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Human-in-the-Loop Decision Support for Water-Quality Monitoring Using Interpretable Machine Learning

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Abstract

Automated water-quality monitoring systems rely on human analysts to receive and act upon sensor alarms that can have important consequences for human and ecosystem health. Threshold-based alarms can lead to high false alarm rates that tax operators' cognitive load and decrease reliance (trust) on decision-support technology. Here we describe a human-in-the-loop anomaly detection framework for ground and surface-water applications that leverages contextual baseline models of normal behavior and interpretable machine learning to improve alarm accuracy. Time series sensor data were utilized to train flexible normal ranges, providing contextual ground truth for labeling anomalous sensor values. Predictive models including Logistic Regression (LR) and Random Forest (RF) were applied to determine interpretability-sensitivity tradeoffs. Our results indicate that RF increased the sensitivity of anomaly detection, whereas LR provided explainable probability scores that allow for human-understandable decisions. Using signal detection theory, we frame the utility of interpretability in automated decision support to decrease false alarms, alleviate cognitive load and increase decision confidence in human-in-the-loop environmental monitoring.

Keywords
Decision Support, Machine learning, Water-quality sensors, Human factor, health system monitoring.

1. Introduction
Continuous monitoring of groundwater (GW) and surface water (SW) quality is essential for safeguarding public health, ensuring regulatory compliance and maintaining the operational reliability of drinking water distribution systems. Modern sensor networks routinely measure physicochemical parameters such as pH, turbidity, conductivity, oxidation-reduction potential (ORP), temperature and residual disinfectants (Hall et al. 2007; Storey et al. 2011; Tyagi et al. 2013). However, these variables exhibit natural temporal and environmental variability, making fixed regulatory thresholds insufficient for reliable anomaly detection and early warning (Byer and Carlson 2005).

Recent advances in machine learning have enabled data-driven approaches capable of learning complex, multivariate relationships from sensor time-series data and distinguishing abnormal conditions from normal system behavior (Breiman 2001). In particular, supervised classifiers such as LR and RF have demonstrated strong performance in environmental monitoring due to their balance between interpretability and predictive power (Kanyama et al. 2024). While anomaly detection accuracy is important, system effectiveness ultimately depends on how operators interpret and respond to automated alerts (Zhang et al. 2022). Excessive false alarms can increase cognitive workload, reduce trust and contribute to alarm fatigue in safety critical monitoring (Bisantz and Seong 2001; Adamolekun et al. 2025). Therefore, water-quality anomaly detection should be evaluated not only by predictive accuracy but also by its impact on human judgment and decision reliability.

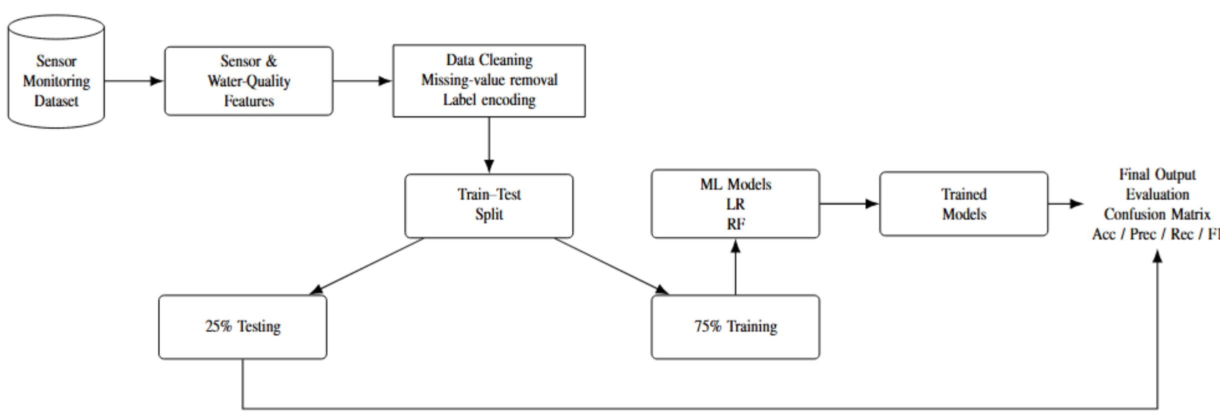

Figure 1. Workflow of the proposed machine learning framework

This study addresses this gap by proposing a unified machine-learning framework for defining data-driven normal water-quality envelopes and detecting anomalies in GW and SW systems. As illustrated in Figure 1, the workflow integrates data cleaning, feature construction, train–test partitioning, supervised learning and quantitative evaluation into a coherent decision-support pipeline. Using real-world sensor data, the framework enables adaptive, interpretable and operationally meaningful anomaly detection suitable for real-time environmental monitoring and decision making.

