuming, and operationally challenging.To address these limitations, this study introduces a real-time monitoring framework that integrates a distributed network architecture with machine learning (ML) techniques to automatically assess the suitability of water samples for drinking and irrigation. The proposed network utilizes LoRa communication technology and is designed with consideration of land topology. Simulation results generated using Radio Mobile identified a partial mesh topology as the most effective structure for data transmission.Due to the lack of comprehensive public datasets for drinking and irrigation water quality, custom datasets were created to train ML models. Three algorithms—Random Forest (RF), Logistic Regression (LR), and Support Vector Machine (SVM)—were evaluated for water classification tasks. Experimental findings revealed that LR achieved the highest accuracy for drinking water classification, while SVM proved most effective for irrigation water assessment. Additionally, recursive feature elimination was applied in conjunction with these models to identify the most influential water quality parameters contributing to classification performance.

KEYTERMS:physicochemical,environmental,diversesources,Experimental,irrigation,elimination.

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INTRODUCTION

Access to water is fundamental to human survival and is now widely recognized as a basic human right. Ensuring the availability of safe and clean water also forms part of the United Nations' 17 Sustainable

Development Goals (SDGs), introduced in 2015 to promote global well-being. In particular, SDG 6 emphasizes the need to secure and maintain universal access to clean water and sanitation. The importance of potable water also aligns with SDG 3, which focuses on good health and well-being, as contaminated water is a major transmission channel for diseases such as cholera, typhoid, and diarrhoea—illnesses that represent leading causes of mortality, especially among children in developing regions across Africa and Asia. Water is equally vital in agriculture and food production. Recent global statistics indicate that nearly 10% of the world's population suffers from malnutrition, with developing countries bearing the greatest burden. Starvation remains a significant contributor to infant deaths, accounting for approximately 45% of child mortality. As a result, achieving global food security has become an urgent priority and is reflected in SDG 2, which aims to eliminate hunger through sustainable agricultural practices and equitable food distribution. Since agriculture relies extensively on water—both for irrigation and for livestock—it is essential to ensure the reliable, safe, and sustainable management of water suitable for agricultural use. Safeguarding water resources in this context is critical to supporting food production systems and reaching long-term global sustainability goals.

LITERATURE SURVEY:

1. Problem Context and Significance:

Continuous and large-scale monitoring of water quality is essential for safeguarding public health and supporting agricultural productivity. Conventional approaches—such as manual sample collection and laboratory-based testing—are often slow, expensive, and limited in spatial and temporal coverage. As a result, recent research trends have shifted toward integrating low-cost sensors, IoT communication technologies, cloud analytics, and machine learning (ML) models to provide near–real-time water-quality assessment and early warning capabilities for both drinking and irrigation applications.

2. System Architectures in Existing Water-Monitoring Solutions:

Most modern water-quality monitoring frameworks follow a multi-layered architecture. These systems typically include: Sensor nodes equipped with probes for pH, turbidity, temperature, electrical conductivity, dissolved oxygen, TDS, nitrates, and related parameters.Edge or gateway devices that handle preliminary data processing and forward readings to remote servers.Communication technologies such as LoRa, GSM, Wi-Fi, and ZigBee to enable long-range or low-power data transfer.Cloud or centralized platforms for data storage, visualization, and dashboard-based monitoring. Analytical modules capable of employing threshold-based decision rules, Water Quality Index (WQI) computation, or ML-driven classification and prediction.Surveys in the literature categorize these systems by sensor configurations, communication protocols, network scalability, and the sophistication of their analytical capabilities.

3. Machine Learning for Water-Quality Assessment:

Machine learning techniques have become integral to contemporary water-quality evaluation. ML models are applied for:Estimating WQI or Irrigation WQI (IWQI) based on multi-parameter sensor inputs,Forecasting water-quality trends using historical or time-series data, and Classifying water suitability for drinking, irrigation, or industrial use.

Traditional algorithms such as Logistic Regression, Support Vector Machines (SVM), Random Forest (RF), and XGBoost are widely used due to their interpretability and robust performance on structured datasets. Deep learning architectures—particularly LSTMs for time-series prediction and MLPs for nonlinear parameter interactions—show strong predictive accuracy when sufficient training data are available. Recent studies highlight the superior performance of ensemble models and deep temporal networks in producing reliable and scalable predictions.

