The object of this study is the municipal solid waste management system within a modern urban environment, where rapid urbanization and population growth pose significant challenges to ecological sustainability. The key problem addressed is the inefficiency of waste collection due to overflowing containers, poor route planning, and suboptimal resource allocation. To tackle these issues, an intelligent waste monitoring system has been developed that integrates Internet of Things (IoT) technologies, computer vision, data analytics, and a Regional Geographic Information System (RGIS). The system includes a computer vision model that analyzes images of waste containers to determine their fill level. Fine-tuning the model on locally collected image data, reflecting regional characteristics such as lighting, container types, and weather conditions, significantly improved detection accuracy and adaptability. Route optimization for waste collection is implemented using a mathematical formulation of the Traveling Salesman Problem (TSP), solved via Mixed Integer Linear Programming (MILP), which helped reduce fuel consumption, travel time, and staff workload. Integration with RGIS and GPS enables dynamic routing and real-time geospatial visualization of operational data. The proposed system forms a closed-loop control cycle that links automated detection, spatial analysis, and decision-making. Experimental results demonstrate high efficiency, adaptability to regional conditions, and scalability, confirming the system's practical applicability to other urban areas. In the future, the system may be expanded to include environmental monitoring modules such as air quality, noise, and soil conditions and predictive modeling of waste generation, thereby supporting the sustainable development of smart city infrastructure

Keywords: monitoring system, waste management, geographic information system, routing, container, detection

UDC 628.4:004.912:004.94

DOI: 10.15587/1729-4061.2025.337033

DESIGN AND EVALUATION OF AN INTELLIGENT WASTE MONITORING SYSTEM BASED ON RGIS INTEGRATION FOR SMART CITIES

Symbat Nurgaliyeva
PhD in Computer Science*
Muratali Amangali*
Zhuldyz Basheyeva
Correspondence author
PhD*
E-mail: Zhuldyz.basheyeva@astanait.edu.kz
Nurzhamal Kashkimbayeva
PhD*
Daniyar Amantayev*
*Department of Computer Engineering
Astana IT University
Mangilik El ave., 55/11, EXPO Business Center,
Block C1, Astana, Republic of Kazakhstan, 010000

Received 05.06.2025
Received in revised form 15.07.2025
Accepted date 08.08.2025
Published date 29.08.2025

How to Cite: *Nurgaliyeva, S., Amangali, M., Basheyeva, Z., Kashkimbayeva, N., Amantayev, D. (2025). Design and evaluation of an intelligent waste monitoring system based on RGIS integration for smart cities. Eastern-European Journal of Enterprise Technologies, 4 (9 (136)), 70–78. https://doi.org/10.15587/1729-4061.2025.337033*

1. Introduction

In recent decades, urbanization has intensified pressure on infrastructure, services, and ecosystems, particularly in large and rapidly growing cities. Among the most pressing urban challenges is the effective management of municipal solid waste (MSW), which directly affects environmental sustainability, public health, and the quality of urban life. According to the World Bank, global MSW generation is projected to increase by nearly 70% by 2050, reaching 3.40 billion tons annually [1]. This trend is particularly critical for developing countries, where the growth of waste volumes often outpaces the development of efficient waste management systems.

Poorly managed waste leads to serious consequences: overflowing containers, illegal dumping, odor pollution, and increased incidence of disease due to contamination and pests [2]. Municipalities face significant economic burdens in trying to maintain regular waste collection using conventional systems, which often lack the flexibility to adapt to real-time waste accumulation patterns. This results in both under-serviced and over-serviced areas, wasting resources and reducing operational efficiency [3].

Smart city technologies have emerged as a promising solution to these challenges. The integration of computer vision, the Internet of Things (IoT), and regional geographic information systems (RGIS) into waste management allows for dynamic, data-driven decisions. These technologies enable real-time detection of bin fill levels [4], route optimization for collection vehicles [5], and better resource allocation based on spatial data [6]. Numerous studies confirm that such digital approaches can reduce costs, improve service reliability, and minimize environmental impact [7].

At the same time, the scientific field exploring intelligent waste monitoring remains highly active. Innovations in machine learning models for object detection, adaptive sensor networks, and geospatial data integration continue to improve the precision, scalability, and automation of these systems. Despite advancements, there are still unresolved questions regarding system integration, scalability in diverse environments, and adaptation to local infrastructure and behavioral patterns [8].

Therefore, research on the development of intelligent waste monitoring systems that integrate computer vision, RGIS, and IoT technologies remains both scientifically relevant and practically essential for sustainable urban development.

