Archives available at journals.mriindia.com

International Journal of Recent Advances in Engineering and Technology
ISSN: 2347-2812
Volume 14 Issue 02, 2025

Gramnagar Live: An Analytical Study on Humanity in Service and Unity in Future

[1]Dr. A. B. Gavali , [2]Barde Pritee , [3]Bhise Dipak , [4]Thorat Pooja , [5]Wagh Neha
[1 2 3 4 5]S. B. Patil College of Engineering, Indapur
Email: dnayne.ash@gmail.com[1], priteebarde151@gmail.com[2], dipakbhise154@gmail.com[3], poojathorat736@gmail.com [4], nehawagh9920@gmail.com [5]

Peer Review Information

Submission: 11 Sept 2025

Revision: 10 Oct 2025

Acceptance: 22 Oct 2025

Keywords

Smart Waste Management, Machine Learning , Cleanliness , Citizen Engagement Platform, Geo-spatial Hotspot Detection.

Abstract

Gramnagar Live is an integrated digital platform designed to enhance the efficiency and transparency of rural and urban governance. The system connects Gramin Panchayat and Nagarpalika functions into a single framework for better community management. At the village level, it focuses on social welfare, education, health, agriculture, and the timely reporting of issues related to water, electricity, and roads. It also includes features such as government scheme tracking, financial record management, and disaster alerts. For urban areas, Gramnagar Live supports services like sanitation, garbage collection, public health, and tax collection. It also facilitates licenses, construction permits, and urban planning. The platform promotes citizen engagement through feedback, complaint systems, and voting participation. By combining transparency, accountability, and participation, Gramnagar Live aims to create a smarter, more responsive governance ecosystem.

Introduction

Local sanitation and civic service delivery remain among the most tangible measures of governmental effectiveness at the grassroots. In many countries, the responsibility for on- the-ground services is split between rural Gram Panchayats and urban Nagarpalikas, two administrative tiers that historically evolved with different operational models, resource levels, and stakeholder expectations. This dichotomy produces a practical problem: interventions, technologies, and performance metrics that work in an urban municipal corporation rarely translate directly to a rural Gram Panchayat where connectivity, staffing, and citizen interaction patterns differ drastically. Any engineering solution intended to improve cleanliness, complaint resolution, or waste management must therefore be designed from the outset to straddle this rural–urban continuum rather than assume a single homogeneous deployment environment.

Designing a trustworthy cleanliness metric is central to making the platform useful to both citizens and administrators. Unlike single-source indicators (e.g., number of complaints), a composite Cleanliness Scoring Index must reconcile evidence from computer vision (trash density, waste types), sensor fill-levels, ticket-resolution SLAs, and citizen satisfaction feedback. Operationally, the platform must be resilient to intermittent or asymmetric connectivity. Edge ML inference (model quantization, pruning, and on-device caching) reduces latency and bandwidth use, but it also introduces lifecycle concerns model updates, drift, and heterogeneity of edge hardware. A layered architecture that blends lightweight on-device checks (e.g., image quality, coarse classification), intermittent bulk synchronization, and cloud-side heavy analytics offers a pragmatic balance

Literature Survey:

1. **A systematic literature review on municipal solid waste management using machine learning and deep learning:**
This recent conference paper evaluates several convolutional and transformer-based classifiers for fine-grained waste sorting and reports encouraging accuracy for common categories (plastic, paper, metal) when trained on curated datasets.
The contribution is directly relevant for on-device classification and backend sorting assistance. But like many lab studies, dataset curation biases (clear backgrounds, well-lit items) limit generalization to noisy citizen photos or cluttered street scenes. For GramNagar, this suggests the need for curated fine-tuning datasets that specifically represent low-resolution, multi-language reporting contexts and the development of uncertainty flags to route low-confidence cases to human validators.[1]

2. Smart waste management: A paradigm shift enabled by artificial intelligence. Waste Management Bulletin:
Olawade reviews modern smart-bin architectures, sensor fusion (ultrasonic + camera), and data-driven route optimization algorithms. The article summarizes case studies where sensorized bins reduced collection costs and emissions, and it surveys ML models used for fill-level prediction and fault detection. It also highlights maintenance, lifecycle cost, and data governance as persistent challenges. Olawade's work, however, assumes that physical infrastructure investment is feasible; for many Gram Panchayats the capital cost is constrained, so our research must specifically test low-capex patterns (citizen reports
+ opportunistic edge inference) as a complement to sensorized deployments.[2]

