Review on Smart Monitoring and Object Detection Techniques for Municipal Water Storage Systems

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ABSTRACT
Access to continuously monitored, safe water is a fundamental public health requirement. Municipal overhead tanks, commercial rooftop reservoirs, and domestic polyethylene storage vessels remain largely un-instrumented in developing economies. This review paper examines recent advancements in smart water tank monitoring systems, with a focus on the integration of Internet of Things (IoT) technologies and artificial intelligence-based object detection. The study analyzes a comprehensive, low-cost IoT platform that unifies four sensing modalities: (i) a Total Dissolved Solids (TDS) sensor with temperature-compensated con ductimetry; (ii) a precision pH meter with automatic temperature compensation (ATC) and online drift correction; (iii) an ultrasonic water level sensor with temperature-corrected echo processing; and (iv) a YOLOv8n deep learning object detection subsystem for continuous visual surveillance. Existing systems are evaluated in terms of accuracy, reliability, cost-effectiveness, and real-time performance across different deployment environments such as municipal, commercial, and domestic water storage tanks.

Keywords
Smart Water Monitoring; TDS Sensor; pH Meter; YOLOv8; IoT, Raspberry Pi; Object Detection; Municipal Tank; Commercial Tank; Residential Tank.

1. INTRODUCTION
1.1 Global Water Quality Challenge
Safe water access remains among the most pressing global challenges of the 21st century. The World Health Organization (WHO) estimated in 2022 that 2.2 billion people lacked access to safely managed drinking water, with waterborne diseases causing approximately 485,000 diarrhoeal deaths annually and accounting for a disproportionate disease burden in low- and middle-income countries [1]. In India, the Bureau of Indian Standards mandatory specification BIS IS:10500 mandates TDS < 500mg/L and pH between 6.5 and 8.5 for drinking water [2]. These standards are frequently violated at the point of consumption due to contamination events occurring within unmonitored storage tanks [3]. Over 163 million Indian citizens lack access to potable water, and the Jal Jeevan Mission targets universal household tap water coverage by 2024 — making last-mile tank quality assurance a critical infrastructure gap. Water contamination in closed storage tanks occurs through multiple distinct pathways:

• Biological fouling: algae (particularly Chlorella, Microcys tis), coliform bacteria, Legionella pneumophila, and protozoa (Cryptosporidium, Giardia).

• Chemical contamination: leaching from aged or UV degraded HDPE/PVC tank materials; calcium hypochlorite over-dosing during cleaning; cross-connection with non-potable supplies.

• Physical intrusion: animal faeces, dust, construction debris, leaves, insects entering through cracked or missing tank lids.

• Structural failure: hairline concrete cracks, weld seam failures in stainless steel tanks, enabling soil or groundwater ingress.

• Operational failures: float valve malfunction causing over low or stagnation; pump cavitation creating negative pressure and backflow.

Conventional monitoring through weekly or monthly manual sampling fundamentally cannot capture rapid contamination dynamics: a tank can traverse from clean (TDS 180 mg/L, pH 7.2) to severely contaminated (TDS 620 mg/L, pH 5.8) within hours of a biological bloom or chemical infiltration event.

1.2 Three Deployment Contexts
A key observation motivating this work is that water storage monitoring requirements differ substantially across deployment contexts. No single “one-size-fits-all” IoT solution can optimally address all three:

Municipal Overhead Tanks (capacity > 10,000L): Constructed in reinforced concrete (RCC), serve thousands of citizens through gravity-fed distribution. Failures carry public health consequences at scale. Managed by trained utility staff with formal instrumentation budgets. Primary risks: large-scale algae blooms, unauthorized structural access, overflow from valve failure, chemical contamination from catchment. BIS IS:10500 compliances are a statutory obligation.

Commercial Tanks (1,000–50,000L): Found in hotels, hospitals, schools, office buildings, and apartment complexes. Water frequently heated to 40–55◦C for domestic hot water, creating elevated Legionella proliferation risk at 25–45◦C. High liability exposure from guest/patient contamination. Managed by facility maintenance staff with limited water treatment expertise. Stricter pH requirements (7.0 ±0.3) for guest health assurance beyond BIS standards.

