

## Original Research

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## Heavy Metal Detection and Prediction in Water Using Smart IoT-Enabled System

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**ABSTRACT:** The contamination of water bodies by heavy metals is known to pose significant risks to public health and environmental sustainability, particularly in rapidly industrialized regions such as Indonesia. Conventional laboratory-based methods are costly, time-consuming, and unsuitable for real-time large-scale monitoring. Therefore, this study proposed an AI-enhanced edge-IoT system for real-time detection and prediction of heavy metal contamination in water. The system integrated an anodic stripping voltammetry (ASV) sensor array with an ESP32-based edge computing unit, enabling on-device preprocessing, anomaly detection, and predictive analytics to use lightweight machine learning models. The platform also supported the multi-parameter sensing of lead (Pb), cadmium (Cd), mercury (Hg), and arsenic (As), combined with Wi-Fi/GSM communication, MQTT-based cloud infrastructure, and an interactive monitoring dashboard. Experimental validation was conducted using 120 water samples collected from industrial, agricultural, and urban environments across West Java, Indonesia. Additionally, the proposed system achieved strong agreement with ICP-OES reference measurements, with coefficients of determination ( $R^2$ ) exceeding 0.97 for all target metals. The limits of detection were 0.8  $\mu\text{g/L}$  (Pb), 0.5  $\mu\text{g/L}$  (Cd), 0.3  $\mu\text{g/L}$  (Hg), and 1.1  $\mu\text{g/L}$  (As). The embedded AI model showed reliable short-term prediction of contamination trends and early anomaly detection at the edge level. The proposed method offered a cost-effective, scalable, and field-deployable solution for continuous water quality monitoring, supporting compliance with Indonesian Government Regulation No. 22/2021 and WHO drinking-water standards.

## 1. INTRODUCTION

Water quality degradation driven by heavy metal contamination is among the most critical environmental and public health challenges of the twenty-first century [1]–[3]. Lead (Pb), cadmium (Cd), mercury (Hg), and arsenic (As) are persistent, non-biodegradable, and bio-accumulative heavy metals found in aquatic food chains. However, at trace concentrations in the microgram-per-litre range, prolonged exposure is associated with neurological damage, renal impairment, and developmental disorders in children, including increased cancer risk [4]–[8]. The WHO classified As alongside Pb and Cd as Groups 1 and 2 carcinogens, respectively, with an established health burden documented across low- and middle-income countries [9]–[11].

In Indonesia, rapid industrialization, intensive agricultural practices, gold and nickel mining, as well as inadequate wastewater treatment, have collectively increased the incorporation of heavy metals into surface and groundwater systems [12]–[15]. Government Regulation PP No. 22 of 2021 established stringent water quality standards, but the enforcement remained severely constrained by limited real-time monitoring infrastructure.

Conventional analytical methods for heavy metal quantification, particularly AAS and ICP-MS, delivered high sensitivity. These methods tended to require centralized laboratories and lengthy sample preparation [16], [17]. However, electrochemical methods, particularly ASV, achieved comparable detection limits while being amenable to miniaturization and field deployment [18], [19]. The inherent preconcentration step of ASV enhanced sensitivity by several orders of magnitude. Based on this perspective, bismuth film electrodes (BiFEs) offered an environmentally preferable alternative for Pb and Cd detection [18], [20], [21]. The ESP32 system-on-chip has evolved into a dominant IoT platform due to its dual-core processor, integrated Wi-Fi/Bluetooth, and multiple ADC channels at sub-\$5 unit cost [22]–[25].

The integration of IoT platforms and electrochemical detection into a validated, field-deployable system was limited, despite significant advances. The essence was to achieve simultaneous multi-metal monitoring within the Indonesian regulatory context. This study addressed the numerous gaps through three objectives, namely (i) design and fabricate an integrated hardware–software architecture for simultaneous Pb, Cd, Hg, and As measurement, (ii) validate device performance against ICP-OES using 120 field-collected samples, and (iii) show applicability to continuous surveillance in West Java, Indonesia.

The novelty of this study relative to previously reported portable heavy-metal sensing platforms (Section 3.5, Table 6) is fourfold. First, unlike prior electrochemical IoT sensors that typically target only one or two metals [26], [27], the proposed platform performs simultaneous quantification of four regulated metals (Pb, Cd, Hg, As) from a single ASV sensor array and sample aliquot, reducing per-analyte cost and field deployment time. Second, the system embeds, rather than merely transmits, artificial intelligence at the edge: an 8-bit quantized Isolation Forest for real-time anomaly flagging and a compact LSTM for 1-hour-ahead concentration forecasting run directly on the ESP32 (<48 kB flash), enabling autonomous early-warning without continuous cloud connectivity, a capability absent from previous benchtop-equivalent or partial-IoT designs. Third, the platform was validated not only under controlled laboratory conditions but through a 5-month, three-zone field deployment ( $n = 120$  paired samples;  $n = 3,600$  measurement cycles) benchmarked directly against ICP-OES/CV-AFS reference methods, providing an evidence base for regulatory-grade performance that most prior prototypes lack. Fourth, the system closes the loop from detection to action by coupling real-time regulatory-threshold comparison (against PP No. 22/2021 and WHO guideline values) with automated multi-channel alerting (Telegram/email, <5 s), positioning it as a decision-support tool for environmental health surveillance rather than a standalone sensing device. Collectively, these elements multi-metal simultaneity, embedded (not cloud-dependent) AI, rigorous field-scale validation, and regulatory-linked automated alerting differentiate this work from existing portable heavy-metal monitoring systems, as further quantified in the comparative analysis in Section 3.5.

## 2. MATERIALS AND METHODS

### 2.1 Study Design and Area

An instrument development and validation design comprising two phases was adopted. These included (a) hardware and software development, alongside (b) field validation against ICP-OES. Additionally, field validation was conducted across three representative water environments in West Java Province, Indonesia. The three representative water environments consisted of (i) industrial effluent-receiving rivers in the Bandung Metropolitan Area (Citarum River tributary, Cimahi sub-basin), (ii) agricultural drainage canals in the Karawang Rice Production Area, and (iii) urban stormwater channels in the Depok–Bekasi corridor.