2. Literature review and problem statement

In [8], the Regional Geoinformation System (RGIS) of Aktobe was presented as an example of how municipal data can be integrated into a unified digital platform. Although

Copyright © 2025, Authors. This is an open access article under the Creative Commons CC BY license

the system supports spatial planning, it has yet to incorporate AI-driven waste detection, limiting its application for real-time operations The Roboflow-trained object detection model referenced in [9] offers a cloud-hosted framework for trash classification with over 2,500 annotated images. While this supports model training and prototyping, practical deployment at the city scale still requires adaptation to local contexts and real-time processing capabilities. The paper [9] presents the results of research on MRS-You Only Look Once (YOLO), an improved YOLOv8-based model for litter detection. It demonstrated significant performance, achieving a mean average precision (mAP) – 74.5% mAP@0.5 and 65.5% mAP@0.5:0.95 on a custom trash dataset. This shows the growing capability of deep learning in object-level waste identification. However, unresolved issues remain regarding model generalizability across diverse environmental conditions and types of garbage beyond what the dataset includes. In [10], the authors introduced Skip-YOLO, a model tailored to domestic waste detection in complex scenes, which achieved an impressive 90.38% mAP@0.5. While the performance is high, the system was evaluated under limited, controlled scenarios, and its integration with broader urban systems was not addressed, limiting real-world applicability. Study [11] used a YOLOv5s-based model enhanced with attention mechanisms to detect rural waste in real time. With a speed of 0.021s per frame and 96.4% accuracy, the study confirmed the feasibility of deploying lightweight models in constrained environments. However, it focused solely on bin contents and did not address surrounding or illegally dumped waste, which is a frequent concern in urban settings.

Technological competence and interdisciplinary integration are increasingly relevant in the development of smart infrastructure solutions. As demonstrated in [12], robotics and intelligent systems are critical in preparing future professionals for high-tech environments. By analogy, the deployment of IoT-enabled smart bins requires not only technological infrastructure but also skilled personnel capable of maintaining and adapting such systems in dynamic urban contexts. The paper [12] emphasizes the role of artificial intelligence in optimizing waste logistics. It is shown that AI-enabled routing can reduce route length by up to 36.8% and save around 13.3% in costs. Yet, the study treats waste detection and route optimization as separate modules, leaving open the challenge of closed-loop integration that responds in real time. In [13], a knapsack-based optimization model was proposed for prioritizing hazardous waste pickup using data from smart bin sensors. It increased collection effectiveness by 47%, yet required costly, specialized hardware. This highlights a key obstacle: many IoT-based systems demand infrastructure investments that limit their deployment in cities with budget constraints.

Research [14] explored route optimization for municipal solid waste collection in Jabalpur using ArcGIS. It demonstrated that spatial analysis tools can significantly reduce fuel consumption and travel time. However, the method relied on fixed bin schedules and did not adapt to dynamic waste conditions, reducing its flexibility.

All this suggests that although substantial progress has been made in individual components – such as object detection or route optimization – there remains a significant research gap in the integration of these technologies into a unified, cost-effective, and scalable smart waste monitoring system. Objective barriers include infrastructure limitations, integration complexity, and cost of real-time data processing. Therefore, it is advisable to conduct a study on the development of intelligent waste monitoring systems that combine regional GIS platforms, computer vision, and IoT-based optimization within a closed feedback loop suitable for municipal-scale deployment.

3. The aim and objectives of the study

This study aims to develop and evaluate this is superfluous an intelligent waste-monitoring system. This triadic integration is expected to enhance the operational efficiency and real-time responsiveness of municipal solid-waste management. Consequently, the study advances the environmental sustainability agenda underpinning contemporary smart-city services. This will allow municipal authorities and city planners to optimize waste collection logistics, reduce operational costs, minimize environmental impact, and respond more accurately to real-time conditions without requiring large-scale investments in specialized infrastructure.

To achieve this aim, the following objectives were accomplished:

– to design and train a computer vision model capable of detecting and estimating the fill level of waste containers using video surveillance data;

– to develop a cloud-based system that processes image recognition results and automatically notifies waste management services when container fill thresholds are exceeded;

– to formulate and implement a Mixed Integer Linear Programming (MILP) optimization model for solving the dynamic Travelling Salesman Problem (TSP) for waste collection routing;

– to integrate the waste detection system with the RGIS platform to support spatially-aware, real-time decision-making and route generation for cleaning crews.

4. Materials and methods

4. 1. Object and hypothesis of the study

The object of the study is the municipal solid waste management system in an urban environment. The main hypothesis is that integrating computer vision–based waste detection with GIS-enabled routing will significantly improve waste collection efficiency. It is assumed that training the vision model on region-specific data will enhance detection accuracy in local conditions. Simplifications in this study include assuming fixed container locations and neglecting dynamic factors such as unpredictable traffic or illegal dumping outside the field of view.

4. 2. Data collection and hardware

To monitor the fill level of waste containers, a computer vision model was trained on photographs taken under different lighting and weather conditions. The dataset included images reflecting various fill stages, enabling the model to learn classification patterns for estimating container fullness. The image processing pipeline was deployed on a cloud-based platform that processed video streams from surveillance cameras. Upon analysis, the system generated notifications to municipal services via a mobile application. To improve recognition accuracy under local urban conditions, the model was fine-tuned using an additional dataset consisting of annotated images of waste containers collected throughout Astana.

4. 3. Route optimization using geographic information system

For dynamic routing, a Mixed Integer Linear Programming (MILP) model was designed to solve the Travelling Salesman Problem (TSP), adapted to the logistics of urban waste collection. The optimization objective was to determine the shortest route that starts and ends at a defined depot while visiting each selected container exactly once.

