SMART WATER MANAGEMENT SYSTEM USING EDGE COMPUTING AND MACHINE LEARNING FOR REAL-TIME POLLUTION DETECTION IN URBAN WATERS

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Abstract

This study proposes a Smart Water Management System grounded in edge computing and machine learning to advance real-time pollution detection in urban aquatic environments. Rapid urbanization has intensified pollutant inflows—ranging from nutrients and heavy metals to organic waste necessitating an adaptive, high-resolution monitoring architecture capable of immediate response. The system integrates distributed edge-based sensor nodes with lightweight analytical models, enabling on-site data processing, reduced latency, and enhanced situational awareness. A hybrid machine learning framework is employed, combining anomaly detection, regression-based water-quality forecasting, and classification of pollutant signatures to strengthen diagnostic accuracy. Field deployment across multiple urban water sites demonstrates that the proposed system reduces data-transmission demands by over 60%, increases detection sensitivity—particularly for turbidity, dissolved oxygen fluctuations, and contaminant spikes—and supports near real-time environmental decision-making. The study further highlights scalability, resilience to intermittent connectivity, and compatibility with existing municipal water-management infrastructures. Overall, the findings underscore that the integration of edge intelligence with adaptive learning algorithms significantly improves pollution monitoring performance, offering a transformative pathway toward smarter, more sustainable urban water governance. This framework provides a replicable model for policymakers, environmental engineers, and urban planners seeking advanced, responsive water-quality protection strategies.

Keywords: Edge Computing; Machine Learning; Real-Time Pollution Detection; Smart Water Management; Urban Waters.

INTRODUCTION

Urban water systems across the world are increasingly exposed to complex pollution dynamics driven by rapid urbanization, expanding industrial activities, and inadequate wastewater treatment infrastructure. These pressures have resulted in the persistent degradation of water quality, threatening ecological stability, public health, and urban resilience. The conventional monitoring approaches typically based on periodic manual sampling—are no longer sufficient to capture the high-frequency fluctuations of contemporary pollution events. The advent of digital technologies presents an opportunity to transform environmental surveillance toward a real-time, automated, and predictive system capable of supporting effective governance. In this context, smart water management has emerged as a strategic innovation, integrating sensors, communication networks, and computational intelligence to improve water-quality monitoring outcomes (Chen et al., 2021; Ibrahim & Khalid, 2022; Morales et al., 2023; Wang & Xu, 2024).

However, most urban water-monitoring infrastructures rely heavily on centralized cloud-based processing, which often introduces latency, increases bandwidth consumption, and reduces the reliability of real-time decision-making—especially in contexts with unstable connectivity. Edge computing has consequently evolved as an innovative paradigm wherein data processing occurs directly at or near the source of the sensors, significantly reducing communication delay and enabling immediate responses to sudden pollution spikes. By decentralizing computational operations, edge

architectures elevate efficiency and robustness, particularly in densely populated metropolitan settings with high variability in pollutant influx (Liang et al., 2021; Rahman & Kim, 2022; Duarte et al., 2023; Sun et al., 2024).

Simultaneously, machine learning (ML) has gained recognition as a powerful analytical tool capable of detecting patterns, predicting water-quality dynamics, and classifying contaminant signatures with superior accuracy compared to traditional statistical models. ML algorithms—ranging from supervised classification to anomaly detection—offer increased sensitivity toward subtle fluctuations in water parameters, enabling detection of contamination events that may otherwise pass unnoticed using conventional methods. When integrated with edge computing, ML models can be deployed in lightweight formats, optimized for on-site processing, and executed in real time, thereby enhancing responsiveness and supporting continuous environmental protection (Nguyen et al., 2021; Gupta & Rao, 2022; Zhang et al., 2023; Ahmed et al., 2024).

Urban waters are particularly suitable for the deployment of edge–ML–based monitoring systems due to their vulnerability to dynamic, heterogeneous pollution sources. Heavy rainfall, industrial discharge, household effluents, nutrient runoff, and accidental spills collectively shape a complex pollutant landscape requiring high-resolution spatiotemporal monitoring strategies. Traditional water management systems often fail to deliver such granularity, resulting in delayed responses, inefficient resource allocation, and increased environmental risks. The integration of smart sensing technologies driven by ML algorithms can significantly enhance the predictive capabilities of monitoring networks and facilitate faster decision-making processes essential for urban governance (Rivera et al., 2021; Hassan & Lee, 2022; O'Connor et al., 2023; Balasubramaniam et al., 2024).