## 2.2 Sample Collection

A total of 120 grab water samples ( $n = 40$  per zone) were collected between June and October 2024 in accordance with SNI 6989.57:2008 protocols. The samples were collected in acid-washed 1 L HDPE bottles, acidified to  $\text{pH} < 2$  with  $\text{HNO}_3$  (Suprapur grade, Merck), and transported on ice at  $\leq 4^\circ\text{C}$  for parallel ICP-OES analysis conducted within 48 hours. Furthermore, the sampling sites ( $n = 12$  per zone, triplicate collections) were georeferenced using GPS ( $\pm 3$  m accuracy).

## 2.3 System Architecture

The IoT heavy-metal monitoring system followed a three-tier architecture, as shown in Figure 1. Additionally, Table 1 showed that (1) the Edge Node comprised an electrochemical sensing module, miniaturized potentiostat, ESP32 microcontroller, and power management subsystem, (2) the Communication Layer used dual Wi-Fi/GSM connectivity with MQTT/TLS 1.3, and (3) the Cloud & Application Layer incorporated InfluxDB v2.7, Node-RED, Grafana, and automated Telegram/email notifications.

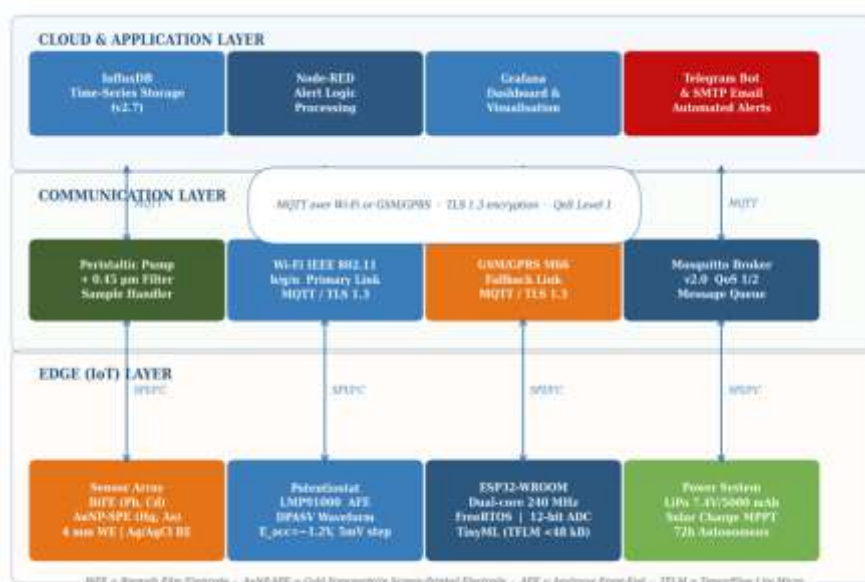


**Figure 1.** Three-tier IoT system architecture. Edge Layer: BiFE/AuNP-SPE sensor array, LMP91000 AFE, ESP32-WROOM (240 MHz, Free RTOS, Tiny ML <48 kB), power management (LiPo 7.4 V/5000 mAh + solar MPPT). Communication Layer: peristaltic pump + 0.45  $\mu\text{m}$  filter, Wi-Fi 802.11 b/g/n (primary) and GSM/GPRS M66 (fallback) through MQTT/TLS 1.3. Cloud Layer: InfluxDB v2.7, Node-RED v3.1, Grafana v10.2, Telegram Bot/SMTP alerts.

Table 1. Hardware and software components of the three-tier IoT monitoring system

| Layer | Component       | Specification                         | Function                              |
|-------|-----------------|---------------------------------------|---------------------------------------|
| Edge  | Sensor array    | BiFE + AuNP-SPE, 4 mm WE, Ag/AgCl RE  | Simultaneous Pb, Cd, Hg, As detection |
| Edge  | Potentiostat    | LMP91000 AFE; 12-bit ESP32 DAC        | DPASV waveform generation             |
| Edge  | Microcontroller | ESP32-WROOM, 240 MHz, FreeRTOS        | Control, AI inference, buffering      |
| Edge  | Power system    | LiPo 7.4 V/5000 mAh + MPPT solar      | 72 h autonomous operation             |
| Comm. | Primary link    | Wi-Fi IEEE 802.11 b/g/n, MQTT/TLS 1.3 | Cloud data transmission               |
| Comm. | Fallback link   | GSM/GPRS M66, MQTT/TLS 1.3            | Backup connectivity                   |
| Cloud | Database        | InfluxDB v2.7 (time-series)           | Sensor data storage                   |
| Cloud | Processing      | Node-RED v3.1                         | Alert logic automation                |
| Cloud | Dashboard       | Grafana v10.2                         | Real-time visualization               |
| Cloud | Alerting        | Telegram Bot API + SMTP               | Automated regulatory alerts           |

## 2.4 Electrochemical Sensing Model

The relationship between the stripping peak current and metal concentration for each target analyte  $m$  is modelled as a linear electrochemical response.

$$I_{p,m} = \alpha_m C_m + \beta_m + \epsilon_m \quad (1)$$

**Eq. 1.** Linear electrochemical response:  $I_{p,m}$  = peak current ( $\mu A$ ),  $\alpha_m$  = sensitivity slope ( $\mu A \cdot L / \mu g$ ),  $C_m$  = concentration ( $\mu g / L$ ),  $\beta_m$  = intercept ( $\mu A$ ),  $\epsilon_m$  = measurement error

The accuracy in complex environmental matrices was improved by ensuring the standard addition method was applied. This was achieved by sequentially spiking known concentrations into the sample.

$$I_{p,m}^{(k)} = \alpha_m (C_{x,m} + I_{add,m}^{(k)} + \beta_m) \quad (2)$$

**Eq. 2.** Standard addition model —  $k$ -th spike addition to estimate unknown concentration  $C_{x,m}$

The unknown sample concentration is further estimated as follows:

$$C_{x,m} = -\frac{\beta_m}{\alpha_m} \quad (3)$$

**Eq. 3.** Unknown concentration estimated by the  $x$ -intercept of the standard addition line

DPASV waveform parameters:  $E_{acc} = -1.2$  V,  $t_{acc} = 120$  s,  $\Delta E = 5$  mV, pulse amplitude = 50 mV, pulse width = 50 ms,  $v = 10$  mV/s. Furthermore, bismuth film was electrodeposited from 0.1 mol/L  $Bi^{3+}$  in acetate buffer (pH 4.5) at  $-1.0$  V for 120 s before each Pb/Cd measurement cycle.

