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IOT - ENABLED SMART DUSTBIN NETWORK WITH AI BASED GARBAGE REPORT VERIFICATION SYSTEM

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ABSTRACT

This paper presents the Smart Garbage Management System (SGMS), a three-component platform that addresses inefficiencies of traditional waste collection in dense urban zones. The system integrates an IoT smart bin equipped with an fill-level sensor, and LED status indicators; a browser-based management centre dashboard that displays live bin fill levels across multiple locations in specific zone on an OpenStreetMap base map and auto-generates demand-driven collection schedules; and a mobile-first public reporting application through which citizens submit AI-verified photographic evidence of illegal dumping. AI Vision API performs automated image analysis and rejects non-genuine submissions before they reach the operations team. All components communicate via MQTT over the HiveMQ public broker. The complete system is deployed as a web application at sgms26.web.app on Firebase Hosting. Evaluation demonstrates sensor accuracy within 1.6% mean absolute error, end-to-end MQTT latency below 800 ms at the 95th percentile, and AI verification accuracy of 93.3% across 30 test images.

KEYWORDS — IoT, smart waste management, MQTT, ESP32, AI image verification, Gemini Vision, citizen reporting, real-time dashboard, Firebase Hosting, urban computing.

I. INTRODUCTION

Solid waste management in rapidly urbanising Indian cities faces a structural tension: waste volume grows daily while collection infrastructure lags significantly behind. Traditional systems operate on fixed schedules insensitive to actual bin fill levels, producing two costly failure modes — overflowing bins that create public health hazards before the next scheduled collection, and vehicles dispatched to nearly empty bins, wasting fuel and labour.

Simultaneously, illegal dumping in public spaces remains a persistent issue. Existing national platforms such as Swachh City accept citizen photo submissions but apply no automated quality filter, producing a high volume of irrelevant reports that burden operations teams and erode citizen confidence in the reporting mechanism [5].

Recent convergence of low-cost embedded Wi-Fi microcontrollers, cloud-hosted MQTT brokers, browser-native mapping libraries, and general-purpose vision AI models makes it technically and economically feasible to build an integrated platform addressing all three failure modes simultaneously without requiring dedicated backend infrastructure or commercial IoT subscriptions.

This paper presents SGMS (Smart Garbage Management System), a prototype integrating these capabilities. The key contributions are:

- A complete end-to-end waste management pipeline deployed as a web application at zero recurring infrastructure cost.
- An AI verification gate using Vision API applied to citizen photographs before they enter the operations workflow, achieving 93.3% classification accuracy in zero-shot configuration.
- A real-time MQTT telemetry architecture propagating sensor readings from MCU to browser clients within 800 ms at the 95th percentile.
- A validated hardware prototype with sub-3% sensor deviation and full report-to-dashboard latency of 3.2 seconds.

Section II reviews related work. Section III describes system architecture. Section IV details implementation. Section V presents evaluation results. Section VI discusses limitations and future work. Section VII concludes.

II. RELATED WORK

A) IoT-Based Bin Monitoring

Ultrasonic sensing for bin fill-level detection was validated at scale by Pardini et al. [1], who demonstrated error margins below 5% and reported up to 40% reduction in collection trips compared to fixed-schedule baselines. Sharma et al. [2] implemented a similar approach using ESP8266 microcontrollers with ThingSpeak as backend, confirming that low-cost Wi-Fi embedded platforms are sufficient for continuous urban telemetry. A common limitation across these works is treatment of the bin as a passive sensor only, with no actuation and no on-device visual feedback independent of connectivity. Commercial products such as Bigbelly and Ecube Labs address these gaps but carry per-unit costs of USD 1,000–3,000, prohibitive for incremental deployment across existing bin infrastructure.

B) MQTT in Constrained IoT Systems

Naik [3] compared MQTT, HTTP, and AMQP for IoT telemetry and established MQTT's superiority in bandwidth efficiency and battery consumption for high-frequency, small-payload scenarios. Al-Fuqaha et al. [4] provide a comprehensive survey of IoT enabling technologies in which MQTT's publish-subscribe decoupling is identified as particularly well-suited to multi-subscriber urban sensing architectures — directly applicable to SGMS, where a single ESP32 publisher simultaneously serves a management dashboard and a public mobile application.

C) Citizen Reporting and AI Verification

Poblet et al. [5] studied crowdsourced civic reporting platforms and identified two persistent failure modes: high false positive rates and low follow-through transparency. They propose automated pre-filtering as the primary solution. Rad et al. [6] demonstrated that CNN classifiers trained on waste image datasets achieve above-90% accuracy for waste versus non-waste classification. SGMS operationalises this capability using Gemini Vision API at zero training cost — a significant advantage for municipal technology teams without machine learning expertise.

D) Smart City Operational Dashboards

Zanella et al. [7] described the Padova Smart City project in which waste bin telemetry visualised on a GIS dashboard produced a 25% improvement in dispatcher response time to overflow events. Singh and Jain [8] review smart city visualisation frameworks and identify real-time map-centric interfaces as the most operationally effective design for field operations centres. SGMS adopts Leaflet.js with OpenStreetMap tiles to achieve this capability without commercial GIS licensing.