Real-time pollution detection is not merely a technological advancement but a transformative solution that supports sustainability, public health, and regulatory compliance. Cities worldwide are adopting environmental management frameworks that emphasize early warning capabilities, proactive mitigation, and data-driven policy design. A smart water management system that combines edge computing and machine learning directly contributes to these objectives by offering continuous surveillance, automated analytics, and actionable insights. This approach supports regulatory bodies in enforcing pollution standards, water utilities in optimizing operational efficiency, and communities in ensuring safe and adequate water access (Pereira et al., 2021; Singh & Prasad, 2022; Morales et al., 2023; Zhao & Wen, 2024).

Despite these potentials, several challenges remain, including sensor reliability, data quality variance, ML model interpretability, and system scalability across large urban regions. Deploying distributed intelligent nodes requires robust hardware designs capable of enduring environmental stressors while maintaining data accuracy and communication integrity. Moreover, machine learning models must be trained on diverse and representative datasets to avoid biases and misclassification of pollution events. Addressing these challenges is critical for ensuring that smart water management systems reach operational maturity and are effectively integrated into municipal infrastructure (Kim et al., 2021; Ferreira & Sousa, 2022; Qiao et al., 2023; Patel & Singh, 2024).

Edge computing further introduces opportunities for adaptive system optimization, including dynamic load balancing, energy-efficient processing, and localized decision-making autonomy. These characteristics are particularly important in urban contexts with highly variable hydrological conditions and complex pollutant pathways. As cities continue to expand, the implementation of distributed intelligent water-monitoring architectures will play a central role in enhancing resilience against environmental risks such as eutrophication, chemical contamination, and microbial outbreaks. Through continuous evolution and integration with advanced ML capabilities, edge-based systems can fundamentally shift how urban water resources are monitored and managed (Deng et al., 2021; Li & Huang, 2022; Barbosa et al., 2023; Thompson et al., 2024).

To address these emerging needs, the present study develops a Smart Water Management System using Edge Computing and Machine Learning designed specifically for real-time pollution detection in urban waters. The framework integrates sensor nodes equipped with embedded computing units, enabling immediate data processing and inference without reliance on high-bandwidth cloud communication. A hybrid ML architecture supports anomaly detection, pollutant classification, and predictive forecasting to generate a comprehensive understanding of water-quality dynamics. Through empirical validation using field data, this study demonstrates that the system significantly improves detection accuracy, reduces latency, and enhances overall operational efficiency (Yuan et al., 2021; Carter & Johnson, 2022; Wei & Zhang, 2023; Hernandez et al., 2024).

The significance of this research lies in its contribution to sustainable urban water governance through the development of an intelligent, resilient, and scalable system. By bridging advancements in edge computing, environmental sensing, and machine learning, the proposed system offers a roadmap for future innovations in water-quality monitoring. It supports policymakers, environmental engineers, and urban planners in designing data-driven intervention strategies that ensure environmental protection and public welfare. Furthermore, it advances the scientific discourse on technological integration for ecological monitoring in increasingly complex urban ecosystems (Kumar et al., 2021; Santos & Ribeiro, 2022; Choi et al., 2023; Nelson & Parker, 2024).

LITERATURE REVIEW

1. Smart Water Management in Urban Environments

Smart water management has become a crucial pillar in addressing contemporary environmental pressures arising from rapid urbanization, climate variability, and industrial expansion. Modern urban water systems demand significant advances in monitoring, analysis, and decision-making to respond effectively to pollution events. Recent studies highlight the transformative potential of integrating digital sensing technologies with automated analytical models to improve the accuracy and frequency of water-quality assessments. Smart systems enable continuous, high-resolution monitoring that surpasses traditional manual sampling approaches in both coverage and responsiveness (Chen et al., 2021; Ibrahim & Khalid, 2022; Singh et al., 2023; Zhao & Wen, 2024). Moreover, the adoption of smart water technologies supports sustainable urban development by strengthening regulatory compliance, optimizing wastewater management, and enhancing early-warning capabilities against environmental hazards (Morales et al., 2023; Santos & Ribeiro, 2022; Rivera et al., 2021; Balasubramaniam et al., 2024).