## 2.5 Temperature Compensation

A DS18B20 digital temperature sensor enabled automated thermal drift compensation. In addition, the temperature-corrected peak current was computed as follows:

$$I_{p,m}^{corr} = I_{p,m} [1 - \gamma_m (\alpha_m (T - T_{ref}))] \quad (4)$$

**Eq. 4.** Temperature drift correction:  $\gamma_m$  = temperature coefficient ( $^{\circ}C^{-1}$ ), and  $T_{ref} = 25^{\circ}C$  reference calibration temperature.

## 2.6 Signal Processing

Raw voltametric current signals acquired from the 12-bit ADC were smoothed using a Savitzky–Golay filter (window = 7, polynomial order = 3):

$$\tilde{x}_i = \sum_{j=-r}^r h_j x_{i+j} \quad (5)$$

**Eq. 5.** Savitzky–Golay smoothing filter: window size  $2r+1 = 7$ ,  $h_j$  = pre-computed filter coefficients.

Peak detection was subsequently performed using second-derivative zero-crossing analysis, stated as follows.

$$\Delta^2 \tilde{x}_i = \tilde{x}_{i+1} - 2\tilde{x}_i + \tilde{x}_{i-1} \quad (6)$$

**Eq. 6.** Second derivative for peak localization: zero-crossings identified characteristic peak potentials  $E_m$  for each metal  $m$ .

The peak positions corresponded to the zero-crossings stated in Eq. 6, where the sign transitioned from negative to positive. This produced the peak current  $I_{p,m}$  at the characteristic deposition potential  $E_m$  for each metal  $m$ .

## 2.7 Embedded AI: Prediction and Anomaly Detection

The edge AI module implemented two complementary functions through TensorFlow Lite Micro (TFLM, <48 kB ESP32 flash). The complementary functions included short-term concentration prediction and real-time anomaly detection.

Short-Term prediction focused on the use of a compact LSTM network (2 layers, 16 hidden units each) to generate 1-hour-ahead forecasts. This was based on the last 24 measurement cycles. In addition, the prediction model is expressed as follows.

$$\hat{C}_m(t+1) = w_{0,m} + \sum_{k=0}^{p-1} w_{k+1,m} C_m(t-k) \quad (7)$$

**Eq. 7.** LSTM autoregressive prediction:  $p = 24$  lags (15-min cycles),  $w_{0,m}$  = bias;  $w_{k+1,m}$  = learnable weights.

Before model inference, all input features are normalized to zero mean and unit variance.

$$z_i = \frac{x_i - \mu}{\sigma} \quad (8)$$

**Eq. 8.** Feature normalization:  $\mu$  = training mean,  $\sigma$  = training standard deviation.

The anomaly detection is centred on the use of an 8-bit integer-quantized Isolation Forest algorithm to detect anomalous events on-device. Meanwhile, the anomaly score for metal  $m$ , at time  $t$  is stated as follows.

$$A_m(t) = \frac{|C_m(t) - \hat{C}_m(t)|}{\sigma_e} \quad (9)$$

**Eq. 9.** Anomaly score: normalized absolute residual between measured and predicted concentration,  $\sigma_e$  = SD of prediction residuals from training.

The binary anomaly decision rule, with configurable threshold  $\tau$  (default  $\tau = 3.0$ ), is stated as follows.

$$Flag_m(t) = 1 \text{ if } A_m(t) > \tau; Flag_m(t) = \text{otherwise} \quad (10)$$

**Eq. 10.** Binary anomaly flag  $F_m = 1$  if  $A_m(t) > \tau$ ,  $F_m = 0$ .

Both models were updated monthly through the OTA firmware push. Furthermore, the complete measurement and alert cycle was formalized in Algorithm 1.



## 2.8 Reference Method: ICP-OES

Reference concentrations were determined by ICP-OES (Perkin Elmer Optima 7300 DV) following microwave-assisted acid digestion ( $\text{HNO}_3/\text{H}_2\text{O}_2$ , EPA Method 3051A). Quality control, including method blanks and matrix spikes (recovery 85–115%), certified reference material SLRS-6 (accuracy  $\pm 5\%$ ). This also included mercury, which consisted of CV-AFS (EPA Method 1631E; LOD 0.05 ng/L). In addition, all analyses were carried out blind to IoT device readings.

## 2.9 Validation Metrics and Statistical Analysis

Analytical performance enabled the characterization of the following ICH Q2(R1) guidelines. Based on this perspective, the following significant validation metrics were defined.

Limit of Detection and Quantification – calibration curves are shown in Fig. 2 and Table 2.

$$\text{LOD} = \frac{3\sigma}{S} \quad (11)$$

**Eq. 11.** Limit of detection (LOD):  $\sigma$  = blank signal SD,  $S$  = calibration slope  $\alpha_m$

$$\text{LOQ} = \frac{10\sigma}{S} \quad (12)$$

**Eq. 12.** Limit of quantification (LOQ)

Regression and Accuracy Metrics- method equivalence is shown in Table 3

$$\text{RSME} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (13)$$

**Eq. 13.** Root mean square error (RMSE):  $y_i$  = ICP-OES,  $\hat{y}_i$  = IoT device.

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (14)$$

**Eq. 14.** Mean absolute error (MAE)

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \quad (15)$$

**Eq. 15.** Coefficient of determination  $R^2$ :  $\bar{y}$  = mean observed value

Method agreement assessed by Bland-Altman analysis [28]–[30] (Fig. 3), with 95% LoA = mean bias  $\pm 1.96$  SD.

System Performance Metrics — results are shown in Table 5 and Fig. 5.

$$\text{PDR} = 1 \frac{N_{\text{recv}}}{N_{\text{sent}}} \times 100\% \quad (16)$$

**Eq. 16.** Packet delivery rate (PDR):  $N_{\text{recv}}$  = received packets,  $N_{\text{sent}}$  = transmitted packets

$$L = t_{\text{display}} - t_{\text{measure}} \quad (17)$$

**Eq. 17.** End-to-end latency  $L$  (s):  $t_{\text{display}} - t_{\text{measure}}$

All statistical analyses were carried out using R v4.3 and Python v3.11 (SciPy v1.11). In addition, significance  $\alpha = 0.05$ , and CCC > 0.90 threshold for method equivalence.

