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An intelligent and explainable IoT-Edge-Cloud architecture for real-time water quality monitoring

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ABSTRACT

Continuous and reliable monitoring of water quality is critical for early detection of environmental deterioration, yet conventional monitoring approaches are often slow and lack timely data availability. This study proposes an intelligent and explainable internet of things (IoT)–Edge–Cloud architecture to monitor water quality in real time, using IoT sensing, edge-based artificial intelligence (Edge AI), cloud-stream processing, and explainable artificial intelligence (XAI). The system calculates the water quality index (WQI) directly at the edge and predicts its evolution using a stacking ensemble model trained on physicochemical measurements taken from the Moulouya River Basin in Morocco. An explainability module based on Shapley additive explanations (SHAP) values gives a clearer image of the contribution of various parameters to WQI predictions, providing transparency of the features, which builds trust in the model's output. The proposed architecture was implemented as an end-to-end prototype and validated using a simulation-based experimental that mimicked realistic sensor dynamics and connectivity interruptions. The experimental results show strong predictive performance (R^2 =0.945), stable system operations, and reliable interpretability highlighting the potential of the proposed approach for scalable, intelligent, and transparent environmental monitoring.

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1. INTRODUCTION

The deteriorating condition of water quality is one of the most critical global environmental problems, especially in areas currently faced with increased stress due to urbanization, agricultural intensification, industrial emissions, and climate-induced changes within hydrological cycles. Conventional water quality monitoring and control tools, including but not limited to regular samplings and laboratory testing, are costly, labor-intensive, and poorly suited for detecting abrupt changes that can adversely affect aquatic ecosystems and human health [1], [2]. These limitations have driven growing interest in automatic or intelligent monitoring of water quality systems.

Despite recent advancements in environment monitoring technologies, many existing solutions remain predominantly cloud-centric, which can result in latency, limited responsiveness, and reduced functionality under unstable connectivity conditions. To address these challenges, recent studies have explored the integration of internet of things (IoT) sensors, edge computing, and artificial intelligence (AI) to support smarter water management [3], [4]. However, several limitations persist, including insufficient interoperability between monitoring, edge, and cloud layers, as well as the lack of explainable artificial intelligence (XAI) techniques to support transparent and trustworthy water quality prediction. Only a limited number of studies have shown this comprehensive end-to-end architectures capable of real-time operation and interpretability [3], [5].

In the Moulouya River Basin in northeastern Morocco, water quality monitoring is further complicated by pronounced spatial and temporal variability in physicochemical parameters driven by agricultural return flows, industrial discharges, and natural hydrological cycles [6]. To date, no functional monitoring system capable of early anomaly detection, continuous monitoring, and automatic interpretation of water quality data has been deployed in this region. Moreover, the integration of IoT, edge-based artificial intelligence (Edge AI), and explainable modeling approaches tailored to the specific characteristics of the Moulouya Basin remains largely unexplored.

To overcome these issues, this work presents a holistic IoT-Edge-AI-XAI architecture design for real-time water quality monitoring. This work encompasses continuous IoT sensing, edge computations of water quality index (WQI), prediction using ensemble approaches, cloud analytics, and Shapley additive explanations (SHAP)-based explainability to explain each prediction result. A comprehensive end-to-end prototype was developed using open-source resources and evaluated through simulation, enabling the emulation of realistic sensor behavior, connectivity disruptions, edge fallback mechanisms, and real-time visualizations. The novelty of this research is to prove that Edge AI and XAI can work hand-in-hand within an IoT-cloud system to accomplish water quality monitoring tasks that are both resilient, transparent, and performed in real-time. Compared to other studies, this work is unique because it offers: i) a functional prototype environment that simulates a true-to-life setting, ii) a traceable forecast engine that is capable of pointing out what factors contribute to variability within WQI, and iii) a versatile system design amenable to more intricate watersheds like the Moulouya Basin. The outcomes prove that this work is an improvement over other approaches toward making smart and trustful monitoring systems.

Recent research in water resources management highlights a growing shift toward integrating IoT, edge computing, and AI for a more responsive and intelligent assessment of the water system. This convergence method aims to overcome the challenges of centralized monitoring architectures by relocating analytical capabilities closer to data sources. It thereby improves system reactivity, scalability, and long-term sustainability efforts [1], [2], [7].

