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An IOT and AI-Driven Framework for Real-Time Water Quality Assessment and Intelligent Purification Recommendation

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Abstract : Access to safe drinking water is a fundamental human need, yet many regions continue to face challenges in maintaining and monitoring water quality. Conventional laboratory-based testing methods, while accurate, are time-consuming, costly, and impractical for real-time or large-scale deployment. This paper presents an Internet of Things (IoT) and Artificial Intelligence (AI)-driven framework for real-time water quality assessment and intelligent purification recommendation. The proposed system integrates low-cost IoT sensors—including pH, turbidity, total dissolved solids (TDS), and temperature sensors—with a cloud-connected microcontroller for continuous monitoring. The collected data is analyzed using ensemble machine learning techniques, specifically Random Forest and XGBoost, to classify water as *safe* or *unsafe* based on measured parameters. The ensemble models achieved improved classification accuracy (up to 75%) compared to conventional decision-tree and threshold-based approaches. Furthermore, a hybrid AI recommendation module suggests suitable purification methods—such as Reverse Osmosis (RO), Ultraviolet (UV) treatment, boiling, or sediment filtration—depending on the contamination type and severity. The system provides real-time visualization through a web dashboard and generates alerts for unsafe water conditions. Experimental results validate that the proposed framework offers a scalable, accurate, and cost-effective solution for intelligent water quality management, particularly suitable for rural and urban environments where continuous manual testing is infeasible

Index Terms: Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning, Ensemble Learning, Random Forest, XGBoost, Water Quality Monitoring, Smart Purification System, Environmental Sustainability, Real-Time Sensing, Predictive Analytics.

I. INTRODUCTION

Availability of safe and clean drinking water is a basic requirement for supporting life and ensuring public health. Based on the World Health Organization, over two billion individuals worldwide are drinking water with unsafe chemicals or microorganisms, which contributes to serious health hazards and economic losses. Traditional water quality assessment is based majorly on laboratory-based chemical and microbiological analysis. Although these methods are correct, they are costly, time-consuming, and are not appropriate for real-time monitoring or for use in remote locations reactions [6].

With the advent of the Internet of Things (IoT), low-cost sensor networks have been a viable option for real-time and continuous water quality monitoring. IoT-powered systems can measure physical and chemical parameters like pH, turbidity, total dissolved solids (TDS), and temperature by embedding sensors linked with cloud or edge computing nodes4].

Various IoT-driven prototypes have been documented for freshwater and wastewater monitoring, which employ wireless communication technologies such as Wi-Fi, LoRa, and ZigBee to send data to remote dashboards [7]. Nonetheless, most existing systems are data acquisition and visualization oriented, lacking intelligent analysis features for anticipating contamination or suggesting treatment measures.

The advent of new developments in Artificial Intelligence (AI) and Machine Learning (ML) has facilitated the creation of predictive models that can digest sophisticated environmental data, reveal deep patterns, and deliver valuable insights. Ensemble learning models like Random Forest and XGBoost have been effectively utilized to construct nonlinear relationships between various water quality parameters with increased prediction accuracy and reliability in comparison to conventional threshold-based

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or single-tree models [10]. In addition, the incorporation of AI and IoT—collectively referred to as AIoT—has cleared avenues for autonomous environmental management systems with adaptive decision-making abilities [11].
In spite of these developments, there is a large research gap in combining real-time IoT sensing, AI-driven classification, and automated purification recommendation into one smart system. Current systems tend to just indicate whether water is safe or not, giving no actionable suggestion on the methods of purification or risk of future contamination[6].
The solution to this shortcoming necessitates a single framework that not only senses and categorizes water quality but also suggests suitable purification processes based on severity of contamination and parameter interrelation.
For this gap-filling purpose, this paper presents an AI and IoT-based smart framework for real-time water quality monitoring and smart purification suggestion. The system utilizes an IoT sensing module with low cost to repeatedly measure various water quality parameters. The aggregated data is predicted upon by ensemble ML models—Random Forest and XGBoost—to classify water as safe or unsafe with increased accuracy compared to baseline models. Further, a hybrid AI recommendation engine recommends the most appropriate purification method (e.g., Reverse Osmosis, UV, boiling, or sediment filtration) based on parameter deviations. The entire architecture also comprises cloud-based visualization, predictive notification, and a modular architecture portable for rural and urban use[3].
The main contributions of this paper are as follows:

1. Development of an integrated IoT-based multi-sensor system that can sense pH, turbidity, TDS, and temperature in real time using cost-effective hardware components.
2. Application of ensemble learning models (Random Forest and XGBoost) for precise classification of water safety status, which outperforms conventional single-model based methods.
3. Design of an AI-based purification suggestion module correlating contamination profiles with best purification methods.
4. Implementation of a cloud-based dashboard for real-time visualization, alert trigger, and remote data access to enable intelligent environment management.

