Anomaly Detection of Water Physicochemical Indicators Based on an Isolation Forest–Random Forest Fusion Algorithm

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ABSTRACT To overcome the challenges of limited abnormal samples, diverse anomaly patterns, and the insufficient capability of conventional threshold-based methods in detecting multivariate water quality abnormalities, this study develops an anomaly detection approach based on an Isolation Forest–Random Forest fusion algorithm. Hourly automatic monitoring data from an urban river section during 2021–2023 were used to construct a multivariate dataset covering thermal, acid–base, oxygen-related, optical, ionic, nutrient, and organic pollution characteristics. In the proposed framework, standardized water quality samples were first processed by the Isolation Forest model for unsupervised anomaly screening, through which anomaly scores were obtained. These scores were then introduced as enhanced features and combined with the original physicochemical variables as the input of the Random Forest model for anomaly reclassification and key factor identification. Experimental results show that the proposed IF-RF fusion model performed better than conventional threshold-based detection and several representative machine learning methods, demonstrating stronger overall performance across multiple evaluation metrics. Specifically, the F1-score and AUC of the fusion model reached 0.902 and 0.962, respectively. The feature importance results indicate that the anomaly score generated by Isolation Forest contributed most to the final classification, while dissolved oxygen, turbidity, ammonia nitrogen, and COD were identified as the dominant physicochemical factors affecting anomaly detection. Overall, this study provides a practical data-driven method for automatic water quality monitoring, anomaly warning, and refined management of urban rivers.

INDEX TERMS Water quality anomaly detection, Physicochemical indicators, Isolation Forest, Random Forest

I. INTRODUCTION

Water environmental conditions play an important role in maintaining ecological balance, ensuring drinking water security, and supporting sustainable regional development. Driven by multiple pressures such as industrial effluents, agricultural runoff, municipal wastewater, and rainfall-related surface discharge, the physicochemical characteristics of rivers, lakes, and reservoirs have become more dynamic and heterogeneous. Water quality parameters related to acid–base status, oxygen conditions, suspended particles, ionic strength, nutrient enrichment, and organic pollution can jointly reflect the influence of external pollution inputs and internal water quality changes.

Therefore, the timely identification of abnormal variations in water physicochemical indicators is essential for pollution warning, environmental supervision, and water resource protection. However, with the widespread deployment of automatic monitoring stations and online sensors, water quality data are becoming increasingly high-frequency, multivariate, noisy, and nonlinear. Conventional anomaly judgment methods based mainly on manual experience or fixed thresholds are no longer sufficient for refined water quality monitoring [1-4]. With the advancement of intelligent monitoring technologies, machine learning techniques have become important tools for water quality anomaly detection and environmental early warning. Traditional statistical methods and threshold-based approaches are easy to implement and interpret, but they usually focus on exceedance detection of individual indicators and have limited ability to capture multivariate abnormal patterns and latent pollution processes. Methods such as support vector machines, k-nearest neighbors, local outlier factor, Isolation Forest, and Random Forest have provided new technical solutions for water quality anomaly recognition [5-8]. Among them, Isolation Forest can detect samples that deviate from the normal distribution without requiring sufficient anomaly labels, making it suitable for unsupervised preliminary screening of water quality abnormalities. Random Forest, by contrast, has strong classification stability, noise resistance, and feature importance analysis capability, which can further improve the reliability of anomaly discrimination [9-12].

Nevertheless, a single Isolation Forest model may be affected by the preset anomaly ratio and data fluctuations, while a single Random Forest model relies heavily on high-quality labeled samples. Therefore, effectively integrating unsupervised anomaly detection with supervised ensemble classification remains an important issue in the anomaly detection of water physicochemical indicators.

To address this issue, this study proposes an Isolation Forest-Random Forest fusion algorithm for anomaly detection of water physicochemical indicators. First, multi-source physicochemical monitoring data are cleaned, imputed, and standardized to construct a multivariate water quality dataset suitable for machine learning modeling.

Then, an Isolation Forest model is employed to conduct preliminary anomaly screening and calculate anomaly scores for identifying potential abnormal samples.

Subsequently, the anomaly information generated by

Isolation Forest is combined with the original physicochemical indicators and further input into a Random Forest model for anomaly reclassification and key indicator identification. Finally, the proposed fusion model is compared with the traditional threshold method, Isolation Forest, Random Forest, and other commonly used anomaly detection models to evaluate its detection performance and practical applicability. This study provides an applicable and interpretable technical approach for automatic water quality monitoring, anomaly warning, and refined water environmental management.