Gowri *et al.* [1] explain how intelligent water management systems can modernize urban and rural infrastructures by integrating IoT, edge computing, and AI. The authors emphasize decentralized decision-making as a key factor for optimizing monitoring, distribution, and quality control. They also identify socio-technical barriers, such as interoperability and policy integration.

Also, Jin *et al.* [2] discuss smart water management in relation to digital transformation, where they identify four key pillars: IoT-enabled sensing, digital twins for dynamic water dispatching, intelligent emergency response, and collaborative management. These examples illustrate that there is a growing interest within this community to leverage cyber-physical approaches that combine sensing infrastructures with digital twins. Edge computing plays a crucial role in enhancing bandwidth efficiency and resilience at the operational level.

Sreedevi *et al.* [7] present an edge-supported monitoring framework using Node-RED-based preprocessing. They achieve significant reductions in communication (more than 70%) overhead without degrading alerting accuracy. Such localized computing strategies are particularly relevant for rural and basin-scale monitoring contexts such as the Moulouya River.

Kukadiya and Meva [3] describe a broad range of IoT applications within smart city water management, including water quality monitoring, leaks, consumption analytics, and flood prediction. This literature review shows both what is possible with IoT on a mass scale and what is not, particularly concerning cybersecurity, compatibility, and expenses. As complementary work to such city-centric research, Sathio *et al*. [4] offer a real-time industrial water pollution assessment system integrating IoT technology with Edge Cloud processing. Employing multiparameter probes such as pH, temperature, turbidity, and total dissolved solids (TDS), they successfully demonstrated precise event detection regarding contamination, proving the effectiveness of hybrid Edge Cloud architecture within environmental monitoring applications.

Despite such breakthroughs, there exist some gaps to fill. Most available solutions exist for data acquisition and/or visualization aspects but fail to encompass edge analytics, big data analytics, and XAI together. Further, these works do not incorporate aspects related to model explainability and retrainability due to varying hydrological conditions.

2. PROPOSED ARCHITECTURE

Owing to technological and methodological gaps identified by some recent studies [1], [2], [4], [7], this paper attempts to present an intelligent and explainable system architecture for continuous and interpretable water quality assessment. The involved architecture of this system consists of five functional layers: sensing, Edge AI, cloud analytics, explainability, and application. Each layer works independently, but they are interconnected via message queuing telemetry transport protocol (MQTT) [2], [7]. It is an extension to the previously developed big data system by authors for intelligent management of water resources [8], incorporating real-time, edge-level intelligence, and interpretability. This design incorporates low latency processing, adaptability during learning processes, and explainability within AI-driven decision support.

2.1. Layer 1 – the sensing layer

The sensing layer comprises a distributed network of IoT devices, each outfitted with specialized multi-parameter probes specifically designed to measure a diverse array of physicochemical characteristics. This setup facilitates data collection and early detection of contaminants [9]. Data transmission occurs through various communication protocols, including Wi-Fi, GSM/4G, and LoRaWAN, selected based on the geographic location of the monitoring stations [9]. The sensor readings are encapsulated in lightweight JSON payloads and transmitted to an MQTT broker, facilitating efficient data management [10]. This architectural layer guarantees extensive spatial and temporal coverage of water quality metrics, thus establishing robust foundation for sub-sequent analytical and predictive endeavors [11].

2.2. Layer 2 – the edge AI layer

Low-power computing units such as Raspberry Pi and Jetson Nano perform real-time data preprocessing and inference at the network edge [12]. To deal with outliers and missing values, incoming data are filtered, normalized, and validated [13]. This method uses lightweight ensemble learning models that have been improved by metaheuristic algorithms like particle swarm optimization (PSO) and genetic algorithms (GA) to predict the WQI in real time. The system reduces network traffic and latency by processing data at the edge layer, providing immediate feedback even under intermittent connectivity [14]. Edge devices also buffer data during outages and automatically synchronize with the cloud once communication is restored [15].

2.3. Layer 3 – the cloud analytics layer

The cloud layer acts as the big data backbone for large-scale storage, processing, and model management. Apache flume and Apache sqoop ingest data streams into the Hadoop distributed file system (HDFS), enabling parallel and fault-tolerant storage [16]. Apache spark streaming performs real-time analytics, while Apache hive provides a structured query interface for data aggregation and retrieval [17]. This infrastructure enables periodic retraining of models to ensure they remain accurate and relevant, adapting to changing environmental conditions [18]. The retrained models are validated and securely deployed to edge nodes using APIs or message queues. In the cloud environment, applications are containerized with Docker and orchestrated through Kubernetes, allowing for elastic scalability and fault tolerance across distributed deployments [18].