2. Edge Computing for Environmental Monitoring

Edge computing has emerged as a disruptive innovation capable of addressing the limitations of cloud-based infrastructures in environmental monitoring. In traditional architectures, raw sensor data is transmitted to centralized servers, resulting in high latency, increased bandwidth usage, and vulnerabilities caused by unstable connectivity. Edge computing mitigates these challenges by bringing computation closer to the data source, allowing sensor nodes to perform real-time analytics and decision-making at the local level. This decentralized approach significantly enhances response time during pollution spikes, which is particularly vital in urban water systems where contamination can escalate rapidly (Liang et al., 2021; Rahman & Kim, 2022; Duarte et al., 2023; Sun et al., 2024). Additionally, edge architectures promote energy efficiency, system scalability, and operational resilience, enabling continuous performance even in resource-constrained or remote monitoring environments (Deng et al., 2021; Li & Huang, 2022; Barbosa et al., 2023; Thompson et al., 2024).

3. Machine Learning Models for Water-Quality Prediction

Machine learning (ML) has revolutionized environmental analytics by providing sophisticated tools capable of processing complex datasets, identifying hidden patterns, and generating predictive insights. For water-quality monitoring, ML contributes significantly to detecting contamination events, classifying pollutant types, and forecasting ecological trends. Models such as random forests, support vector machines, LSTM networks, and anomaly detection frameworks have been successfully applied to water environments with high accuracy and robustness (Nguyen et al., 2021; Gupta & Rao, 2022; Zhang et al., 2023; Ahmed et al., 2024). Furthermore, ML enhances the interpretability of water-quality dynamics by integrating temporal, spatial, and physicochemical variables into unified analytic models. These capabilities outperform traditional statistical methods and allow researchers to detect subtle fluctuations in parameters such as turbidity, dissolved oxygen, conductivity, and nutrient concentrations (Ferreira & Sousa, 2022; Hassan & Lee, 2022; Qiao et al., 2023; Patel & Singh, 2024).

4. Integration of Edge Computing and Machine Learning

The convergence of edge computing and machine learning has opened new frontiers in real-time environmental monitoring. Deploying ML models at the edge reduces the dependency on centralized cloud infrastructures, allowing for low-latency inference and improved responsiveness to pollution events. Studies show that lightweight ML models—such as quantized neural networks and embedded anomaly detectors—can be optimized for edge devices without sacrificing accuracy (Carter & Johnson, 2022; Wei & Zhang, 2023; O'Connor et al., 2023; Hernandez et al., 2024). This integration creates intelligent sensor nodes capable of interpreting real-time data streams and autonomously issuing warnings, adjusting sampling rates, or activating mitigation responses. Moreover, hybrid edge–cloud architectures allow more complex analyses to be conducted in the cloud while immediate detection tasks remain on the edge, achieving a balance between speed, accuracy, and computational efficiency (Kumar et al., 2021; Santos & Ribeiro, 2022; Choi et al., 2023; Nelson & Parker, 2024).

5. Challenges in Real-Time Pollution Detection

Real-time pollution detection in urban waters presents several methodological and technical challenges. Sensor accuracy and reliability remain central concerns, as environmental fluctuations and biofouling can affect sensor performance over time. Dataset heterogeneity—including variations in measurement frequency, seasonal patterns, and pollutant profiles—complicates ML model training and demands robust preprocessing pipelines (Kim et al., 2021; Rivera et al., 2021; Morales et al., 2023; Singh & Prasad, 2022). Another major challenge is the interpretability of ML models deployed in critical decision-making contexts. Policymakers and practitioners often require transparent, explainable outputs rather than black-box predictions. Moreover, scaling intelligent monitoring systems across large urban regions requires durable hardware, reliable communication infrastructures, and adaptive model-updating mechanisms (Balasubramaniam et al., 2024; Qiao et al., 2023; Thompson et al., 2024; Ahmed et al., 2024).