2. Objectives
The objectives of this report are to:

1. Establish data-driven normal operating ranges for water quality parameters using historical sensor data, thereby reducing cognitive burden and false-alarm rates in human decision-making.
2. Develop an interpretable human-in-the-loop anomaly detection framework for water-quality states, enabling consistency and evidence-based decision support.
3. Evaluate false alarm trade-offs using signal detection based metrics to study Logistic Regression and Random Forest models to assess decision reliability.

3. Background

Water is vital for human health, agriculture and industry. Therefore, creating effective methods for analyzing water quality and identifying unusual conditions is crucial. Many studies have focused on water-quality monitoring, detecting anomalies and forecasting in various environments such as drinking-water systems, SW and GW.

Initial research on online monitoring in drinking-water networks demonstrated the feasibility of detecting contamination events using continuously measured physicochemical indicators. For example, Byer and Carlson (2005) were among the first to develop and test online monitoring of drinking-water distribution systems by introducing credible contaminants into tap water and assessing detectability using indicators such as pH, chlorine residual, turbidity and total organic carbon. Their findings indicate that contamination events can be detected at relatively low concentrations, reinforcing the value of real-time sensor-based monitoring for early warning applications.

Recent research has emphasized anomaly detection through statistical and time-series methods. Zhang et al. (2017) introduced a technique that uses dual moving time window approach, enabling real-time identification of abnormal water quality by comparing current data with historical trends. Their approach, based on statistical models like autoregressive structures, minimizes false alarms and enhances detection accuracy relative to traditional methods. These findings show that pattern-based, adaptive decision rules can surpass fixed threshold systems.

Machine-learning methods have been widely adopted in water-quality modelling due to their ability to learn complex nonlinear relationships from multivariate data (Nuamah and Seong 2019). Mohammadpour et al. (2015) investigated water-quality prediction using support vector machines (SVMs) and artificial neural networks (ANNs), evaluating performance with metrics such as R^2, RMSE, and MAE. Their results indicate that SVM has been shown to be competitive with neural approaches under certain conditions. Related studies, such as Kang et al. (2017), also report strong performance from ANN-based models for water-quality prediction, particularly when nonlinear dynamics are present. Additionally, Xiang and Jiang (2009) applied least square SVM (LS-SVM) optimized with particle swarm optimization, addressing limitations of conventional backpropagation and demonstrating improved predictive accuracy in river water-quality estimation.

In recent years, deep learning methods have gained attention for time-series water-quality problems because they capture temporal dependencies more effectively than classical linear methods (Ramanathan et al. 2021). Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have also demonstrated strong capabilities in learning patterns from long sequences and handling multivariate inputs (Ghojogh and Ghodsi 2023). This is particularly beneficial for sensor-driven water-quality data, where system behaviour changes develop gradually across time-series observations (Che et al. 2018). However, most existing research focuses primarily on detection or prediction, with fewer studies explicitly emphasizing the data-driven establishment of local normal ranges as a foundational step before anomaly detection. Drawing on insights from these related works, the present study aims to define normal water-quality envelopes directly from data and subsequently detect anomalies using RF and LR. This approach enables interpretable, adaptive detection across GW and SW contexts. This present work also extends prior environmental monitoring research by embedding anomaly detection within a human-in-the-loop decision framework.

4. Approach

A. Data Description

The data used for this work was obtained from **Mendeley Data** (Sela et al. 2023). A continuous time-series subset of the data was used, comprising 68,325 observations recorded between 3rd April 2022 and 26th November 2022. Each observation corresponds to a single timestamped measurement across six critical water-quality indicators that collectively describe the physical, chemical, and operational characteristics of the water system. Specifically, physical indicators included temperature and turbidity, while chemical indicators comprised pH, oxidation-reduction potential (ORP), conductivity, and combined chlorine concentration. These indicators can be conceptualized as environmental cues within a hierarchical Lens Model framework, where multiple sensor-derived signals inform system state assessment and support human and automated decision-making processes (Brunswik 2023).