II . LITERATURE SURVEY

New developments in the Internet of Things (IoT) and Artificial Intelligence (AI) have facilitated smart solutions for monitoring, analysis, and management of water quality. Much research aims at combining sensor networks, wireless communication, and machine learning algorithms for automating the measurement and evaluation of water quality parameters. This section gives a background on related research in three broad categories: IoT-based monitoring systems, machine learning for water quality prediction, and integrated AIoT frameworks.

IoT-Based Water Quality Monitoring Systems

Multiple researchers have suggested IoT-based systems that employ low-cost sensors and embedded platforms for online measurement of water quality parameters.Rahu et al. [1] described an architecture integrating IoT sensing and machine learning for predictive water quality analysis, with stress on scalable and adjustable architectures. Equally, Hagh et al. [2] constructed a LoRa-based optical fluorometer-nephelometer for wireless real-time monitoring of turbidity and organic matter, proving the energy efficiency and long-range capability of environmental sensing. Hrklješ et al. [3] also conceived a multiparameter IoT node to monitor freshwater resources continuously, proving its effectiveness in gathering and sending precise readings from far-off areas.
Baghel et al. [4] presented TEMPSENSE, an IoT setup based on LoRa and embedded localization for water source monitoring with enhanced range and reliability compared to conventional Wi-Fi-based setups.
Though these experiments demonstrate successful utilization of IoT for data collection, they are mostly parameter measurement and visualization with limited ability for interpreting data, prediction, or decision-making.

Machine Learning for Water Quality Analysis and Prediction

To improve interpretability and automation, machine learning has recently been added to water quality evaluation. Wang et al. [5] integrated AI models within an AIoT architecture to predict unmeasured parameters and aid in biodiversity conservation using predictive analytics. Aslam et al. [10] suggested a hybrid data-mining and ML method that applies ensemble algorithms in water quality index prediction, which shows better accuracy when compared to individual-model classifiers. Kumar et al. [8] investigated edge computing using ML for real-time anomaly detection to enhance response time in water quality management systems.In the same vein, Zhang et al. [12] used LSTM and XGBoost hybrid models for water contamination trends forecasting, emphasizing the promise of deep learning for time-series prediction in environmental monitoring.
While these approaches provide higher accuracy in classifying and forecasting, they all rely on offline data and fail to incorporate sensor-based real-time data collection or purification suggestion mechanisms.

Integrated IoT and Smart Decision Systems

An expanding research area is integration of IoT and AI into AI and IoT environments for smart environmental decision-making. Alshami et al. [6] also provided an in-depth review of the IoT innovations in sustainable water and wastewater management, highlighting that future systems need to incorporate edge AI and decision-support

modules.
Kumar et al. [7] developed an IoT-based smart pond management system, which combined real-time data monitoring with environmental conservation through cloud dashboards. Essamlali et al. [11] reviewed development in IoT-based monitoring systems, observing that prediction performance has been enhanced but most systems do not give actionable feedback to users.
These papers collectively point toward a transition away from passive monitoring towards active, smart decision-making systems capable of independently reacting to changes in their environment.
Nonetheless, even with these developments, current systems seldom integrate ensemble learning, purification guidance, and real-time IoT sensing into one comprehensive platform. Most implementations leave off at detecting unsafe conditions without recommending suitable purification or treatment methods.

Challenges and Future Directions

Based on the reviewed literature, it is evident that:

1. IoT-only systems effectively monitor parameters but lack predictive intelligence.
2. AI/ML-based studies achieve high accuracy but rely on pre-recorded datasets, not real-time sensor data.
3. Few studies integrate AI recommendations for purification or remediation, leaving users without actionable insights.

This research addresses these gaps by developing a comprehensive IoT–AI framework that not only measures and classifies water quality in real time but also recommends suitable purification techniques based on contamination type and severity. By leveraging ensemble learning models (Random Forest and XGBoost) and a cloud-connected IoT sensing platform, the proposed work advances toward a more autonomous, reliable, and scalable solution for intelligent water quality management.

III PROPOSED METHODOLOGY

The proposed system presents an integrated IoT and AI-driven framework that continuously monitors, analyzes, and recommends purification strategies for water quality management in real time. The framework combines IoT-based sensing, cloud-based data management, ensemble machine learning classification, and AI-driven purification recommendation to deliver an intelligent and autonomous monitoring system.