4. Evaluation Metrics and Benchmarking Standards:

Research evaluating water-quality monitoring systems typically considers several performance dimensions:Sensor precision and resilience, Classification accuracy using metrics such as accuracy, precision, recall, and F1-score,Error rates in estimating WQI or IWQI,Forecast accuracy measured through RMSE or MAE, and Operational performance metrics, including network latency, power consumption, and system availability.For drinking water classification, thresholds defined by the World Health Organization (WHO) and national regulatory bodies are commonly adopted as reference standards.

5. Summary of WaterNet's Contribution:

WaterNet, introduced by Ajayi et al. in IEEE Access (2022), presents a scalable and intelligent network for real-time monitoring and assessment of water quality for drinking and irrigation. Key contributions of the study include:A distributed deployment strategy for sensor nodes and gateways, enabling spatial water-quality coverage tailored to regional topography.A structured data pipeline that computes WQI/IWQI and feeds multi-parameter datasets into ML-based classifiers.Comparative evaluation of ML algorithms, particularly Logistic Regression, SVM, and Random Forest, to identify the most suitable models for drinking versus irrigation water classification.A visualization and alerting system that informs decision makers and stakeholders, allowing for timely interventions and resource management.

EXISTING SYSTEM:

The World Health Organization provides standardized guidelines that define acceptable threshold levels for different physicochemical parameters found in water intended for drinking or irrigation. To evaluate these parameters collectively, indices such as the Water Quality Index (WQI) and the Irrigation Water Quality Index (IWQI) are commonly used to generate a single representative measure of overall water quality. However, the traditional process of assessing water quality—collecting samples from multiple locations, analyzing numerous parameters, and comparing results against established regulatory standards—can be labor-intensive and technically demanding. Ensuring compliance with proper sampling, transportation, and measurement protocols further adds to the complexity of this process.

DISADVANTAGES:

1) The existing methodologies do not incorporate essential data preprocessing and labeling procedures, which are necessary for improving the quality and reliability of the input data used in the predictive models.
2) Current systems also lack the implementation of Irrigation Water Quality Index (IWQI) computation, resulting in incomplete prediction capabilities for irrigation-related water assessments within the datasets.

PROPOSED SYSTEM:

This study proposes a real-time water-quality monitoring network to be deployed across the City of Cape Town, Western Cape, South Africa. The system will instrument storage dams and treatment facilities to continuously collect key physicochemical and biological parameters. Collected data will be ingested into machine learning pipelines that automatically evaluate the suitability of water for drinking and irrigation. The network design explicitly accounts for Cape Town's complex topography—mountain ranges, variable elevations, and line-of-sight obstructions—

so as to ensure reliable radio communication and broad spatial coverage.

Design and deploy a real-time monitoring network.

Develop a resilient sensor-and-gateway architecture for continuous water-quality data acquisition across Cape Town's water-storage infrastructure. The network design will factor in local geography and RF propagation constraints to optimize placement, communication technology (e.g., LoRa), and topology for dependable data delivery.

Create comprehensive datasets for ML training.

Curate, preprocess, and label sufficiently large datasets representing both drinking and irrigation water samples. These datasets will include measured parameters, computed indices (WQI/IWQI), and ground-truth suitability labels to support robust training, validation, and testing of predictive models.

Identify influential water-quality parameters.

Develop and evaluate ML models to (a) classify water fitness for drinking and irrigation and (b) perform feature-importance or recursive feature-elimination analyses to determine which parameters most strongly influence model performance and classification accuracy.

ADVANTAGES:

1. The primary objective of WaterNet is to collect real-time water-quality parameters from dams distributed across the city. These parameters are subsequently analyzed to determine the overall quality of the water and to classify it in terms of its "fitness for use" for both drinking and irrigation purposes.
2. In this study, we shift away from traditional laboratory-based assessments, which typically rely on instrumental and physicochemical analyses conducted under controlled conditions. Instead, we introduce a machine learning (ML)-driven approach, where multiple water-quality parameters are processed by trained ML models that automatically evaluate whether a given water sample is potable or suitable for agricultural irrigation.