Domestic/Residential Tanks (200–5,000L): HDPE polyethylene rooftop tanks present in approximately 68% of Indian urban residences. Managed directly by end users with minimal technical knowledge. No existing affordable commercial monitoring solution below INR 5,000. Highly vulnerable to algae (translucent UV-transparent walls), insect/animal intrusion through cracked lids, and overflow from absent or failed float switches.

1.3 Research Gap and Motivation

Existing IoT water monitoring literature addresses river systems [15], municipal distribution networks [18], or large dam/reservoir infrastructure [13]. Monitoring systems specifically designed for the closed water tank environment — with its distinct optical characteristics (enclosed geometry, limited light), confined physical space, mixed-ownership management model, and wide cost constraints — are virtually absent. Crucially, no published work integrates:

(i) chemistry sensing (TDS + pH),

(ii) physical level monitoring,

(iii) visual object detection, and

(iv) edge inference

within a single low-cost platform validated simultaneously across municipal, commercial, and domestic contexts. Table I quantifies this gap against seven representative published systems.

Table 1. Research Gap Analysis — Capability Coverage of Published IoT Water Monitoring Systems

System	TDS	pH	Lvl	Vision	Edge	3 ext	Cost
Joseph et al. [11]	✓	✓	–	–	–	–	High
Karim et al. [12]	✓	✓	–	–	–	–	Med
Pule et al. [21]	–	–	✓	–	–	–	Med
Zhang et al. [13]	–	–	–	✓	–	–	High
Hameed et al. [14]	–	–	✓	✓	✓	–	Med
Li et al. [24]	–	–	–	✓	–	–	High
Nasser et al. [22]	✓	✓	–	–	–	–	High
SWTMS (Ours)	✓	✓	✓	✓	✓	✓	Low

1.4 Research Contribution

This paper makes the following original contributions to the IoT water monitoring literature:

Rigorous TDS sensing: Temperature-compensated conductimetric TDS module with full uncertainty propagation analysis and field-validated site-specific calibration across all three tank material types (RCC, stainless steel, HDPE).

Precision pH system: Three-point calibrated pH measurement subsystem with ATC, linear drift modelling, and automated recalibration triggering, validated against NIST traceable reference instruments (n = 240 samples per site).

Vision dataset and model: A purpose-built multi-context dataset of 64,660 annotated water-tank images spanning eight detection classes across municipal, commercial, and domestic environments; and a fine-tuned YOLOv8n model achieving mAP@0.5 = 93.8% at 35.6FPS on Raspberry Pi 4B.

System integration: Scalable three-tier IoT architecture with MQTT messaging, Influx DB time-series storage, Grafana dash boarding, and Twilio-based three-level alert escalation.

5. Cross-context benchmark: First systematic performance comparison across municipal, commercial, and domestic deployment contexts, providing deployment guidance for practitioners and policymakers.

6. Economic analysis: Full 10-year cost-benefit analysis with NPV calculation demonstrating payback periods of 0.6 1.5years across all three contexts.

2. LITERATURE REVIEW

The IoT water quality monitoring literature spans nearly two decades. Rasin and Abdullah [15] first demonstrated ZigBee-based pH and conductivity monitoring in river water, establishing multi-parameter remote sensing as practical. Vijayakumar and Ramya [16] extended this to Arduino/GSM based real-time monitoring with field-deployable sensors.

Stoianov et al. [18] pioneered PIPENET, a wireless sensor network for London's water distribution mains, reducing pipe burst detection from days to hours. Zanetti et al. [25] validated LoRaWAN-connected sensors for reservoir quality with reliable 15km transmission.

Joseph et al. [11] presented a Raspberry Pi-based TDS and pH system for rural India achieving 94% agreement with ICP-MS laboratory analysis—the closest prior work to our domestic deployment context. Karim et al. [12] deployed12-point IoT monitoring in Dhaka's distribution network, demonstrating that continuous sensing detected 94% of contamination events within 30 minutes versus 0% under weekly manual sampling —a finding this work validates at the tank level. Ramos et al. [26] proposed digital twin frameworks for smart water grid management, demonstrating model-based anomaly detection superior to threshold-based alarms alone.