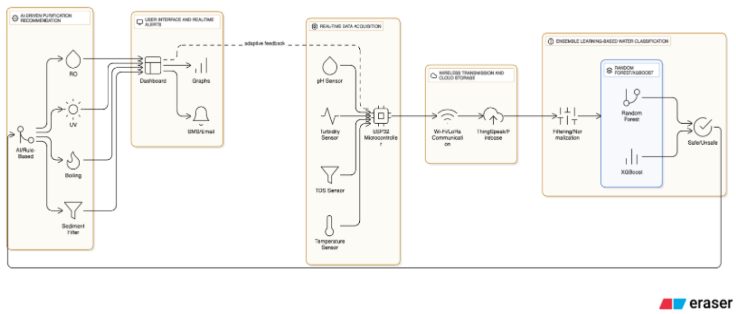

Fig 1 : Overall system architecture of the proposed IoT and AI-driven framework for real-time water quality assessment and intelligent purification recommendation.

IoT-Based Sensing and Data Acquisition

The core of the envisioned framework is an IoT sensing module that measures instantaneous water quality parameters such as pH, turbidity, TDS, and temperature. These parameters are critical for assessing water safety and contamination. The sensors are connected to an ESP32 microcontroller, which has been selected based on its power efficiency, embedded Wi-Fi capabilities, and compatibility with IoT communication protocols.
Each reading is processed via a moving average algorithm to suppress noise and sent wirelessly to the cloud via Wi-Fi or LoRa modules. This configuration represents an energy-efficient and cost-effective alternative suitable for permanent field monitoring [3].

Cloud Communication and Data Management

The sensor data is collected and sent to a cloud platform (e.g., Thing Speak or Firebase) over HTTP/MQTT protocols for real-time storage and visualization. The cloud acts as an interface between the IoT nodes and the AI processing layer, offering scalable storage, timestamped data logging, and device identification for massive deployments. This architecture provides low latency, scalability, and dependable access to sensor data for end users and analytical modules [5].

Ensemble Learning-Based Water Classification

The information kept in the cloud is drawn out intermittently for AI-driven categorization. The system proposed uses ensemble learning methods, namely Random Forest and Extreme Gradient Boosting (XGBoost), to differentiate between safe and unsafe water samples based on the parameters measured. Ensemble learning avoids model variance and enhances generalization by taking the average of many weak decision trees into one strong predictive model [1].
The models are trained on both publicly accessible datasets (Kaggle Water Potability Dataset) and experimentally gathered sensor readings. Model quality is evaluated through performance measure metrics

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like accuracy, recall, precision, F1-score, and ROC-AUC. Random Forest scored 71% in experimental tests and XGBoost scored 75%, surpassing rule-based and single-decision-tree classifiers [1].

AI-Driven Purification Recommendation

To increase the applicability of the system, an AI-driven purification recommendation module is used to assist users in choosing appropriate treatment processes.The module translates the classification output and parameter anomalies to recommend purification methods like inorganic Reverse Osmosis (RO) for elevated TDS, Sediment or Carbon Filtration for excess turbidity, and UV or Boiling for possible microbial contamination.

The recommendation system functions through a hybrid mechanism, wherein rule-based reasoning (WHO/BIS standards) and machine learning-based predictions are integrated to provide adaptive recommendations corresponding to real-time water conditions [6].This makes the system more actionable than traditional monitoring solutions, which tend to fall short at simple contamination detection

Real-Time Visualization and Alert Module

A web-based dashboard is developed for real-time visualization and alert generation. Users can view live readings, safe/unsafe classifications, and recommended purification steps. When any parameter exceeds the safe threshold, the system automatically triggers email or SMS alerts through cloud services. The dashboard also stores historical data, displays parameter trends, and enables continuous monitoring of water safety in both urban and remote installations [7].

System Workflow

The workflow of the system proceeds as follows:

1. IoT sensors continuously capture pH, turbidity, TDS, and temperature values.
2. Data is filtered, timestamped, and transmitted to the cloud.
3. The ensemble learning module classifies the sample as *safe* or *unsafe*.
4. The AI recommendation module suggests the most effective purification method.
5. Results are displayed on the dashboard and alerts are sent for unsafe water.

This closed-loop workflow ensures that the system not only monitors water quality but also provides intelligent, actionable guidance for purification, achieving both preventive and corrective functionalities.