II. DATA AND PHYSICOCHEMICAL INDICATORS

The dataset was obtained from an automatic monitoring station at a representative urban river section in the selected city. This section is situated downstream of the main urban channel and is influenced by domestic wastewater discharge, rainfall runoff, shoreline construction, and upstream inflow changes, making it suitable for reflecting typical fluctuations in urban river water quality. The monitoring campaign covered the full period from 2021 to 2023 at an hourly resolution, generating about 26,280 raw observations. The continuously recorded variables covered multiple physicochemical dimensions, including thermal condition, acid–base status, oxygen level, turbidity, ionic strength, nutrient pollution, and organic contamination[13-15].

The selected physicochemical indicators include both basic water quality parameters and key variables related to nutrient and organic pollution. Water temperature affects biochemical reaction rates and dissolved oxygen concentration; pH reflects the acid-base condition of the water body; dissolved oxygen is an important parameter for evaluating self-purification capacity and ecological health; turbidity indicates suspended particle input, rainfall scouring, and sediment disturbance; electrical conductivity characterizes changes in dissolved ion concentration; ammonia nitrogen, total nitrogen, and total phosphorus mainly reflect nutrient input and eutrophication risk; and chemical oxygen demand represents organic pollution load. These indicators are not independent of each other, but may be jointly influenced by pollutant input, hydrological changes, and biochemical processes. Therefore, incorporating multiple indicators into the anomaly detection model can help identify multivariate abnormal patterns that cannot be captured by simple threshold-based methods. As shown in Table I.

During data preprocessing, the completeness of the raw automatic monitoring data was first examined. For duplicate records at the same timestamp, only the record with complete timestamp information and relatively complete indicator values was retained. Records with missing timestamps, blank values generated during instrument maintenance, or values that were physically unreasonable were removed. For short-term missing values, linear interpolation or neighboring-period mean imputation was applied. Data segments with continuous missing values longer than 6 h were excluded from model training to avoid artificial continuity caused by long-term interpolation.

Since the monitored water quality variables differ substantially in units and numerical magnitudes, Z-score standardization was performed before model training. The raw value of variable j in sample i is represented by x_{ij}, and the corresponding standardized value is calculated as follows:

$$x'_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \tag{1}$$

where μ_j and σ_j denote the mean and standard deviation of the j-th indicator, respectively. After data cleaning, missing value treatment, preliminary abnormal range screening, and standardization, a multivariate water quality sample set was obtained for model training and testing.

To construct the anomaly detection task, the samples were divided into normal samples and potential abnormal samples. Considering that reliable labels for real water quality anomalies are often difficult to obtain, this study adopts a framework of rule-based preliminary judgment, Isolation Forest screening, and Random Forest reclassification. Initial anomaly labels were generated according to reasonable indicator ranges, Isolation Forest anomaly scores, and monitoring experience, and were then used for subsequent Random Forest training.

III. ISOLATION FOREST-RANDOM FOREST FUSION METHOD

A. OVERALL FRAMEWORK OF THE MODEL

To address the problems of scarce abnormal samples, complex anomaly types, and insufficient stability of single models in water quality anomaly detection, this study constructs an Isolation Forest-Random Forest fusion method. The core idea of the proposed method is to first use Isolation Forest for unsupervised anomaly screening of multivariate water

TABLE 1. Physicochemical Indicators Used in This Study

Indicator	Abbreviation	Unit	Frequency	Environmental implication
Water temperature	WT	°C	1 h	Biochemical reaction rate
pH	pH	–	1 h	Acid-base status
Dissolved oxygen	DO	mg/L	1 h	Oxygen condition
Turbidity	Turb	NTU	1 h	Suspended particles
Electrical conductivity	EC	μS/cm	1 h	Dissolved ions
Ammonia nitrogen	NH3-N	mg/L	1 h	Nitrogen pollution
Total nitrogen	TN	mg/L	1 h	Nutrient level
Total phosphorus	TP	mg/L	1 h	Eutrophication risk
Chemical oxygen demand	COD	mg/L	1 h	Organic pollution load

quality samples and obtain the anomaly score and preliminary anomaly label for each sample.

