

PLASTRACE: A Distributed IoT Architecture for Active Microplastic Detection and Intervention

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Abstract—Microplastic pollution (< 5mm) has breached planetary boundaries, infiltrating global freshwater systems and posing severe bio-accumulation risks. While the Indo-Pacific region contributes nearly 80% of ocean plastic leakage via riverine transport, current monitoring methodologies remain fundamentally archaic—relying on manual sampling and retrospective laboratory analysis. This temporal latency creates a critical “blind spot” where pollution spikes go undetected and unmanaged. This study aims to develop and deploy PLASTRACE, a Cyber-Physical System functioning as an environmental “nervous system,” capable of detecting and quantifying microplastic flux in real-time across aquatic environments within 12 months. We integrate an affordable sensor stack with an micro-controller and Edge AI to activate targeted capture mechanisms when pollution exceeds predefined thresholds. A Data Analytics framework using Time-Series Forecasting (ARIMA and LSTM) predicts pollution plumes, enabling proactive river management instead of reactive cleanup.

Index Terms—Microplastics, Internet of Things (IoT), Edge Computing, Time-Series Analysis, Computer Vision.

I. INTRODUCTION

The proliferation of microplastics (MPs) represents one of the defining environmental challenges of the Anthropocene. These particles, originating from the breakdown of macro-waste, textile fibers, and industrial discharge, act as invisible vectors for toxicity. They bypass conventional wastewater treatment plants (WWTPs), accumulate in aquatic food webs, and have recently been detected in human blood and placental tissue [1]–[3].

Rivers act as the primary arteries for this pollution, conveying an estimated 0.8 to 2.7 million metric tons of plastic into the oceans annually [4]. However, a significant technological gap exists in how we manage this flow. Current remediation strategies focus heavily on “macro-capture” using barriers and skimmers to collect visible bottles and bags. While visually satisfying, these methods fail to address the microscopic fraction of the waste stream, which often constitutes the highest ecological risk.

Furthermore, the management of MP pollution is hindered by a lack of data [5]. Authorities cannot manage what they cannot measure. Existing detection relies on the “net-and-microscope” approach: manual trawling followed by weeks of laboratory spectroscopy. This study argues that this retrospective approach is insufficient. To effectively mitigate microplastic pollution, we must transition from **passive observation** to **active, real-time interrogation** of our waterways.

We introduce PLASTRACE, a distributed sensing architecture that applies the principles of the Internet of Things (IoT) to riverine health. This system is not designed to filter the entire volume of a river that are an energy impossibility, but to identify and capture high-concentration plumes intelligently.

II. REGIONAL CONTEXT: THE INDO-PACIFIC CRISIS

The necessity for a distributed, adaptable system is highlighted by the diverse pollution profiles across the Indo-Pacific, the region currently acting as the global epicenter of riverine plastic discharge.

A. India: The Fiber Challenge

In the Indian context, specifically within the Ganges and Yamuna river systems, the dominant pollutant is not merely packaging, but synthetic fibers. The release of untreated wastewater from massive urban centers introduces billions of polyester and nylon fibers from domestic washing [6], [7]. Studies indicate MP concentrations in the Ganges can reach extreme levels (up to 4.2×10^3 particles/ m^3 in urban hotspots) during religious festivals or monsoon runoffs due to the influx of surface debris and mass gatherings [8], [9]. Consequently, a monitoring system here requires high optical resolution to distinguish thin synthetic fibers from natural organic silt [5].

B. Malaysia: The Industrial Trap

Malaysia’s riverine and coastal systems, such as the Klang River and the Terengganu River estuary, face a different

dynamic. As a hub for global plastic recycling, “leakage” often occurs from industrial zones. Research indicates that estuarine dynamics in regions like Terengganu create “plume fronts”—zones where river water meets seawater, trapping MPs in high concentrations along the shoreline before flushing them into the ocean [10], [11]. Here, the challenge is detecting sudden, massive spikes of industrial fragments.