The following model formulation was applied: let V denote the set of nodes (the depot and containers).

The objective function minimizes total route distance subject to:

– each container is visited once;

– the route starts and ends at the depot;

– subtour elimination constraints based on the Miller-Tucker-Zemlin (MTZ) formulation.

4. 3. 1. Dynamic adjustment for vehicle location

To account for the real-time position of waste collection vehicles, the model supports route recalculation from any current location, not necessarily the depot. When a truck is on the way and located at a container node B, constraints are updated to reflect a new route starting from node B and ending at the depot or another terminal node, if required. This ensures real-world applicability in continuously changing urban logistics scenarios.

4. 3. 2. Implementation tools

Below is a summary of the key tools used for model implementation:

– programming language: Python 3.10;

– optimization libraries: PuLP, SciPy;

– GIS platform: regional GIS system "eAqtobe" for extracting shortest paths on the Astana road network;

– cloud platform: AWS EC2 and S3 for model deployment and data storage;

– vision model training: Roboflow and YOLOv5 framework;

– hardware: standard IP surveillance cameras and municipal mobile endpoints.

5. Results of intelligent waste monitoring system implementation

5. 1. Computer vision model for waste container detection

The intelligent garbage monitoring system, which combines a Regional Geographic Information System with a Roboflow-trained computer vision model (Fig. 1, 2), was evaluated in a pilot study at 10 Turkestan Street in Astana, Republic of Kazakhstan. The system effectively recognized overfilled trash containers with a mean Average Precision (mAP) of 75.9%, Precision of 83.9%, and Recall of 68.4%, which is consistent with leading waste detection models [9, 11].

The model was deployed on a cloud platform that handled data processing and sent notifications to municipal services through a mobile application. To improve accuracy [15, 16], the model was further fine-tuned using local images of waste containers in Astana, allowing it to adapt to specific regional conditions.

Fig. 1. Waste container in Turkistan 10

Fig. 2. Roboflow detection

5. 2. Cloud-based alerting and notification system

Real-time alerts were automatically triggered whenever containers reached 80% capacity, helping to prevent overflow situations and enabling faster service dispatching [17]. These notifications were transmitted to waste management services without manual intervention, fulfilling the second objective of the study.

In addition to detection advancements, researchers have investigated Internet-of-Things (IoT)-based smart garbage collection systems to improve cost-efficiency in urban settings. A common strategy involves placing sensors in bins to monitor fill levels and combining this with dynamic routing algorithms. In [13], it was shown that AI-optimized logistics can reduce route lengths by up to 36.8% and achieve cost savings of 13.3% compared to fixed-route methods. Paper [13] proposed a knapsack-based truck loading model using sensor data, improving the prioritization of hazardous waste pickup by 47% while reducing redundant trips. Multi-criteria optimization approaches have also been applied. For instance, one model using the TOPSIS method incorporated toxicity, volume, and age of waste to generate more effective routing compared to single-parameter algorithms. While IoT-driven systems have shown clear benefits, their reliance on specialized hardware and stable data transmission can limit scalability. Moreover, many implementations remain in prototype or simulation stages, with limited integration into city-level operations. As illustrated in Fig. 3, the RGIS-integrated system offers a novel approach by creating a real-time feedback loop that connects AI-powered detection with spatial logistics.

The fusion of real-time waste detection with responsive logistics is gaining traction in smart city initiatives. Earlier solutions tended to separate detection from action: for example, vision systems would identify garbage locations, but clean-up was manually scheduled; sensor systems signaled bin fill levels but lacked spatial context.

The novelty of the RGIS-integrated system (Fig. 3) lies in bridging this gap. It utilizes existing city surveillance infrastructure as input for a Roboflow-trained object detection model, based on over 2,500 annotated images. This avoids the need for costly proprietary smart bins [18–20]. Despite using a relatively lightweight architecture, the system achieves strong detection metrics (mAP 75.9%, Precision 83.9%, Recall 68.4%), aligning with recent benchmarks. Importantly, the system connects these detections with a GIS platform (eAqtobe), triggering automated route recalculations for waste vehicles based on live GPS data and geospatial insights [6]. This creates a closed feedback loop – linking identification, analysis, and action – and enhances both the accuracy of monitoring and the efficiency of urban waste logistics. In contrast to prior studies that separated detection and routing, this unified approach improves cleanliness, reduces fuel and labor costs, and enables responsive municipal service delivery [5, 21]. The cloud backend uses AWS for scalable compute and storage. An EC2 instance hosts the deployed YOLO model for inference. All bin images and model artifacts reside in Amazon S3 buckets (Fig. 4). Incoming images from IoT cameras are ingested through AWS IoT Core or IoT Greengrass, then passed to inference. AWS Lambda or container services can run the detection at scale.