3. Artificial intelligence for waste management in smart cities: A review.
This survey traces AI applications across waste management: smart bin fill-level prediction, route optimization for collection, image-based classification/sorting, and policy optimization using demand forecasts. The paper's gap for GramNagar is its focus on well- resourced urban pilots; it lacks concrete patterns for low-budget, intermittent-connectivity deployments or for integrating citizen-reported imagery with sensor data—both critical for mixed rural/urban rollouts.[3]

4. Task scheduling mechanisms for fog computing: A systematic survey:
Singh et al. survey recent advances in Edge AI architectures, hardware accelerators, scheduling algorithms, and privacy-aware on-device processing.This paper reinforces system design choices for GramNagar: dynamic partitioning (do cheap checks on device, defer heavy analytics to cloud when connectivity allows) and careful orchestration for heterogeneous equipment across villages and towns. The surveyed solutions are strong technically but again mainly validated on industrial testbeds; a gap remains in robust mechanisms for provenance, auditability, and trust when citizen evidence is used to compute public scores.[4]

5. Deep learning-based waste detection in natural and urban environments. Waste Management:
This paper applies object detection networks (e.g., Faster R-CNN, YOLO variants) to detect waste items in unconstrained outdoor scenes, assembling and annotating a dataset of street/park/beach images. Majchrowska et al.'s work demonstrates that modern detectors can identify visible litter at usable accuracy, supporting automated hotspot detection and event-triggered workflows.[5]

6. Edge machine learning for AI-enabled IoT devices:
Sensors. This review surveys techniques for running machine learning on constrained IoT devices: model compression (pruning, quantization), lightweight architectures (MobileNet, TinyML variants), on-device inference pipelines, and hardware/software co-design for microcontrollers and single-board computers. This leaves a gap for field-validated strategies to keep models accurate across the heterogeneity found between Gram Panchayats and Nagarpalikas.[6]

7. Sanitation sustainability index: A pilot approach for assessing community sanitation:
Hashemi et al. propose a composite index to evaluate sanitation sustainability, combining technical, social, and economic sub-indices. The SSI paper is directly relevant to designing a Cleanliness Scoring Index: it provides a defensible recipe for composing diverse indicators and for running sensitivity checks. Its limitation is context specificity the pilot communities differ from the Gram/Nagar administrative mix and it does not incorporate live computer-vision signals or citizen- reporting provenance, leaving an opportunity to extend SSI techniques with time-stamped, uncertainty-aware multimodal inputs.[7]

8. Experiences from a field deployment of a mobile sensing system for beach monitoring:
This field paper reports on a deployed civic sensing system for beach pollution: technical stack, volunteer onboarding, data quality issues, and governance lessons. Their limitations are domain specificity (beaches) and volunteer demographics; nevertheless, the deployment lessons (UX, training, audit procedures) are highly transferable to GramNagar pilots and point to the need for an explicit social-tech operations playbook.[8]

9. **Incentive mechanisms for crowdsourcing platforms:**
Several survey papers synthesize incentive designs for crowdsourcing: monetary rewards, reputation systems, gamification, and social incentives. These surveys guide how to design GramNagar's incentive layer: reputation and non- monetary badges plus occasional financial micro-rewards and random verification can discourage spam while keeping participation inclusive. Open questions remain about how to scale audits cost-effectively across many small villages and how to design incentives that do not bias reporting toward affluent neighbourhoods an ethical and operational research gap.[9]

10.A simple index to measure hygiene behaviours. Journal of Health, Population and Nutrition:
Webb et al. present a compact, household-level index for hygiene behaviours and show its validity against health outcomes using survey data. They describe pragmatic choices for binary/categorical indicator aggregation and demonstrate that simple indices can be predictive and actionable for program evaluation. The work emphasizes reproducibility and transparency in index construction.However, Webb focuses on survey and observational data rather than automated sensing; merging such survey-style indices with noisy, image- based signals will require careful alignment of scales and uncertainty modelling an explicit gap for future research.[10]

Research Gap:

- The current literature shows progress in edge ML, smart waste management, and incentive mechanisms, but lacks an integrative solution tailored for rural–urban governance.
- Existing waste detection models are trained on urban, high-quality datasets and struggle with noisy, low-resolution, rural inputs, highlighting the need for multimodal benchmark datasets.
- No standardized Cleanliness Scoring Index exists that combines vision outputs, sensor data, SLA tracking, and citizen feedback with transparency and auditability. Edge– cloud orchestration methods remain largely untested in low-bandwidth field settings, making sync strategies and OTA update mechanisms an open challenge.
- Incentive schemes show promise with mixed rewards, but audits are resource-intensive, so scalable, privacy-preserving fraud detection mechanisms are needed.
- User experience, onboarding, and governance have proven to be critical drivers of adoption, yet operational playbooks for Gram Panchayat and Nagarpalika contexts are missing.

Problem Statement
The Fragmented rural urban governance plus noisy, low-bandwidth inputs cause slow complaint resolution, inefficient waste collection, and no comparable cleanliness metric. A unified, scalable platform is needed edge ML, explainable cleanliness indices, low- bandwidth protocols, fraud-resistant incentives, and SLA-aware workflows to enable timely, transparent local sanitation management.

Conclusion
We conclude that, while significant advances exist in edge ML, smart waste systems, and incentive design, the challenge lies in integrating these strands into a unified, field-validated platform that works across both Gram Panchayats and Nagar Palikas. A successful system must combine robust datasets, an explainable Cleanliness Scoring Index, efficient edge–cloud orchestration, scalable fraud-resistant incentives, and strong human- centered operational playbooks. By addressing these gaps, future research can deliver a practical, low-cost, and transparent governance solution that improves complaint resolution, enhances cleanliness outcomes, and strengthens citizen trust in local administrations.

References
Dawar, I., Srivastava, A., Singal, M., et al. (2025). A systematic literature review on municipal solid waste management using machine learning and deep learning. Artificial Intelligence Review, 58, 183. https://doi.org/10.1007/s10462-025-11196-9

Olawade, D. B., Fapohunda, O., Wada, O. Z., Usman, S. O., Ige, A. O., Ajisafe, O., Oladapo, B. I. (2024). Smart waste management: A paradigm shift enabled by artificial intelligence. Waste Management Bulletin. https://doi.org/10.1016/j.wmb.2024.05.001

Fang, B., Yu, J., Chen, Z., et al. (2023). Artificial intelligence for waste management in smart cities: A review. Environmental Chemistry Letters, 21, 1959–1989. https://doi.org/10.1007/s10311-023-01604-3

Hosseinzadeh, M., et al. (2023). Task scheduling mechanisms for fog computing: A systematic survey. IEEE Access, 11, 50994–51017. https://doi.org/10.1109/ACCESS.2023.3277826

Majchrowska, S., Mikołajczyk, A., Ferlin, M., Klawikowska, Z., Plantykow, M. A., Kwasigroch, A., Majek, K. (2022). Deep learning-based waste detection in natural and urban environments. Waste Management, 153, 1–13. https://doi.org/10.1016/j.wasman.2021.12.001

Merenda, M., Porcaro, C., & Iero, D. (2020). Edge machine learning for AI-enabled IoT devices: A review. Sensors, 20(9), 2533. https://doi.org/10.3390/s20092533

Hashemi, S., et al. (2020). Sanitation sustainability index: A pilot approach for assessing community sanitation. Journal of Water, Sanitation and Hygiene for Development, 10(3), 453–465. https://doi.org/10.2166/washdev.2020.112

Komninos, A., Plessas, A., & Kaklanis, N. (2019). Experiences from a field deployment of a mobile sensing system for beach monitoring. Journal of Ambient Intelligence and Smart Environments, 11(2), 125–141. https://doi.org/10.3233/AIS-190524

Kou, Y., Chen, J., & Li, C. (2018). Incentive mechanisms for crowdsourcing platforms: A survey. ACM Computing Surveys, 51(1), 1–34. https://doi.org/10.1145/3148148.

Webb, A. L., et al. (2006). A simple index to measure hygiene behaviours. Journal of Health, Population and Nutrition, 24(3), 222–229. PMID: 17366771