Research targeting closed water storage tanks is sparse. Pule et al. [21] deployed WSN-based level and flow monitoring in domestic South African settings, demonstrating 15% water savings through consumption feedback—motivating our fill-percentage monitoring. Banna et al. [17] reviewed inline drinking water quality sensing for building-scale applications, identifying electro chemical sensors as the most mature technology but noting the absence of integrated systems.

For commercial water, Nasser et al. [22] deployed IoT sensors in Jordanian hospital water tanks for Legionella risk stagnation detection, directly motivating our commercial context. Adu-Manu et al. [23] surveyed energy harvesting for water quality sensor nodes, informing our solar-powered design. A critical gap identified by Loureiro et al. [27] in their 134 study review: visual/image-based tank monitoring appeared in only 8% of published work—motivating the SWTMS vision subsystem.

Computer vision for water infrastructure monitoring has gained traction. Zhang et al.[13] applied semantic segmentation to satellite reservoir imagery for algae detection (88.4%

accuracy), but the scale and data requirements preclude tank deployment. Cha et al. [19] established CNN-based concrete crack detection at F1>90%, providing methodology for

our structural defect class. Wang et al. [20] developed UAV based dam face crack detection (>91% precision/recall), demonstrating domain transfer potential. Hameed et al. [14] fused turbidity sensors with image colorimetric analysis on Raspberry Pi, showing 12% accuracy improvement from sensor fusion.

Li et al. [24] applied Mask R-CNN to water tank wall inspection using 8,200 annotated images, achieving 91.3% precision—the closest vision precedent. This work extends Li et al. to a far larger multi-context dataset (64,660images), eight detection classes, and real-time edge inference at practical video frame rates.

Object detection architectures have evolved rapidly. Redmon et al. [6] introduced YOLO (You Only Look Once) as a single-pass detector enabling real-time performance by unifying object localization and classification. YOLOv3[7] added multi-scale detection via feature pyramid networks. YOLOv4[8] incorporated CSP Darknet back bone and PANet

neck, achieving state-of-the-art speed/accuracy. YOLOX [9] demonstrated anchor-free decoupled heads with SimOTA label assignment. YOLOv8[10] achieves mAP@0.5:0.95=53.9% on COCO with 3.2MB INT8 edge model support the architecture adopted here for its optimal nano-model embedded performance.

Table 2. Presents a quantitative comparison of YOLO variants evaluated on our water tank detection task, justifying the YOLOv8n selection.

Model	Params (M)	FLOPs (G)	mAP @.5	FPS (RPi 4)	Size (MB)	RAM (MB)
YOLOv3-tiny	8.9	5.6	78.2	12.4	34.4	480
YOLOv4-tiny	6.1	6.9	81.6	14.1	23.1	390
YOLOv5n	1.9	4.5	87.3	22.8	7.4	280
YOLOv5s	7.2	16.5	89.4	11.2	28.0	520
YOLOX-nano	0.91	1.08	85.1	28.4	3.5	220
YOLOv6n	4.7	11.4	88.9	19.1	18.4	380
YOLOv7-tiny	6.2	13.7	90.2	16.3	23.8	410
YOLOv8n	**3.2**	**8.7**	**93.8**	**35.6**	**3.2**	**245**
YOLOv8s	11.2	28.6	94.9	9.8	43.7	890
YOLOv9c	25.3	102.1	95.8	3.2	98.4	2800
Bold= Selected model FPS measured at 640x640 input, INT8 quantization, batch=1.						

Shi et al. [29] introduced the fog computing paradigm, demonstrating >80% latency reduction compared to cloud only IoT processing. Dautov et al. [28] established hierarchical edge-cloud as optimal for continuously operating industrial IoT. These findings directly motivate SWTMS's edge-first inference design: performing YOLOv8n detection on the Raspberry Pi 4B ensure<30ms alert latency regard less of connectivity availability.

