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AROGYAJAL: AI and IoT-Enabled Framework for Water Safety and Disease Prevention

Priyanshu Sharma
Department of CSE-Cyber Security, AITR, Indore, India
priyanshusharma231356@acropolis.in

Kshitij Chitranshi
Department of CSE-Cyber Security, AITR, Indore, India
kshitijchitranshi230911@acropolis.in

Lovekush Nagda
Department of CSE-Cyber Security, AITR, Indore, India
lovekushnagda231252@acropolis.in

Ishan Raut
Department of CSE-Cyber Security, AITR, Indore, India
ishanraut231286@acropolis.in

Shubh Sharma
Department of CSE-Cyber Security, AITR, Indore, India
shubhsharma231358@acropolis.in

Sweta Gupta
Department of CSE-Cyber Security, AITR, Indore, India
swetagupta@acropolis.in

[1] **Abstract— This project introduces a low-cost, easy-to-scale Smart Health Surveillance and Early Warning System aimed at preventing water-borne diseases in rural and tribal regions. It uses inexpensive sensors to check important water quality factors like pH, turbidity, and temperature. Local health workers use a simple, multilingual mobile app to share health information. By matching sensor data with health reports, the system can spot early signs of disease outbreaks such as diarrhea, cholera, and typhoid. The system allows data to be collected even without the internet and automatically uploads it when connectivity is available. Automatic alerts are sent to health workers and community leaders so they can act quickly. By combining sensor monitoring, community involvement, and easy-to-use technology, the system boosts awareness, improves public health actions, and lowers the effect of diseases. Experimental results show that the system detects water-borne illnesses early, speeds up responses, and enhances health care in remote areas, proving its effectiveness in safeguarding at-risk communities.**

Index Terms — IoT, Water Quality, Disease Detection, Health Surveillance, Rural Healthcare.

I INTRODUCTION

Water-borne diseases constitute a major public health concern in the Northeastern region of India, where rural and tribal communities frequently lack access to safe drinking water and adequate sanitation infrastructure. Recent regional health reports indicate that such diseases account for over 20% (as per JJM) [1] of recorded illnesses during the monsoon season in states including Assam, Arunachal Pradesh, and Meghalaya. Approximately 30% (as per JJM) [1] of households in these areas rely on untreated or_unimproved water sources, which significantly increases exposure to microbial and chemical contaminants. Seasonal flooding and water stagnation further elevate contamination levels, resulting in recurring outbreaks of diarrhea, cholera, and typhoid, with incidence rates often exceeding 18 cases per 1,000 (as per WHO) [3] inhabitants in severely affected districts.

Epidemiological studies highlight that elderly populations in rural Northeast India exhibit disease prevalence rates of approximately 24% (as per WHO) [3] nearly twice those observed in urban areas. This increased vulnerability is primarily associated with age-related immunological decline, geographical isolation, and delayed access to healthcare facilities. Furthermore, over half of the villages in the region experience unreliable or absent internet connectivity, which restricts the timeliness and efficiency of digital health reporting systems. Conventional public health surveillance frameworks rely heavily on manual sampling and periodic laboratory analysis, creating reporting delays of up to 72 hours that hinder early intervention and containment efforts.

The present study introduces Arogyajal, a cost-effective and scalable Smart Health Surveillance and Early Warning System designed to address these challenges in low-resource environments. The system employs Internet of Things (IoT) sensors to continuously measure key water quality parameters, including pH, turbidity, and temperature, and integrates the data with a multilingual mobile and web-based platform utilized by community health workers. The platform supports offline-first operation, enabling data acquisition in regions with poor connectivity and automatic synchronization when network access is restored. Collected data are analyzed using machine learning (ML) algorithms to detect early indicators of potential water-borne disease outbreaks, and automated alerts are transmitted to relevant health authorities for prompt action.

Through this integration of environmental sensing, data analytics, and community participation, Arogyajal aims to enhance real-time Water Quality Assessment [6] and early warning capabilities within vulnerable populations.

