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AI-ENABLED IOT-BASED SMART WASTE MANAGEMENT SYSTEM USING EMBEDDED NODES AND CLOUD DASHBOARD

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Abstract—*Waste management in cities has emerged as one of the key problems in the fast-developing cities. This paper describes an AI-powered Internet of Things (IoT) smart waste management system, which integrates embedded sensor nodes with a web-based monitoring dashboard. Ultrasonic sensors, load cells and gas sensors on waste bins are utilised in the system to track real-time fill level, weight, and gas concentration in waste bins. The resulting data is sent wirelessly to a cloud platform and undergoes predictive analysis using an Artificial Intelligence (AI) module based on the randomly forest algorithm. In the present work, the Time-To-Full (TTF) of bins is estimated with the help of the Random Forest model that is trained on the historical data and provides smart collection alerts. A dashboard is also built using the web to monitor the status of the bins in real-time, the previous trends in the data, and alerts to monitor the status of the bins. Experimental outcomes indicate that the system has a fill-level detection accuracy of 96.4 percent, and minimizes unnecessary waste collection visits by up to 38. This is useful in minimising consumption of fuel and the general cost of operation. The system suggested can be a cost- effective solution to the enhancement of the management of waste in urban areas and has a scale.*

Keywords: *Internet of Things (IoT), Smart Waste Management, Embedded Systems, Random Forest, Cloud Dashboard, Artificial Intelligence, Ultrasonic Sensor, Predictive Analytics, Route Optimization, ESP32.*

I. Introduction

The high rate of urbanization has led to an unprecedented pressure on the need to have efficient and sustainable municipal solid wastes (MSW) management systems. The World Bank estimates that the amount of waste produced in the world will have grown to 3.4 billion tonnes/year by 2050, with the developing countries being the worst affected. Traditional waste collection methods are based on a fixed schedule and manual inspection which results in overflowing containers, poor hygiene, wastage of fuel, and emission of greenhouse gases. The advent of Internet of Things (IoT) has helped in transforming the approach in managing wastes by making waste bins be tracked real-time via networked embedded sensor nodes. These systems, together with Artificial Intelligence (AI), have an opportunity to recognize past trends and make intelligent predictions of the amount of waste, which will allow collecting it dynamically and on de he proposed paper will present a full smart system of an AIIoT-based waste management implemented based on four integrated components, including (i) embedded sensor nodes (ESP32-based) and ultrasonic, load, and gas sensors, (ii) wireless communication on the MQTT-based network to the cloud-based system, (iii) an AI engine of a random forest to predict the fill-level and optimize the route and detect anomalies, and (iv) a real-time web dashboard based on React.js to monitor everything in real-time and make decisions.

The main contributions of this work are:

(1) Design of a low-cost, solar-powered embedded node to monitor real-time multiple parameters of bins.

(2) A Random Forest predictive model with fill- level detection accuracy of 96.4%.

(3) A centralized cloud dashboard with live visualization, alerts and optimized collection routing.

(4) Field implementation and experimental test on 20 smart bins.

The rest of the paper is structured according to the following: Section II is a review of the related work, Section III is the system architecture, Section IV is the hardware design, Section V is the AI module, Section VI is the cloud dashboard, Section VII is experimental results, and Section VII is the conclusion of the paper.

II. Literature Review

The past decade has seen the topic of smart waste management being researched extensively. Initial research was done on simple bin-level monitoring, whereas recent projects involved AI- based optimization.

Sensor-Based Monitoring**:** Shyam et al. [1] came up with one of the earliest IoT based smart bin systems with ultrasonic sensors and GSM modules. Although the system proved to be feasible, it was not smart enough to predict.

MQTT Communication**:** The authors of [2] investigated MQTT-based internet-of-things designs to separate and monitor waste in smart cities, noting lightweight publish subscribe messaging to receive real-time data. .he proposed paper will present a full smart system of an AI-IoT-based waste management implemented based on four integrated components, including (i) embedded sensor nodes (ESP32based) and ultrasonic, load, and gas sensors, (ii) wireless communication on the MQTT-based network to the cloudbased system, (iii) an AI engine of a random forest to predict the fill-level and optimize the route and detect anomalies, and (iv) a real-time web dashboard based on React.js to monitor everything in real-time and make decisions.