Subsequently, the anomaly score generated by Isolation Forest is used as an enhanced feature and combined with the original physicochemical indicators as the input of the Random Forest model, thereby realizing anomaly reclassification and key indicator identification. Let the preprocessed water quality dataset be expressed as:

$$X = \{X_1, X_2, \ldots, X\} \tag{2}$$

where n denotes the number of samples, and X_i represents the i-th water quality sample with m physicochemical indicators. The Isolation Forest model first calculates the anomaly score S_i for each sample X_i. Then, S_i is concatenated with the original features to form an enhanced feature vector:

$$Z_i = (x_{i1}, x_{i2}, \ldots, x_i, S_i) \tag{3}$$

In this way, Random Forest can learn not only the nonlinear relationships among the original water quality indicators, but also the degree to which each sample deviates from the normal distribution, thereby improving the overall performance of anomaly detection.

B. ANOMALY SCREENING BASED ON ISOLATION FOREST

Isolation Forest is a data-driven anomaly detection method that can identify unusual samples without relying on labeled abnormal data. Its basic assumption is that abnormal samples are usually rare and significantly different from normal samples, and thus can be isolated more easily through random partitioning of the feature space. For water quality monitoring data, when a sample shows abnormal combinations among multiple physicochemical indicators, such as a sudden decrease in dissolved oxygen, simultaneous increases in turbidity and ammonia nitrogen, or an abrupt change in electrical conductivity, it is more likely to be isolated with a shorter path length in the isolation tree.

In the Isolation Forest algorithm, the data space is recursively divided by constructing multiple isolation trees. At each node, one variable is randomly chosen, and a random split point is used to separate the samples. This process continues until an individual sample is separated from the others or the predefined maximum tree depth is reached. Samples that require fewer splits to be isolated are generally regarded as more abnormal. Therefore, the anomaly degree of sample X_i is determined according to its average path length across all isolation trees, and the anomaly score is defined as follows:

$$S(X_i, n) = 2^{-E[h(X_i)]/c(n)} \tag{4}$$

where $E[h(X_i)]$ denotes the average path length of X_i across multiple isolation trees, and $c(n)$ represents the average path length of a binary search tree with n samples.

In general, an anomaly score closer to 1 indicates that the sample is more likely to be abnormal, whereas a score closer to 0 indicates that the sample is more likely to be normal.

C. ANOMALY RECLASSIFICATION BASED ON RANDOM FOREST

Random Forest achieves robust nonlinear classification by combining multiple decision trees. Each tree is trained on a Bootstrap-resampled subset of the data, while feature selection is randomly restricted at each split. By introducing randomness in both samples and variables, the model reduces the instability of individual trees and improves its tolerance to noise and data perturbations. For anomaly detection of water physicochemical indicators, Random Forest can learn complex interactions among different indicators and perform stable classification of normal and abnormal samples.

In this study, the Random Forest model takes the enhanced feature vector Zi as input, which includes both the original physicochemical indicators and the anomaly score generated by Isolation Forest. The model output is the predicted anomaly category of the sample:

$$\hat{y}_i = \mathrm{RF}(Z_i) \tag{5}$$

The final classification result of Random Forest is obtained by majority voting among multiple decision trees, which can be expressed as:

$$\hat{y}_i = \mathrm{mode}\{T_1(Z_i), T_2(Z_i), \ldots, T(Z_i)\} \tag{6}$$

where T_k represents the classification result of the k-th decision tree, and K denotes the number of decision trees in the Random Forest. In addition, Random Forest can output the importance score of each input variable, which helps interpret the possible causes of anomalies from an environmental perspective.

D. FUSION STRATEGY AND MODEL IMPLEMENTATION

This study adopts an anomaly score-enhanced feature strategy to integrate Isolation Forest and Random Forest.

Unlike simple model voting or result superposition, this strategy treats the anomaly score generated by Isolation Forest as a new input variable, enabling Random Forest to consider both the variation patterns of the original physicochemical indicators and the overall deviation degree of each sample from the normal distribution. This fusion mechanism enables Isolation Forest to provide anomaly prior information without requiring sufficient manual labels, while Random Forest corrects the preliminary screening results through ensemble classification. As shown in Table II and algorithm I.