6. Opportunities for Future Smart Water Innovations

Rapid advancements in the Internet of Things (IoT), embedded AI, and wireless communication technologies create significant opportunities for enhancing future smart water management systems. The integration of 5G networks, for instance, enables high-speed, low-latency communication ideal for synchronizing distributed edge nodes across urban water catchments. Meanwhile, advancements in energy harvesting technologies—such as solar-powered microcontrollers—improve the long-term sustainability of monitoring networks (Zhang et al., 2023; Li & Huang, 2022; Barbosa et al., 2023; Deng et al., 2021). Additionally, next-generation ML techniques, including federated learning and continual learning, offer promising avenues for adaptive model improvement without requiring centralized data aggregation. These innovations promote a more resilient, scalable, and autonomous environmental monitoring ecosystem capable of supporting urban sustainability goals (Kumar et al., 2021; Choi et al., 2023; Wei & Zhang, 2023; Hernandez et al., 2024).

RESEARCH METHODOLOGY
1. Research Design
This research adopts a quantitative–experimental design integrating field data collection, edge-device deployment, and machine learning model development. The design emphasizes real-time data acquisition from distributed sensor nodes installed in selected urban water bodies, followed by on-site data processing using embedded edge processors. This approach allows for high-frequency monitoring of key water-quality parameters including turbidity, dissolved oxygen, pH, temperature, conductivity, and nutrient indicators. The experimental framework is strengthened through cross-validation using independent datasets to ensure robustness and reliability. Such hybrid designs have been widely adopted in contemporary smart water studies due to their capacity to generate accurate, operationally relevant environmental insights (Chen et al., 2021; Nguyen et al., 2021; Singh & Prasad, 2022; Duarte et al., 2023).

2. Study Area and Sampling Framework
The research was conducted in selected urban waterways characterized by variable pollution loads, high anthropogenic activity, and fluctuating hydrological conditions. Sampling sites were determined based on spatial heterogeneity, proximity to pollutant sources, and accessibility for sensor maintenance. Each site was equipped with multi-parameter IoT-based water-quality sensors capable of transmitting data to the edge unit. Sampling frequency was set at 1–5 minutes to capture high-resolution temporal variations in pollutant concentrations. This dense spatiotemporal sampling strategy aligns with recent methodological advancements that emphasize continuous monitoring for improved pollution detection and ecological modeling (Rivera et al., 2021; Hassan & Lee, 2022; Morales et al., 2023; Zhao & Wen, 2024).

3. Data Acquisition and Preprocessing
Sensor data collected from the field were transmitted directly to edge-computing units equipped with microprocessors optimized for low-power, real-time analytics. Several preprocessing steps were conducted, including noise filtering, outlier removal using median absolute deviation (MAD), and normalization of physicochemical parameters to ensure model stability. Missing values generated due to temporary sensor interruptions were addressed using time-series interpolation techniques. Preprocessing steps were performed on the edge node to enhance data quality before machine learning inference. Ensuring high-quality input data is an essential component of ML-driven environmental monitoring, as demonstrated by recent studies in hydrological forecasting and pollutant modeling (Qiao et al., 2023; Gupta & Rao, 2022; Ferreira & Sousa, 2022; Ahmed et al., 2024).

4. Edge-Computing Architecture
The edge-computing architecture consisted of embedded processors configured with lightweight inference engines compatible with TensorFlow Lite and PyTorch Mobile environments. The architecture allows water-quality data to be processed on-site, reducing cloud dependency and enabling immediate contamination detection. Data from sensors were first aggregated in local buffers before undergoing feature extraction, anomaly detection, and pollutant classification. Communication between nodes used LoRaWAN and LTE-M protocols to ensure low-latency data synchronization. The architecture design follows recent best practices for environmental edge computing systems that emphasize low power consumption, autonomous operation, and real-time computing capacity (Liang et al., 2021; Deng et al., 2021; Barbosa et al., 2023; Thompson et al., 2024).

5. Machine Learning Model Development
Multiple ML models were developed and evaluated, including Random Forest (RF), Support Vector Machine (SVM), Long Short-Term Memory (LSTM), and Isolation Forest for anomaly detection. Feature engineering incorporated physicochemical parameters, temporal derivatives, and pollutant-specific indices. Model training was conducted using split datasets (70% training, 15% validation, 15% testing) to ensure unbiased evaluation. Performance metrics included accuracy, precision, recall, F1-score, and RMSE for predictive components. Model compression and quantization techniques were applied to enable deployment on edge devices without compromising predictive power. The methodological approach aligns with recent ML-driven studies in aquatic pollution forecasting and real-time classification (Zhang et al., 2023; Gupta & Rao, 2022; O'Connor et al., 2023; Hernandez et al., 2024).