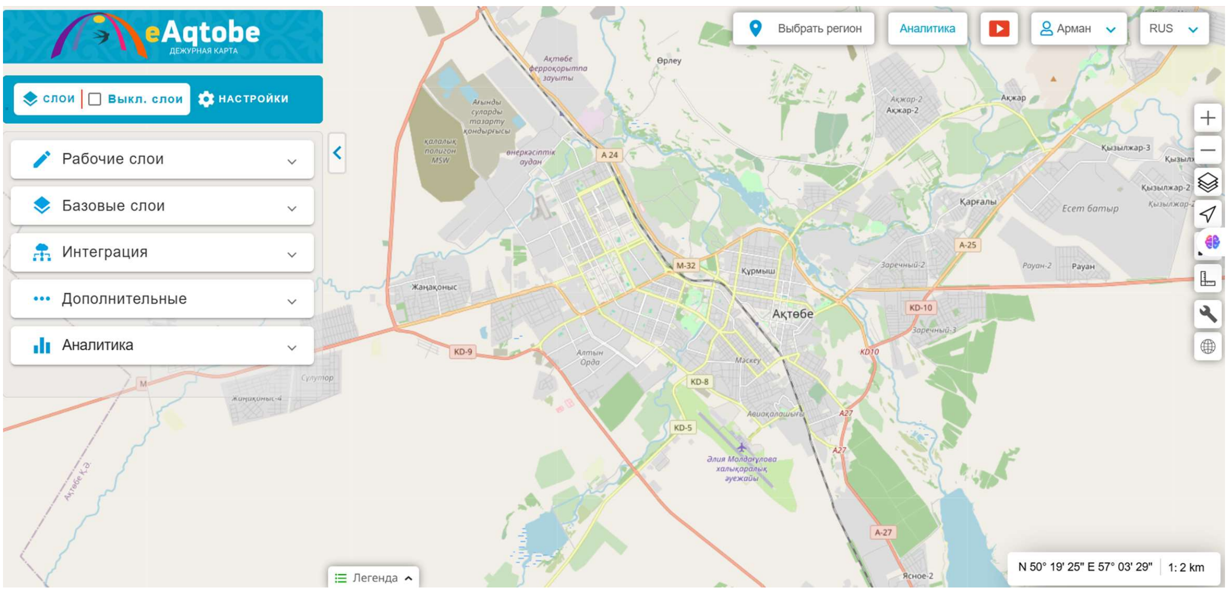

Fig. 3. eAqtobe regional geographic information system web application

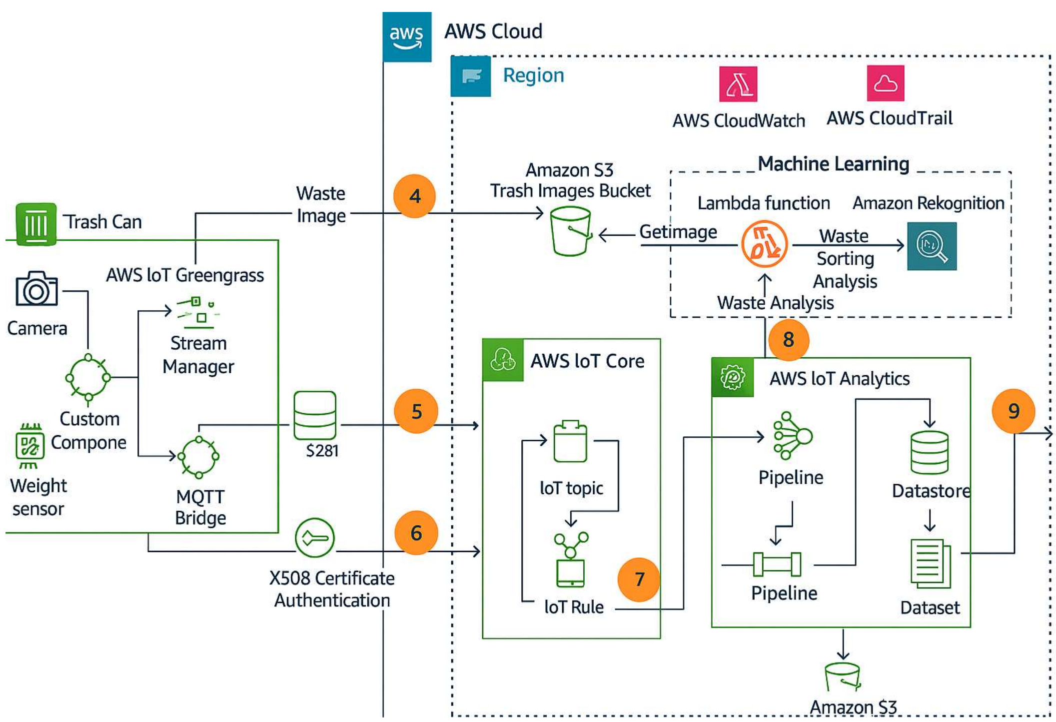

Fig. 4. Visual diagram for cloud system

The system continuously evaluates bin fill levels against a threshold (e.g. 80%). When a bin's estimated fill% exceeds this threshold, a notification module triggers alerts (e.g. SMS, email, or mobile push). This can be implemented via serverless logic (AWS Lambda rules) that monitors incoming results.