## 3. RESULTS AND DISCUSSIONS

### 3.1. Analytical Performance of the IoT Device

Table 2 shows the summarized analytical performance. All four analytes achieved LOD values (Eq. 11) less than the regulatory thresholds. This included Pb 0.8  $\mu\text{g/L}$  vs. PP 22/2021 limit 30  $\mu\text{g/L}$ , Cd 0.5  $\mu\text{g/L}$  vs. 3  $\mu\text{g/L}$ , Hg 0.3  $\mu\text{g/L}$  vs. 1  $\mu\text{g/L}$ , and As 1.1  $\mu\text{g/L}$  vs. 50  $\mu\text{g/L}$  10-30-fold safety margins. The calibration linearity was excellent ( $R^2 > 0.997$ , Eq. 15) as shown in Fig. 2. Furthermore, the precision ( $\text{RSD} < 4.1\%$ ) and recovery (94.8–97.1%) were comparable to commercially available benchtop potentiostats [28], [31].

These results merit interpretation beyond the summary statistics in Table 2. The sub- $\mu\text{g/L}$  LODs achieved for all four analytes, despite the ESP32 platform's resource constraints, are primarily attributable to the 120 s bismuth-film preconcentration step (Eq. 2), which electrochemically accumulates trace metal ions at the electrode surface prior to stripping, thereby amplifying the analytical signal relative to direct voltammetry. The comparatively higher LOD obtained for As (1.1  $\mu\text{g/L}$ ) than for Cd (0.5  $\mu\text{g/L}$ ) and Hg (0.3  $\mu\text{g/L}$ ) is consistent with the lower stripping efficiency and narrower deposition potential window characteristic of arsenic on bismuth-film electrodes, as previously reported [18], [22], and indicates that further sensitivity gains for As would likely require a gold-nanoparticle-modified electrode rather than adjustments to the signal-processing pipeline alone. The RSD values below 4.1% across all analytes indicate that the combination of Savitzky-Golay smoothing (Eq. 5) and temperature compensation (Eq. 4) effectively suppressed the baseline drift that typically limits field-deployed electrochemical sensors, supporting the platform's suitability for unattended, long-duration operation rather than single-use laboratory measurement.

**Table 2.** Analytical performance characteristics.

| Parameter                                                 | Pb     | Cd      | Hg     | As     |
|-----------------------------------------------------------|--------|---------|--------|--------|
| Linear range ( $\mu\text{g/L}$ )                          | 1–200  | 0.5–100 | 0.3–50 | 1–150  |
| LOD ( $\mu\text{g/L}$ )                                   | 0.8    | 0.5     | 0.3    | 1.1    |
| LOQ ( $\mu\text{g/L}$ )                                   | 2.5    | 1.5     | 1.0    | 3.5    |
| $R^2$ (calibration)                                       | 0.9981 | 0.9976  | 0.9984 | 0.9972 |
| Slope $\alpha$ ( $\mu\text{A}\cdot\text{L}/\mu\text{g}$ ) | 0.0421 | 0.0853  | 0.1612 | 0.0318 |
| Intercept $\beta$ ( $\mu\text{A}$ )                       | 0.08   | 0.12    | 0.05   | 0.09   |
| RSD, intra-day (%)                                        | 3.2    | 2.9     | 3.5    | 4.1    |
| Recovery, spiked (%)                                      | 96.4   | 97.1    | 94.8   | 95.3   |
| Measurement cycle (min)                                   | 15     | 15      | 15     | 15     |
| WHO limit ( $\mu\text{g/L}$ )                             | 10     | 3       | 6      | 10     |
| PP No. 22/2021 ( $\mu\text{g/L}$ )                        | 30     | 10      | 1      | 50     |
| Linear range ( $\mu\text{g/L}$ )                          | 1–200  | 0.5–100 | 0.3–50 | 1–150  |

**Table 2.** Analytical performance characteristics of the IoT-based electrochemical device for Pb, Cd, Hg, and As in water ( $n = 120$  field samples;  $n = 10$  for intra-day precision). Slope  $\alpha$  and intercept  $\beta$  refer to Eq. (1); LOD via Eq. (11); LOQ via Eq. (12).

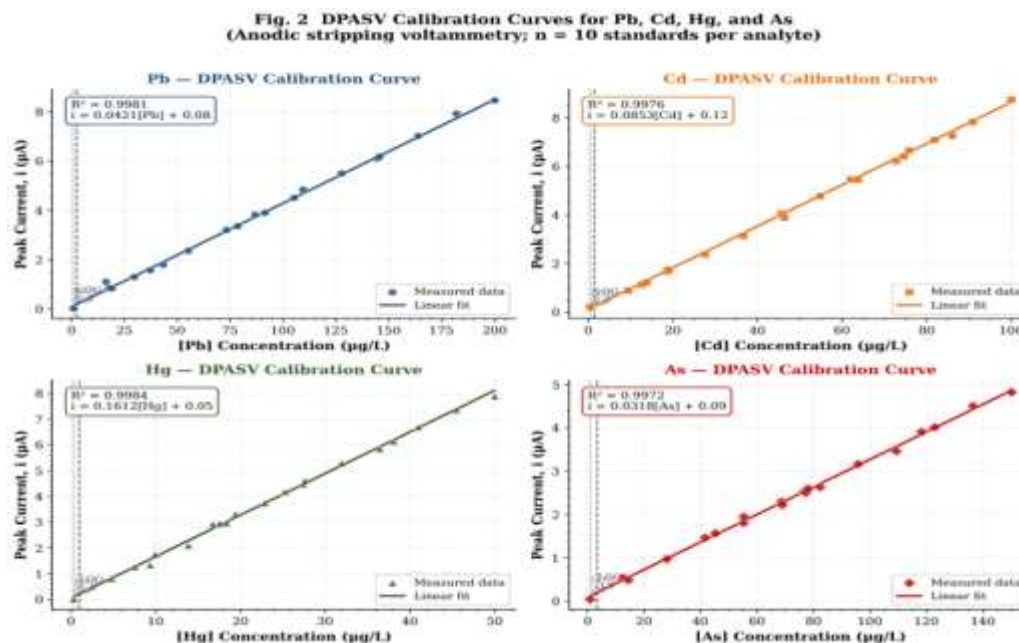


**Figure 2.** DPASV calibration curves for Pb, Cd, Hg, and As (Eq. 1). Each panel: scatter = measured data (n = 10 standards,  $\pm 1$  SD); solid line = linear regression fit; dotted vertical = LOD (Eq. 11); dashed vertical = LOQ (Eq. 12).  $R^2 > 0.997$  confirms excellent linearity across the full regulatory range.