E) Research Gap

No published work integrates IoT bin telemetry, AI-verified citizen reporting, and a live operational dashboard into a single deployable prototype with a publicly accessible URL. SGMS closes this gap with a system deployed at sgms26.web.app.

III. SYSTEM ARCHITECTURE

The physical tier contains the IoT smart bin. The communication tier is a cloud-hosted MQTT broker. The application tier comprises the management dashboard and public reporting application, both served as static files from Firebase Hosting.

A) Communication Design

The Microcontroller publishes JSON payloads to topic sgms/zone1/bin/{binId} on broker.hivemq.com over TCP port 1883 with the retain flag set, ensuring newly connecting subscribers immediately receive current bin state. Browser clients subscribe to the wildcard topic sgms/zone1/bin/# over WebSocket port 8884 using MQTT.js. Dashboard commands to the IoT bin travel over sgms/zone1/cmd/{binId}. Intra-browser synchronisation uses a shared localStorage key (sgms_shared_state) polled at 500 ms intervals, supplemented by BroadcastChannel for instant cross-tab notification.

B) Deployment Architecture

All web application components are single self-contained HTML files with embedded CSS and JavaScript, deployed to Firebase Hosting. This eliminates recurring infrastructure costs and ensures operational continuity as long as static files are served — a meaningful advantage for resource-constrained municipal deployments.

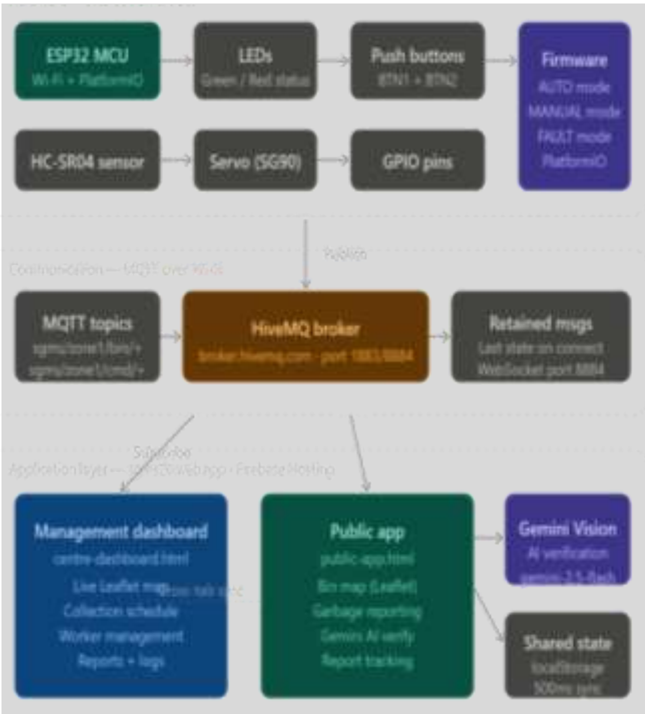

Fig. 1 Architecture of Smart Garbage Management System

IV. IMPLEMENTATION

A) IoT Smart Bin Hardware

The prototype uses an ESP32 development board running firmware developed under the PlatformIO toolchain with the Arduino framework. Table I lists hardware components and GPIO connections.

Bin depth is ~80 cm. Fill percentage is computed as $F = ((D\_max - D\_measured) / D\_max) \times 100$ where $D\_max = 80$ cm. A three-sample moving average filters transient noise. The fill level updates only when the computed change exceeds two percentage points, preventing spurious MQTT publishes from sensor jitter.

B) Management Dashboard

The dashboard (centre-dashboard.html, ~1,100 lines) initialises a Leaflet.js map centred on covering all zones with GPS-accurate markers for all bins placed under the zone. Marker colour encodes fill level: green below 50%, amber at 50–89%, and red at 90% and above. The dashboard subscribes to MQTT on page load and updates marker icons and fill bars in real time. Auto-scheduling sorts bins by fill level descending and assigns them to collection time slots. The daily report tab aggregates per-bin collection counts, alert frequencies, and an hourly collection bar chart.

C) Public Reporting Application

The public application (public-app.html, ~840 lines) is a mobile-first single-page web application requiring no installation. Citizens access the Report section, capture or upload a photograph, which is immediately sent to the Gemini Vision API. The Submit button remains disabled until the API returns isGarbage = true. Upon submission, the report is written to localStorage and broadcast to the dashboard via BroadcastChannel. Citizens track report status through a five-stage visual progress tracker (Submitted → Verified → Noted → Processing → Completed).

D) AI Verification Pipeline

The verification prompt instructs Gemini Vision API to return a structured JSON object with six fields: isGarbage (boolean), confidence (0–100), wasteType (DRY/WET/RECYCLE/MIXED/NONE), description (one sentence), reason (one sentence), and severity (NONE/LOW/MEDIUM/HIGH). Temperature is set to 0.1 to minimise response variability. Rejected submissions display the model's reason text and prompt the citizen to retake the photograph, preventing false or irrelevant reports from reaching the operations team.