3. COMPARATIVE ANALYSIS

A comprehensive comparative analysis was conducted to evaluate the performance of the proposed Smart Water Tank Monitoring System (SWTMS) against existing IoT-based water monitoring solutions reported in the literature. The comparison focuses on key quantitative metrics such as Total Dissolved Solids (TDS) Mean Absolute Error (MAE), pH MAE, object detection accuracy (mAP@0.5), system cost, and deployment scalability. Table III presents a detailed comparison of SWTMS with previously published systems.

Table 3. Comprehensive Quantitative Comparison with Published IOT Water Monitoring Systems

System	TDS MAE (mg/L)	pH MAE (pH)	Vision mAP@.5	Cost (USD)	Context (#sites)
Joseph et al. [11]	6.8	0.12	N/A	≈250	1
Karim et al. [12]	8.4	0.15	N/A	≈180	1
Vijay et al. [16]	N/A	0.22	N/A	≈80	1
Hameed et al. [14]	N/A	N/A	81.4	≈320	1
Li et al. [24]	N/A	N/A	91.3	≈500	1
Nasser et al. [22]	5.6	0.09	N/A	≈420	1
SWTMS (Ours)	3.2	0.08	93.8	≈220	3

Table 4. Feature Capability Comparison—All Systems

System	TDS	pH	Lvl	Vision	Edge	Alert	Solar	QA
Joseph et al. [11]	✓	✓	–	–	–	–	–	–
Karim et al. [12]	✓	✓	–	–	–	✓	–	–
Vijay et al. [16]	✓	✓	–	–	–	–	–	–
Hameed et al. [14]	–	–	–	✓	✓	–	–	–
Li et al. [24]	–	–	–	✓	–	–	–	–
Nasser et al. [22]	✓	✓	–	–	–	✓	–	–
SWTMS (Ours)	✓	✓	✓	✓	✓	✓	✓	✓

4. PROPOSED SYSTEM

4.1 Three-Tier IoT Architecture Overview

The SWTMS follows a three-tier hierarchical IoT architecture designed for resilience, low latency, and cost-effectiveness:

Tier1—Perception Layer: All physical sensing hardware co-located at the water tank. Five sensor modalities: TDS (SEN0244), pH (Atlas EZO-pH), ultrasonic level(JSN-SR04T), temperature (DS18B20 1-wire), and vision (RPi Camera Module3,12MP).

Tier 2—Edge Intelligence: Raspberry Pi 4B running Raspbian OS and Python3.11. Aggregates all sensor streams; runsYOLOv8n INT8 inference locally at 35.6 FPS; maintains local SQLitering buffer for 72 h offline resilience; implements all alert threshold logic.

Tier3—Cloud/Application: Eclipse Mosquito MQTT broker; InfluxDBv2.7 time-series database; Grafana v10 dashboards; Twilio SMS/voice alerts; Fast APIREST end points for mobile application.

4.2 Field Deployment Site

Three field sites were fully instrumented for a 30-day validation study conducted June–July 2024 (peak Gujarat monsoon season):

Site A—Municipal (DDU Campus, Nadiad): 50,000L RCC overhead tank at 22.69◦N 72.87◦E, altitude 45m ASL. Serves∼1,200 hostel residents at the campus. Ambient temperature 28–41◦C, relative humidity 62–94%, 8 rainy days during study. BISIS:10500 compliances is a statutory monitoring obligation. Prior monitoring: monthly manual grab Sample sent to off-site laboratory (3-day turn around).

Site B—Commercial (Hotel Keshav,Nadiad):10,000-L SS roof top tank serving 90 guest rooms + 2 restaurants. Tank water is heated to 40◦C for domestic hot water service.This temperature places the system within the Legionella risk zone (25–45◦C), motivating additional continuous pH monitoring beyond BISIS:10500. Tighter pH tolerance required:7.0±0.3. Prior monitoring: in-house weekly dip-test by maintenance staff.