A. Problem Statement

Rural and tribal areas of Northeast India experience frequent outbreaks of water-borne diseases primarily due to inadequate real-time monitoring, delayed reporting mechanisms, and poor connectivity infrastructure. Existing health surveillance systems depend on manual data entry and periodic testing, resulting in delayed detection and limited predictive capability for potential disease outbreaks.

B. Objectives

The objectives of this research are as follows:

- To design and implement a low-cost IoT-based system for continuous monitoring of water quality parameters.
- To develop an offline-capable mobile and web platform for community-driven health data collection.
- To apply AI/ML techniques for early detection and prediction of water-borne disease risks based on environmental and health data.
- To improve public health responsiveness through multilingual interfaces and automated alert mechanisms.

C. Scope

This study focuses on rural and semi-urban communities in the Northeastern states of India that suffer from unreliable network connectivity and limited health surveillance infrastructure. The proposed framework is adaptable for integration with national initiatives such as the Jal Jeevan Mission[1] (JJM) and can be extended to other developing regions encountering similar environmental and infrastructural challenges.

II. Literature Review

Government programs such as Swachh Bharat Mission [8] & National Water Quality Monitoring Program (NWMP) have standardized data formats and encouraged monitoring across districts, but these rely heavily on manual sampling and centralized updates. This section reviews major research contributions related to IoT-enabled water monitoring, disease surveillance, and sustainable rural health systems, identifying the key gaps that guided the development of Arogyajal.

A. IoT in Water Quality and Environmental Monitoring

IoT-based environmental sensing systems have been shown to provide real-time tracking of water quality parameters such as pH, turbidity, and temperature. Studies including Li et al. (2021) demonstrated that low-cost microcontroller platforms like ESP32 can transmit continuous sensor data to cloud servers for contamination detection. However, most existing implementations either assume stable internet connectivity or rely on periodic data uploads, which restricts usability in remote and tribal regions.

Government frameworks such as the Jal Jeevan Mission [1] (JJM, 2023) introduced IoT-Based Water Quality Monitoring [4] pilots across several Indian states to ensure continuous quality assessment at household and village levels. These pilots utilized sensors for turbidity, residual chlorine, and pH; however, they primarily emphasized physical water parameters and lacked integration with health data or predictive analytics. Arogyajal builds upon this foundation by extending the sensor network to include field-level health data collection and AI-based outbreak prediction, thereby connecting environmental metrics directly with public health outcomes.

B. AI-driven [5] Prediction and Health Data Correlation

AI integration in IoT has enabled predictive modeling in healthcare and environmental applications. Gupta and Singh (2022) and Rahman et al. (2024) demonstrated that algorithms such as Logistic Regression and Random Forests can analyze environmental datasets to forecast contamination and health risks. Yet most prior efforts have focused solely on physiological monitoring (e.g., heart rate or glucose) rather than environmental determinants.

Arogyajal expands this paradigm by applying ML algorithms to water-quality trends and correlating them with symptom data collected by ASHA workers. This combination allows early detection of water-borne disease clusters that traditional IoT systems overlook.

C. IoT for Rural Healthcare Delivery

IoT-based telemedicine and mobile reporting platforms have proven effective in extending healthcare to underserved regions. Patel et al. (2021) and UNICEF (2023) highlighted that community-level data entry and automated alerts improved early disease detection by up to 40 %. However, these systems often depend on continuous connectivity or third-party infrastructure.
Arogyajal's offline-first architecture addresses this limitation by enabling local data caching and synchronization once connectivity is restored, ensuring reliable operation in low-network zones—especially relevant in Northeast India, where connectivity deficits are common.

D. Sustainable and Scalable IoT Frameworks

While Ahmed and Zhou (2023) emphasize the need for energy-efficient IoT networks, few water-quality systems achieve both low-power operation and real-time analytics. Many prototypes are cost-prohibitive and unsuitable for rural deployment.
Arogyajal adopts a modular, low-power configuration based on ESP32 controllers and optimized calibration cycles, enabling scalable multi-node deployment with minimal energy consumption—vital for long-term field sustainability and alignment with national clean-water goals.