2.4. Layer 4 – the explainability layer

The XAI layer improves the interpretation and understanding of AI models' predictions, which is especially crucial in environmental monitoring [5]. It utilizes algorithms such as SHAP, local interpretable model-agnostic explanations (LIME), and permutation importance to determine the influence of each input variable on the predicted WQI [5], [19]. Feature attribution visualizations illustrate how physicochemical parameters, such as electrical conductivity (EC), dissolved oxygen (DO), and ammonium (NH_4), affect the model's results, allowing environmental experts to validate and trust the AI-supported decisions [19].

2.5. Layer 5 – the application layer

The application layer transforms analytical results and explanatory insights into actionable intelligence through interactive dashboards [20]. By providing feature-importance plots produced by the XAI layer, spatial heatmaps of water-quality indicators, and dynamic visualizations of time-series trends, these dashboards help identify pollution hotspots and priority intervention zones [19], [20]. Using secure web and mobile interfaces, decision-makers may access complete reports or visualization modules, and when specific criteria are exceeded, real-time warnings are automatically generated [20]. This layer provides multi-user access, including operators, researchers, and regulatory agencies, and facilitates data-driven decision-making for adaptive and sustainable water management [20].

2.6. Data flow and communication

A complete data flow across the five layers of the suggested architecture is depicted in Figure 1. At the sensing layer, where IoT devices continuously detect physicochemical parameters and send readings to a MQTT broker, data acquisition starts. The Edge AI layer subscribes to these data streams, performing local preprocessing and near real-time inference of the WQI. Processed data and prediction results are transmitted to the cloud analytics layer via secure MQTT or hypertext transfer protocol secure (HTTPS) channels for large-scale aggregation, model retraining, and data storage.

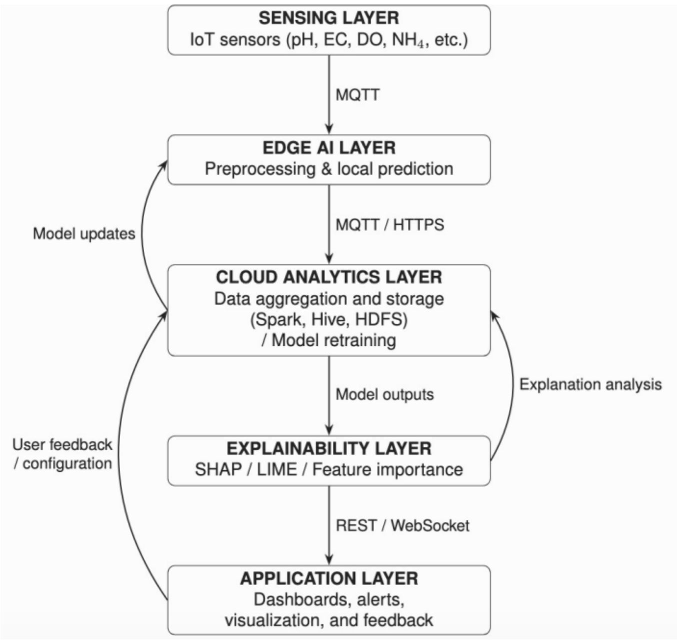


Figure 1. Data flow and communication across the five layers of the proposed intelligent and explainable architecture for real-time water quality monitoring

The explainability layer, implemented as a transversal cloud-based microservice, consumes model outputs and historical records to compute interpretability metrics using SHAP, LIME, and related algorithms. These explanatory insights are then integrated with analytical summaries and delivered to application layer (through RESTful APIs or WebSocket connections) for visualization, alert generation, and decision support. Bidirectional communication ensures system adaptability and transparency. Validated models and configuration updates flow from the cloud to edge nodes, while interpretability metrics and drift signals are returned from the explainability layer to enhance model monitoring and retraining. User feedback collected at the application level is also routed back to the analytics and explainability services to refine predictive performance and improve system responsiveness. This modular and feedback-driven communication design guarantees interoperability, scalability, and continuous improvement across all layers, enabling the system to adapt dynamically to evolving environmental conditions [10], [21].

