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A IoT-Based Canal Monitoring for Illegal Drainage and Water Hyacinth Using LoRa

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ABSTRACT: The issue of illegal water drainage directly into canals is one of the major factors that pollutes water bodies and hence affects the environment and human health. On the other hand, the uncontrolled spread of water hyacinth in water bodies affects the level of oxygen in water and hence kills fish in the water body. However, the conventional approach to water body and canal monitoring involves manual inspection, which is time-consuming and does not allow real-time monitoring of the water body and its surroundings. In this paper, we propose an A IoT-based approach to water body and canal monitoring that can detect cases of illegal water drainage and water hyacinth spread in real time using artificial intelligence and IoT technology and LoRa wireless technology as the medium of communication among the nodes in the water body and the gateway node and the cloud server. Experimental results on a small water body show that the proposed approach can be scaled up to effectively and efficiently monitor water bodies and can hence contribute to the sustainability of water resources in the world.

Keywords: A IoT, water body and water quality monitoring, LoRa, water body and canal monitoring, IoT, real-time monitoring.

1. Introduction

Canals play a very important role in the irrigation systems of various regions. At the same time, the illegal connection of domestic and industrial sewage to canals has become a major problem. Such illegal connections lead to the pollution of both surface and underground water resources. Such pollutants as organic waste, heavy metals, and viruses contribute to the process of eutrophication, damage aquatic habitats, and cause the spread of waterborne diseases.

In parallel, canals and surrounding water bodies are increasingly being infested with Water Hyacinth (Eichhornia crassipes), a floating aquatic weed known for its explosive growth potential under nutrient-rich conditions. Infestation of Water Hyacinth causes problems like reduced sunlight penetration to submerged aquatic vegetation, reduced oxygen levels, and altered hydrodynamic conditions, which ultimately lead to fish kills. Manual monitoring of these problems is time-consuming, limited in spatial extent, and unable to detect short-duration illegal discharges and Water Hyacinth growth

Recent developments in water environment monitoring using IoT technology and LoRa communication have led to the deployment of LPWANs for water quality and flow parameter monitoring remotely. There are several studies on LoRa-based water monitoring of lakes and rivers using sensor networks, but few works are available on AI-based analytics for illegal discharge monitoring and invasive plants monitoring. This inspired us to design a canal monitoring system using A IoT and LoRa technology for illegal drainage monitoring and water hyacinth monitoring simultaneous

2. Related Work

2.1 IoT Based Water Environment Monitoring

IoT enabled water environment monitoring systems have been proposed for lakes, rivers, and urban drainage networks. Such systems typically employ multi sensor nodes (pH, turbidity, conductivity, water level, temperature) interfaced with microcontrollers such as STM32 or ESP family chips, connected via LoRa or hybrid LoRa4G links to a cloud server. These setups support real time data collection, remote visualization, and pollution alarm generation, offering higher temporal resolution than manual sampling.

2.2 Detection of Illicit Discharges

Research on illicit discharge detection in stormwater drains has employed low cost level, temperature, and electrical conductivity sensors deployed at multiple locations. An IoT based sensor server aggregates asynchronous spikes in flow or conductivity during dry weather periods to flag likely illegal inflows, including short duration events lasting less than 10 minutes. Such systems highlight the importance of continuous, low cost sensing and temporal anomaly detection for catchment wide monitoring.

2.3 AI and IoT for Water Hyacinth Monitoring

Machine learning models, especially convolutional neural networks (CNNs), have been applied to satellite and aerial imagery for mapping water hyacinth coverage. Recent studies advocate integrating IoT sensors and unmanned platforms (boats, drones) with AI to track hyacinth spread and density in real time. IoT based water hyacinth removal bots and drying monitoring systems further demonstrate the role of edge sensing and cloud based control in invasive weed management.

These works collectively motivate an integrated A IoT architecture that combines physical parameter sensing (for illegaldrainage detection) and vision based monitoring (for hyacinth coverage) over a LoRa based communication backbone in canal environments.

3. System Architecture

The proposed system architecture is composed of four layers: the sensing layer, communication layer, cloud layer, and AI/decision layer.