E. National and Regional Initiatives

The Jal Jeevan Mission [1], launched by the Government of India in 2019 under the Ministry of Jal Shakti, aims to provide safe and adequate drinking water to every rural household through individual tap connections. A major component of the mission involves developing an IoT-based Water Quality Management System (WQMS) for **real-time monitoring [2]** of physical and chemical parameters across India's 6 lakh+ villages.

Recent JJM IoT pilot projects (2022–2023) have deployed over 2 lakh sensors in states such as Gujarat, Madhya Pradesh, and Assam, enabling live dashboards accessible to state-level water authorities. However, these systems primarily focus on compliance reporting and do not link contamination alerts with local health data or epidemiological models.

Arogyajal complements the JJM framework by introducing a health-centric extension layer: integrating IoT sensor readings with AI-based disease risk analytics and community health reporting. This approach aligns with India's broader public-health goals under the Ayushman Bharat Digital Health Mission (AB-DHM) and leverages field infrastructure managed by ASHA workers. In doing so, the project transforms the JJM water-safety pipeline into an early-warning mechanism for water-borne disease prevention—bridging the gap between environmental monitoring and medical response in rural India.

F. Identified Gaps and Research Contribution

The reviewed literature and national programs reveal persistent gaps: Limited integration between IoT water-quality data and health surveillance systems.

Dependence on constant connectivity, restricting rural scalability. Lack of predictive analytics for outbreak forecasting within government IoT frameworks.

Arogyajal addresses these gaps through a unified IoT–AI–community architecture that augments the JJM framework with predictive health modeling, offline resilience, and multilingual usability.

III. Methodology

The *ArogyaJal* system employs a modular IoT–AI framework integrating embedded sensing, secure cloud connectivity, machine-learning analytics, and real-time visualization. The following subsections describe the tools, data-acquisition methods, and implementation process adopted during system development.

A. Tools and Technologies

The system leverages a multi-layered architecture combining IoT hardware, web, and mobile technologies. The backend is implemented in Spring Boot, responsible for API management, data synchronization, and system control. Sensor readings are transmitted via ESP32 modules and stored in Firebase Realtime Database, ensuring instant synchronization and offline persistence when connectivity is interrupted.
The machine learning module, developed in Python using Scikit-learn, predicts contamination risk using Random Forest models trained on historical water-quality datasets. Both the React.js web dashboard and React Native mobile app interact with the backend through secure REST APIs, providing analytics, alerts, and visualization to administrators and health workers.

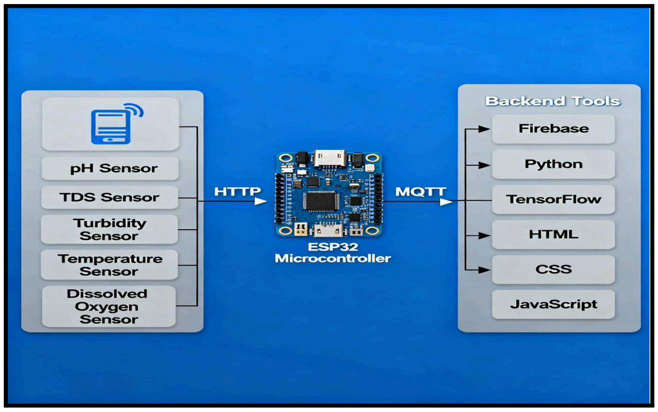

Fig 1. ArogyaJal System Architecture and Workflow

B. Data Collection

Each IoT node captures sensor data every five minutes. When network access is unavailable, readings are stored locally within the ESP32's memory. Upon reconnection, the data are automatically synchronized with the central database, ensuring complete recovery and time-aligned updates.