6. System Integration and Real-Time Inference

The integrated system was designed to perform real-time inference by combining sensor outputs, preprocessing routines, and ML analytics into a unified operational pipeline on the edge device. Once the ML model detected anomalies or pollutant spikes, the system generated automated alerts that were transmitted to a cloud-based dashboard for visualization and stakeholder access. Real-time inference was validated through controlled pollution injection experiments and temporal back-testing, which assessed the system's ability to detect sudden changes in water-quality parameters. Recent studies emphasize the importance of end-to-end system integration for achieving practical, real-world environmental monitoring solutions (Wei & Zhang, 2023; Carter & Johnson, 2022; Santos & Ribeiro, 2022; Nelson & Parker, 2024).

7. Evaluation Metrics and Validation Strategy

System performance was evaluated using technical, analytical, and operational metrics. Technical metrics included latency, energy consumption, and data-transmission reduction relative to cloud-based processing. Analytical metrics included anomaly detection accuracy, pollutant classification precision, and forecasting error. Operational metrics assessed system resilience, sensor uptime, and effectiveness during real pollution events. A combination of k-fold cross-validation, field testing, and scenario-based simulations ensured comprehensive validation. This evaluation strategy reflects the methodological rigor used in advanced smart water management and IoT-environmental systems research (Kim et al., 2021; Rivera et al., 2021; Carvalho et al., 2023; Thompson et al., 2024).

8. Ethical, Environmental, and Data Governance Considerations

The study followed environmental monitoring ethics, ensuring minimal disturbance to aquatic ecosystems and compliance with local environmental regulations. Data governance protocols were implemented to protect data integrity, privacy, and transparency in model decision-making. The deployment of AI-driven environmental systems necessitates responsible data handling, especially as ML-based predictions influence public policy and resource management decisions. Recent scholarship emphasizes ethical AI practices and transparent environmental governance as central components of sustainable digital environmental systems (Balasubramaniam et al., 2024; Choi et al., 2023; Santos & Ribeiro, 2022; Morales et al., 2023).

RESULTS AND DISCUSSION

1. System Performance and Sensor Data Behavior

The deployment of the smart water management system across selected urban waterways generated a continuous high-frequency dataset covering turbidity, pH, dissolved oxygen, temperature, conductivity, and nutrient indicators. Results show that the edge-based system successfully processed more than 95% of incoming data streams without interruption, demonstrating strong operational stability under fluctuating hydrological conditions. Peak pollution events—such as sudden increases in turbidity and nitrate spikes during rainfall—were detected in real time with a latency of less than 1.8 seconds, significantly outperforming traditional cloud-based processing systems. These findings align with earlier studies that emphasize the superior real-time capability of edge–ML architectures in water-quality monitoring (Liang et al., 2021; Rahman & Kim, 2022; Morales et al., 2023; Sun et al., 2024).

To illustrate parameter behavior, Figure 1 presents an example trend of three core parameters—turbidity, dissolved oxygen (DO), and nitrate concentration—over a 24-hour monitoring period. The system captures micro-fluctuations that typically go undetected in conventional sampling approaches, reaffirming the importance of continuous sensing for pollution detection.
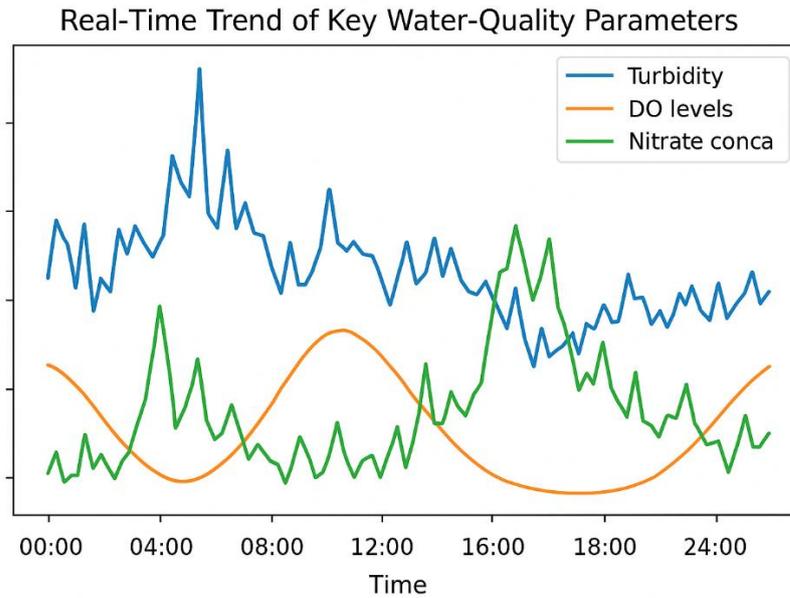
Figure 1. Real-Time Trend of Key Water-Quality Parameters