2.7. Security, reliability, and scalability

Security, reliability, and scalability are considered at the architectural design level in the proposed system. Secure communication between system components is envisioned through standard encryption mechanisms such as transport layer security (TLS)/secure sockets layer (SSL) to protect data confidentiality and integrity during transmission [22]. In addition, token-based authentication and role-based access control (RBAC) are incorporated into the system design to regulate access to edge and cloud services and restrict interactions to authorized users and devices [23]. From a reliability and scalability perspective, the architecture is designed to support fault tolerance through modular microservices, redundant messaging brokers, replicated databases, and failover mechanisms [24]. Container-based deployment and orchestration technologies (e.g., Docker and Kubernetes) are considered to facilitate horizontal scaling and flexible integration of new sensors and analytical components as the system evolves [25]. It should be noted that these mechanisms are discussed to demonstrate the feasibility of secure, reliable, and scalable deployment.

3. IMPLEMENTATION AND SIMULATION
3.1. Experimental setup

To validate the proposed intelligent and explainable architecture for real-time water quality assessment, a complete prototype was deployed locally using open-source technologies. The experimental environment was implemented on a macOS workstation (Intel Core i5, 8 GB RAM) running Python 3.11, Node-RED v3.1, and the Eclipse Mosquitto 2.0 MQTT broker. The prototype reproduces the five layers of the proposed system: sensing, edge intelligence, cloud analytics, explainability, and visualization. Each layer was functionally mapped to a lightweight implementation component, allowing complete emulation of the end-to-end workflow. Table 1 summarizes the correspondence between each architectural layer and its implementation components, detailing each architectural layer, its functional role in the system, and the corresponding technologies used in the simulation.

Figure 2 illustrates the simulation-based experimental setup of the proposed IoT–Edge–Cloud architecture for water quality monitoring, covering data preprocessing, WQI computation, model training, sensor data simulation, edge inference, explainability, and visualization. The system is evaluated through software-based simulation to ensure reproducibility. As a complement, all scripts and configuration files used to implement this methodology are publicly available at https://github.com/sabouziane-coder/water-quality-iot-edge-xai, allowing independent verification of the experimental workflow.

Table 1. Implementation mapping of the proposed architecture

Layer	Implementation component	Main technologies
Sensing	Python sensor simulator (sensor_sim.py)	Paho-MQTT, JSON telemetry
Edge AI	Edge inference service (edge_inference.py)	scikit-learn ensemble (RF + XGBoost + extra trees), weighted WQI formula
Cloud stream	MQTT broker and Node-RED runtime	Mosquitto QoS 1, buffered publishing
Explainability	Flask microservice (xai_service.py)	SHAP (TreeExplainer / simulated impacts)
Visualization	Node-RED dashboard	Real vs predicted WQI chart, gauge (Moroccan standards), SHAP table

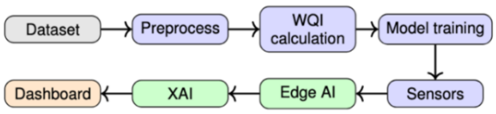


Figure 2. Simulation-based experimental workflow of the proposed intelligent IoT–Edge–Cloud system for water quality monitoring

Figure 3 presents the global Node-RED flow responsible for orchestrating the data ingestion, edge predictions, explainability requests, and dashboard visualization. This diagram illustrates the real-time interactions between MQTT topics, inference formatting nodes, XAI microservice calls, and visualization widgets. It confirms the operational integration of all layers.

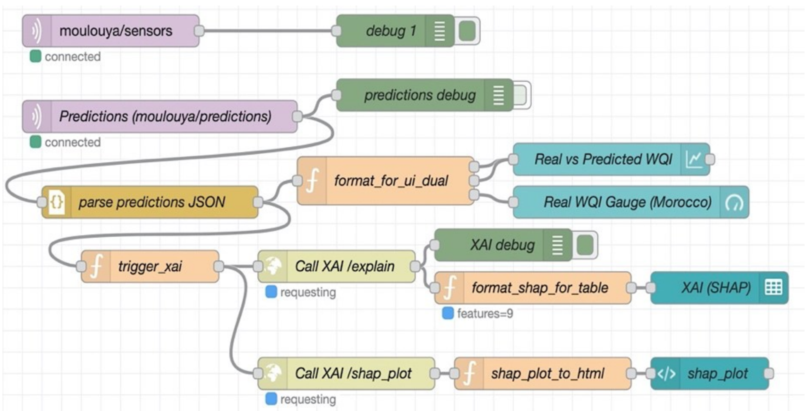


Figure 3. Global Node-RED flow implementing the real-time orchestration between sensing, edge inference, explainability, and dashboard visualization

The sensing and edge layers were implemented in Python. Node-RED provided the runtime environment for message routing, integration logic, and graphical monitoring. This modular setup enabled real-time validation of data acquisition, WQI computation, machine-learning inference, and explainability integration within a unified execution pipeline.