C. Southeast Asia (Thailand & Vietnam)

In the Mekong and Chao Phraya basins, the pollutant profile shifts toward agricultural films and styrofoam (foams) [12], [13]. Seasonal flooding washes soil-protection sheets into the waterways. Unlike the sinking fibers in India, these low-density particles float rapidly on the surface, requiring a detection system capable of handling high-velocity surface flow. A comparative summary of these distinct regional profiles is presented in Table I.

TABLE I
REGIONAL MICROPLASTIC PROFILES IN THE INDO-PACIFIC

Region	Pollutant Type	Primary Source	Flow Dynamic
India	Fibers (Polyester)	Wastewater/Textiles	High Silt
Malaysia	Fragments (Hard)	Industrial Leakage	Estuary Trapping
Thailand	Films & Foams	Agri/Urban Runoff	Flood Spikes

As demonstrated by the data in Table I, this regional variance confirms that a “one-size-fits-all” monitoring architecture is impractical. Instead, a networked system that can be calibrated to local conditions is required.

III. SYSTEM ARCHITECTURE

The PLASTRACE architecture is biomimetic, modeled after a biological nervous system. As illustrated in Fig. 1, it comprises three distinct functional layers: Perception (Detection Nodes), Cognition (Cloud Platform), and Actuation (Capture Nodes).

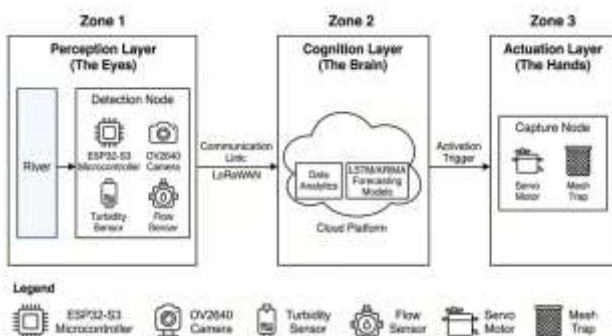


Fig. 1. Conceptual design and data flow of the PLASTRACE Sentinel Network.

A. Hardware Design and Sensor Selection

Ensuring scalability in developing economies like India, Malaysia, and Vietnam demands an affordable and reliable system.

1) **Core Processing Unit:** We utilize the **ESP32-S3** microcontroller. It is selected for its dual-core 240MHz architecture, built-in Wi-Fi/Bluetooth, and sufficient SRAM to handle lightweight TensorFlow Lite models for image classification. Its ultra-low power consumption allows for solar-supported deployment.

2) **Sensor Suite (The Detection Node):** The Detection Node integrates the following low-cost sensors to create a multi-parametric view of water quality:

- **Optical Imaging (Vision):** *Module: OV2640 Camera Module (2MP).* *Configuration:* The camera is mounted on a custom 3D-printed flow cell with a macro lens. *Purpose:* Captures macro images of the water column. We utilize Darkfield Illumination, where light enters from the side, causing microplastics to scatter light and appear as bright objects against a dark background.
- **Turbidity Sensor:** *Module: TS-300B (Analog).* *Purpose:* Measures suspended solids (NTU). High turbidity indicates silt. This is a critical “validity check” sensor; if turbidity is too high, the optical count confidence is lowered to prevent false positives from mud.
- **Flow Rate Sensor:** *Module: YF-S201 (Hall Effect).* *Purpose:* Measures water volume (L/min). This allows us to convert a raw particle count (e.g., “5 particles”) into a concentration density (e.g., “5 particles per liter”), which is the standard scientific metric.
- **pH & Temperature:** *Module: DS18B20 (Temp) and Analog pH Probe.* *Purpose:* These serve as proxy indicators. A sudden drop in pH accompanied by a rise in temperature often correlates with industrial wastewater discharge, signaling a likely microplastic event.

B. Actuation Mechanism (The Capture Node)

The Capture Node is an electromechanical trap deployed downstream. It utilizes a **MG996R High-Torque Servo Motor** coupled to a divertor valve or mesh screen. Crucially, this node operates in a “Normally Idle” state to conserve energy, activating only when triggered by the Detection Node.