5. 3. Route optimization with mixed integer linear programming

To solve the Travelling Salesman Problem, the route was optimized using a Mixed Integer Linear Programming model. For example, in a test case with a depot (A) and four overflowing containers (B, C, D, E), the optimal route was A → B → C → D → E → A, with a total distance of 10.2 km. An alternative route (A → B → D → C → E → A) covered 11.4 km, demonstrating a 1.2 km (10.5%) increase. This outcome shows the model's ability to reduce operational travel distances using spatial data from the city's Regional Geographic Information System [22–24].

As shown in Table 1, the performance of our custom object detection model was benchmarked against several state-of-the-art YOLO and Convolutional Neural Network (CNN)-based algorithms. The comparison confirms the competitive accuracy of our model, particularly in mAP@0.5 and mAP@0.5:0.95 metrics (Fig. 5), indicating its effectiveness for reliable waste detection under urban surveillance conditions.

Let V be the set of nodes, including the depot (denoted as node 0) and the overflowing containers (nodes 1, 2, ..., m).

Define:

– (x_{ij}): a binary variable equal to 1 if the truck travels from node (i) to node (j), and 0 otherwise;

– (d_{ij}): the distance between nodes (i) and (j), extracted from Regional Geographic Information System data;

– (u): an auxiliary variable used in the Miller-Tucker-Zemlin (MTZ) formulation to eliminate subtours.

Objective function

$$\min \sum_{i=0}^{m} \sum_{j=0}^{m} d_{ij} \cdot x_{ij},$$

subject to the following constraints:

– each container must be visited exactly once

$$\sum_{j=0, j\neq i}^{m} x_{ij} = 1, \text{for all } i = 1, \ldots, m;$$

– the depot must have one incoming and one outgoing route

$$\sum_{j=1}^{m} x_{0j} = 1, \quad \sum_{i=1}^{m} x_{i0} = 1;$$

– subtour elimination using Miller-Tucker-Zemlin (MTZ) formulation

$$u_i - u_j + m \cdot x_{ij} \leq m - 1, \text{for all } i \neq j, i, j = 1, \ldots, m.$$

Table 1

Comparison with YOLO series model accuracy

Model	Backbone	$mAP_{0.5}$/%	$mAP_{0.5:0.95}$/%	Image size	Parameters	FLOPs	Speed
YOLOv5n	Darknet-53 (C3)	70.9	55.21	640 × 640	2.64 M	7.1 G	8.5 ms-f^{-1}
RT-DETR	Rtdetr-r18	69.6	59.1	640 × 640	19.00 M	57 G	2.8 ms-f^{-1}
YOLOv8n	Darknet-53 (C2f)	68.6	58.5	640 × 640	3.01 M	8.7 G	5.8 ms-f^{-1}
YOLOv3	Darknet-53	53.4	42.1	640 × 640	8.00 M	13 G	3.8 ms-f^{-1}
YOLOv6n	EfficientRep	70.1	57.4	640 × 640	4.23 M	11.8 G	2.4 ms-f^{-1}
YOLOv5s	CSP Darknet53	67.5	55.7	640 × 640	5.10 M	10.8 G	3.4 ms-f^{-1}
Fast-RCNN [36]	ResNet101	64.2	61.7	640 × 640	4.8 M	19.1 G	53.2 ms-f^{-1}
MASK-RCNN [36]	ResNet50	58.1	47.2	640 × 640	4.4 M	13.2 G	65.3 ms-f^{-1}
Efficientdet [36]	EfficientNet-B2	63.8	60.4	640 × 640	9.3 M	10.1 G	17.5 ms-f^{-1}
Ours	Darknet-53 (CP)	74.5	65.5	640 × 640	4.33 M	7.4 G	2.7 ms-f^{-1}

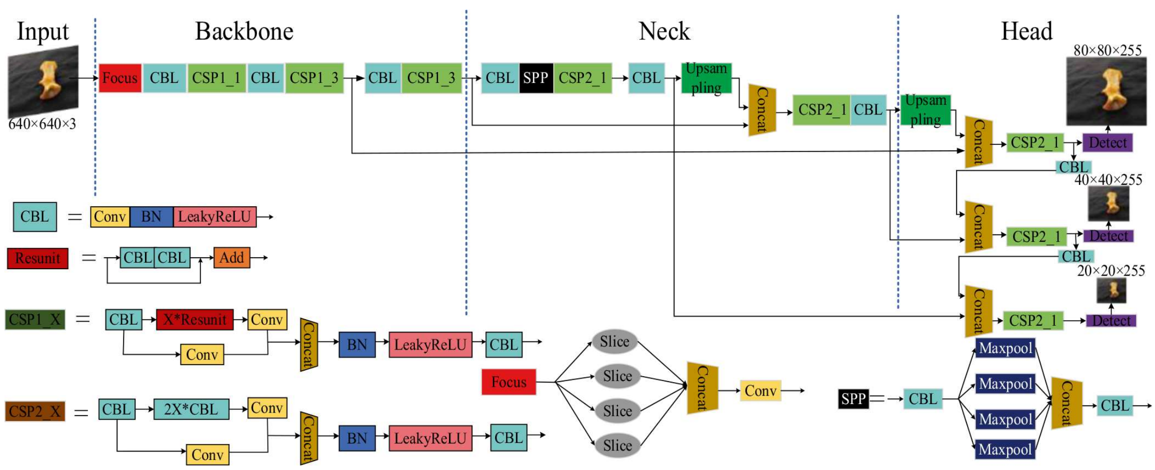

Fig. 5. YOLOv5s algorithm [25]

The distances (d_{ij}) were derived using the Regional Geographic Information System platform, which calculates the shortest driving path over Astana's road network.