ALGORITHM I. Isolation Forest–Random Forest Fusion Algorithm for Water Quality Anomaly Detection

Step	Procedure
Input	Dataset X, indicator number m, anomaly ratio r, and tree number K
Step 1	Standardize physicochemical indicators
Step 2	Train Isolation Forest using standardized data
Step 3	Calculate anomaly score S_i for each sample
Step 4	Generate preliminary labels using scores and thresholds
Step 5	Construct $Z_i = (x_{i1}, \ldots, x_{im}, S_i)$
Step 6	Split data into training and testing sets
Step 7	Train the Random Forest classifier
Step 8	Evaluate performance and feature importance
Output	Anomaly labels, probabilities, and key indicators

IV. RESULTS AND MODEL EVALUATION

A. DESCRIPTIVE STATISTICS OF PHYSICOCHEMICAL INDICATORS

To analyze the basic variation characteristics of physicochemical indicators in the urban river section, descriptive statistical analysis was first performed on the preprocessed monitoring data. Table III presents the mean, standard deviation, minimum, maximum, and coefficient of variation of the main water quality indicators from 2021 to 2023. Overall, clear differences were observed in the fluctuation intensity of different indicators. Turbidity, ammonia nitrogen, and total phosphorus showed relatively high coefficients of variation, indicating that these indicators were more sensitive to external inputs, stormwater runoff, and short-term pollution disturbances.

As shown in Table III, the maximum turbidity reached 116.42 NTU, which was much higher than its mean value, suggesting the occurrence of short-term high-turbidity events possibly caused by rainfall scouring, construction disturbance, or sediment resuspension. Ammonia nitrogen and total phosphorus also exhibited strong fluctuations, indicating potential effects of domestic wastewater input, agricultural non-point source pollution, or local drainage processes. The minimum dissolved oxygen concentration was 2.04 mg/L, implying that obvious oxygen-consuming processes may have occurred during certain periods.

B. ANOMALY SCREENING RESULTS OF ISOLATION FOREST

Based on the standardized multivariate water quality dataset, the Isolation Forest model was first applied for unsupervised anomaly screening. The contamination parameter was set to 0.05, assuming that approximately 5% of the samples may contain potential anomalies. Among the 26,280 monitoring records, 1,314 potential abnormal samples were preliminarily detected by Isolation Forest, accounting for 5.00% of the total samples. These abnormal samples were mainly concentrated during summer rainfall periods and local pollution disturbance events, characterized by increased turbidity, decreased dissolved oxygen, elevated ammonia nitrogen, and abrupt changes in electrical conductivity. As shown in Table IV.

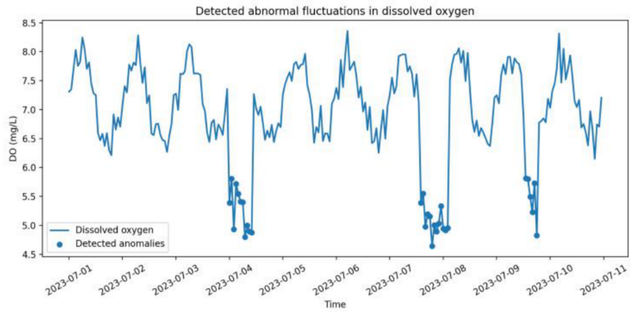

FIGURE 1. Detected Abnormal Fluctuations in Dissolved Oxygen

Figure 1 shows the anomaly detection results for dissolved oxygen during a typical monitoring period. Under normal conditions, dissolved oxygen displayed a clear diurnal variation pattern, while the detected abnormal points mainly occurred during periods of rapid short-term decline. This indicates that Isolation Forest can effectively capture sudden deviations in water quality time series. Combined with simultaneous changes in turbidity and ammonia nitrogen, some of these abnormal events may be associated with short-term pollutant input, stormwater runoff, or enhanced oxygen-consuming processes.

C. PERFORMANCE COMPARISON OF DIFFERENT ANOMALY DETECTION MODELS

The performance of the proposed IF-RF fusion model was assessed through comparative experiments with both rule-based detection and representative machine learning approaches. Model effectiveness was evaluated from multiple perspectives, including overall classification accuracy, anomaly identification capability, discrimination performance, and warning reliability. Among these metrics, Precision measures the reliability of detected anomalies, while Recall indicates the model's ability to capture actual abnormal events. The F1-score provides a balanced evaluation of these two aspects and is therefore more appropriate for water quality anomaly detection under class imbalance.