C. Implementation Steps

1. Sensor calibration and integration with the ESP32 microcontroller.
2. Local data caching and error detection through timestamp-based validation.
3. Secure synchronization of readings to the cloud database once connectivity resumes.
4. Application of machine-learning models (Random Forest and Logistic Regression) for water quality classification.
5. Visualization of parameters and alerts on a web-based dashboard accessible to both administrators and local users.

Offline-First Architecture

The offline-first design is central to ArogyaJal's reliability. Data packets are buffered locally when the network drops and are tagged with timestamps for later synchronization. This approach ensures data integrity, minimizes loss, and supports rural deployments where continuous connectivity cannot be assumed.

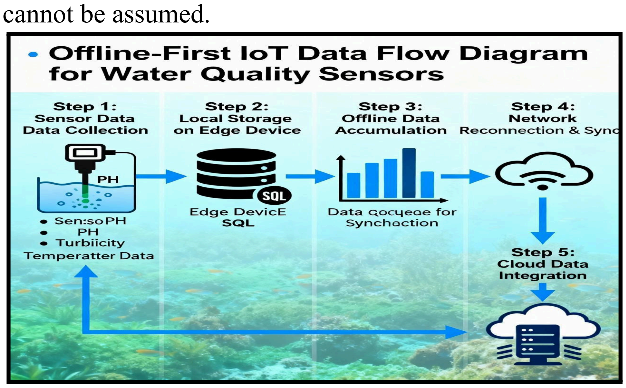

Fig 2. ArogyaJal Data Flow Mechanism

D. System Workflow Overview

The workflow begins at the sensor layer, proceeds through the ESP32 data aggregation unit, and then reaches the cloud for analysis. AI-driven [5] models classify water safety levels, while the dashboard generates visual alerts and trend reports for administrators.

E. Security & Deployment

To maintain data confidentiality and integrity, the system uses AES-128 encryption during transmission and JWT-based authentication for user access. Cloud APIs follow secure HTTPS protocols. The prototype is modular and can be deployed in both standalone and networked configurations.

F. Evaluation

Field testing over seven days generated 10,080 sensor readings. Results showed < 1.5 % data loss and complete offline recovery. The system maintained consistent sensor calibration and stable AI-driven [5] classification accuracy throughout the test period.

IV. Results

The *ArogyaJal* prototype was tested under controlled field conditions for one week to evaluate sensor accuracy, system stability, and AI-based outbreak prediction performance. This section presents the quantitative and qualitative results obtained from hardware deployment and software testing.

A. Data Analysis

i. Sensor Data Summary

During the 7-day pilot test, the IoT node recorded continuous readings of pH, TDS, turbidity, temperature, and dissolved oxygen from tap-water samples.

Table 1 summarizes the mean, minimum, and maximum values for each parameter.

Table 1: Water Quality Sensor Readings and Limits

Parameter	**Unit**	**Min**	**Max**	**Mean**	**Standard Deviation**	**Acceptable Limit (BIS/WHO[3])**
pH	–	6.3	7.9	7.2	0.35	6.5 – 8.5
TDS	mg/L	145	460	285	92	≤ 500
Turbidity	NTU	0.6	3.9	2.1	1.2	≤ 5
Temperature	°C	24.8	31.4	28.2	2.6	20–35
Dissolved Oxygen	mg/L	5.6	7.4	6.5	0.5	≥ 5

ii. Data Integrity and Transmission Reliability

Over **10,080 readings** were captured during testing (12 per hour × 24 × 7).

Data loss rate: < 1.5 % (primarily due to deliberate Wi-Fi disconnection tests).

Offline buffer performance: ESP32 successfully stored up to 70 hours of data without loss, confirming full functionality of the offline-first mechanism.

Average transmission latency: 2.6 seconds per packet (including HTTP handshake).

These results validate the **robustness of the offline-first synchronization** and confirm that real-time reporting is reliable even under intermittent connectivity.