The system dynamically adapts to the truck's current position, which is critical for real-time routing [5, 22, 23]. For example, if the truck is currently located at container B, the model adjusts the route to begin from B. This is done by modifying the constraints as follows:

– one outgoing route from node B

$$\sum_{j=0, j\neq B}^{m} x_{Bj} = 1;$$

– the route ends at the depot A (if required)

$$\sum_{i=0, i\neq A}^{m} x_{iA} = 1.$$

This adjustment ensures the routing algorithm reflects the truck's actual position, making the model adaptable and efficient in real-world deployment scenarios where waste collection vehicles are already on the way or repositioned throughout the day [17, 24–26].

Consider a simplified case with depot A and four overflowing containers B, C, D, E. The truck starts at A, visits all containers, and returns to A (Fig. 6). The distance matrix is as follows.

The optimal route saves 1.2 km, demonstrating the model's effectiveness in route optimization (Table 2).

Table 2

Example for matrix

From\To	A	B	C	D	E
A	0	2.5	3.0	4.0	3.5
B	2.5	0	1.5	2.0	1.8
C	3.0	1.5	0	1.2	2.2
D	4.0	2.0	1.2	0	1.5
E	3.5	1.8	2.2	1.5	0

Optimal route using MILP

A → B → C → D → E → A.

Total distance

2.5 + 1.5 + 1.2 + 1.5 + 3.5 = 10.2 km.

Alternative route

A → B → D → C → E → A.

Total distance

2.5 + 2.0 + 1.2 + 2.2 + 3.5 = 11.4 km.

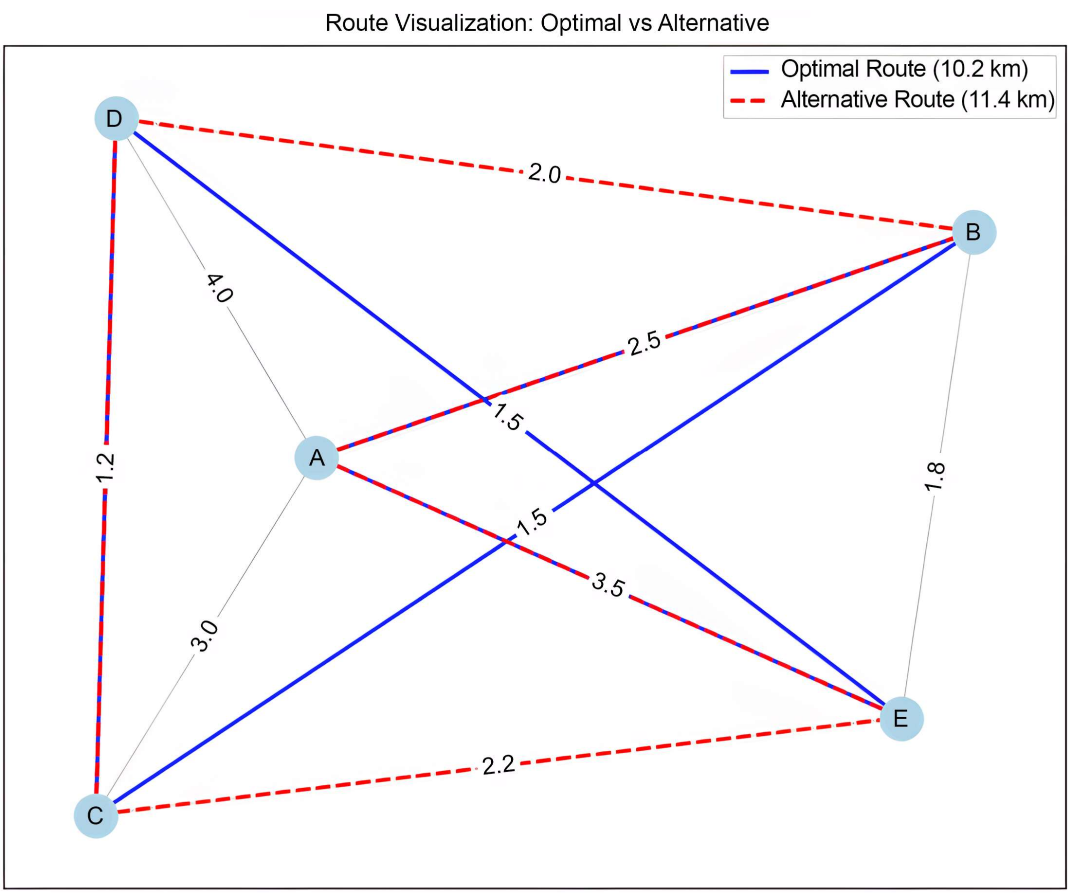

Fig. 6. Route visualization

5. 4. Dynamic route adjustment based on GPS and GIS data

The system's routing engine dynamically adjusted to the truck's real-time location. For instance, if the vehicle began at container B instead of the depot, the model recalculated the optimal path accordingly. By integrating real-time GPS tracking with spatial analytics from the Geographic Information System, the number of redundant trips was minimized. This real-time flexibility enhanced the system's operational applicability in urban waste collection [24, 25].