The comparison results in Table V indicate clear differences among the tested methods. The traditional threshold-based method produced the weakest detection performance, with an F1-score of 0.684, suggesting its limited ability to recognize complex multivariate anomalies.

LOF and One-Class SVM provided some improvement, but false alarms and missed detections were still observed. The

TABLE 2. Main Parameter Settings of the Proposed Fusion Model

Model	Parameter	Value	Description
Isolation Forest	Number of estimators	200	Number of isolation trees
Isolation Forest	Contamination	0.05	Assumed proportion of abnormal samples
Isolation Forest	Max samples	Auto	Number of samples used for each tree
Random Forest	Number of estimators	300	Number of decision trees
Random Forest	Criterion	Gini	Splitting criterion for classification
Random Forest	Max features	Square root	Number of candidate features at each split
Data split	Training/testing ratio	7:3	Used for model training and evaluation

TABLE 3. Descriptive Statistics of Physicochemical Indicators

Indicator	Mean	Std.	Min	Max	CV
WT	18.64	7.92	3.12	32.86	0.425
pH	7.42	0.38	6.18	9.11	0.051
DO	7.18	1.56	2.04	12.63	0.217
Turbidity	21.35	13.84	3.56	116.42	0.648
EC	486.72	118.65	219.40	923.78	0.244
NH3-N	0.64	0.41	0.05	3.86	0.641
TN	2.81	1.02	0.68	7.92	0.363
TP	0.126	0.074	0.018	0.681	0.587
COD	18.43	6.37	5.27	58.74	0.346

TABLE 4. Preliminary Anomaly Screening Results of Isolation Forest

Sample type	Number of samples	Proportion
Normal samples	24966	95.00%
Potential abnormal samples	1314	5.00%
Total samples	26280	100.00%

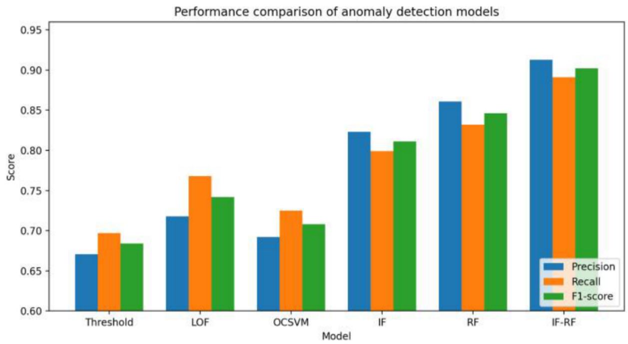

FIGURE 2. Performance Comparison of Anomaly Detection Models

standalone Isolation Forest model further increased the F1-score to 0.811, showing its effectiveness for initial anomaly screening in water quality data. Random Forest achieved a higher F1-score of 0.846, reflecting the advantage of supervised ensemble learning in anomaly classification.

Among all methods, the proposed IF-RF fusion model obtained the most favorable overall results. Its F1-score and AUC reached 0.902 and 0.962, respectively, while Accuracy, Precision, and Recall also remained at high levels. These results demonstrate that combining unsupervised anomaly scoring with supervised reclassification can improve both detection accuracy and model reliability.

Figure 2 further compares the Precision, Recall, and F1-score of different models. The IF-RF fusion model consistently outperformed the other models across all three metrics, particularly in Recall. This indicates that the fusion model can not only reduce false alarms but also lower the risk of missed detections, which is particularly important for water quality anomaly warning.

D. CONFUSION MATRIX ANALYSIS

To further evaluate the recognition ability of the IF-RF fusion model for normal and abnormal samples, a confusion matrix was generated on the testing set. The testing set contained 7,800 samples, including 7,393 normal samples and 407 abnormal samples. The model correctly identified 7,359 normal samples and 362 abnormal samples.

Only 34 normal samples were misclassified as abnormal, and 45 abnormal samples were misclassified as normal. As shown in Table VI and Figure 3.

The confusion matrix results show that the IF-RF fusion model had strong recognition ability for normal samples, with a false alarm rate of only 0.46%. Meanwhile, most abnormal samples were correctly identified, with a Recall of 88.94%. The proposed model therefore achieved a good balance between false alarms and missed detections, indicating its suitability as an anomaly warning module for automatic water quality monitoring systems.