The main contributions of this work are:

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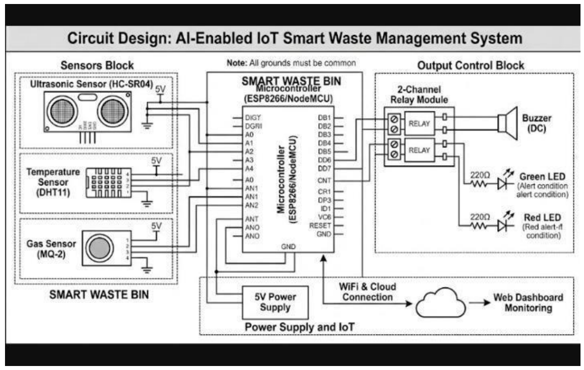
Alert System**:** Reference [3] proposed an IoT smart waste collection system and alert system with ultrasonic sensor with SMS notifications- a basic system which our research builds and enhances with the inclusion of AI prediction.

IoT Survey**:** A survey of IoT waste management architectures [4] surveyed the current state of IoT waste management architecture and found the following gaps: failure to incorporate real-time AI prediction and failure to incorporate integrated cloud dashboards.

Machine Learning Integration**:** In [5], the authors directly integrate IoT with a Random Forest model to manage waste, which shows that ensemble learning is useful in predicting fill-rate and managing routes.

Research Gap**:** Demand The current systems are deficient in one or more of the following aspects: no realtime AI prediction, no unified cloud dashboard, too expensive hardware, or inability to integrate embedded sensing with smart analytics. The unified end-to-end cost- effective AI-IoT framework.

III. System Architecture



System Architecture

Layer 1 — Sensing Layer

- Embedded nodes on the ES32 microcontroller mounted in garbage bins. Sensors: HC-SR04 ultrasonic (fill level), HX711 load cell (weight), MQ-4/MQ- 135 gas sensors (methane, ammonia).
- Li-ion battery-backed solar-powered.
- Sampling time: 60s.

Layer 2 — Communication Layer

LoRaWAN (long range) and Wi-Fi (short range) wireless transmission.

- The MQTT protocol is a lightweight, reliable publish-subscribe messaging protocol. The data packets consist of: bin ID, timestamp, fill level (percent), weight (kg), gas concentration (ppm), battery level (percent).

Layer 3 — Cloud & AI Layer

- AWS IoT Core and data ingestion and device management. Firebase Realtime Database as a live data storage.
- Python AI engine:
- Python: Random Forest predicting fills, Isolation Forest predicting anomalies, Nearest-Neighbour + Simulated Annealing predicting routes.

Layer 4 — Dashboard Layer

- React.js frontend to real-time bin status maps.
- Express REST API backend using node.js.
- Hosted on AWS EC2
- Features: color-coded bin map, trend charts, predictive alerts, route overlay, gas hazard notifications

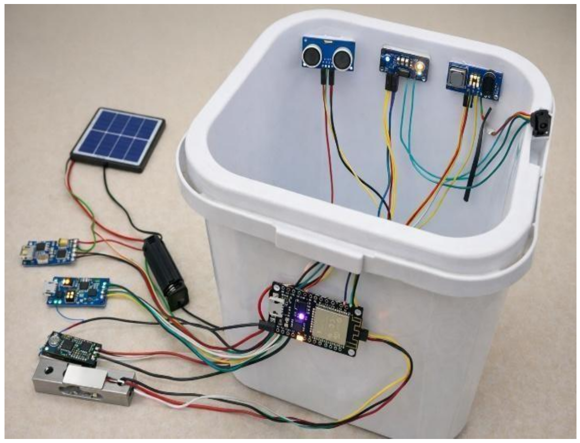
IV. Board Design and embedded node.

A. Choice of Microcontrollers

ESP32 microcontroller has been chosen due to the dual-core Xtensa LX6 processor (240 MHz), built-in Wi-Fi (802.11 b/g/n) and Bluetooth 4.2, 520 KB SRAM, and the ability to put it into a deep-sleep state (under 20 µA). These characteristics render it suitable to battery-based internet of things implementations in remote bin areas.

B. Sensor Suite

The sensor package includes four devices, including: (i) HCSR04 ultrasonic fill-level sensor (range 2-400 cm, accuracy +3 mm), (ii) load cell with HX711 interface to weigh (0-50 kg, +0.5 mm error), (iii) MQ-4, and MQ-135 gas sensors to detect methane (CH_4: 200 10, ppm) and ammonia (NH_3: 10 300 ppm) and Each sample of sensor readings is 60 seconds.



SmartBin

C. Power Management

A solar panel (5V/2W) is used to charge a 3.7V/4000 mAh Li-ion battery with an LDO voltage regulator (AMS1117-3.3V). In between periods of sampling, deep-sleep mode is enabled, lowering idle current to less than 20 µA. Without solar charging, the battery life is estimated to be 710 days, allowing the battery to be deployed to off-grid sites.