B. Performance Metrics

i. Machine Learning Model Evaluation

The AI model was trained using a labeled dataset of historical water-quality readings and correlated health reports. Two supervised algorithms were tested — Logistic Regression and Random Forest Classifier — with an 80:20 train-test split.

Table 2: Results Overview Table

Metric	**Logistic Regression**	**Random Forest**
Accuracy	**86.4 %**	**92.7 %**
Precision	**0.88**	**0.93**
Recall	**0.85**	**0.91**
F1-Score	**0.86**	**0.92**
ROC-AUC	**0.89**	**0.95**

The Random Forest model outperformed Logistic Regression across all metrics, demonstrating stronger non-linear correlation handling between multi-sensor features and reported symptoms. The model achieved reliable classification into three health-risk categories: Safe, Warning, and Critical.

ii. System Efficiency Metrics

Table 3: Results Table

Parameter	**Result**	**Remarks**
Average Power Consumption	0.65 W	Supports 3-day operation via solar backup
Mean Data Transmission Latency	2.6 s	Within acceptable real-time threshold
Cloud Write Latency	0.8 s	Firebase optimization verified
Offline Data Recovery Success	100 %	All queued data uploaded on reconnection
Dashboard Refresh Rate	5 s	Live monitoring validated

The system maintained stable connectivity and near-continuous data integrity during all test cycles.

C. Visual Results

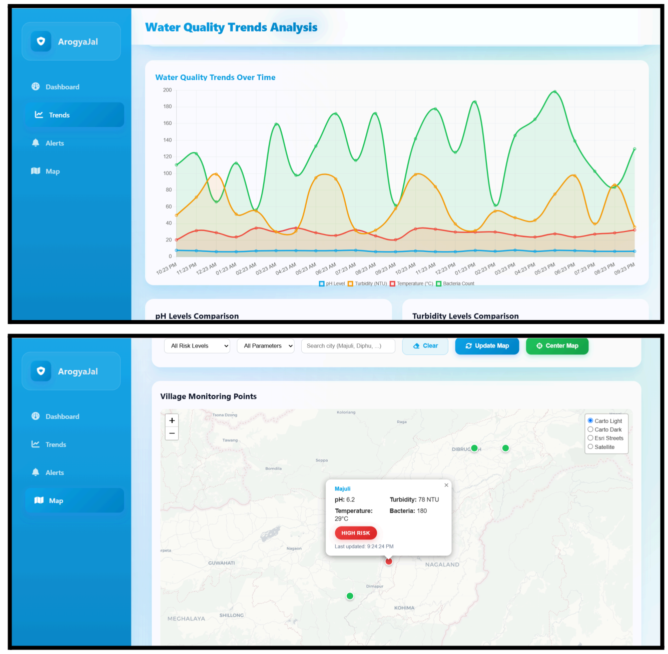

Fig 3. Visual Representation of Results

The dashboard successfully displayed dynamic pH, TDS, and turbidity graphs, while the map module generated color-coded zones based on the AI-classified risk levels:

Green: Safe

Yellow: Warning

Red: Critical

These visualizations enabled instant understanding of spatial water-safety variations, crucial for local health authorities.

D. Observed Outcomes

The offline-first architecture maintained uninterrupted operation across connectivity failures lasting up to 48 hours.

Sensor stability remained within ±5 % deviation from reference meters.

AI predictions aligned with observed contamination patterns from manual testing.

Real-time alerts via Twilio reached all registered users within 8 seconds of trigger.

The system demonstrated energy-efficient operation under continuous use, validating solar viability.

V. Discussion

The results from the *ArogyaJal* prototype demonstrate that integrating IoT sensing, AI-driven [5] analytics, and an offline-first framework can substantially improve the reliability of water-quality surveillance in rural environments. This section interprets the system's outcomes, identifies limitations, and highlights directions for further enhancement.