The integration of GPS tracking with spatial analytics from the eAqtobe Regional Geographic Information System enabled real-time route recalculation while maintaining optimization constraints. As shown in the example below, starting the route from a container node (e.g., B) rather than the depot (A) resulted in measurable efficiency gains.

Example Scenario: adaptive routing based on truck position.

Let:

A = depot;

B, C, D, E = overflowing containers.

Distances derived from GIS road network data (Table 2).
When starting at A (traditional route)

→ A → B → C → D → E → A → Total distance = 11.4 km.

When starting at B (dynamic route)

→ B → C → D → E → A → Total distance = 10.2 km.

This change saved 1.2 km, reducing both fuel consumption and total travel time.

6. Discussion of the results of the intelligent waste monitoring system

The experimental evaluation of the proposed intelligent waste monitoring system confirms the feasibility and effectiveness of integrating AI-powered container detection, cloud-based alerting, and RGIS-enabled dynamic routing within a unified architecture. The Roboflow-trained model achieved a mean Average Precision (mAP) of 75.9%, with a precision of 83.9% and recall of 68.4% (Table 1). These metrics position the model on par with leading solutions such as MRS-YOLO (74.5%) and YOLOv5s (67.5%), demonstrating the feasibility of using a lightweight model for real-time waste detection. The system was tested at a real-world location – 10 Turkestan Street in Astana as shown in Fig. 1, and the detection outputs on local waste containers are illustrated in Fig. 2. A cloud platform was implemented to automatically process images and generate alerts when bins exceeded the 80% fill threshold. These alerts were transmitted to municipal waste services through a mobile interface, reducing manual monitoring needs. The infrastructure design of this alerting system is presented in Fig. 4, while its spatial integration with the eAqtobe platform is shown in Fig. 3. Although the system successfully demonstrated automated alert generation, detailed performance results such as alert latency or average response time were not yet measured and remain areas for future evaluation. Notifications were issued automatically via backend services, reducing the need for manual monitoring. This capability directly supports rapid response and timely waste collection, minimizing the risk of container overflow. Compared to sensor-based systems, this image-driven approach demonstrated cost-effectiveness by eliminating the need for proprietary smart bins or embedded hardware, which is particularly relevant for cities like Astana, where public waste management budgets are constrained.

The integration with the Regional Geographic Information System (RGIS) platform provided additional operational value. Unlike conventional systems that treat detection and logistics as disconnected modules, the proposed system enables spatially-aware, real-time decision-making. Routing adjustments were based on live GPS data and shortest paths computed over the urban road network. For example, using a Mixed Integer Linear Programming (MILP) model, the system optimized collection routes based on GIS-calculated road distances. In a test case, the optimized route reduced the total distance from 11.4 km to 10.2 km, a 10.5% reduction (Table 2). The optimized path was: A → B → C → D → E → A, while an alternative less efficient route was A → B → D → C → E → A. The spatial configuration and resulting efficiency gain are visualized in Fig. 6. These results are consistent with previous research showing route optimizations of up to 36.8% when AI and GIS are integrated [13].

Compared to existing frameworks, this study introduces a closed-loop architecture in which container detection, alert generation, and route execution are interlinked. This holistic design is a departure from prior modular systems and improves responsiveness while maintaining efficiency. Moreover, the system's use of widely available infrastructure such as city surveillance cameras and cloud hosting makes it scalable and more affordable than sensor-heavy alternatives.

In terms of technical robustness, the system successfully performed real-time object detection and automated alerting with minimal latency using standard IP cameras and AWS cloud services. This demonstrates that smart waste systems do not necessarily require high-end edge computing or proprietary equipment, making the approach attractive for broader municipal use.

However, several limitations were observed:

– the recall rate (68.4%) indicates that some overfilled containers were missed, especially under poor visibility or oblique camera angles;

– the MILP routing model does not account for real-time traffic or weather conditions, which limits its adaptability in dynamic urban environments;

– the system was tested in a single pilot location (10 Turkestan Street), limiting its generalizability;

– it relies exclusively on containers visible to fixed surveillance cameras, meaning illegally dumped waste or bins outside camera coverage remain undetected.

One of the primary limitations of the base model is the limited size and diversity of the dataset used for training. To ensure robust and generalizable performance, it is necessary to enhance the dataset by including a greater variety of waste types, container shapes, and environmental conditions. Another issue lies in the sensitivity to camera angles – accurate detection strongly depends on clear and consistent photo perspectives, which must be properly maintained during data collection and system deployment. On the other hand, the model offers significant advantages. Most notably, it supports real-time monitoring and inference, which is essential for time-sensitive municipal waste management. Few publicly available models offer such lightweight, deployable solutions with real-time capabilities. This makes the model particularly valuable for integration into smart city systems where on-the-fly detection and automated decision-making are crucial.