These parameters, summarized in **Table 1,** served as input features for the machine-learning framework, which establishes normal water ranges and detects anomalies using RF and LR models.

In contrast to pre-labelled benchmark datasets, this dataset lacks explicit anomaly annotations. Consequently, a data-driven labelling strategy was implemented. Normal operational ranges for each parameter were statistically defined using percentile thresholds (5th to 95th) and standard deviation boundaries (mean ± two standard deviations). Measurements falling outside these ranges were identified as potential anomalies and subsequently refined through machine-learning classification to detect multivariate abnormal patterns, reflecting realistic detection scenarios in drinking-water networks.

Table 1. Description of the given time series data

ColumnName	**Unit**	**Description**
DateTime	-	Time stamp of measurement (Five-minute interval)
Temperature	°C	Water temperature measured in degrees Celsius
ORP	mV	Oxidation-Reduction Potential
pH	-	Acidity or alkalinity level of the water
Turbidity	NTU	Measure of water clarity in Nephelometric Turbidity Units
Conductivity	µS/cm	Electrical conductivity representing dissolved ion concentration
Combined Chlorine	mg/L	Concentration of residual chlorine compounds present in water.

B. Data Preparation

Real-world water-quality databases are frequently affected by factors such as noise, inconsistent sampling, missing observations and redundant measurements. To mitigate these issues, data preparation steps including cleaning, transformation, normalization and noise identification were implemented prior to model training **(García et al. 2015).**

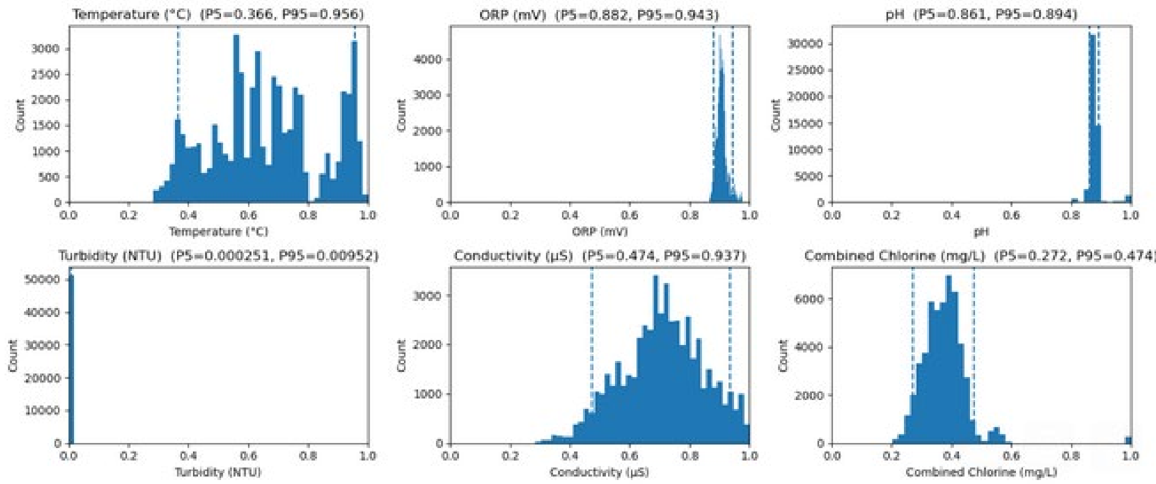

Figure 2. Distribution of water-quality features.

To evaluate data completeness and sensor reliability, missing values were first identified through a missing inspection. The dataset contained fewer than 1% missing observations, primarily due to sensor downtime or temporary communication errors. Several studies have emphasized that imputation methods which consider temporal and contextual similarity provide better reconstruction of missing sensor data compared to zero-filling or random substitution (Little and Rubin 2019).