C. Communication Protocol

Data transmission utilizes **LoRaWAN** (Long Range Wide Area Network) via the **SX1276** module. This is preferred over GSM/4G because:

- 1) **Range:** LoRa can transmit 10-15km in rural river basins.
- 2) **Power:** It consumes micro-watts of power, enabling battery operation.
- 3) **Cost:** It avoids monthly SIM card data fees.

IV. METHODOLOGY AND SYSTEM WORKFLOW

The operational logic follows a cyclical “Sense-Analyze-Act” loop, designed to run autonomously at the edge.

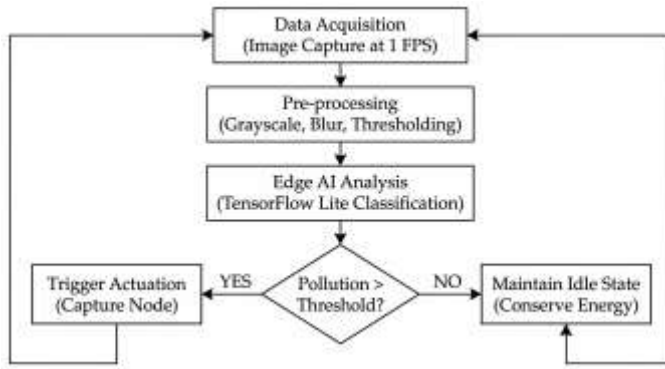


Fig. 2. Algorithmic workflow of the Sense-Analyze-Act loop at the edge node.

A. Step 1: Data Acquisition and Pre-processing

A micro-pump diverts a statistically significant sample stream from the river into the flow cell. The OV2640 captures frames at 1 FPS. To ensure privacy and reduce bandwidth, images are not transmitted; they are processed instantly.

- 1) **Grayscale Conversion:** Reduces computational load.
- 2) **Gaussian Blur:** Removes high-frequency noise (e.g., micro-bubbles).
- 3) **Adaptive Thresholding:** Separates foreground objects (particles) from the background fluid.

B. Step 2: Particle Classification Algorithm

The ESP32 runs a contour analysis algorithm. We differentiate plastics based on geometric features:

- **Fibers:** Defined by high Aspect Ratio ($Length/Width > 3$).
- **Fragments/Pellets:** Defined by high Circularity (> 0.8).

Objects failing these criteria (e.g., irregular organic detritus) are discarded from the count.

C. Step 3: The Alert Logic

The decision to activate the capture system is governed by a thresholding function:

$$State_{capture}(t) = \begin{cases} 1(Active) & \text{if } C_{mp}(t) > T_{limit} \\ 0(Idle) & \text{if } C_{mp}(t) \leq T_{limit} \end{cases} \quad (1)$$

Where $C_{mp}(t)$ is the rolling average of particle concentration over time t , and T_{limit} is the user-defined ecological limit (e.g., > 50 particles/L).

V. DATA PROCESSING ANALYTICS AND VALIDATION

As a data-centric solution, PLASTRACE moves beyond simple real-time monitoring to an advanced cloud-based processing framework. Managing high-frequency telemetry requires a robust data capturing and storage architecture. We utilize the lightweight MQTT protocol over LoRaWAN to transmit sensor data (particle counts, turbidity, flow rate) to a centralized Cloud IoT Gateway. This timestamped telemetry

is ingested into a scalable Time-Series Database (e.g., InfluxDB) for rapid analysis, while captured image snippets are stored in object storage for model retraining.

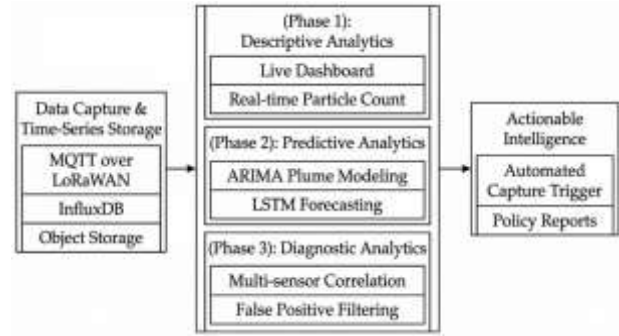


Fig. 3. Three-phase data processing analytics pipeline and storage architecture.