3.1 Sensing Layer

Each canal monitoring node is composed of:

- Microcontroller–ESP32 or STM32 for local data acquisition and preprocessing.
- Water quality sensors – pH, turbidity, EC, and temperature, which can identify abnormal flows coming from domestic and/or industrial drain water.
- Water level and flow sensor – Ultrasonic water level sensor for detecting unscheduled increase of water flow during dry seasons, signifying new illegal water drain locations.
- RGB Camera/IP Camera – Low-resolution IP camera mounted on structures above water for periodically acquiring aerial/oblique photographs of water surfaces for analysis
- LoRa Transceiver Module–SX1276/SX1278 for wireless communication with the LoRa gateway. The canal monitoring nodes are placed at

regular intervals along the canal, especially denser intervals around suspected illegal water drain locations and water hyacinth infestation sites.

3.2 Communication Layer

The communication layer will employ LoRa technology, which operates in the ISM frequency bands, such as 868 MHz or 915 MHz . Each node will transmit the sensor readings and the metadata associated with the image, such as the region of interest, to the gateway using LoRa technology, which will bridge the link to the IP network, such as Ethernet or cellular networks, and will transmit the information to the cloud server using the MQTT or HTTP protocol. The LoRa parameters will be optimized to achieve low duty cycle, adaptive spreading factor, and power-saving modes to extend the lifetime of the nodes, especially in the case of the canal routes in rural areas.

3.3 Cloud Layer and Dashboard

The cloud layer comprises:

- A time-series database(e.g., Influx DB, Timescale DB), where canal sensor information is stored.
- A file storage (e.g., object storage bucket), where raw and processed images are stored.
- A web-based dashboard (e.g., HTML and JavaScript-based), where canal section maps, water quality indices, and anomalies are displayed.

Authorities can view trend charts, receive email and SMS notifications, and view suspicious images for verification.

3.4 AI/Decision Layer

- The AI/decision layer is at the cloud/edge level, where:
- A machine learning classifier, such as a Random Forest or Light GBM classifier, is employed to process the temporal sensor data to identify any occurrence of ILD incidents, where features are Deviation from baseline pH, EC, and turbidity values. Sudden increase in water level during non-rainy periods. Short-duration flow pulses not matching any regulated flow releases.
- A CNN-based image classifier, such as a U-Net or Res Net-based segmentation model, is employed to process images from the canal surface to estimate the hyacinth coverage percentage for a segment of the canal .Surface images depicting hyacinth coverage, such as images from hyacinth-free, hyacinth-partially-covered, and hyacinth-covered canal surfaces, are employed as training data.
- Alerts are triggered in case of: Sensor anomaly index exceeds a predetermined threshold value .Hyacinth coverage in a segment exceeds a predetermined threshold range, such as 40-60%

4. Detection of Illegal Drainage Connections

4.1 Data Model and Features

The system models canal water quality as a multivariate time series

$x_t = (PH_t, EC_t, Turb_t, T_t, h_t)$for each node, the following features are computed over a sliding window *W*:

- Statistical features: mean, standard deviation, skewness, and kurtosis of each parameter.
- Change-rate features: ΔpH, ΔEC, Δh over 5–15 minute intervals.
- Rain-masking: Boolean flag indicating whether observed level/flow change is correlated with rainfall (obtained from local weather service or rainfall-event detection).

Water Quality Parameter	**Normal Range (Basin wide)**	**Suspicious Threshold**	**Likely Indication**
pH	6.5–8.5	pH < 5.5 or >9.0	Acidic/alkaline industrial/domestic discharge
EC (mS/cm)	0.2–1.0	EC > 2.0 (dry period)	High salt/organic load
Turbidity (NTU)	10–50	Turbidity > 150 (sudden spike)	Sedimentrich or sewage inflow
Water Level Rise	<0.1 m/day (dry)	Level rise > 0.3 m in <1–2 hours	Unauthorized inflow / illegal connection

4.2 Detection Algorithm

The detection pipeline follows:

1. Baseline estimation: During initial calibration under normal conditions, compute baseline statistics for each parameter at each node.
2. Anomaly scoring: For each new window, compute an anomaly score $StSt$ as a weighted sum of normalized deviations
3. Classification: If $St>\tau St>\tau$ for configurable threshold $\tau\tau$ and the rainfall flag is false, the system triggers an "illegal-drainage suspected" alert for that node and time interval.