3.2. Dataset and model training

The dataset used in this study was collected from field sampling campaigns conducted at 22 monitoring stations across the Moulouya River Basin in northeastern Morocco [6]. In total, 66 samples of three hydrological periods (March–April, May–June, and July–August 2014) were collected over representative seasonal transitions. The physicochemical parameters analyzed included water temperature (T °C), pH, EC, DO, biochemical oxygen demand (BOD_5), orthophosphates (PO_4), NH_4, sulfate (SO_4), and nitrate (NO_3) [6]. Although the dataset size is limited, it reflects realistic constraints commonly encountered in river basin monitoring, where field sampling campaigns are often costly and logistically demanding. The inclusion of multiple monitoring stations and distinct hydrological periods ensures both spatial and seasonal representativeness [6]. An overview of the variability observed across the physicochemical parameters is provided in Table 2, which summarizes their minimum, maximum, mean, and quartile values.

Table 2. Descriptive statistics of measured physicochemical parameters used for WQI modeling (n =66)

Statistic	T (°C)	pH	EC (μS/cm)	DO (mg/L)	BOD_5 (mg/L)	PO_4 (mg/L)	NH_4 (mg/L)	SO_4 (mg/L)	NO_3 (mg/L)
Count	66	66	66	66	66	66	66	66	66
Mean	20.34	7.42	1180.09	7.00	5.86	0.67	0.36	182.38	14.58
Std	4.89	0.43	610.59	1.52	7.07	0.82	0.87	136.01	23.88
Min	11.10	6.12	413.00	1.01	0.35	0.01	0.01	27.00	1.12
25%	15.70	7.11	528.50	6.48	1.90	0.02	0.02	55.00	2.76
50%	21.30	7.40	1260.00	7.21	3.43	0.17	0.04	144.50	5.85
75%	24.88	7.74	1706.75	7.90	7.29	1.09	0.10	307.50	10.46
Max	28.60	8.90	2249.00	9.80	39.55	2.79	4.07	495.00	102.95

The data set was subjected to a systematic preprocessing phase; the quality of the data was ensured by a step-by-step procedure before model build process. No missing values were detected in the dataset; however, it was necessary to reorganize the data in order to standardize feature alignment and parameter naming. Measurement scales were normalized using standard feature scaling to ensure comparable parameter ranges and stable model training. We split the cleaned dataset into one set (70%) for training and one set for testing (30%) to facilitate model training, validation and performance estimation.

Model learning was conducted on a stacking ensemble learning approach that uses three base regressors: random forest (RF), XGBoost, and adaptive boosting (AdaBoost). This approach was chosen due to its ability to model complex and nonlinear relationships that commonly characterize environmental datasets. Previous studies have shown that ensemble strategies outperform single models by leveraging the complementary strengths of diverse learners and mitigating their individual biases [20], [26]. A ridge regression model was employed as the meta-learner to combine base model predictions and enhance generalization. Hyperparameters for each learner were optimized using grid-based search within cross-validation loops.

To assess model robustness and generalization, 5-fold cross-validation was conducted. The training and hyperparameter optimization were conducted in Python with scikit-learn framework. Finally, we serialized the final optimized ensemble model to model.pkl and served at prototype edge layer for real-time prediction of WQI from live sensor data streams. For operational deployment, the trained model can be periodically retrained as new sensor data become available. Retraining may be scheduled seasonally or triggered by performance degradation, allowing the system to adapt to long-term environmental changes and potential data drift.

3.3. Model performance evaluation

This research used the held-out test set (30% of the dataset) as a test set to evaluate the predictive performance of the trained models. The assessment focused on three key metrics: the root mean square error (RMSE), the mean absolute error (MAE), and the coefficient of determination (R^2). The stacking ensemble achieved a high R^2 (0.945), indicating that more than 94% of the variance in the WQI is explained by the model. The low RMSE (0.1149) and MAE (0.082) values reflect minimal deviation between observed and predicted WQI values. Cross-validation results (0.901±0.129) further confirmed stable performance across folds. The higher variance reflects the limited dataset size (N =66), a known constraint in field-based water quality monitoring. These findings demonstrate the suitability of the proposed ensemble model for edge-level, real-time water quality monitoring.