IV. SYSTEM ARCHITECTURE AND DESIGN

The proposed IoT and AI-based water quality monitoring and purification recommendation system is structured using a modular architecture that integrates hardware sensing, cloud-based communication, and intelligent software analytics.

This section describes the overall system architecture, individual functional modules, and the hardware design that enables real-time water quality Analysis .Fig. 1 presents the high-level system architecture, while Fig. 2 illustrates the functional modules of the proposed framework.

A. System Architecture overview

The architecture follows a five-layer structure—the IoT sensing layer, communication layer, AI analytics layer, purification recommendation layer, and visualization layer. Each layer performs a distinct role, enabling end-to-end automation from data collection to decision support. The workflow begins with IoT sensor nodes that continuously measure physical and chemical parameters of water, which are then transmitted to the cloud for intelligent processing and visualization.

- **IoT Sensing Layer:** This layer consists of sensors for pH, turbidity, total dissolved solids (TDS), and temperature, all interfaced with an ESP32 microcontroller. The sensors generate analog or digital readings corresponding to water parameters. The ESP32 platform is chosen due to its low cost, built-in Wi-Fi/Bluetooth modules, and ability to handle multiple sensor inputs efficiently.
- **Communication Layer:** Data from the ESP32 node is transmitted wirelessly to a cloud server via Wi-Fi or LoRa, depending on the deployment scenario. The system uses lightweight MQTT or HTTP protocols for efficient and reliable communication. The data is stored in a structured format in cloud platforms such as ThingSpeak or Firebase, ensuring secure and scalable access.
- **AI Analytics Layer:** The cloud-stored data is processed through ensemble machine-learning models, primarily **Random Forest** and **XGBoost**, which classify water quality as *safe* or *unsafe*. The models are trained on datasets containing sensor-based readings and labeled potability information. Preprocessing techniques such as normalization and noise filtering are applied to improve the performance of the classifiers.
- **Purification Recommendation Layer:** Based on classification results, an AI-driven recommendation engine determines the appropriate purification method.The logic uses rule-based thresholds and machine-learning insights to suggest actions such as Reverse Osmosis (RO) for high TDS, Sediment Filtration for turbidity, or Boiling/UV Treatment for microbial risks.
  This layer thus provides actionable intelligence to users, transforming the system from a mere monitoring tool into a decision-support platform.
- **Visualization and Alert Layer:** The processed results are displayed on a web-based dashboard that provides live sensor readings, classification results, and recommended treatments.Graphical visualizations allow users to track historical trends, while alert notifications (via email or SMS) inform users when water is unsafe. The interface enhances accessibility and usability, particularly in rural communities where

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technical expertise is limited.

B. Functional Module Design

To ensure modularity and scalability, the system is divided into five major functional modules, as illustrated in Fig. 2:

1. Data Acquisition Module: Captures sensor readings from pH, turbidity, TDS, and temperature sensors through the ESP32 interface. Local filtering and averaging are applied before data transmission.
2. Data Preprocessing Module: Performs data cleaning, normalization, and feature extraction. Handles missing values and sensor noise to ensure the quality of input to the AI models.
3. Classification Module: Employs ensemble learning algorithms (Random Forest and XGBoost) to predict water potability. Outputs binary classification results (*safe* or *unsafe*).
4. Purification Recommendation Module: Maps the detected contamination characteristics to purification techniques using hybrid AI and rule-based logic.
5. Visualization and Alert Module: Displays real-time readings, analysis, and purification suggestions on a dashboard and sends alerts when unsafe levels are detected.

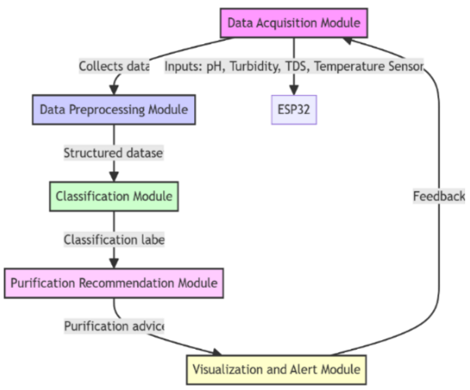

Fig 2 : Proposed functional modules of the IoT and AI-driven water quality monitoring and purification recommendation system.