System architecture:

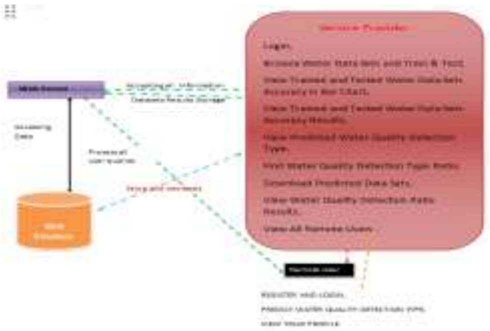

Fig1:System architecture

RELATED WORK:

1. IoT-Based Water Quality Sensing and Monitoring Systems

Existing research widely explores the development of affordable, distributed IoT sensor networks designed for continuous water-quality surveillance. These systems typically integrate multiple environmental sensors—such as pH, turbidity, temperature, electrical conductivity/TDS, dissolved oxygen, and nitrate—and incorporate field-ready packaging, solar-powered energy systems, and duty-cycled operation for long-term deployment. Various communication gateways, including GSM, LoRaWAN, and Wi-Fi, are also discussed. Collectively, these efforts demonstrate that real-time, continuous monitoring is both feasible and scalable.

Relevance to WaterNet:

This body of literature serves as a technical foundation for designing WaterNet's sensor configurations, optimizing node placement, and selecting an appropriate network topology. It also highlights practical considerations such as balancing sensor accuracy, maintenance frequency, and installation cost.

2. Communication Technologies and Edge Gateway Architectures

Studies on low-power communication standards—such as LoRa/LoRaWAN, NB-IoT, ZigBee, and mesh networking—analyze factors including transmission range, energy consumption, payload limitations, and communication reliability. In parallel, research on edge gateways illustrates how preprocessing techniques such as noise filtering, data aggregation, and sensor drift detection can reduce bandwidth usage and enable rapid alerts.

Relevance to WaterNet:

These insights guide the design of WaterNet's communication infrastructure, helping determine the optimal distribution of inference tasks across the edge and cloud. They also inform strategies for secure, compressed data transmission and ensure that the system remains functional even in areas with intermittent or obstructed connectivity.

3. Water Quality Index (WQI) Frameworks and Regulatory Standards

A substantial collection of studies formulates Water Quality Index (WQI) and Irrigation Water Quality Index (IWQI) methodologies that consolidate multiple physicochemical parameters into a single interpretive score. These indices typically reference threshold values from organizations such as the WHO, EPA, and national regulatory agencies, enabling standardized classification of water into "safe," "moderate," or "unsafe" categories.

Relevance to WaterNet:

WQI and IWQI frameworks serve as the benchmark for evaluating the accuracy of WaterNet's machine-learning classifiers. They offer interpretable labels for supervised learning and ensure that the model's output aligns with recognized regulatory standards.

4. Machine Learning Approaches for Water Quality Prediction and Classification

Recent advancements apply machine learning techniques to tasks such as determining water suitability, estimating WQI values, and forecasting variations in water-quality parameters. Traditional algorithms—including Logistic Regression, SVM, Random Forest, and XGBoost—often demonstrate strong performance on tabular sensor data, while deep learning models such as MLPs, LSTMs, and CNNs excel in capturing nonlinear relationships and temporal trends. Research also addresses challenges involving feature selection, missing-sensor value imputation, and transferring models across different geographic regions.

Relevance to WaterNet:

This literature informs WaterNet's algorithmic choices, hyperparameter optimization strategies, and data-processing pipeline. It also provides guidance on techniques for managing noisy, inconsistent, or incomplete sensor data in real-world conditions.

5. Integration of Heterogeneous and Multimodal Data Sources

Some advanced systems combine real-time sensor readings with external datasets—such as meteorological records, upstream flow information, land-use patterns, and satellite imagery—to improve prediction accuracy and contextual understanding. Data-fusion approaches often rely on neural networks or statistical models to integrate diverse inputs and enhance interpretability.