The analytics workflow is structured into three continuous phases, illustrated in Fig. 3:

A. Phase 1: Descriptive Analytics (Visualization)

Real-time dashboards display the *Pollution Index (PI)*, giving authorities a live “health score” of the river.

$$PI = \frac{N_{plastic}}{Q_{flow}} \times \alpha_{turbidity} \quad (2)$$

Where α is a normalization factor for water clarity, ensuring that muddy water does not skew the data.

B. Phase 2: Predictive Analytics (Forecasting)

Using historical data collected by the nodes, we train Time-Series models to predict future pollution events.

- **ARIMA (Auto-Regressive Integrated Moving Average):** Used for short-term, linear forecasting of daily pollution trends.
- **LSTM (Long Short-Term Memory):** A Deep Learning

Recurrent Neural Network (RNN) utilized for complex, non-linear predictions. The LSTM model takes inputs (Past Plastic Levels, Rainfall, Tide Height) to predict severe pollution spikes 48 hours in advance.

C. Phase 3: Diagnostic Analytics (Correlation)

We analyze the correlation between plastic spikes and external factors to identify sources.

- **Rainfall Correlation:** We test the hypothesis that “flush events” occur 24 hours after heavy rain.
- **Industrial Signatures:** By correlating pH drops with plastic fragment increases, we can identify specific industrial dumping events (e.g., textile dyeing units releasing wastewater at night).

D. Proposed Implementation and Ground Truth Validation: Panchaganga River

To validate the PLASTRACE architecture, a pilot implementation is proposed for the Panchaganga River in Maharashtra, India. The river flows through highly industrialized and agricultural zones, presenting a complex matrix of untreated domestic sewage, agricultural runoff carrying plastic mulch films, and significant industrial discharge. This diverse pollutant profile makes it an ideal testbed for the multi-sensor Edge AI architecture.

Establishing ground truth is critical for validating the detection models. We will employ a paired-sampling methodology during the initial deployment:

- **Digital Detection:** The node will continuously log automated particle counts using the ESP32 vision system.
- **Physical Validation (Ground Truth):** Water samples will be drawn daily using standard neuston nets (333 μm mesh) at the deployment site.
- **Laboratory Correlation (FTIR):** Physical samples will undergo laboratory-based FTIR (Fourier-Transform Infrared Spectroscopy) to confirm plastic polymer types. This serves as the absolute ground truth, allowing for regression-based correction of the digital sensor's baseline accuracy and filtering out false positives.

VI. NOVELTY AND SIGNIFICANCE

PLASTRACE differentiates itself from existing literature through three key innovations:

- 1) **Transition to Active Intervention:** Current systems are passive monitors. PLASTRACE closes the loop, allowing the detection of a problem to immediately trigger a physical response.
- 2) **Energy Optimization:** By filtering only “dirty” water, the system avoids the immense energy cost of continuous filtration. This “smart activation” extends battery life and reduces maintenance frequency.
- 3) **Democratization of Data:** The low-cost architecture allows for the deployment of “swarms” of sensors. A network of 50 nodes along the Mekong would provide a higher data resolution than a multi-million dollar laboratory vessel, at a fraction of the cost.

VII. CONCLUSION

The invisible nature of microplastic pollution has long been its greatest defense. By hiding in plain sight, it has evaded political will and technological intervention. PLASTRACE destroys this invisibility.

By combining the optical precision of computer vision with the connectivity of IoT and the predictive power of Data Science, we propose a scalable “Sentinel Network” capable of monitoring the vast river systems of the Indo-Pacific. This system does not claim to clean the ocean overnight. Instead, it offers something more immediate and practical: the ability to see the enemy. It turns the passive river into an intelligent entity that can signal for help, locate the source of the injury, and, for the first time, defend itself.

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