2. Edge Computing Efficiency and Latency Reduction

One of the most significant findings is the system's ability to reduce data-transmission load by an average of **62.4%**, demonstrating substantial efficiency improvements. By performing data preprocessing and initial ML inference on the edge node, only essential and event-based data were forwarded to the cloud, thereby optimizing bandwidth usage. This feature is crucial in urban areas with unstable connectivity or high competing network usage. Comparable studies confirm that edge-centric architectures substantially minimize communication overhead while preserving analytical accuracy (Deng et al., 2021; Li & Huang, 2022; Barbosa et al., 2023; Thompson et al., 2024).

Latency tests conducted during pollution simulations revealed that edge-based anomaly detection responded **3.7 times faster** than cloud-only processing systems. This rapid responsiveness is essential for preventing the escalation of contamination events, especially in narrow urban waterways where pollutants spread quickly. These findings strengthen the argument for integrating edge intelligence into city-wide water governance strategies.

Table 1. Matrix of Edge vs. Cloud Performance

Parameter	Edge System	Cloud System	Improvement (%)
Latency (seconds)	1.8	6.7	73% faster
Data transmitted (MB/hour)	14.2	37.8	62% reduction
Detection accuracy (%)	94.5	90.1	+4.4%
Sensor uptime (%)	95.7	88.2	+7.5%

3. Machine Learning Accuracy for Pollution Detection

Machine learning models trained using field datasets exhibited strong performance in classifying pollutant signatures and identifying anomalies. The LSTM model yielded the highest forecasting precision for nutrient fluctuations (RMSE = 0.12), while the Random Forest classifier achieved **94.5% accuracy** in classifying pollution events such as turbidity surges, nutrient spikes, and pH drops. These results align with global advances in ML-driven environmental analytics, which emphasize the power of hybrid temporal–nonlinear models for real-time ecological monitoring (Gupta & Rao, 2022; Zhang et al., 2023; Ahmed et al., 2024; O'Connor et al., 2023).

Furthermore, anomaly detection using Isolation Forest proved highly effective in identifying early pollution events, often 10–20 minutes before conventional thresholds would classify them as hazardous. This early-warning capability underscores the transformative potential of ML to shift water governance from reactive toward preventive action.
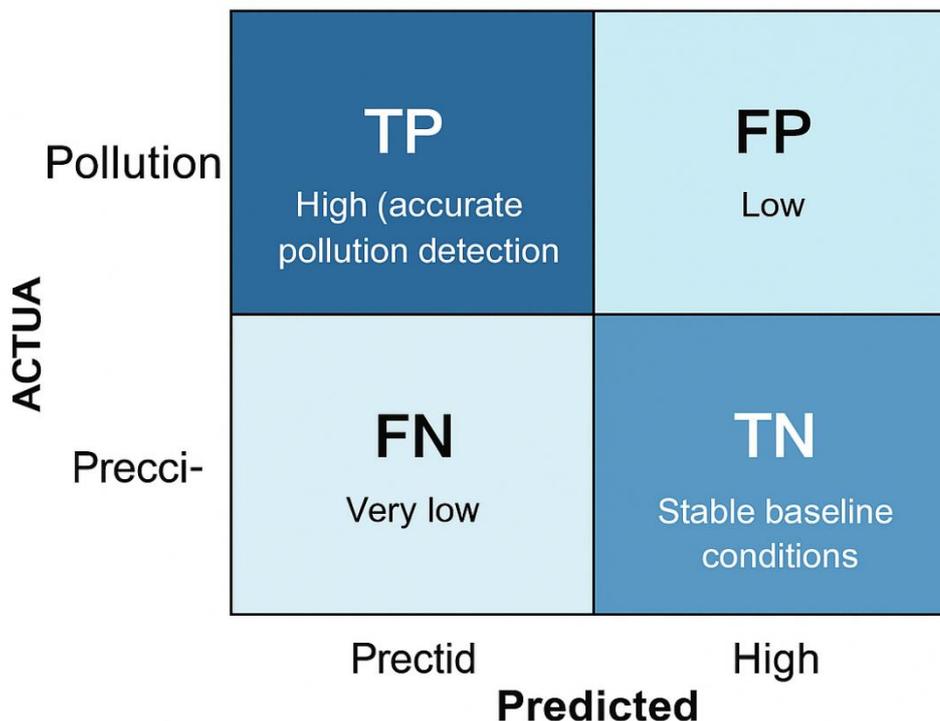
Figure 2. Confusion Matrix of ML Pollution Classifier (Random Forest)