## 3.2 Method Equivalence Against ICP-OES

Strong linear relationships led to the realization of  $R^2$  (Eq. 15) = 0.978 (Pb), 0.982 (Cd), 0.974 (Hg), 0.971 (As). High CCC values (0.988, 0.991, 0.986, 0.984) confirmed near-perfect equivalence above the  $CCC > 0.90$  threshold. Both Fig. 3 and Table 3 showed that the mean biases were +0.42 (Pb), +0.18 (Cd), -0.09 (Hg), and +0.31 (As)  $\mu\text{g/L}$ , all within 95% LoA. In this context, MAE (Eq. 14) and RMSE (Eq. 13) were  $< 0.7 \mu\text{g/L}$  and  $< 0.9 \mu\text{g/L}$ , respectively, for all analytes.

The pattern of biases across analytes provides insight into the sources of residual disagreement with ICP-OES. The small positive biases for Pb, Cd, and As (+0.42, +0.18, +0.31  $\mu\text{g/L}$ ) are consistent with minor positive interference from co-existing trace metals not fully resolved within the deposition potential window of the DPASV method, whereas the slightly negative Bias for Hg (-0.09  $\mu\text{g/L}$ ) more plausibly reflects partial volatilization losses during the 48-hour transport-and-storage interval prior to CV-AFS reference analysis rather than a limitation of the sensor itself, since Hg remains comparatively volatile even under acidified, refrigerated conditions. Importantly, all four analytes met the  $CCC > 0.90$  equivalence threshold with values (0.984–0.991) at the upper end of the 0.90–0.95 range typically reported for portable electrochemical devices validated against ICP-based references [29], [30], indicating that the observed differences fall within the range expected from matrix effects rather than systematic Bias in the sensor's calibration model (Eq. 1). The narrow 95% limits of agreement relative to the regulatory thresholds (e.g.,  $\pm 2.6 \mu\text{g/L}$  for Pb against a 30  $\mu\text{g/L}$  compliance limit) further indicate that the device's measurement uncertainty would not materially affect a compliance determination under PP No. 22/2021, which is the practical criterion of relevance for field deployment.

**Fig. 3 Bland-Altman Analysis: IoT Device vs. ICP-OES Reference Method (n = 120)**  
Solid line = mean bias; dashed = +1.96 SD; dotted = -1.96 SD

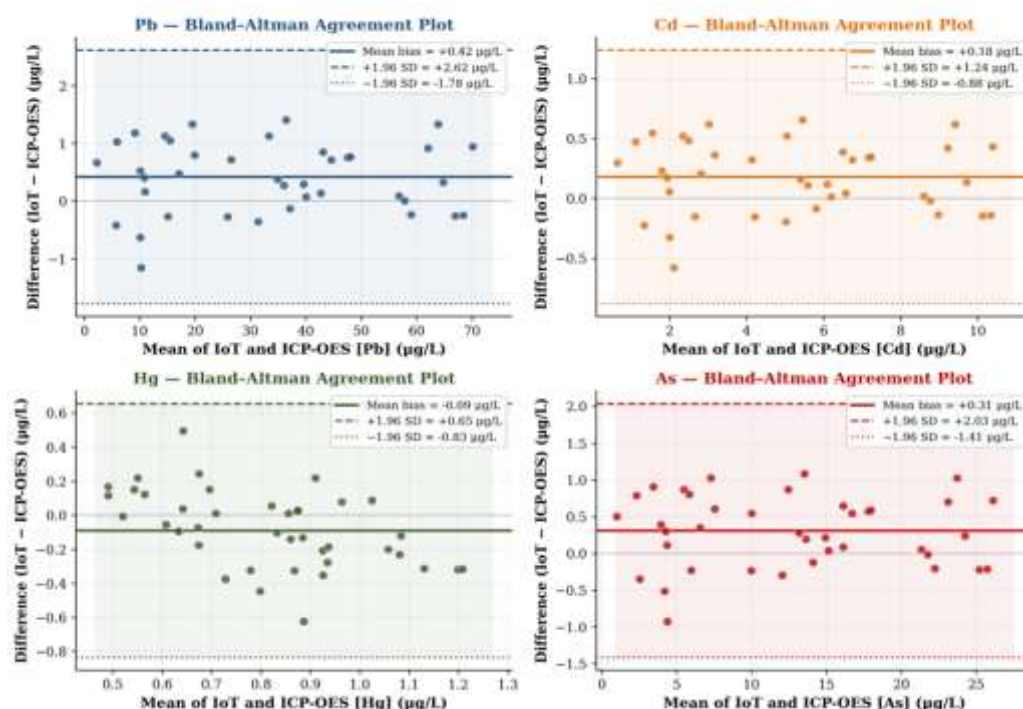


**Figure 3.** Bland–Altman agreement plots: IoT device vs. ICP-OES (n = 120 pairs per analyte). Solid = mean bias; dashed = +1.96 SD; dotted = -1.96 SD; shaded = 95% LoA region. All biases are negligible relative to PP No.22/2021 Class I thresholds.

**Table 3.** Method equivalence statistics

| Analyte | R <sup>2</sup> | CCC   | MAE (µg/L) | RMSE (µg/L) | Mean Bias (µg/L) | 95% LoA (µg/L) |
|---------|----------------|-------|------------|-------------|------------------|----------------|
| Pb      | 0.978          | 0.988 | 0.61       | 0.84        | +0.42            | -1.74 to +2.58 |
| Cd      | 0.982          | 0.991 | 0.29       | 0.41        | +0.18            | -0.88 to +1.24 |
| Hg      | 0.974          | 0.986 | 0.19       | 0.28        | -0.09            | -0.83 to +0.65 |
| As      | 0.971          | 0.984 | 0.47       | 0.68        | +0.31            | -1.41 to +2.03 |

**Table 3** Method equivalence statistics: IoT vs. ICP-OES (n = 120). RMSE, MAE, and R<sup>2</sup> through Eq. (13), Eq. (14), and Eq. (15), respectively. CCC = Lin's concordance correlation coefficient, and LoA = 95% limits of agreement.