Figure 2 demonstrates that all variables display distinct statistical patterns and ranges showing Temperature (°C), ORP (mV), pH, Turbidity (NTU), Conductivity (µS), and Combined Chlorine (mg/L). Temperature and Conductivity exhibit approximately uniform to bimodal distributions, while ORP and Combined Chlorine show near-normal patterns centered within their expected operating intervals. The typical neutral range is concentrated by the pH values, indicating stable water chemistry during most of the sampling period. Turbidity displays a sharp peak at very low levels, reflecting generally clear water conditions with occasional spikes that may result from short-term disturbances or sensor noise. The dashed lines in each subplot represent the 5th and 95th percentile boundaries, which were used to define the data-driven normal range envelopes for subsequent anomaly detection.

C. Feature Selection

It is well known that some machine learning algorithms perform less effectively when input data are highly correlated. As shown in Figure 3, there are several moderate correlations among the measured parameters. For example, Temperature is positively correlated with Turbidity ($r = 0.62$) and negatively correlated with Conductivity ($r = -0.61$) and ORP ($r = -0.56$).

Additionally, Conductivity shows a positive correlation with Combined Chlorine ($r = 0.45$). These relationships suggest that some variables may share overlapping information, which can negatively impact model learning by causing redundancy and raising the likelihood of overfitting, especially in algorithms sensitive to multicollinearity.

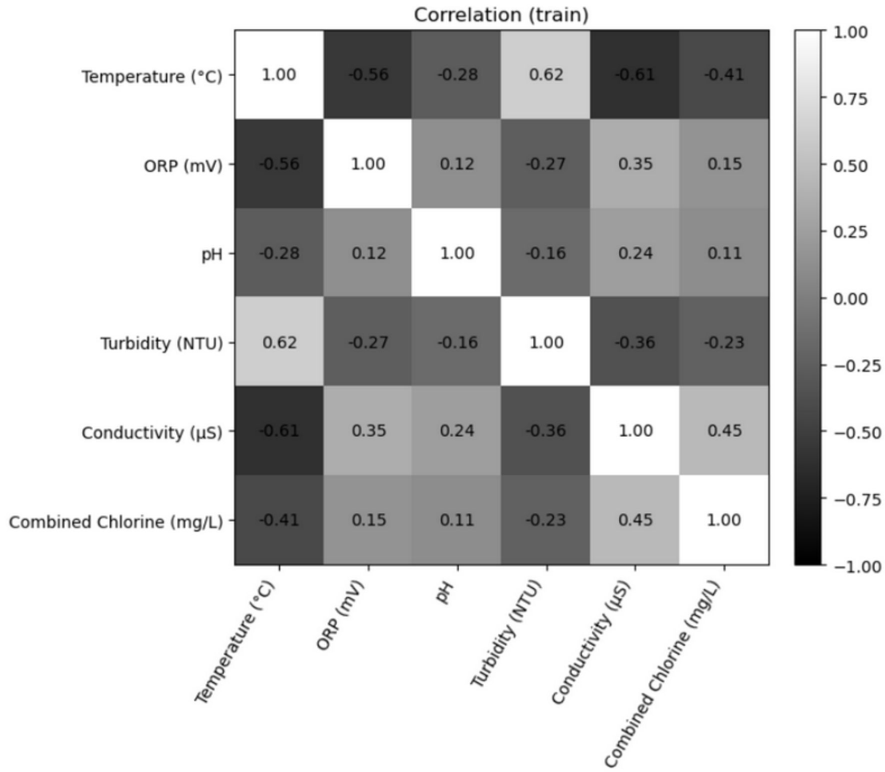

Figure 3. Correlation table

Expanding the number of features used for modeling does not necessarily improve classifier accuracy, as some features may be redundant or lack strong predictive value for the target class (event/not event). Therefore, feature selection is essential to identify the most informative features and eliminate redundancy. Feature selection techniques are generally categorized as filter methods, wrapper methods, or embedded methods (Zhang and Sawchuk 2011). Filter methods evaluate features based on general data characteristics without involving a classifier. Wrapper methods use the accuracy of a specific classifier to guide feature selection (Li et al. 2017). Embedded methods integrate feature selection within the classifier’s training process, making both wrapper and embedded approaches dependent on the chosen classifier. Selecting feature subsets that yield similar classifier performance to the full set can reduce computational demands and support real-time implementation.