3.4. Weighted water quality index computation

The WQI was calculated using the weighted arithmetic method. Each physicochemical parameter was assigned a weight (Wi) ranging from 1 to 5 according to its relative importance in assessing water quality [27]. For each parameter, a quality rating (Qi) was derived from the ratio between the measured concentration (Ci) and the corresponding standard limit (Si), using (1).

$$Q_i = \left(\frac{C_i}{S_i}\right) \times 100 \quad (1)$$

The overall WQI was computed as the weighted mean of all sub-indices, using (2).

$$WQI = \frac{\sum_{i=1}^{n} W_i Q_i}{\sum_{i=1}^{n} W_i} \quad (2)$$

In this study, TDS were calculated from EC and incorporated into the WQI computation, using (3). This inclusion provides a more comprehensive assessment of mineralization and salinity, which are critical indicators of water quality in the Moulouya Basin.

$$TDS = 0.64 \times EC \quad (3)$$

The computed WQI values were interpreted according to the classification proposed [27], where lower values denote better water quality conditions. The adopted classes are: excellent (WQI <25), good (25≤ WQI <50), moderate (50≤ WQI <75), poor (75≤ WQI <100), and very poor (WQI ≥100). These WQI values provide a standardized synthesis of the measured physicochemical data, allowing comparison across stations and sampling periods. They also serve as quantitative reference targets for model training and for validating the predictive performance of the edge deployed ensemble model.

3.5. Simulation procedure

The sensing layer was emulated through a Python based simulator that continuously published realistic water quality readings (pH, EC, DO, BOD_5, PO_4, NH_4, SO_4, NO_3, and T °C) to the MQTT topic moulouya/sensors at three-second intervals. The Edge AI service subscribed to this topic and computed a real time WQI based on the weighted aggregation of all parameters, while simultaneously generating a predicted WQI using the trained ensemble model (model.pkl). The resulting data stream was published to the topic moulouya/predictions, which fed the node-RED dashboard for real-time monitoring and analysis.

The dashboard displayed both the computed (real) and model-estimated (predicted) WQI values over time. A dual-series graph enabled direct comparison between the two outputs, allowing validation of the responsiveness and the consistency of the model under continuous data flow. Figure 4 presents the temporal evolution of the real versus predicted WQI during the simulation. This figure illustrates the model's real-time predictive performance and its ability to track short-term WQI fluctuations

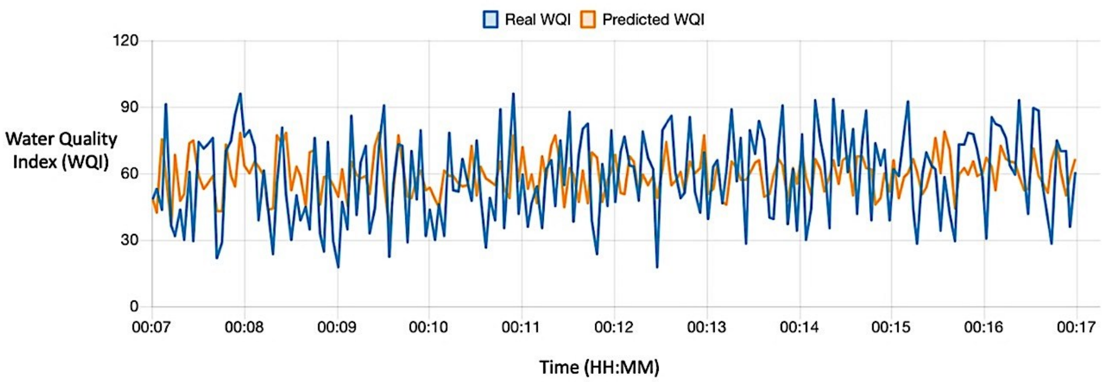


Figure 4. Temporal evolution of observed and predicted WQI values during the simulation

When the sensor stream was intentionally interrupted, the edge node detected the inactivity (15 s timeout) and automatically switched to a prediction-only mode. This ensured uninterrupted operation despite the absence of new sensor data. Each enriched message also triggered an HTTP POST request to the explainability microservice (xai_service.py), which returned feature-level SHAP values quantifying the contribution of each input parameter to the predicted WQI.