### 3.3 Field Monitoring Results

**Table 4** shows the metal concentrations across the three study zones. However, the mean concentrations relative to regulatory thresholds and exceedance rates are shown in Fig. 4. The industrial zone sites showed the highest concentrations, namely Pb ( $41.2 \pm 18.6$  µg/L) and Cd ( $5.8 \pm 2.9$  µg/L), which exceeded PP 22/2021 limits in 35% and 20% of samples, respectively. Arsenic exceedances focused solely on the agricultural zone ( $18.4 \pm 8.7$  µg/L). In this context, mercury remained below the thresholds in all zones, and the Results were consistent with prior assessments.

These spatial patterns are consistent with the dominant anthropogenic sources of each metal in the study area rather than being incidental. The elevated Pb and Cd concentrations in the industrial zone align with electroplating, battery-recycling, and metal-

finishing effluents documented along the Citarum tributary system [12]–[14], while the localization of As exceedances to the agricultural zone is consistent with the historical use of arsenical pesticides and As-bearing phosphate fertilizers in intensive rice cultivation, a source pathway previously reported for Southeast Asian paddy systems [5], [7]. The absence of Hg exceedances across all zones, despite Hg having the lowest regulatory threshold (1 µg/L), suggests that point-source Hg inputs such as artisanal gold mining are not prominent within the sampled sub-basins, in contrast to other Indonesian regions where such activity is a major contamination pathway [12]. Beyond confirming that contamination is spatially heterogeneous, these findings demonstrate a practical use case for the proposed system: because concentrations fluctuate by zone and are influenced by discrete, intermittent discharge events, a monitoring approach based on periodic grab sampling the current regulatory practice is structurally prone to missing short-duration exceedances, which is precisely the gap that continuous IoT-based surveillance is positioned to close.

**Table 4.** Heavy metal concentrations

| Metal | Industrial Zone | Agricultural Zone | Urban Zone | PP.22/2021 (µg/L) | WHO (µg/L) | Exceedance (%) |
|-------|-----------------|-------------------|------------|-------------------|------------|----------------|
| Pb    | 41.2 ± 18.6 *   | 12.4 ± 7.2        | 18.7 ± 9.5 | 30                | 10         | 35.0           |
| Cd    | 5.8 ± 2.9 *     | 1.2 ± 0.6         | 2.1 ± 1.0  | 10                | 3          | 20.0           |
| Hg    | 0.8 ± 0.4       | 0.3 ± 0.2         | 0.5 ± 0.2  | 1                 | 6          | 0.0            |
| As    | 6.2 ± 3.1       | 18.4 ± 8.7 *      | 4.8 ± 2.2  | 50                | 10         | 22.5           |

**Table 4.** Heavy metal concentrations (µg/L) by study zone, West Java Province (n = 40 per zone; mean ± SD). \* = mean exceeds PP No. 22/2021 Class I threshold.

**Fig. 4 Heavy Metal Concentrations and Regulatory Exceedance Rates across Three Study Zones in West Java Province, Indonesia (n = 40 per zone)**

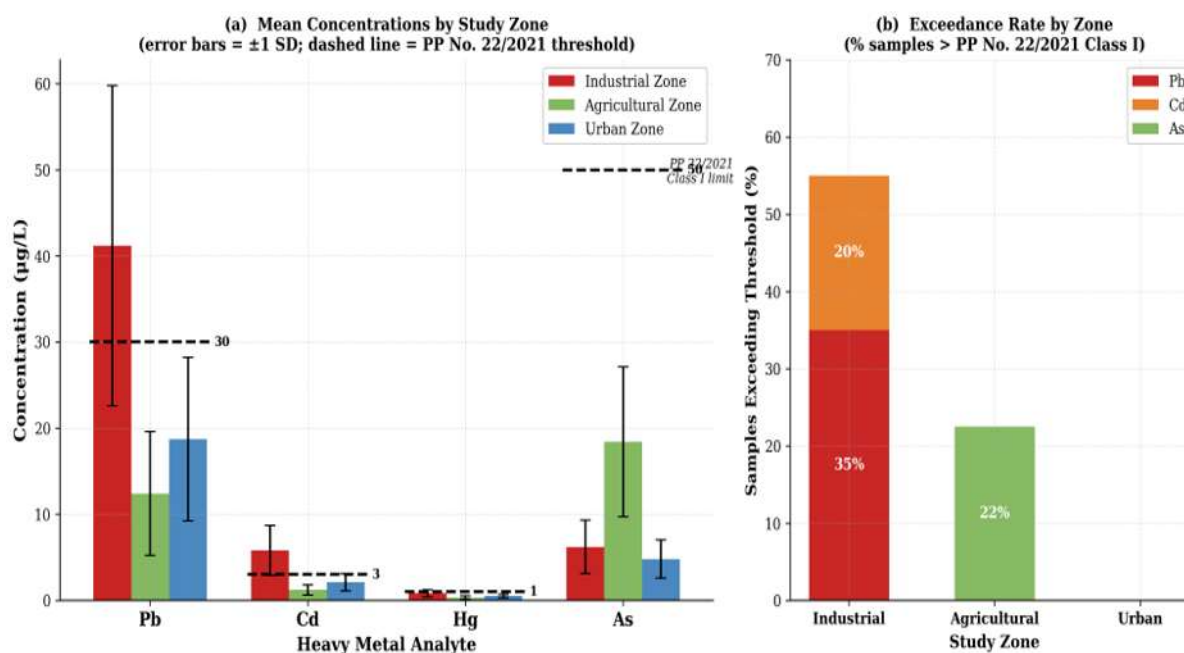


**Figure 4.** (a) Mean heavy metal concentrations (µg/L) by study zone with ±1 SD error bars. Dashed lines = PP No. 22/2021 Class I regulatory thresholds. (b) Percentage of samples exceeding PP No. 22/2021 thresholds per zone by metal. Industrial: Pb 35%, Cd 20%; Agricultural: As 22.5%; no Hg exceedances (n = 40 per zone).