For feature selection, we utilize an embedded approach by applying the RF classifier's internal feature-importance mechanism to quantify the information gain (predictive power) of each feature and rank those with the highest contributions. RF offers clear metrics for feature selection, including mean decrease impurity (*Gini importance*) and mean decrease accuracy (Breiman 2001). Mean decrease impurity is defined as the total reduction in node impurity, weighted by the probability of reaching each node and averaged across all trees in the ensemble. Individual decision trees inherently perform feature selection by choosing optimal split points; features used more frequently in splits, particularly near the root, are more influential in the final decision for a larger proportion of samples. This concept extends to RF by averaging feature importance across the ensemble. The resulting relative importance ranking is presented in Figure 4. The RF model identifies Combined Chlorine and ORP as the most influential predictors, followed by Conductivity and Temperature, while Turbidity and pH contribute less. These findings suggest that disinfection-related and oxidation-reduction parameters (Combined Chlorine and ORP), along with ionic-strength effects (Conductivity), offer the most significant signals for distinguishing abnormal conditions in this dataset.

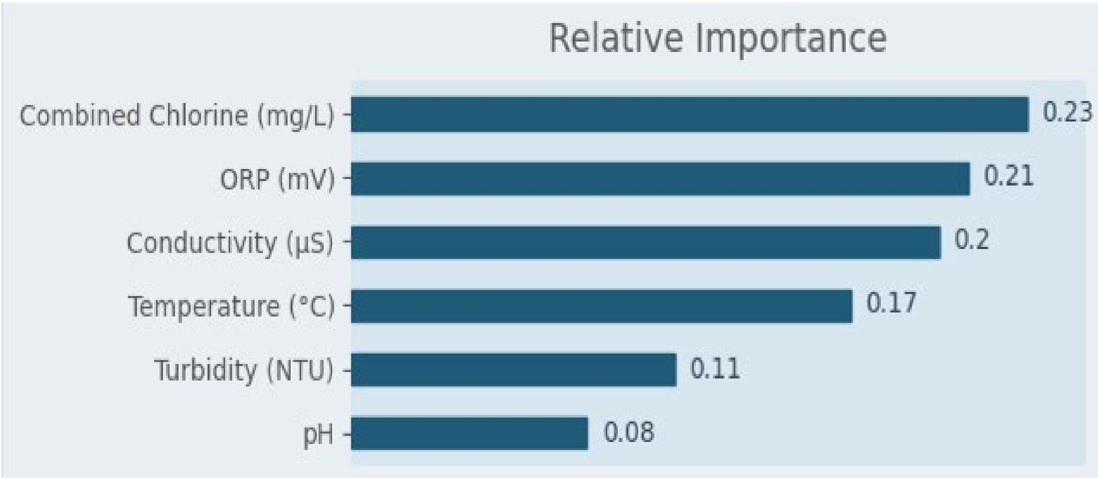

Figure 4. Relative Importance using Random Forest

D. Modelling

We developed two classification models to detect anomalies in multivariate water-quality time series: LR and RF. These models were chosen because the target is a binary variable (normal vs anomaly), and the predictors are continuous physico-chemical indicators. LR provides a straightforward, interpretable baseline, while RF models nonlinear relationships between features and generally excels in handling complex environmental datasets.

(i) Logistic regression

LR models the probability of an abnormal event as a logistic (sigmoid) transformation of a weighted linear combination of the input variables, thereby describing the relationship between one binary outcome and multiple continuous predictors (Hosmer et al. 2013; Sperandei 2014). Because the indicators are measured in different units and numerical ranges, predictors were standardized prior to training to ensure stable model estimation and consistent interpretation of feature effects. In addition to producing a hard class label, LR outputs a continuous probability scores $\mathrm{P(Abnormal)}$, which is valuable for monitoring because it provides a graded "risk level" over time rather than a single yes/no flag. The LR model outputs a continuous abnormality score (Menard 2001). A decision threshold of 0.50 was then used to convert these probabilities into binary predictions, such that observations with $\mathrm{P(Abnormal)} \geq 0.50$ They were classified as anomalies and those below the threshold were classified as normal.

(ii) Random Forest

RF is a supervised ensemble learning algorithm that constructs a collection of decision trees using bootstrap sampling and random feature selection at each split (Khan et al. 2022). Final predictions are obtained by majority voting across trees (Breiman 2001). RF is well-suited for water-quality anomaly detection because it (i) captures nonlinear relationships, (ii) learns feature interactions automatically, and (iii) is generally robust to noise and outliers commonly present in real sensor data.