3.6. Explainability integration

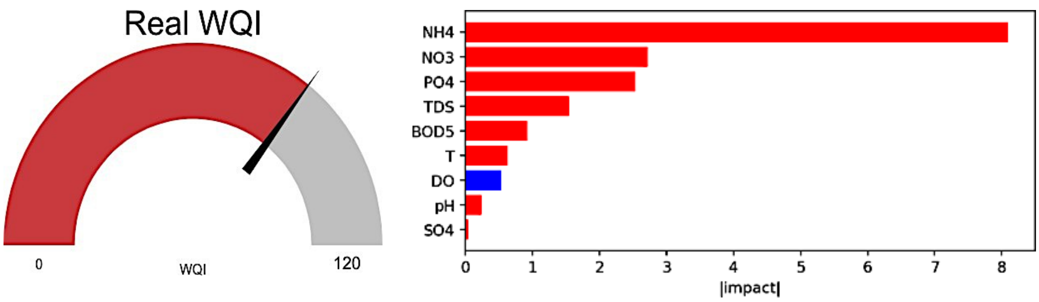
In order to improve the transparency of the model decision-making mechanism, we have incorporated the explainability layer to this system. For every new prediction, the XAI microservice is granted the entire feature vector from the edge layer as input, and computes SHAP values, reflecting the contribution magnitude of each input parameter to the predicted WQI. The resultant explanations are also sent to the Node-RED dashboard, which displays them as a dynamically updated feature-impact table to show users in real time which features are contributing to WQI changes. Figure 5 demonstrates, for a given prediction, a visualization of the generated dynamic of the real-time feature-impact table in the simulated design, highlighting the relative contribution of each physicochemical parameter to WQI prediction. This integration enables domain experts to assess whether the model's reasoning is consistent with known physicochemical relationships governing water quality variations in the Moulouya River Basin.

Feature	Value	Impact	Percent
NH4	0.37	10.212	61%
PO4	0.91	2.5	14.9%
BOD5	6.92	1.029	6.2%
SO4	215.79	0.876	5.2%
T	35.32	0.678	4.1%
TDS	1148.63	0.616	3.7%
NO3	7.68	0.357	2.1%
DO	5.31	-0.266	1.6%
pH	8.87	0.199	1.2%

Figure 5. SHAP-based feature impact table for a representative WQI prediction

3.7. Dashboard and visualization

A lightweight visualization layer was implemented using the Node-RED dashboard to support monitoring and decision making. The dashboard provides three complementary views: i) a WQI gauge offering an immediate interpretation of water quality status, ii) a time-series plot comparing observed and predicted WQI values, and iii) a feature-impact visualization (table and bar chart) highlighting the most influential parameters driving model predictions. These components can be customized to the operational needs of environmental agencies, allowing users to track pollutant fluctuations, verify model behavior, and identify emerging anomalies. Figure 6 presents representative dashboard views integrated into the prototype, demonstrating the system's suitability for real-time alerting and decision-support scenarios.



(a) (b)

Figure 6. Node-RED dashboard views obtained from the simulated environment: (a) a real-time WQI gauge for instant status and (b) feature impact view produced by the explainability microservice

4. RESULTS AND DISCUSSION

The proposed intelligent water quality monitoring architecture was designed and tested by implementing a fully end-to-end simulation to evaluate the approach on a real-time monitoring system in the Moulouya River Basin. Continuous multi-parameter measurements representing the natural variability of the water quality, commonly observed in the basin, were continuously generated and transmitted over MQTT to the edge layer. The edge service adeptly processed the high-frequency data stream and computed the authentic WQI using the weighted arithmetic approach. Concurrently, the stacking ensemble model generated forecasted WQI values, providing consistent and adaptive estimations aligned with the fluctuations of the input data.