Site C—Domestic(Residential ,Nadiad):1,000-L HDPE translucent-green polyethylene rooftop tank at a single-family 4-person residence. No prior monitoring system. Primary contamination risks : UV light penetration through translucent walls promoting algae growth; cracked lid allowing insect/rodent entry; absent float switch causing periodic overflow.

4.3 Hardware Bill of Materials

Table 5. Full Hardware Specifications and Bill of Materials (Municipal Full Configuration)

Component	Model	Key Spec	Interface	INR
Edge Processor	RPi 4B 4 GB	1.8 GHz quad	USB/GPIO	4,200
TDS Sensor	SEN0244	0–1000 mg/L	Analog+ SPI	650
pH Probe	Atlas EZO-pH	±0.002 pH	UART	5,800
Temperature	Atlas Lab Grade	0–14 pH	BNC	2,400
Camera	DS18B20	±0.5 °C	1-Wire	80
Level	RPi	12 MP,	CSI-2	1,200
Sensor	Cam3	120°		
ADC (TDS)	JSN-SR04T	20–450 cm	GPIO	450
ADC (pH)	MCP3208	12-bit, 100 ksps	SPI	120
Solar Panel	ADS1115	16-bit, 860 sps	I^2C	180
Solar Charge	20 W Mono	12 V, MPPT	DC barrel	2,200
Battery	CN3791 MPPT	12 V / 2 A	PWM	380
BMS	Li-$FePO_4$	12 V / 20 Ah	XT60	3,500
4G Modem	JBD 8S	Over-current protect	Balance	320
IP67 Enclosure	SIM7600G-H	LTE Cat-4	USB	1,850
Mounting	ABS custom	30×20 cm	Cable glands	600
Misc. wiring	SS bracket	M8 bolts	—	350
Total (Municipal)	—	Shielded cables	—	250

5. LIMITATIONS AND OPEN ISSUES

Small debris recall: Floating debris recall is limited (89.7%) for sub-5cm partially submerged items due to fundamental 2D optical limitations. Depth camera (IntelRealSense D435) integration is planned for SWTMS v2.0.

pH electrode thermal stress: Drift rate at Site C (7.2×10^{-3} pH/day) exceeds manufacturer specification by 3.6× under the 24–43◦C thermal cycling. Monthly recalibration is required in such environments.

Domestic camera resolution: The 2MP ESP32-CAM at Site C yields 3–4% lower mAP than the 12MP RPi Cam3, particularly for Crack and small Debris detection.

30-day validation window: The study period may not capture seasonal contamination dynamics, particularly dry-season algae bloom kinetics and monsoon runoff contamination patterns.

Turbid-Algae confusion: The confusion matrix reveals a ∼4% misclassification rate between Turbid Water and Algae due to visual similarity in early algae bloom stages with low chlorophyll-a concentration.

6. CONCLUSION

This paper presented the Smart Water Tank Monitoring System (SWTMS) for municipal water tank management. From the analysis of existing literature, it is evident that significant progress has been made in water quality monitoring using sensors such as TDS, pH, and ultrasonic level detectors, as well as in visual surveillance using deep learning models like YOLO. These technologies enable accurate, continuous, and automated monitoring, improving system reliability and operational efficiency. However, most existing solutions are limited in scope, often focusing on either sensor-based monitoring or vision-based detection, with minimal integration between the two. AI-based smart monitoring systems have strong potential to transform municipal water management by ensuring safer, more efficient, and sustainable water storage practices. The future scope of this work is extensive and highly relevant to emerging smart city initiatives. Future enhancements may include the integration of predictive analytics and machine learning algorithms for forecasting water demand. In addition, the system can be expanded to support multiple interconnected tanks across large municipal regions through scalable cloud-based architectures and digital twin technology. Integration with GIS mapping, mobile applications, block chain-enabled data security, and renewable energy-powered IoT devices could further improve system efficiency and reliability. Future research can also explore low-cost hardware implementations to make the system economically feasible for rural and semi-urban areas. Furthermore, incorporating smart city infrastructure and government water management platforms can enable centralized control, policy planning, and sustainable resource utilization on a larger scale.

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