E. Evaluation metrics

Many real-life monitoring applications produce highly imbalanced data because abnormal events occur far less frequently than normal operation. In such cases, relying on accuracy can be misleading, since a trivial classifier that predicts only the majority class can still obtain a high accuracy while failing to detect anomalies. When the minority class (anomalies) is more important to identify than overall correctness, performance should be assessed using metrics derived from the confusion matrix, which reports **true positives (TP)**, **true negatives (TN)**, **false positives (FP)**, and **false negatives (FN)** (Bekkar et al. 2013).

In this work, we emphasize **Precision, Recall, and F1-score**, because they reflect performance on the minority class:

- **Precision:** proportion of predicted anomalies that are correct.

$$\text{Precision} = \frac{TP}{TP+FP} \qquad (1)$$

- **Recall (True Positive Rate):** proportion of true anomalies detected.

$$\text{Recall} = \frac{TP}{TP+FN} \qquad (2)$$

- **F1-score:** harmonic mean of Precision and Recall

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \qquad (3)$$

Because false negatives can represent missed abnormal water-quality episodes, recall and F1-score are particularly important for this application. Confusion matrices were also used to visualize model outcomes for both classifiers and threshold-dependent plots can be added to assess performance stability across decision thresholds.

From a human-factors perspective, precision and recall were interpreted as indicators of false-alarm burden and missed event risk. FP can increase cognitive workload and reduce trust in automated alerts, whereas FN can undermine system confidence by increasing the risk of missed abnormal events. Accordingly, model evaluation was grounded in signal detection theory to assess implications for human decision support, not just statistical performance.

5. Result and Discussion

Two classifiers, LR and RF, were trained and tested. Their performance was evaluated using imbalance-aware metrics from the confusion matrix, with a focus on Precision, Recall, and F1-score.

Table 2. Summary of results

	RF	**LR**
TP	1342	1126
FP	98	182
TN	116,508	115,984
FN	186	400
Precision	0.93	0.86
Recall	0.88	0.74
F1	0.90	0.79

As shown in Table 2, the RF outperformed LR overall, with 1,342 TP, 186 FN, 98 FP, and 116,508 TN. It achieved a Precision of 0.93, a Recall of 0.88, and an F1-score of 0.90, demonstrating a strong capacity to detect anomalies accurately while keeping false alarms low. The high recall indicates that the RF model effectively identified most abnormal episodes, which is crucial in water-quality monitoring, where missing events can cause delays in response.