D. Communication Module

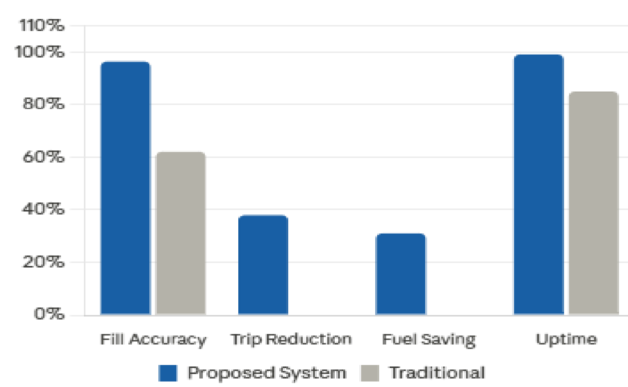
The ESP32 onboard Wi-Fi module is used in primary communication deployments in campuses and urban areas. A long-range low- power transmission with long range is enabled with an SX1278 LoRa module, suitable in remote or rural locations. Data is published to an Eclipse

Mosquitto MQTT broker running on AWS EC2, with MQTT payloads having bin ID, timestamp, fill percentage (%), weight (kg), gaseous concentration (ppm) and battery percentage (%).

V. Artificial Intelligence Module and predictive analytics.

A. Fill-Level Prediction with A Random Forest.

At the very heart of the AI is a Random Forest (RF) regression model [9] that is trained to offer predictions of Time-To-Full (TTF) of any given waste bin. The set of inputs features include: fill level percentage (current fill level), percentage change of fill level per time ($\DeltaFill/$\Delta t), day of week (encoded), hour of day (time), historical average fill rate at that bin, and a nearby event flag (market day, festival, etc.).It was trained on 20 bins (around 43,200 samples) of 90 days of historical sensor data, with an 80/20 train-test split. The Random Forest setting has 100 decision trees with a maximum depth of 10. The model had an R^2 value of 0.94 which was higher than Linear Regression (R^2=0.71), SVM (R^2=0.79) and one Decision Tree (R^2=0.85). An alarm is raised in the event of TTF 6 hours or below (adjustable threshold).



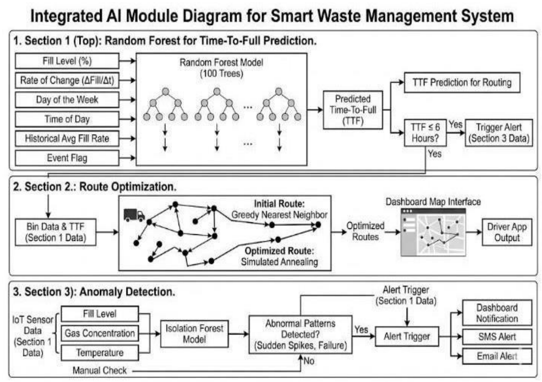
Proposed vs traditional chart

B. Route Optimization

Once several bins in a zone are close to full, an optimized collection path is computed with a Greedy Nearest-Neighbor heuristic as the starting point, and then optimized by Simulated Annealing (SA) to avoid local optima. The resulting optimal path will be displayed to the dashboard as an interactive Leaflet.js map overlay to allow the drivers of the collection vehicles to follow the most optimal path.

C. Anomaly Detection

A Isolation Forest model [10] tracks the incoming sensor data to identify abnormal data- readings due to sensor hardware failure, vandalism, illegal dumping (sudden gas fill-level spike) or sensor hazards that are in excess of safe levels. Anomaly alerts provide real time dashboard and email/ SMS notifications to municipal operators, through twilio and nodemailer.