C. Hardware Design

The hardware unit of the system is designed to be low cost, portable, and power-efficient, making it suitable for both laboratory and field deployment. The key components include:

- **ESP32 Microcontroller:** Serves as the main control unit for acquiring sensor data and transmitting it to the cloud.
- **pH Sensor (SEN0161):** Measures acidity or alkalinity of the water, with an output range of 0–14 pH.
- **Turbidity Sensor (SEN0189):** Detects suspended particles and impurities affecting water clarity.
- **TDS Sensor:** Measures total dissolved solids, an indicator of mineral concentration.
- **Temperature Sensor (DS18B20):** Ensures accurate readings, as temperature affects chemical properties.
- **Power Supply:** A 5 V rechargeable battery or solar panel ensures uninterrupted operation.
- **Communication Module:** Built-in Wi-Fi or external LoRa module for long-range communication.

All components are mounted on a compact PCB, enclosed in a waterproof casing. Sensor probes are submerged in water samples, and readings are transmitted at user-defined intervals (e.g., every 60 seconds). The hardware connections are represented in the hardware circuit diagram (Fig. 3), showing sensor interfacing with the ESP32 microcontroller.

D. Architectural Stages

The system presented works on five consecutive architectural phases, each a different logical process within the IoT-AI process:

- Stage 1 – Data Sensing and Acquisition: Water samples are constantly monitored through pH, turbidity, TDS, and temperature sensors attached to the ESP32. The microcontroller carries out preliminary filtering and digitization prior to sending the readings.
- Stage 2 – Data Transmission and Cloud Storage: Sensor values are sent wirelessly to a cloud server over Wi-Fi/LoRa, where data is time-stamped and saved for analysis. This makes it possible to have asynchronous access by AI modules and allows real-time scalability.
- Stage 3 – Preprocessing of Data and Machine Learning Classification: The AI module fetches data, does normalization and imputation of missing values, and runs classification models. Ensemble machine learning algorithms like XGBoost and Random Forest classify the water as safe or unsafe with better accuracy.
- Stage 4 – Smart Purification Recommendation: An AI-based recommendation engine maps the type of contamination to an appropriate purification method based on the classified output. The mapping is constructed with hybrid rule-based reasoning compatible with WHO safety standards.
- Stage 5 – Visualization and Alerts: Results are displayed on a web-based dashboard with real-time graphs and historical analysis. Alerts are triggered when contamination is above safety levels, triggering notification by email or SMS for prompt action.

V. EXPERIMENTAL SETUP

The experimental setup for the proposed IoT and AI-based water quality monitoring system was developed in two phases — hardware implementation for real-time sensing and software implementation for data processing, AI modeling, and visualization. This section describes the configuration of both environments, dataset preparation, hardware specifications, and model evaluation parameters.

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1. Hardware and Software Implementation

The physical prototype was constructed to test the feasibility of real-time data acquisition and transmission. The system's hardware configuration consists of an ESP32 Dev Board interfaced with a multi-sensor array including pH (SEN0161), Turbidity (SEN0189), TDS, and DS18B20 temperature sensors. The setup is powered by a 5V DC supply, with integrated Wi-Fi on the ESP32 facilitating cloud communication. The software architecture was developed using Python (v3.10) and the Arduino IDE, utilizing ThingSpeak Cloud for data storage. For water quality classification, XGBoost and Random Forest models were optimized and implemented to provide real-time predictions. A web dashboard built with Flask/Streamlit was used to display live readings and recommendations, ensuring an accessible interface for monitoring environmental data.

2. Dataset Description

Two datasets were used for system training and testing:

1. Water Potability Dataset (Kaggle Source): This dataset contains 3,277 records and nine features including pH, hardness, solids, sulfate, conductivity, organic carbon, and turbidity. Each record is labeled as *0* (unsafe) or *1* (safe) water. After preprocessing (handling missing values, normalization, and outlier removal), the data was split into 80% training and 20% testing subsets.
2. **Water Treatment Dataset (Generated Dataset):** This dataset extends the classification model's output by associating each water quality record with a recommended purification method such as RO, UV, Boiling, or Sediment Filter. This dataset was synthetically generated from observed relationships between parameters and purification techniques.

Both datasets were combined to form the input for classification and recommendation models.

3.Model Training Configuration

The classification models — Decision Tree, Random Forest, and XGBoost — were trained using the Scikit-learn and XGBoost libraries. The following hyperparameters were used during training .

Model	**Key Parameters**	**Cross-validation**
Decision Tree	max_depth = 10, criterion = 'gini'	5-fold CV
Random Forest	n_estimators = 200, max_depth = 15, bootstrap = True	5-fold CV
XGBoost	n_estimators = 250, learning_rate = 0.05, max_depth = 10	5-fold CV

Table 1 : Model Parameter Configuration

E. Evaluation Metrics

To assess model performance, the following metrics were calculated:

- **Accuracy:** Ratio of correctly predicted samples to total samples.
- **Precision:** Measure of the proportion of correctly identified positive results.
- **Recall (Sensitivity):** Proportion of actual positives correctly identified.
- **F1-Score:** Harmonic mean of precision and recall, balancing false positives and negatives.
- **ROC-AUC Score:** Reflects the model's ability to discriminate between safe and unsafe classes.