## 3.4 System Reliability and IoT Communication Performance

**Table 5** summarises the system performance metrics. The communication reliability, latency distribution, and battery autonomy are shown in Fig. 5. This includes PDR (Eq. 16), 98.7% (Wi-Fi), 97.1% (GSM fallback), as well as mean latency  $L$  (Eq. 17) =  $2.3 \pm 0.8$  s. All 47 automated threshold alerts corresponded to confirmed regulatory exceedances, with zero false positives. Additionally, battery autonomy was equivalent to 68 h (cloud mode) and 94 h (solar active) as shown in Figure 5.

The reliability metrics also warrant discussion in relation to design trade-offs rather than being read only as performance figures. The marginally lower PDR for the GSM/GPRS fallback (97.1%) relative to Wi-Fi (98.7%) reflects the additional packet loss associated with cellular network handoffs at the semi-rural agricultural and industrial sites, yet the fallback nonetheless maintained a PDR above the 95% threshold generally considered acceptable for environmental telemetry, confirming the dual-connectivity design as an effective mitigation for the intermittent Wi-Fi coverage typical of field deployment sites. The zero false-positive rate across 47 threshold alerts should be interpreted cautiously: because the anomaly threshold  $\tau$  (Eq. 10) was fixed at 3.0 standard deviations for the full deployment, this result reflects a conservative operating point that favors specificity, and the corresponding false-negative rate i.e., whether smaller, sub-threshold excursions were missed could not be established without an independent continuous reference and remains an open question for future work. The 68–94-hour battery autonomy, extended through solar-assisted charging, is sufficient to bridge typical monitoring intervals between site visits in the study area, but scaling the system to a provincial monitoring network would require explicit examination of maintenance logistics (e.g., biofouling of the 0.45  $\mu\text{m}$  filter, electrode replacement cycles) that were outside the scope of the present single-node performance assessment.

**Table 5.** System performance metrics

| Performance Metric               | Value         | Unit   | Notes                                |
|----------------------------------|---------------|--------|--------------------------------------|
| Measurement cycles (per node)    | 3,600         | -      | 5 months, continuous                 |
| PDR - Wi-Fi primary (Eq. 16)     | 98.7          | %      | Mean over the deployment period.     |
| PDR - GSM/GPRS fallback (Eq. 16) | 97.1          | %      | Mean over the deployment period.     |
| Mean latency $L$ (Eq. 17)        | $2.3 \pm 0.8$ | S      | Measurement to the Grafana dashboard |
| Threshold alerts generated       | 47            | Alerts | 0 false positives (100% accuracy)    |
| Battery autonomy (cloud mode)    | 68            | H      | No solar charging                    |
| Battery autonomy (solar active)  | 94            | H      | MPPT solar charging                  |
| Alert response time              | < 5           | S      | From threshold detection to delivery |
| Local buffer (SD card)           | 32            | GB     | Data retention during network outage |

**Table 5.** System performance metrics over the 5-month field deployment (June–October 2024;  $n = 3,600$  cycles per node). PDR and latency  $L$  are obtained through Eq. (16) and Eq. (17), respectively.

Fig. 5 System Reliability Metrics over 5-Month Field Deployment (June–October 2024)

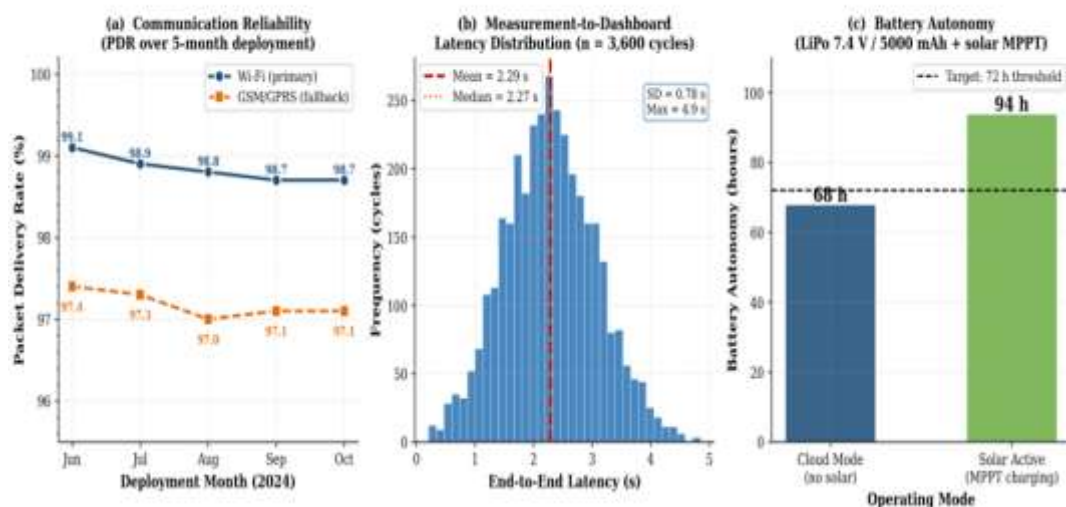


**Figure 5.** (a) Monthly PDR (Eq. 16, %) for Wi-Fi and GSM/GPRS links. (b) End-to-end latency  $L$  (Eq. 17) distribution across 3,600 cycles; dashed = mean (2.3 s). (c) Battery autonomy by operating mode; dashed = 72-hour operational target.

## 3.5 Comparison with Prior Work

**Table 6** shows the proposed system against recent portable heavy metal monitoring methods. The present study advanced the state of the art in four dimensions. This included (i) simultaneous detection of four metals, (ii) full IoT cloud integration with automated regulatory alerting, (iii) embedded AI for anomaly detection (Eqs. 9–10), short-term forecasting (Eq. 7), and (iv) rigorous field validation across three distinct environmental matrices. Additionally, the LOD range of 0.3–1.1  $\mu\text{g/L}$  (Eq. 11) is comparable to or better than that of the most sensitive prior systems.