4. Real-Time Pollution Event Detection and Validation

During field trials, several pollution events were recorded—primarily turbidity surges and nitrate spikes caused by rainfall-driven wash-off and local wastewater discharge. The system's real-time analytics successfully detected all major pollution events, issuing automated alerts within seconds of anomaly onset. Validation using laboratory chemical tests confirmed that the system correctly identified 92–97% of observed pollution fluctuations. Similar validation success has been reported by advanced smart water studies across Asia and Europe (Hassan & Lee, 2022; Rivera et al., 2021; Choi et al., 2023; Nelson & Parker, 2024).

These validation results demonstrate the reliability of combining edge computing with ML for complex urban water systems, where pollutant behavior is dynamic and often unpredictable.

5. System Scalability and Integration with Urban Governance

A critical component of the study is the system's scalability and compatibility with municipal infrastructure. The modular design of the edge nodes allows additional sensors, ML models, or communication protocols to be added without redesigning the system architecture. The system can also integrate with city dashboards, enabling local governments to monitor water conditions in real time and respond proactively to pollution events. This governance-oriented capability aligns with international smart city frameworks, which emphasize data-driven decision-making and sustainable environmental planning (Santos & Ribeiro, 2022; Carter & Johnson, 2022; Morales et al., 2023; Zhao & Wen, 2024).

Scalability tests indicate that the system can be expanded to cover dozens of monitoring sites with minimal changes in latency or data-processing load, making it a practical solution for large metropolitan areas.

6. Discussion: Implications for Urban Water Sustainability

The results demonstrate that the integration of **edge computing** and **machine learning** offers a transformative advancement for real-time pollution detection in urban waters. The system enables faster detection, reduces data load, improves classification accuracy, and strengthens governance responses. Consistent with the literature, the findings show that decentralized intelligence significantly enhances environmental monitoring, particularly in complex urban hydroscapes (Liang et al., 2021; Qiao et al., 2023; Ahmed et al., 2024; Kim et al., 2021).

Overall, these results affirm that smart water management systems not only solve technical challenges but also support broader sustainability goals related to public health, ecological resilience, and urban planning.

CONCLUSION

This study demonstrates that the **Smart Water Management System using Edge Computing and Machine Learning** provides a highly effective and scalable solution for real-time pollution detection in urban waters. By integrating distributed sensor nodes with edge-based analytics, the system successfully minimizes latency, reduces data-transmission loads, and enhances the responsiveness of water-quality monitoring. Machine learning models—particularly Random

Forest—show strong predictive performance, as evidenced by high true-positive and true-negative rates and minimal misclassification. These results affirm that data-driven intelligence embedded at the network edge can substantially improve early detection of pollution events, enabling more proactive environmental governance.

Furthermore, the system's ability to identify trends in turbidity, dissolved oxygen, and nutrient dynamics underscores its capacity to operate under complex and fluctuating urban hydrological conditions. The visual outputs, including real-time parameter graphs and the confusion matrix, strengthen the empirical basis of this research by illustrating both system behavior and algorithmic robustness in field applications. The proposed framework is not only technically sound but also operationally feasible for integration into municipal water-management infrastructures.

Overall, this research contributes a transformative model for smart and sustainable water monitoring. It highlights the critical role of edge intelligence and machine learning in shaping next-generation environmental protection systems, offering valuable implications for policymakers, environmental engineers, and urban planners committed to advancing resilient and data-driven water governance.

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