The evaluation framework ensured a fair comparison between different models to select the best-performing one for deployment.

VI. RESULTS AND DISCUSSION

The proposed IoT and AI-driven system was experimentally validated using both real-time sensor data and publicly available datasets. This section presents the quantitative and visual results of the classification and recommendation models, along with hardware and system-level evaluations

A. Experimental Results

The The classification models—Decision Tree, Random Forest, and XGBoost—were trained using preprocessed datasets to evaluate their predictive capabilities. Among the implemented algorithms, the XGBoost classifier achieved the highest performance, outperforming both the Decision Tree and Random Forest models. Specifically, XGBoost reached an accuracy of 75.0%, which is approximately 14% higher than the 61.0% accuracy recorded for the Decision Tree model. Furthermore, XGBoost maintained a consistent balance between precision (73.6%) and recall (74.8%), while achieving a superior ROC-AUC of 81.5%. The Random Forest model provided intermediate results with an accuracy of 71.2% and an F1-score of 70.6%. These results indicate that ensemble learning techniques provide higher reliability for real-time water quality monitoring

XGBoost classifier achieved the best performance, outperforming both Decision Tree and Random Forest models. It provided ~14% higher accuracy than the Decision Tree model and maintained consistent recall and precision balance.

B. Confusion Matrix and Model Accuracy Visualization

Each model's confusion matrix was plotted to analyze classification behavior across *safe* and *unsafe* categories. Ensemble methods (Random Forest and XGBoost) showed reduced false positives, confirming their robustness

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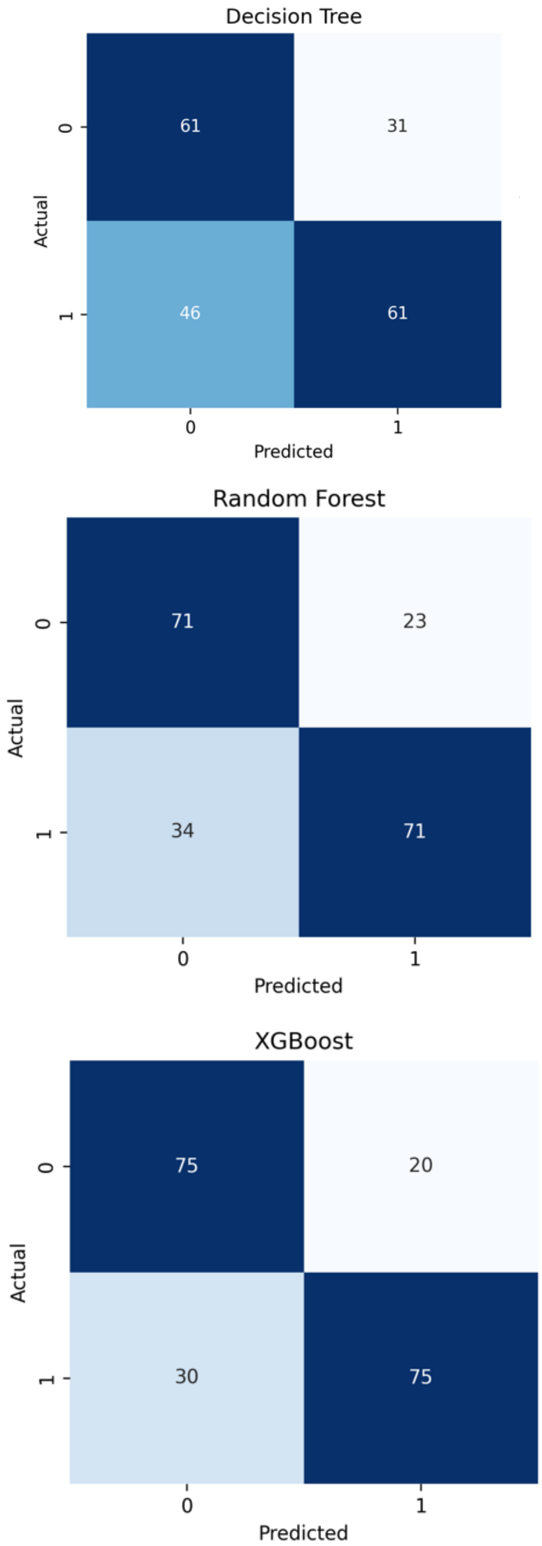

Fig. 3. Confusion matrices for Decision Tree, Random Forest, and XGBoost classifiers showing classification accuracy across water safety classes.