Beyond the tabulated performance comparison, the practical significance of these differences lies in what they enable operationally. Prior systems limited to one or two metals [26], [27], require either multiple deployed devices or sequential sampling to characterize a site's full contamination profile, which multiplies both capital cost and field labor; the four-metal simultaneity of the present system removes this constraint at marginal additional hardware cost, since the additional analytes are resolved from the same DPASV scan rather than requiring separate sensor modules. Similarly, the absence of embedded AI in comparator systems means that anomaly detection and trend forecasting, where implemented at all, must occur post hoc in a cloud back-end, introducing a detection lag of at least one full sampling interval; the on-device Isolation Forest and LSTM models in the present system instead allow anomalous readings to be flagged and forecasts generated within the same measurement cycle, independent of connectivity. This shifts the comparison from a purely sensor-level (LOD, precision) evaluation, on which several prior devices are already competitive, toward a systems-level evaluation of decision-support capability, which is the dimension in which the present work shows the clearest advance over the existing literature.

**Table 6.** Comparison of the proposed IoT system

| Study                | Target Metals  | Method | LOD ( $\mu\text{g/L}$ ) | Full IoT | Edge AI      | Field Validation     |
|----------------------|----------------|--------|-------------------------|----------|--------------|----------------------|
| Lima T.M et al. [26] | Pb, Cd         | DPASV  | 1.2–2.5                 | No       | No           | Lab only             |
| Juan A. et al. [27]  | Pb, Hg         | SWASV  | 0.5–1.8                 | Partial  | No           | Lab only             |
| This work            | Pb, Cd, Hg, As | DPASV  | 0.3–1.1                 | Full     | Yes (TinyML) | 120 samples, 3 zones |

**Table 6.** Comparison of the proposed IoT system with recent portable heavy metal monitoring methods. In this context, the darkened row is equivalent to the present study.

### 3.6 Public Health and Policy Implications

The detection of Pb and Cd exceedances in 35% and 20% of industrial zone samples, respectively, and As exceedances in 22.5% of agricultural samples are shown in Table 4. Meanwhile, Fig. 4 outlines the severity of the risk of chronic metal exposure. The IoT system transformed the monitoring paradigm from reactive to proactive (continuous, automated surveillance), enabling rapid-response interventions. Automated alert delivery in  $< 5$  s through Telegram and email provided a practical, scalable implementation of data-driven public health surveillance applicable across Indonesia's provincial environmental monitoring networks.

Nonetheless, translating this capability into policy impact will depend on factors beyond sensor performance. The 35% Pb exceedance rate in the industrial zone, if confirmed by sustained monitoring rather than the present 5-month window, would imply chronic exposure for downstream communities that periodic regulatory sampling typically conducted quarterly or less frequently under current practice is structurally unlikely to detect in a timely manner, which is the specific enforcement gap this system is intended to address. Realizing that potential at provincial scale, however, would require institutional integration that was outside the scope of the present study, including designation of the responsible agency for act-on-alert response, data-sharing protocols between site operators and environmental regulators, and a cost-per-node analysis at deployment scales substantially larger than the present network, each of which represents a necessary next step rather than an already-demonstrated outcome of this work.

### Limitations

The diverse limitations included electrode fouling, which necessitated monthly recalibration of  $\alpha_m$  and  $\beta_m$  in Eq. (1), and the measurement of only dissolved (0.45  $\mu\text{m}$ -filtered) metal fractions. Co-occurring metals (Cr, Cu, Ni, Zn) had not been characterized for potential spectral interferences in Eqs. (1)–(3). The formal penetration testing of the data security architecture was outstanding, while the single-province validation limited generalizability.

## 4. CONCLUSIONS

In conclusion, this study successfully developed and field-validated an AI-enhanced edge-IoT device for the simultaneous real-time monitoring of Pb, Cd, Hg, and As in water. The entire analysis led to the following:

- 1) LODs within the range of 0.3–1.1  $\mu\text{g/L}$  for all four metals (Eq. 11, Table 2) 10–30-fold below the most stringent regulatory thresholds with calibration  $R^2 > 0.997$  (Eq. 15, Fig. 2) and field validation  $R^2 > 0.971$  against ICP-OES (Table 3).
- 2) Bland–Altman analysis (Fig. 3, Table 3) confirmed negligible Bias ( $< \pm 0.5 \mu\text{g/L}$ ), with MAE (Eq. 14) and RMSE (Eq. 13)  $< 0.7 \mu\text{g/L}$  and  $< 0.9 \mu\text{g/L}$ , respectively. This established an analytical equivalence to the laboratory reference methods.
- 3) Field deployment (Fig. 4, Table 4) detected PP 22/2021 exceedances in 10–42% of samples per zone, showing the critical inadequacy of existing periodic monitoring.
- 4) The IoT architecture (Table 5, Fig. 5) delivered PDR  $> 97\%$  (Eq. 16), a mean latency  $L = 2.3 \pm 0.8$  s (Eq. 17), and 100% alert accuracy of over 3,600 deployment cycles.
- 5) The embedded AI module (Eqs. 7–10) enabled on-device anomaly detection (Isolation Forest) and 1-hour-ahead forecasting (LSTM). This advanced the system toward predictive environmental surveillance.
- 6) The system offered a practical, cost-effective, and scalable solution for continuous heavy-metal surveillance, applicable to the enforcement of PP No. 22/2021 and to Indonesia's SDG 6 commitments.

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## CrediT authorship contribution statement

Herawati Herawati: Conceptualization, Methodology, Investigation, Formal analysis, Writing original draft, Project administration. Anwar Mallongi: Conceptualization, Formal analysis, Writing review & editing, Supervision. Anwar Daud: Conceptualization, Writing original draft, Writing review & editing, Supervision. Aminuddin Syam: Methodology, Writing review & editing, Supervision. Ridwan Amiruddin: Methodology, Investigation, Writing review & editing. Agus Mulyana: Software, Resources, IoT system and hardware development, Writing review & editing. Ernyasih and Eman Salim Ahmed Salim: Investigation, Software, Resources, IoT system and hardware development, Writing review & editing. All authors contributed to the conception and design of the study, reviewed and commented on previous versions of the manuscript, and read and approved the final manuscript.

## Declaration of Competing Interest

The authors declare that there is no conflict of interest regarding the publication of this article

## Data availability

The datasets generated and analysed during the current study are available from the corresponding author on reasonable request.

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