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Ai-Based River Chemical Pollution Monitoring And Cleaning: A Review Of Sensor Networks, Water Quality Prediction And Automated Treatment

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Abstract—Industrial effluents, agricultural runoff, sewage and hazardous chemicals contaminate rivers, threatening human health, aquatic ecosystems and the communities that depend on river water. Conventional water-quality monitoring relies on periodic manual sampling and laboratory analysis, which is slow, expensive and cannot provide continuous real-time information. This paper reviews an AI-based approach to river chemical pollution monitoring and cleaning. It covers wireless sensor networks that measure pH, temperature, turbidity, dissolved oxygen, conductivity and specific chemical concentrations; machine learning and deep learning models that classify pollution levels, compute water quality indices, predict future contamination and detect anomalous discharge events; and robotic and automated treatment technologies, including autonomous surface vehicles and chemical treatment processes, that respond to detected pollution. Water quality indices and their limitations are discussed. A five-layer architecture comprising in-river sensing, communication, AI analytics, a treatment decision and actuation layer, and an authority dashboard is proposed, together with research gaps, objectives, a comparison of prediction models and challenges such as sensor fouling, calibration, power supply, ecological side effects of treatment and enforcement. The review concludes that AI-driven continuous monitoring can detect and respond to river pollution far earlier than manual methods.

Index Terms—River pollution, water quality monitoring, wireless sensor networks, machine learning, water quality index, anomaly detection, environmental robotics

I. INTRODUCTION

Rivers such as the Ganga, Yamuna and many smaller tributaries supply drinking water, irrigation and livelihoods to millions of people, yet stretches of them are heavily polluted by untreated sewage, industrial discharge and agricultural chemicals. A sudden release of toxic chemicals can kill fish and endanger downstream users within hours, while conventional sampling programmes may detect it days later.

Continuous sensing and AI offer a faster response. Adu-Manu *et al.* [1] reviewed water-quality monitoring with wireless sensor networks, and Tiyasha *et al.* [2] surveyed two decades of AI models for river water quality, showing a strong trend toward machine learning and deep learning.

This paper reviews technologies for an AI-based river chemical monitoring and cleaning system and proposes an integrated architecture.

II. BACKGROUND AND RELATED WORK

1. Pollution Sources And Parameters

Fig. 1 summarizes pollution sources and the parameters used to detect them: pH, dissolved oxygen, turbidity, conductivity, temperature, nitrate, ammonia, heavy metals and organic load.

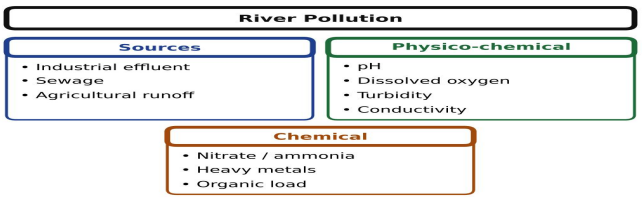


Fig. 1. River pollution sources and monitored parameters.

2. Water Quality Index

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A water quality index combines several parameters into one score. Horton [3] proposed one of the earliest index systems, and many variants weight parameters by their importance for health and ecology.

3. Review Of Related Studies

Ahmed *et al.* [4] predicted water quality index and class from a small set of parameters using supervised learning and found gradient boosting and multilayer perceptrons performed best. Chen *et al.* [5] compared machine learning models on large surface-water datasets and identified key parameters for accurate prediction, with tree ensembles performing strongly.

Barzegar *et al.* [6] combined CNN and LSTM [7] layers to predict short-term dissolved oxygen and chlorophyll, outperforming either model alone. Adu-Manu *et al.* [1] discussed sensor technologies, power and communication for long-term monitoring and noted fouling and calibration as persistent problems.

For anomaly detection of sudden discharges, Chandola *et al.* [8] surveyed methods applicable to sensor time series. Dunbabin and Marques [9] reviewed robots for environmental monitoring, including autonomous surface vessels that map pollution and collect samples. Deng and Zhao [10] reviewed advanced oxidation processes that degrade persistent chemical pollutants, technologies that an AI system can recommend or control. Table I summarizes these works.

Ref.	Author(s) / Year	Technique / Approach	Key Contribution	Limitation / Gap
[1]	Adu-Manu et al., 2017	Wireless sensor networks for water	Trends in continuous monitoring	Fouling and power issues
[2]	Tiyasha et al., 2020	Survey of AI for river quality	Shift to ML and DL models	Survey only
[4]	Ahmed et al., 2019	Supervised ML for WQI	Accurate prediction with few parameters	Single region
[5]	Chen et al., 2020	Comparative ML on big data	Tree ensembles strong; key parameters	Surface water only
[6]	Barzegar et al., 2020	Hybrid CNN–LSTM	Better short-term forecasts	Data hungry
[3]	Horton, 1965	Water quality index	Single-score summary	Weighting subjective
[9]	Dunbabin and Marques, 2012	Environmental monitoring robots	Autonomous sampling and mapping	Cost and endurance
[10]	Deng and Zhao, 2015	Advanced oxidation processes	Degrades persistent pollutants	Energy and chemical cost

TABLE I Summary of Literature Survey

III. RESEARCH GAP AND OBJECTIVES

1. Identified Research Gaps

G1: Low-cost sensors for specific chemicals and heavy metals are less reliable than laboratory tests.