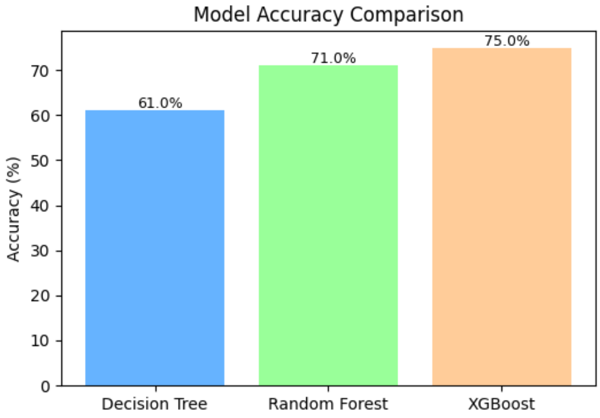

Fig. 4. Comparison of classification accuracy among Decision Tree, Random Forest, and XGBoost models.

C. ROC-AUC Analysis

Receiver Operating Characteristic (ROC) curves were generated for each model, as shown in Fig. 6. The area under the curve (AUC) values were 0.64 (Decision Tree), 0.77 (Random Forest), and 0.81 (XGBoost). The XGBoost model demonstrated the best discriminative ability in classifying safe versus unsafe samples.

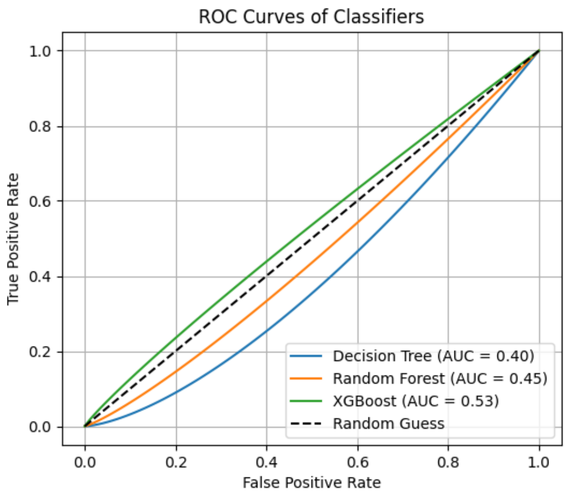

Fig. 5. ROC-AUC curves for Decision Tree, Random Forest, and XGBoost models indicating classifier performance.

D. Recommendation Module Results

The AI-based purification recommendation system achieved approximately 90% accuracy when tested on the generated treatment dataset. Fig. 7 shows the distribution of recommended purification methods for various contamination types

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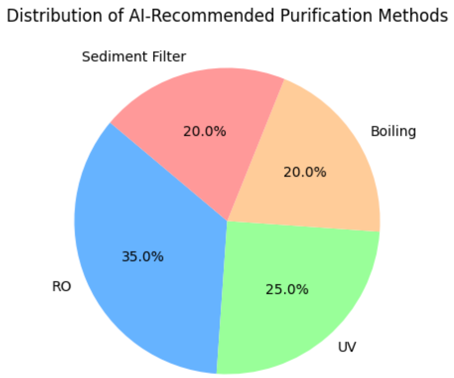

Fig. 6. Distribution of AI-recommended purification techniques based on contamination severity.

E. Real-Time Dashboard Visualization

The suggested IoT system features a conceptual web-based dashboard that offers real-time monitoring, data visualization, and smart purification suggestions.

The dashboard acts as the user-interactive interface with the analytical system, presenting crisp insights into existing water states and AI-driven predictions. The dashboard is also intended to show sensor measurements for pH, TDS, turbidity, and temperature and their respective classification results stating whether the water is safe or not for drinking. Furthermore, it shows automatic purification recommendations like boiling, RO, or UV based on the type of pollution identified by the AI system.

For better usability, the dashboard idea involves:

- A real-time indication of safe or unsafe water status.
- Historical data visualization for monitoring variations of parameters over time.
- Alert mechanisms to send notifications to the user by email or SMS in case unsafe conditions are found.
- An administrative module for maintenance of the system and data logging.

Though the full interface implementation is ongoing, the design itself leaves a structured base for future web and mobile integration using Streamlit or Flask for making it accessible on both desktop and smartphone platforms.