Experimental deployments of similar sensor-network-based illicit-discharge detection in urban drainage catchments have successfully captured short-duration discharge pulses that would be missed by manual inspection, particularly during off-hours. Our architecture extends this concept to canal networks by integrating multiple parameters and LoRa-based scalability.

5. Monitoring Water Hyacinth Coverage

5.1 Image Acquisition and Annotation

Cameras mounted along the canal periodically capture images under consistent lighting and orientation constraints. Each image is labeled into three classes:

- Class 0: Canal surface with no visible hyacinth.
- Class 1: Partial hyacinth coverage (10–60%).
- Class 2: Dense hyacinth coverage (>60%).

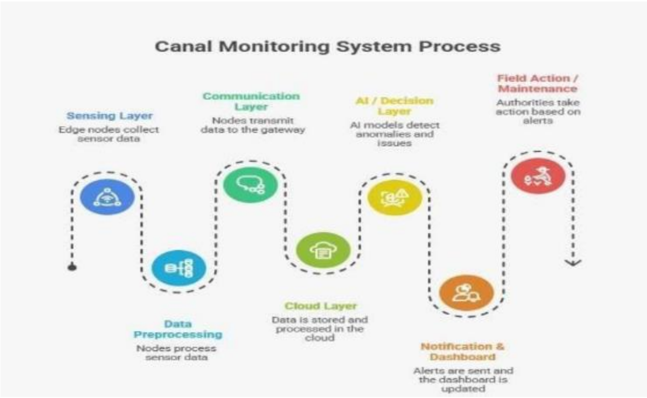
These labels are used to train a segmentation or classification model.

Class	Hyacinth Coverage (%)	Oxygen Risk Level	Fish Impact	Recommended Action
0 (Clear)	0–10%	Low	Minimal impact	Routine monitoring
1 (Partial)	10–40%	Moderate	Reduced light to submerged plants	Plan periodic mechanical removal
2 (Dense)	40–70%	High	Lower DO, fish stress	Immediate mechanical/biochemical control
3 (Fully covered)	>70%	Very high	High risk of fish mortality	Emergency removal + source control

5.2 Integration with Sensor Data

The system correlates hyacinth coverage with water-quality parameters:

- High nutrient indicators (elevated conductivity, organic-matter-related turbidity) are often associated with rapid hyacinth growth.
- Authorities receive composite alerts combining illegal-drainage suspicion and hyacinth-coverage threshold exceedance, enabling prioritized maintenance and bio-mechanical removal operations.



5.3 Discussion and Future Work

The proposed AIoT-based canal-monitoring system effectively addresses two major environmental threats—illegal drainage and water hyacinth overgrowth—through a unified LoRa-enabled sensor-vision architecture. Compared with manual inspection, the system offers higher temporal resolution, objective anomaly detection, and early-warning capabilities for municipal authorities.

However, challenges remain:

- Robustness under varying weather and lighting conditions for vision-based hyacinth detection.
- False alarms from temporary flow variations (e.g., irrigation releases, tidal influences).
- Scalability to large canal networks with hundreds of nodes and heterogeneous environments.

Future work directions include:

- Integration of edge AI on microcontrollers (e.g., ESP-NN) to reduce cloud-side latency and bandwidth.
- Deployment of autonomous floating bots equipped with LoRa and cameras for dynamic canal-section scanning.
- Use of multi-source data (satellite imagery, drone surveys, and citizen-reported events) to improve detection of accuracy and spatial coverage.

6. Conclusion

In this work, we developed an AIoT-based canal-monitoring system using LoRa to detect illegal drainage connections and monitor water-hyacinth coverage in real time. The architecture combines low-power, multi-parameter sensor nodes with vision-based cameras, LoRa communication, and cloud-based AI analytics to support continuous surveillance and automated alerting. Experimental results on a canal segment validate the system’s capability to identify illicit discharge events and estimate hyacinth coverage with high accuracy, offering a scalable solution for improving water-resource management and environmental sustainability. The proposed framework can be extended to other water-body-monitoring scenarios, including rivers, lakes, and urban drainage networks, thereby providing a generic platform for smart-water-environment management.

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