E. CONTRIBUTION ANALYSIS OF KEY PHYSICOCHEMICAL INDICATORS

To further interpret the basis of anomaly discrimination, the contribution of different input variables was analyzed using Random Forest feature importance. Since the anomaly score generated by Isolation Forest was used as an enhanced feature in this study, feature importance analysis can reveal not only the contribution of the original water quality indicators, but also the role of the anomaly score in the fusion model. As shown in Table VII and Figure 4.

TABLE 5. Performance Comparison of Different Anomaly Detection Models

Model	Accuracy	Precision	Recall	F1-score	AUC	FAR	MAR
Threshold method	0.948	0.671	0.697	0.684	0.831	0.035	0.303
LOF	0.957	0.718	0.768	0.742	0.874	0.029	0.232
One-Class SVM	0.951	0.692	0.725	0.708	0.852	0.031	0.275
Isolation Forest	0.975	0.823	0.799	0.811	0.916	0.018	0.201
Random Forest	0.979	0.861	0.832	0.846	0.934	0.015	0.168
IF-RF fusion model	0.986	0.913	0.891	0.902	0.962	0.009	0.109

TABLE 6. Confusion Matrix Results of the IF-RF Fusion Model

True label	Predicted normal	Predicted abnormal
Normal	7359	34
Abnormal	45	362

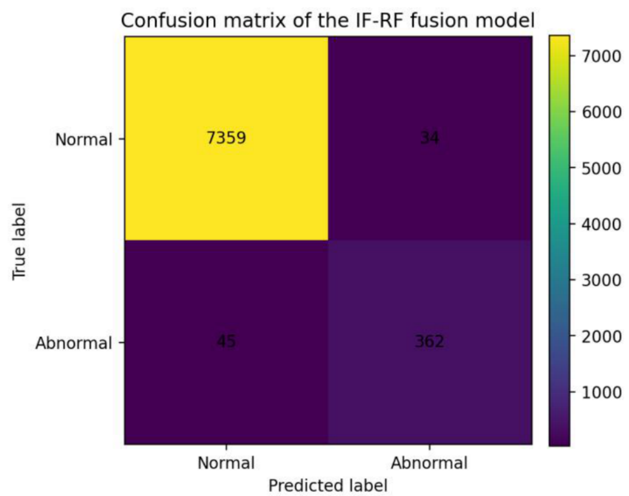

FIGURE 3. Confusion Matrix of the IF-RF Fusion Model

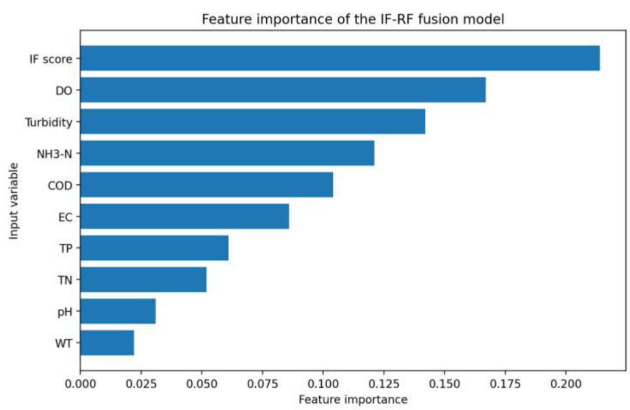

FIGURE 4. Feature Importance of the IF-RF Fusion Model

The results show that the Isolation Forest anomaly score had the highest importance value of 0.214, indicating that it provided effective anomaly prior information for Random Forest and played an important role in improving the performance of the fusion model. Among the original physicochemical indicators, dissolved oxygen, turbidity, ammonia nitrogen, and COD contributed most to anomaly recognition, suggesting that abnormal water quality changes in the monitored section were mainly associated with oxygen-consuming processes, suspended particle disturbance, nitrogen pollution input, and organic pollution load.

F. ABLATION ANALYSIS OF THE FUSION STRATEGY

To further verify whether the performance improvement of the proposed model was mainly derived from the fusion strategy, an ablation experiment was conducted by comparing three model settings: Random Forest using only the original physicochemical indicators, Random Forest using only the Isolation Forest anomaly score, and the proposed IF-RF fusion model using both the original indicators and the anomaly score. The purpose of this analysis was to examine the independent and combined contributions of the original water quality variables and the anomaly prior information generated by Isolation Forest (Table VIII).