In the temporal plots of real and predicted WQI values, the two curves show close agreement, sharing similar trends and a gradual evolution over time (Figure 4). This confirms the effectiveness of ensemble learning models in predicting WQI and managing real-time data streams. Additionally, the system maintained continuous output during simulated sensor outages by automatically switching to prediction-only mode (Figure 7). This capability demonstrates its operational robustness in scenarios with degraded communication.

```
[edge] Loaded model: edge/model.pkl
[edge] MQTT loop started.
[edge] Waiting for sensor data...
[edge] Connected to MQTT broker (rc=0)
[edge] Outgoing buffer flushed.
[edge] No sensor updates for 15.0s → prediction-only mode.
[edge] No sensor updates for 15.0s → prediction-only mode.
```

Figure 7. A demonstration of the local execution of the edge inference service, showcasing model loading, MQTT connection, and an automatic switch to prediction-only mode after the sensor times out

The SHAP-based analysis of the model’s explainability provided valuable insights. The feature impact scores calculated by the explainability microservice revealed the dominant influence of nutrient-related parameters. As shown in Figure 5, NH_4, emerged as the dominant contributor, accounting for approximately 61% of the total feature impact for the illustrated prediction. PO_4 and BOD_5 followed, indicating the strong influence of nutrient enrichment and organic pollution on water quality degradation. SO_4, temperature (T), and TDS (derived from EC) exhibited moderate positive contributions, reflecting mineralization and thermal effects. In contrast, DO showed a negative SHAP contribution, consistent with its known role as a mitigating factor in polluted aquatic systems. NO_3 presented a smaller but non-negligible contribution, suggesting localized or episodic nutrient inputs. These findings are fully consistent with empirical observations reported for the Moulouya Basin, where nutrient enrichment and organic load constitute the primary drivers of water quality degradation [6]. By providing both the magnitude and direction of feature impacts, the SHAP analysis enhances interpretability and supports informed decision-making for targeted pollution control.

The Node-RED dashboard showcased the system’s effectiveness in providing real-time decision support. The pollution gauge provides a clear and immediate interpretation of water quality status through color-coding. Additionally, a plot comparing observed versus predicted WQI facilitated ongoing validation of the model’s reliability. Furthermore, the feature impact table is updated with each inference, allowing experts to identify the parameters responsible for short-term variations. This process confirmed that explainability enhances transparency and fosters operational trust. Overall, the experimental findings confirm the feasibility and effectiveness of our proposed IoT-Edge-AI-XAI architecture. The system provides stable predictions, interpretable outputs, and real-time responses, indicating strong potential for use as a decision-support tool for continuous environmental monitoring in the Moulouya River Basin.

5. CONCLUSION

We have developed a smart and interpretable architecture for real-time water quality assessment that combines IoT sensing, Edge AI inference, cloud-stream processing, and model interpretation. A full end-to-end prototype was realized locally indicating that the system is capable of reliably obtaining physicochemical measurement data, computing the WQI at the edge, and making accurate predictions using a stacking ensemble model. The transparency was enhanced via the explainability layer, such that the contribution of every parameter to the predicted WQI was made available in real time. The model exhibited stable performance during the simulation, and automatic switching to prediction-only mode was performed under sensor disturbance conditions, highlighting the system's robustness and the potential of continuous analysis. The feature impact evaluation reliably detected NH_4, NO_3, PO_4, and organic load as the key contributors for the variations associated with WQI, which is in line with the prevailing pollution behavior observed in the Moulouya River Basin. Beyond technical aspects, the proposed framework holds benefits as well, in providing a potential space for more human-oriented and sustainable intelligence strategies. Future releases may integrate gamification in the application layer to support stakeholder participation, educational efforts and participatory oversight. Implementing intuitive, motivational, and interactive interfaces in such enhancements can increase public awareness, while facilitating proactive community engagement in water quality. Finally, the incorporation of Edge AI, XAI, feedback-based learning in a single architectural model represents a huge step forward from the current methods, providing a transparent, adaptable and scalable means for the intelligent water quality evaluation and long-term conservation.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Badraddine Aghoutane	✓	✓	✓	✓		✓	✓		✓	✓	✓	✓	✓	
Aniss Moumen		✓	✓	✓						✓	✓			
Anas El Ouali				✓	✓	✓	✓	✓		✓				
Ali Essahlaoui				✓	✓		✓	✓		✓		✓	✓	
Abdellah El Hmaidi	✓			✓	✓	✓	✓	✓		✓		✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The dataset used in this study, along with the scripts and configuration files implementing the proposed methodology, is available in a public repository in GitHub at https://github.com/sabouziane-coder/water-quality-iot-edge-xai.

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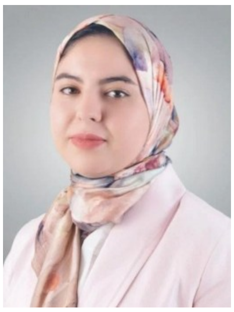

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