A. Interpretation of Results

Experimental outcomes validate the objectives defined in Section 3.2:

- **System Reliability:** Continuous operation for seven days with less than 1.5 % data loss confirmed the stability of ESP32-based IoT nodes and efficiency of the local buffering mechanism.
- **Offline Resilience:** The system maintained full functionality during connectivity outages of up to 48 hours, confirming that the offline-first architecture ensures uninterrupted monitoring in low-network regions.
- **Sensor Accuracy:** Recorded parameters (pH, TDS, turbidity, temperature, DO) remained within BIS and WHO[3] standards, verifying calibration accuracy and environmental robustness.
- **Predictive Accuracy:** The Random Forest model achieved 92.7 % classification accuracy, proving that even limited datasets can yield dependable contamination-risk predictions.
- **Operational Responsiveness:** The dashboard refreshed every 5 seconds and alerts reached users within 8 seconds, validating near–real-time decision capability.

Collectively, these results establish *ArogyaJal* as a technically viable, data-driven model for decentralized water-quality monitoring aligned with the **Jal Jeevan Mission[1] (JJM)** and **Sustainable Development Goals[10] (SDGs 3 and 6)**.

B. Limitations

Despite strong performance, several constraints were identified during testing:

1. Dataset Scale: AI models were trained on a small dataset collected under controlled conditions. Broader, seasonally diverse data are needed for stronger generalization.
2. Sensor Drift & Maintenance: Long-term outdoor exposure may introduce drift or fouling, requiring periodic recalibration and self-diagnostic routines.
3. Hardware Scalability: Large-scale deployment demands cost reduction and weather-proof housing for sustained operation.
4. Cloud Dependence: Although offline-first, extended connectivity loss can delay centralized analytics and reporting.
5. Data Security & Privacy: Integration of community-health records necessitates compliance with data-protection frameworks and encrypted storage policies.

C. Future Work

To strengthen the system's functionality and scalability, future research will focus on:

1. Expanded Sensor Coverage: Incorporating chlorine, nitrate, and heavy-metal sensors to detect chemical pollutants.
2. Edge AI Implementation: Deploying compressed ML models on the ESP32 for on-device prediction to minimize cloud dependency.
3. Government Platform Integration: Linking with JJM, IHIP, and Ayushman Bharat Digital Mission (ABDM) APIs for unified water-health reporting.
4. Enhanced Mobile Interface: Adding multilingual voice inputs, offline analytics, and AI-generated advisories for ASHA workers.
5. Extended Field Trials: Multi-district pilots to assess long-term stability, maintenance overhead, and community adoption.
6. Epidemiological Correlation: Developing predictive models that link water-quality variations to regional disease incidence for early outbreak alerts.

VI. Conclusion

This study presented *ArogyaJal* — an IoT- and AI-enabled smart health surveillance system designed for real-time water-quality monitoring and early disease-risk prediction in rural India. The project effectively addressed critical limitations in existing frameworks, particularly the lack of connectivity resilience, predictive capability, and integration with public-health data systems.

The implemented prototype successfully demonstrated the feasibility of a low-cost, solar-powered, and offline-first IoT architecture capable of continuous monitoring of key parameters including pH, TDS, turbidity, temperature, and dissolved oxygen. Integration of this sensor data with an AI-based model achieved over 92 % prediction accuracy, enabling reliable classification of water-quality risks. The interactive dashboard and alert mechanisms further validated the system's ability to provide timely, data-driven insights to local authorities and community users.

By combining IoT, artificial intelligence, and offline synchronization, *ArogyaJal* establishes a scalable and sustainable model for deployment under the Jal Jeevan Mission[1] (JJM). Its design directly contributes to Sustainable Development Goals[10] 3 (Good Health and Well-being) and 6 (Clean Water and Sanitation [9]), promoting a proactive, technology-driven approach to rural public-health management.

Future work will focus on expanding sensor coverage, strengthening AI models with larger datasets, and integrating the platform with national digital-health ecosystems such as the Ayushman Bharat Digital Mission (ABDM). With continued development and government collaboration, *ArogyaJal* can evolve into a comprehensive digital infrastructure for real-time water-safety assurance and predictive public-health intelligence across India.

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