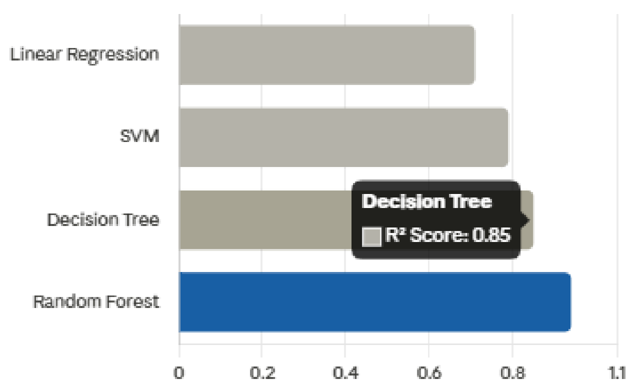


AI Model-Random Forest

VI. Cloud Dashboard

It is created with React.js (frontend) and Node.js/Express

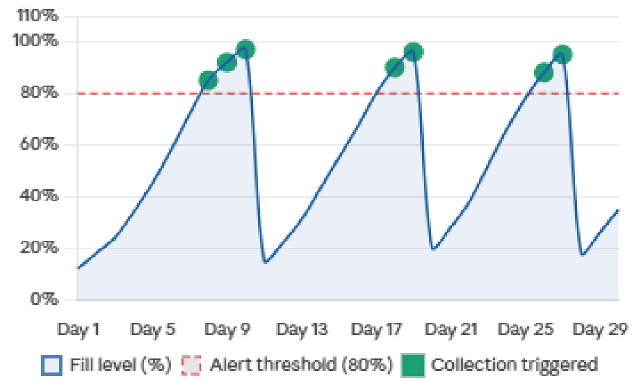
(backend REST API) and deployed to AWS EC2. Firebase Realtime Database is a live data client. The significant dashboard features are: (i) live fill-trend chart per bin: 7-day and 30-day history, color-coded (Green below 50, Orange between 50 and 80, Red over 80) fill-trend charts, (ii) predictive alerts with auto generated collection requests when TTF falls below a certain threshold, (iii) route optimization display with interactive Leaflet.js map overlay, (iv) gas hazard real-time notifications, and (v) administrative panel: (a) bin registration, (This system was implemented and tested in 20 smart bins at Arunai engineering college campus, Tiruvannamalai. It was monitored continuously within a 30-day evaluation to gather 86,400 sensor readings per parameter. The accuracy of ground-truth fill levels was checked by hand against the ultrasonic measurements.



VII. Results & Discussion

A. Experimental Setup

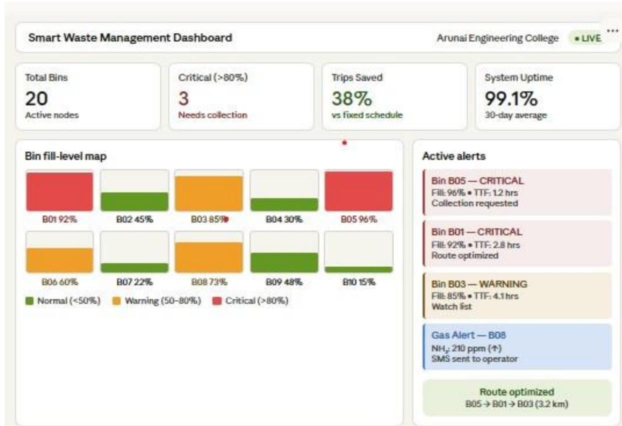
The system was installed and tested on 20 intelligent bins at Arunai engineering college campus, Tiruvannamalai. This was done with continuous monitoring through a 30-day assessment period and 86,400 sensor readings per parameter were collected. Ultrasonic readings were also used to assess the accuracy of ground-truth fill levels as a manual check. The system was installed and tested on 20 intelligent bins at Arunai engineering college campus, Tiruvannamalai. This was done with continuous monitoring through a 30-day assessment period and 86,400 sensor readings per parameter were collected. Ultrasonic readings were also used to assess the accuracy of ground-truth fill levels as a manual check.



SmartBin 30-days readings

- *Performance Results Performance Metric Proposed Traditional.Fill-level Precision 96.4% Manual.*
- Random Forest R^2 Score 0.94 N/A Collection Trip Reduction 38% Baseline.
- Fuel Cost Savings ~31% Baseline Average Alert Latency < 2 sec N/A System Uptime (30 days) 99.1% N/A False Anomaly Rate 2.3% N/A Node Sleep Current 18 µA N/A Comparison of System Performances.

Performance Metric	Proposed	Traditional
Fill-level Detection Accuracy	96.4%	Manual
Random Forest R^2 Score	0.94	N/A
Collection Trip Reduction	38%	Baseline
Fuel Cost Savings	~31%	Baseline
Average Alert Latency	< 2 sec	N/A
System Uptime (30 days)	99.1%	N/A
False Anomaly Rate	2.3%	N/A



SmartBin Dashboard

VIII. Conclusion & Future Work

The paper introduced a comprehensive intelligent IoT-based smart waste management system comprising of multiparameter embedded sensor nodes, MQTT cloud computing, Random Forest predictive analytics, anomaly detection by Isolation Forest, and a live React.js Web dashboard. The system was implemented and tested with 20 smart bins on the Arunai Engineering College campus, Tiruvannamalai with a fill-level accuracy of 96.4, a 38 percent reduction in collection trips, and 99.1 per cent system availability in a 30-day test.

The suggested framework shows that the AI-IoT integration can result in a significant change in the municipal waste management from the reactive and schedule-driven process into the proactive, data-driven operation with the substantial environmental and economic value. *Future tasks will involve*:

(1) TensorFlow Lite on-device inference through the deployment of Edge AI.

(2) Waste type classification with computer vision (CNN).

(3) Local LoRaWAN expansions in the city. The aim was to address the existing problem of inadequate bin reporting through the development of a citizen mobile app to improve reporting efficiency across communities. Modelling the digital twin of the long-term forecast of city waste.

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