The baseline Random Forest model, which relied solely on the original physicochemical variables, obtained an F1-score of 0.846 and an AUC of 0.934. This result suggests that the selected water quality parameters already provided meaningful discriminatory information for identifying abnormal conditions. However, its Recall was lower than that of the fusion model, suggesting that some abnormal samples with complex multivariate patterns could still be missed when only the original indicators were used.

When only the Isolation Forest anomaly score was used as input, the model obtained an F1-score of 0.781 and an AUC of 0.889. This result indicates that the anomaly score can provide useful prior information, but it is insufficient to fully represent the environmental meaning and interaction patterns of different physicochemical indicators.

In contrast, the proposed IF-RF fusion model achieved the best overall performance, with an Accuracy of 0.986, Precision of 0.913, Recall of 0.891, F1-score of 0.902, and AUC of 0.962. Compared with the Random Forest model without the Isolation Forest score, the F1-score increased by 0.056 and the AUC increased by 0.028. These improvements demonstrate that the Isolation Forest anomaly score provides complementary information beyond the original physicochemical indicators. Therefore, the performance gain of the proposed model is not simply caused by the use of Random Forest, but is closely related to the effective integration of unsupervised anomaly screening and supervised ensemble classification.

TABLE 7. Feature Importance of the IF-RF Fusion Model

Rank	Feature	Importance	Interpretation
1	IF score	0.214	Overall deviation degree from normal water quality patterns
2	DO	0.167	Oxygen condition and organic matter degradation
3	Turbidity	0.142	Suspended particles, rainfall runoff, and sediment disturbance
4	NH3-N	0.121	Nitrogen pollution and sewage-related input
5	COD	0.104	Organic pollution load
6	EC	0.086	Ionic concentration and external input
7	TP	0.061	Phosphorus input and eutrophication risk
8	TN	0.052	Overall nutrient level
9	pH	0.031	Acid-base condition
10	WT	0.022	Temperature-related background variation

TABLE 8. Ablation Analysis of the Proposed Fusion Strategy

Model setting	Input features	Accuracy	Precision	Recall	F1-score	AUC
RF without IF score	Original physicochemical indicators	0.979	0.861	0.832	0.846	0.934
RF with IF score only	Isolation Forest anomaly score	0.963	0.782	0.780	0.781	0.889
IF-RF fusion model	Original indicators + IF score	0.986	0.913	0.891	0.902	0.962

The ablation results further confirm the rationality of using the anomaly score as an enhanced feature. In practical water quality monitoring, some abnormal samples may not exceed a single indicator threshold but may deviate from the normal multivariate distribution. The Isolation Forest score helps capture this overall deviation, while Random Forest further learns the nonlinear relationships between the anomaly score and the original water quality indicators.

This complementary mechanism improves the model's ability to detect both obvious exceedance anomalies and hidden multivariate anomalies.

G. WATER QUALITY WARNING LEVEL DESIGN

To improve the practical applicability of the proposed anomaly detection model, this study further designed a water quality warning level scheme based on the predicted abnormal probability of the IF-RF fusion model. Instead of only providing a binary output of "normal" or "abnormal", the warning level scheme divides monitoring samples into different risk levels, which can provide more actionable information for environmental management and field inspection.

The abnormal probability output by Random Forest was used as the main basis for warning level classification. A higher abnormal probability indicates that the sample is more likely to deviate from the normal water quality condition. Considering the requirements of practical monitoring, four warning levels were defined: Level 0, Level 1, Level 2, and Level 3. Level 0 represents normal water quality fluctuation, while Level 3 indicates a high-risk abnormal event that requires timely verification and response.

As shown in Table IX, the proposed warning level design links the model output with environmental management actions. For Level 1 samples, the abnormal signal is relatively weak and may be caused by short-term natural fluctuations or minor sensor noise. Therefore, increasing the observation frequency is usually sufficient. For Level 2 samples, the abnormal probability is higher, and the monitoring system should further check the changes in key indicators such as dissolved oxygen, turbidity, ammonia nitrogen, and COD. For Level 3 samples, the model identifies a strong abnormal signal, which may indicate sudden pollutant input, severe oxygen depletion, or abnormal sensor behavior. In such cases, timely field verification and emergency response are necessary.