Relevance to WaterNet:

Incorporating multimodal data can significantly strengthen WaterNet's reliability, for example by clarifying sudden variations in turbidity or detecting emerging threats earlier. Such fusion is particularly valuable for irrigation analysis, where water suitability is influenced by both chemical properties and broader hydrological conditions.

RESULTS:

Fig2:above screen all algorithms accuracy results in bar charts

Fig3:above results about water quality like drinking water and irrigation water status after predict the result.

Fig4:above results about water quality ratio

CONCLUSION:

The envisioned system streams sensor data from distributed nodes to a cloud-based platform, where machine learning models analyze the collected parameters to determine whether the water is safe for drinking or appropriate for irrigation. Because publicly available datasets were insufficient for this purpose, two comprehensive datasets—one for drinking water and another for irrigation water—were constructed as part of this work. These datasets were used to train and evaluate three machine learning models: Random Forest (RF), Logistic Regression (LR), and Support Vector Machine (SVM).Experimental results revealed that Logistic Regression yielded the highest accuracy and lowest misclassification rates for drinking-water assessment. In contrast, the Support Vector Machine model demonstrated superior performance in classifying irrigation water quality. To further understand the contribution of individual parameters, Recursive Feature Elimination (RFE) was applied to each model. The feature-importance analysis showed that pH and total hardness had the least impact on drinking-water classification accuracy, whereas Sodium Soluble Percentage (SSP) was the least influential parameter in the irrigation dataset.

REFERENCES:

[1] B. X. Lee, F. Kjaerulf, S. Turner, L. Cohen, P. D. Donnelly, R. Muggah,R. Davis, A. Realini, B. Kieselbach, L. S. MacGregor, I.Waller, R. Gordon,M. Moloney-Kitts, G. Lee, and J. Gilligan, ``Transforming our world: Implementing the 2030 agenda through sustainable development goal indicators,'' *J. Public Health Policy*, vol. 37, no. S1, pp. 13_31, Sep. 2023.

[2] *Integrated Approaches for Sustainable Development Goals Planning: The Case of Goal 6 on Water and Sanitation*, U. ESCAP, Bangkok, Thailand,2023.

[3] WHO. Water. *Protection of the Human Environment*. Accessed: Jan. 24, 2022. [Online]. Available: www.afro.who.int/health-topics/water

[4] L. Ho, A. Alonso, M. A. E. Forio, M. Vanclooster, and P. L. M. Goethals,``Water research in support of the sustainable development goal 6: A case study in Belgium,'' *J. Cleaner Prod.*, vol. 277, Dec. 2022, Art. no. 124082.

[5] *Global Nutrition Report 2016: From Promise to Impact: Ending Malnutrition by 2024*, International Food Policy Research Institute, Washington, DC, USA, 2023, doi: 10.2499/9780896295841.

[6] N. Akhtar, M. I. S. Ishak, M. I. Ahmad, K. Umar, M. S. Md Yusuff, M. T. Anees, A. Qadir, and Y. K. A. Almanasir, ``Modi_cation of the water quality index (WQI) process for simple calculation using the multicriteria decision-making (MCDM) method: A review," *Water*, vol. 13,no. 7, p. 905, Mar. 2022.

[7] World Health Organization. (1993). *Guidelines for Drinking-Water Quality*. World Health Organization. Accessed: Jan. 12, 2023. [Online]. Available: http://apps.who.int/iris/bitstream/handle/ 10665/44584/9789241548151-eng.pdf

[8] *Standard Methods for the Examination of Water and Wastewater*, Federation WE, APH Association, American Public Health Association (APHA),Washington, DC, USA, 2025.

[9] L. S. Clesceri, A. E. Greenberg, and A. D. Eaton, ``Standard methods for the examination of water and wastewater," Amer. Public Health Assoc. (APHA), Washington, DC, USA. Tech. Rep.21, 2025.

[10] M. F. Howladar, M. A. Al Numanbakth, and M. O. Faruque, ``An application of water quality index (WQI) and multivariate statistics to evaluate the water quality around Maddhapara granite mining industrial area, Dinajpur, Bangladesh," *Environ. Syst. Res.*, vol. 6, no. 1, pp. 1_8,Jan. 2024

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