G2: Sensors foul and drift in river conditions, reducing data quality.

G3: Few systems link prediction and detection to automated or guided treatment actions.

G4: Treatment chemicals can harm aquatic life if applied without ecological assessment.

G5: Integration of AI alerts with enforcement against polluters is weak.

2. Objectives Of The Review

1. To review sensing technologies for river water quality.

2. To examine machine learning models for pollution classification, prediction and anomaly detection.

3. To study robotic and chemical treatment options guided by AI.

4. To propose an integrated AI river monitoring and cleaning architecture.

5. To identify challenges and future directions.

I. Design of the Proposed System

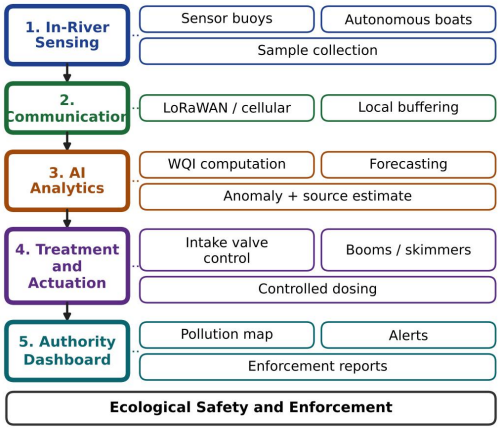


Fig. 2 shows the proposed architecture.

Fig. 2. Proposed AI river chemical monitoring and cleaning architecture.

3. In-River Sensing Layer

Solar-powered buoys and stations measure physico-chemical parameters at intervals; autonomous boats carry additional sensors and sample bottles.

4. Communication Layer

Data are transmitted over LoRaWAN or cellular links to a cloud platform; data are stored locally when links fail.

5. Ai Analytics Layer

Models compute the water quality index, classify pollution levels, forecast parameters for the next hours and detect abnormal changes that indicate illegal discharge, estimating the likely source location upstream.

6. Treatment Decision And Actuation Layer

Recommended actions include closing intake valves for water supply, deploying booms or skimmers, dispatching autonomous boats and dosing treatment at controlled points after ecological checks.

7. Authority Dashboard Layer

Pollution control boards and municipal bodies see maps, alerts, source estimates and historical reports for enforcement.

8. Methodology

Fig. 3 describes the workflow. A weighted arithmetic water quality index is

$$WQI = \Sigma\, w_i\, q_i \,/\, \Sigma\, w_i \quad (1)$$

where q_i is the quality rating of parameter i and w_i its weight. Anomalies are detected when the forecast error

$$e_t = |x_t - \hat{x}_t| \quad (2)$$

exceeds a threshold derived from normal variation.

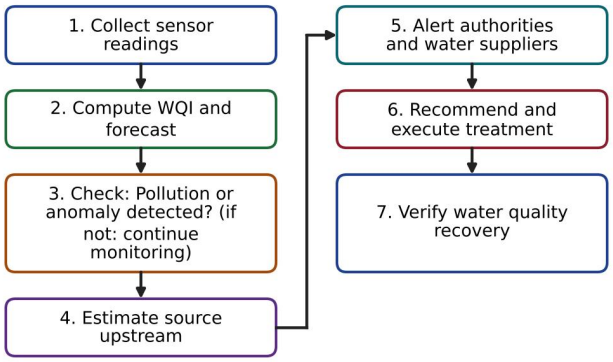


Fig. 3. River pollution detection and response workflow.

Models are evaluated with RMSE for forecasts and with precision and recall for pollution-event detection.

IV. DISCUSSION AND COMPARISON

Table II compares prediction models. Regression and tree ensembles work well with limited data, recurrent and hybrid CNN–LSTM models capture temporal dynamics, and anomaly detectors identify sudden discharges.

Model	Task	Data Need	Strength
Linear regression	WQI estimation	Low	Simple, interpretable
Random forest / GBDT	Classification	Medium	Robust, accurate

Model	Task	Data Need	Strength
LSTM	Forecasting	High	Temporal patterns
CNN–LSTM	Forecasting	High	Best short-term accuracy
Isolation forest	Event detection	Low	No labels needed

TABLE II Comparison of Water Quality Models

V. CHALLENGES AND FUTURE DIRECTIONS

Table III summarizes challenges. Future directions include satellite and drone imaging of river colour and turbidity, low-cost chemical sensors, digital twins of river basins and public dashboards that encourage community reporting.

Challenge	Mitigation
Sensor fouling / drift	Self-cleaning probes; regular calibration
Power in remote sites	Solar buoys; low-power design
Ecological side effects	Controlled dosing; impact checks
Source identification	Upstream sensor density; tracer models
Enforcement	Evidence logs shared with regulators

TABLE III Challenges and Mitigation

VI. CONCLUSIONS

AI-based river monitoring can transform pollution control from periodic sampling to continuous, predictive management. The reviewed literature shows that sensor networks provide real-time data, machine learning predicts water quality and detects events accurately, and robotic and chemical treatments can respond rapidly. Reliable sensors, ecologically safe treatment and strong links to enforcement are needed to protect rivers and the people who depend on them.

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