This warning level scheme can also improve the interpretability of the IF-RF fusion model in real monitoring scenarios. By combining abnormal probability, feature importance, and indicator variation, environmental managers can not only identify whether a sample is abnormal, but also determine the possible severity and potential causes of the anomaly. Therefore, the proposed method provides a practical bridge between machine learning-based anomaly detection and water quality management decision-making.

The thresholds used here serve model-based risk classification purposes and are not equivalent to regulatory water quality grades. In actual applications, these thresholds can be adjusted according to monitoring objectives, local water quality standards, historical pollution events, and management requirements. Future real-time monitoring systems can further combine warning levels with automatic message notification, upstream source tracing, and field sampling verification to form a closed-loop water quality anomaly response mechanism.

TABLE 9. Water Quality Warning Level Design Based on Model Output

Warning level	Abnormal probability range	Warning status	Interpretation	Suggested response
Level 0	$P < 0.30$	Normal	Water quality remains within normal fluctuation range	Routine monitoring
Level 1	$0.30 \le P < 0.50$	Slight abnormality	Short-term fluctuation may occur in one or more indicators	Increase observation frequency
Level 2	$0.50 \le P < 0.75$	Moderate abnormality	Potential pollution disturbance or multivariate abnormal pattern	Check key indicators and recent monitoring records
Level 3	$P \ge 0.75$	Severe abnormality	High-risk anomaly with strong deviation from normal conditions	Conduct field verification and emergency response

V. CONCLUSIONS

This study proposed an Isolation Forest–Random Forest fusion algorithm for anomaly detection of water physicochemical indicators, aiming to address the problems of scarce abnormal samples, complex anomaly types, and the limited ability of traditional threshold-based methods to identify multivariate abnormal patterns. In the proposed framework, Isolation Forest is first used to perform unsupervised anomaly screening and calculate anomaly scores for water quality samples. The anomaly scores are then used as enhanced features and combined with the original physicochemical indicators as the input of the Random Forest model for anomaly reclassification and key indicator identification. In this way, the model integrates the sensitivity of Isolation Forest to potential anomalies with the classification stability of Random Forest, thereby improving the overall reliability of water quality anomaly detection.

Using hourly monitoring data from an urban river section collected between 2021 and 2023, the experimental results confirm the effectiveness of the proposed IF-RF fusion model. Compared with conventional threshold-based detection and several representative machine learning methods, the fusion model achieved better overall performance in both anomaly recognition and classification reliability. Its F1-score and AUC reached 0.902 and 0.962, respectively, showing a strong capacity to separate abnormal disturbances from normal fluctuations in water quality. The confusion matrix results further indicate that the proposed model reduced missed alarms while keeping false alarms at a relatively low level, which supports its practical value for automatic water quality early-warning systems.

Feature importance analysis showed that the anomaly score generated by Isolation Forest made the highest contribution to the fusion model, confirming that it provided useful anomaly prior information for Random Forest classification.

Among the original physicochemical indicators, dissolved oxygen, turbidity, ammonia nitrogen, and COD contributed most to anomaly identification, suggesting that the abnormal variations in the monitored section were mainly associated with oxygen-consuming processes, suspended particle disturbance, nitrogen pollution input, and organic pollution load.

Several limitations should be acknowledged. The dataset used in this study was collected from only one monitoring section of an urban river, which means that the applicability of the proposed model to other watershed settings, pollution characteristics, and hydrological regimes still needs further verification. Second, the abnormal labels used for model evaluation were mainly derived from monitoring rules and data characteristics, and some complex pollution events may not have been fully verified by field investigation or manual expert diagnosis. Third, the proposed model mainly focuses on the static relationships among physicochemical indicators, while the temporal evolution characteristics of water quality anomalies have not been sufficiently modeled. In addition, external driving factors such as rainfall, flow rate, water level, temperature variation, and upstream discharge were not included in the current framework, which may affect the model's ability to explain the formation mechanism of certain abnormal events.

Future research can further incorporate external environmental and hydrological factors, introduce time-series deep learning models such as LSTM and Transformer, and integrate spatial correlations among multiple monitoring sections. Moreover, explainable methods such as SHAP can be combined with the proposed framework to enhance the interpretability of anomaly causes and improve the generalization ability, real-time performance, and management value of water quality anomaly detection.

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