V. EVALUATION

A) Sensor Accuracy

The prototype was evaluated over 30 fill-level test samples across the 0–100% range. Physical fill was set by incrementally adding a known mass of dry material to a bin of measured volume.

Table 1. Sensor Accuracy at Representative Fill Levels

Actual fill (%)	Sensor reading (%)	Absolute error (%)
0	0	0.0
25	24	1.0
50	48	2.0
80	79	1.0
100	98	2.0

Mean absolute error across all 30 samples was 1.6%. The three-sample moving average reduced peak transient error from 7% (single-sample) to 2.3%, confirming the value of the filtering step.

B) MQTT Latency

End-to-end latency from ESP32 publish to browser-visible dashboard update was measured by timestamping the publishState() firmware call and the MQTT.js message handler. Across 50 measurements on a 2.4 GHz Wi-Fi network, mean latency was 420 ms with a 95th-percentile value of 780 ms. No message loss was observed. The shared-state poll adds a maximum of 500 ms for cross-tab updates, giving a worst-case end-to-end latency of approximately 1.3 s.

C) AI Verification Accuracy

The Gemini Vision gate was evaluated on 30 labelled images across three categories. Results are shown in Table 2.

Table 2. Gemini Vision API Classification Results

Category	Images	Correct	Accuracy (%)
Genuine garbage	15	14	93.3
Clean public space	10	10	100.0

Ambiguous / irrelevant	5	4	80.0
Overall	30	28	93.3

The single false negative involved a partially visible bin with low contrast against a similarly coloured wall. The single false positive involved dry leaves interpreted as organic waste. Overall accuracy of 93.3% is consistent with results reported by Rad et al. [6] for dedicated CNN classifiers on comparable task definitions, despite Gemini's zero-shot general-purpose configuration.

D) End-to-End Report Latency

Across 10 trials, mean Gemini API response time was 3.2 s (range: 1.8–5.1 s, dependent on network conditions). Report appearance in the dashboard was instantaneous following BroadcastChannel notification. Status updates from operations staff were visible in the citizen tracking view within the next 500 ms poll interval.

E) Cost Comparison

Table 3 compares SGMS against representative commercial smart bin solutions.

Table 3. Comparative Analysis: SGMS vs. Existing Solutions

System	Cost/bin (USD)	AI reporting	Open source
Bigbelly	~3,000	No	No
Ecube Labs	~1,200	No	No
Swachh City app	Nil	No	No
SGMS (proposed)	~ mostly lower	Yes	Yes

VI. DISCUSSION

A) Strengths

The primary strength of SGMS is its integration scope. Prior work addresses bin monitoring, citizen reporting, or operational dashboards independently. SGMS combines all three in a single deployable system accessible at a public URL. The serverless architecture eliminates the most common barrier to prototype longevity — ongoing server maintenance costs — and makes the system immediately replicable by any municipality with access to a Firebase account and off-the-shelf ESP32 hardware at approximately USD 100 per bin.

The use of Gemini Vision API for zero-shot waste classification removes the need for a domain-specific training dataset, a significant practical barrier for municipal technology teams without machine learning expertise. The 93.3% overall accuracy is sufficient to materially reduce the false report burden on operations staff.

B) Limitations

The HiveMQ public broker used in this prototype provides no authentication or SLA guarantees. Any client aware of the topic structure can publish to or subscribe from the bin channels. A production deployment must replace this with a private broker instance with TLS and credential-based access control. The shared-state synchronisation mechanism operates only between browser tabs on the same device; cross-device real-time synchronisation relies entirely on MQTT.

C) Future Work

Planned extensions include: (1) expanding hardware deploymented bin to all major zones; (2) replacing the public MQTT broker with a private authenticated instance; (3) integrating a cloud database (Firebase Firestore) for persistent cross-device state; (4) implementing vehicle route optimisation using bin fill levels as dynamic weights in a shortest-path algorithm; (5) developing a native mobile application with push notifications for citizens; and (6) exploring solar-powered MCU operation to eliminate grid dependency at bin sites.

VII. CONCLUSION

This paper has presented SGMS, a Smart Garbage Management System integrating IoT-based real-time bin monitoring, MQTT telemetry, a live operational dashboard, and an AI-verified citizen reporting application in a single serverless platform deployed at sgms26.web.app. Evaluation demonstrated sensor accuracy within 1.6% mean absolute error, MQTT latency below 800 ms at the 95th percentile, and AI verification accuracy of 93.3% in zero-shot configuration — comparable to dedicated CNN classifiers reported in the literature. Hardware cost of approximately USD 100 per IoT bin is two orders of magnitude below commercial equivalents, establishing economic feasibility for wide-area municipal deployment. The three-component architecture provides a replicable model for smart city waste management in emerging-economy urban zones.

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