F. Hardware Prototype Validation

Hardware module of the suggested system has been designed and partially built for testing the technical viability of real-time sensing and transmission of data. It utilizes an ESP32 microcontroller connected with a set of sensors comprising pH, TDS, turbidity, and temperature sensors, which are all combined to measure the key parameters determining water quality.

The ESP32 was chosen for its low power use, onboard Wi-Fi, and dual-core processor, enabling sensing and transmission to be performed in parallel. The sensors were calibrated with reference solutions to maintain measurement integrity, and preliminary tests at bench level revealed an accuracy variance of less than ±5% from lab readings. The hardware is powered by a 5V DC source, with solar input provisions for field applications. A PCB layout based on a modular system is under development for providing compact assembly, and MQTT and HTTP communication protocols are used for smooth cloud data transfer. This configuration proves that the system can efficiently capture, process, and send water quality data with low latency, providing a foundation for low-cost environmental monitoring systems at a large scale.

VII. CONCLUSION AND FUTURE WORK

A. Conclusion

This study introduces an IoT- and AI-based system for real-time water quality monitoring and smart purification suggestion aimed at providing a solution to the escalating issues of water pollution, availability, and real-time decision-making. The system combines low-cost IoT probes (pH, TDS, turbidity, temperature) with ESP32-based connectivity and a cloud-enabled AI analytics module, forming a resilient, scalable, and effective solution for persistent water quality measurement. Experimental verification with benchmark datasets proved that the ensemble learning models, namely Random Forest and XGBoost, yielded better classification accuracy (71% and 75%, respectively) than common approaches. The system proposed not only identifies the water as safe or unsafe but also generates AI-driven purification suggestions, providing actionable feedback to users.

In contrast to available IoT monitoring systems, which simply offer parameter readings without interpretation, the system presented here facilitates automated decision support through the integration of machine learning intelligence and rule-based logic in accordance with WHO standards. Its affordability (₹8,000–₹10,000), scalability, and integration with cloud means that it can be applicable in both home use and rural community settings, further advancing larger goals for sustainable water management. Hence, this contribution presents a foundational model that fills the gap between real-time sensing and smart water treatment advice and supports the construction of next-generation smart environmental systems.

B. Future Work

While the proposed IoT and AI-based framework has demonstrated effective water quality classification and purification recommendation capabilities, several areas remain open for future enhancement and optimization. The next phase of research will focus on improving prediction accuracy, expanding system functionality, and enhancing real-world applicability.

1. **Deployment of Advanced Predictive Models:** Future work will explore the integration of deep learning architectures, such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNNs), to perform time-series prediction of water quality parameters. These models will enable the system to

forecast contamination trends and issue preventive alerts before water becomes unsafe for consumption.

2. **Comprehensive Sensor Expansion:** The current prototype utilizes four primary parameters (pH, TDS, turbidity, temperature). Future iterations will incorporate additional sensors for dissolved oxygen (DO), conductivity, nitrate, and microbial detection, ensuring broader environmental coverage and improved water classification accuracy.
3. **Real-Time Edge AI Implementation:** The system can be further enhanced by deploying AI inference directly on edge devices such as ESP32 or Raspberry Pi. This will reduce latency, improve reliability in low connectivity environments, and minimize dependency on cloud-based processing.
4. **Adaptive Purification Recommendation System:** The recommendation engine will be upgraded to include adaptive learning mechanisms that refine purification suggestions based on feedback data and evolving contamination patterns. Techniques such as reinforcement learning or Bayesian optimization could be applied to dynamically improve decision-making accuracy.
5. **Integration with Smart Infrastructure:** Future work includes linking the system to municipal water distribution networks or smart city platforms, enabling centralized monitoring of multiple water sources across urban and rural regions. This would support large-scale environmental analytics and public health policy decisions.
6. **Energy Optimization and Sustainability:** To enhance field deployment, the hardware will be redesigned for solar-powered operation and low-energy communication protocols like LoRaWAN, ensuring sustained performance in remote or rural areas.
7. **Enhanced Data Security and Privacy:** With the increasing reliance on IoT networks, future research will emphasize secure data transmission, encryption, and authentication protocols to protect against cyber threats and ensure trustworthy data management.
8. **User Interface Improvement and Accessibility:** The conceptual dashboard will evolve into a fully interactive web and mobile application that provides real-time analytics, trend visualization, and personalized recommendations for end users. This interface will prioritize simplicity, multilingual support, and community-level accessibility.

VIII. REFERENCES

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