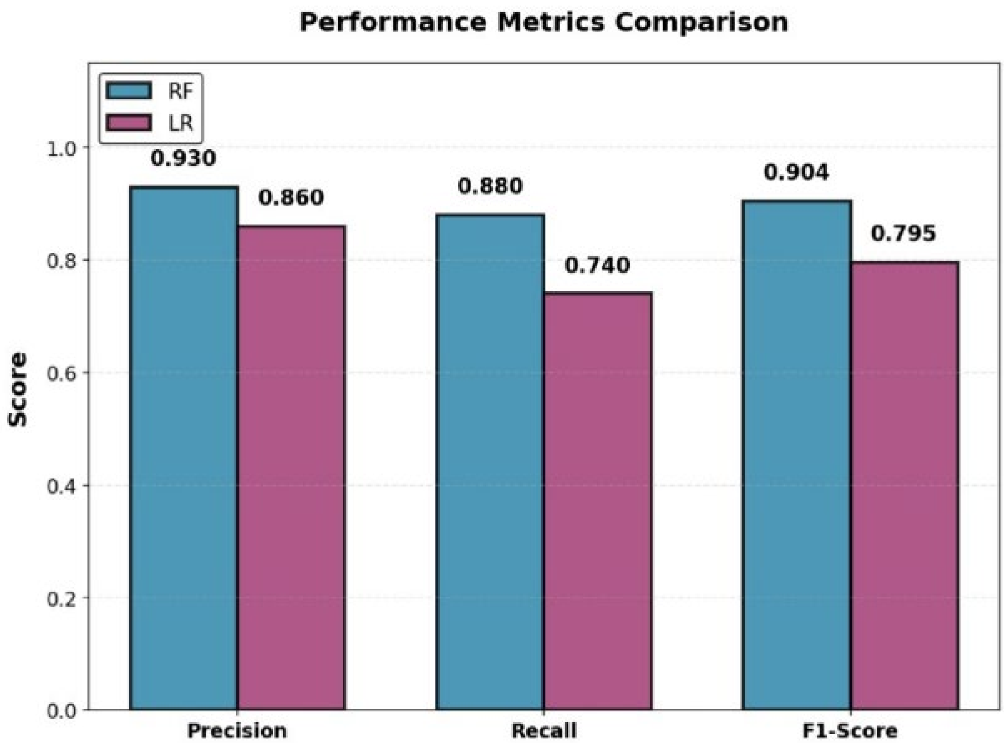

Figure 5. Precision, recall and F1 Score chart of RF and LR

LR also performed competitively as an interpretable baseline model, yielding 1,126 TP, 400 FN, 182 FP, and 115,984 TN. The model achieved a Precision of 0.86, a Recall of 0.74, and an F1-score of 0.79 (Figure 5). While LR maintained relatively good precision, its lower recall indicates that it failed to detect a larger fraction of anomalies compared with RF. This limitation is expected because LR relies on a linear decision boundary, constraining its ability to capture complex nonlinear relationships among physicochemical indicators that characterize real-world monitoring systems.

Within a human-in-the-loop framework, the higher recall achieved by RF reduces the risk of missed abnormal events in safety-sensitive monitoring. However, the interpretability of LR supports calibrated trust and transparent reasoning, highlighting the trade-off between detection sensitivity and explainability in human-centered decision support design.

Overall, the results indicate that both models can support automated anomaly detection using data-driven normal ranges. However, the RF model demonstrates a clearer performance benefit, mainly through better recall and an increased F1-score. These findings confirm that nonlinear ensemble models are more effective at identifying multivariate abnormal behaviour in water-quality time series, whereas LR continues to be useful for its transparency and probability-based risk assessment scoring.

6. Validation

The proposed framework was validated using real-world continuous water-quality monitoring data obtained from a drinking-water distribution system, comprising 68,325 observations collected over several months at five-minute intervals. Model performance was evaluated using imbalance-aware metrics including Precision, Recall, and F1-score to ensure reliable anomaly detection under realistic environmental monitoring conditions. The Random Forest model achieved superior detection performance with high sensitivity and reduced false alarms, demonstrating its effectiveness in identifying abnormal water-quality events. In addition, the use of Logistic Regression provided interpretable probabilistic outputs that support transparent and explainable decision-making in human-in-the-loop monitoring systems. The framework was further validated conceptually through signal detection theory by evaluating the trade-off between missed-event risk and false-alarm burden in operational decision support. These results demonstrate that the proposed methodology provides a reliable, adaptive, and practically applicable approach for intelligent groundwater and surface-water quality monitoring.

7. Conclusion

This study developed a data-driven machine-learning framework for defining normal water-quality operating ranges and detecting anomalous conditions in GW and SW monitoring systems. By deriving normal envelopes directly from historical sensor data, the approach overcomes limitations of fixed thresholds and reduces false alarms that can increase operator workload and decision fatigue. The framework integrates data cleaning, feature construction and time-aware train-test partitioning with supervised classification models to support consistent and repeatable anomaly detection. Overall, anomaly detection in water-quality monitoring should be framed as a human-automation decision support problem rather than solely a classification task. By grounding evaluation in signal detection theory and emphasizing interpretability, the framework supports balance sensitivity, transparency and calibrated human reliance in safety-critical operations.

7.1 Limitations

The framework defines normal operating ranges directly from historical data and does not yet incorporate maintenance logs or operational context, which can lead to false alarms caused by sensor drift, calibration events, or missing data.

7.2 Future Work

We plan to extend the proposed framework by incorporating Brunswik's Lens Model-based representation of human-automation interaction (Seong and Nam 2008; Davis et al. 2021) in water-quality monitoring. This approach will enable quantitative analysis of cue validity and cue utilization across sensor inputs, automated decision aids and human operator judgments, which affect decision accuracy, cognitive workload and trust in automated alerts (Seong and Bisantz 2008; Logah et al.2025; Alabi et al. 2025). The framework will support evaluation of human-automation decision agreement under varying alarm conditions, clarifying the impact of automated support on operator performance.

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