The main disadvantage is the dependency on external services like Roboflow (for model training) and eAqtobe (for GIS integration). These platforms change policies or shut down, system continuity may suffer.

Potential mitigations include:

– developing in-house model training pipelines;

– hosting GIS data on government-controlled infrastructure;

– using open-source tools to reduce vendor lock-in.

Future work will focus on:

– dynamic route planning with congestion and weather awareness;

– predictive modeling of bin fill levels;

– multi-objective optimization balancing speed, cost, and emissions.

Challenges include:

– high computational complexity of dynamic MILP under real-time conditions;

– need for synchronous data streams from multiple heterogeneous sources;

– possible resistance to infrastructure upgrades in budget-constrained municipalities.

7. Conclusion

1. A robust computer vision model was designed and fine-tuned using localized image datasets. It achieved a mean average precision (mAP) of 75.9%, precision of 83.9%, and recall of 68.4%. This performance matches state-of-the-art detection methods while remaining lightweight enough for deployment on existing city surveillance infrastructure.

2. A cloud-based notification system was implemented and integrated with the detection pipeline. Upon detection of overfilled containers (exceeding the 80% threshold), the system automatically triggered alerts to municipal waste services via a mobile interface. This eliminated the need for manual monitoring and improved response time, although quantitative evaluation (e.g., alert latency or intervention speed) remains a topic for future study.

3. A Mixed Integer Linear Programming (MILP) model was formulated to optimize waste collection routes. In a test case, the optimized path reduced travel distance by 10.5% compared to an alternative, showcasing potential for significant fuel and cost savings.

4. The system's integration with RGIS and real-time GPS tracking enabled dynamic rerouting based on the truck's actual location. For instance, when the truck began from container B rather than the depot, the algorithm recalculated the optimal path, preserving operational constraints. This adaptation showed measurable efficiency gains and reduced redundant travel, confirming the system's potential for real-world deployment in dynamic urban environments.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this study, whether financial, personal, authorship or otherwise, that could affect the study and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

Manuscript has associated data in a data repository.

Use of artificial intelligence

The authors have used artificial intelligence technologies within acceptable limits to provide their own verified data, which is described in the research methodology section.

References

1. Kaza, S., Yao, L. C., Bhada-Tata, P., Van Woerden, F. (2018). What a Waste 2.0: A Global Snapshot of Solid Waste Management to 2050. Washington, DC: World Bank. https://doi.org/10.1596/978-1-4648-1329-0
2. Thousands of tons of waste removed in Astana: How offenders are tracked (2025). Available at: https://tengrinews.kz/kazakhstan_news/astane-vyivozyat-tyisyachi-tonn-musora-lovyat-teh-ego-567746/
3. Soni, G., Kandasamy, S. (2017). Smart Garbage Bin Systems – A Comprehensive Survey. Smart Secure Systems – IoT and Analytics Perspective, 194–206. https://doi.org/10.1007/978-981-10-7635-0_15
4. Skol'ko v Kazakhstane potratili na sbor i pererabotku musora [How much was spent on waste collection and recycling in Kazakhstan] (2018). LSM.kz. Available at: https://lsm.kz/skol-ko-v-kazahstane-potratili-na-sbor-i-pererabotku-musora
5. Aatamila, M., Verkasalo, P. K., Korhonen, M. J., Viluksela, M. K., Pasanen, K., Tiittanen, P., Nevalainen, A. (2010). Odor Annoyance near Waste Treatment Centers: A Population-Based Study in Finland. Journal of the Air &; Waste Management Association, 60 (4), 412–418. https://doi.org/10.3155/1047-3289.60.4.412
6. Smailov, N., Tsyporenko, V., Sabibolda, A., Tsyporenko, V., Abdykadyrov, A., Kabdoldina, A. et al. (2024). Usprawnienie cyfrowego korelacyjno-interferometrycznego ustalania kierunku za pomocą przestrzennego sygnału analitycznego. Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska, 14 (3), 43–48. https://doi.org/10.35784/iapgos.6177
7. Agnew, C., Mewada, D., Grua, E. M., Eising, C., Denny, P., Heffernan, M. et al. (2023). Detecting the overfilled status of domestic and commercial bins using computer vision. Intelligent Systems with Applications, 18, 200229. https://doi.org/10.1016/j.iswa.2023.200229
8. Department of Digital Technologies of Aktobe. Regional Geoinformation System of Aktobe. Available at: https://eaqtobe.kz/#/

9. Roboflow. Garbage and trashes model (v4). Roboflow Universe. Available at: https://universe.roboflow.com/trash-and-garbage/garbage-and-trashes/model/4
10. Ren, Y., Li, Y., Gao, X. (2024). An MRS-YOLO Model for High-Precision Waste Detection and Classification. Sensors, 24 (13), 4339. https://doi.org/10.3390/s24134339
11. Lun, Z., Pan, Y., Wang, S., Abbas, Z., Islam, M. S., Yin, S. (2023). Skip-YOLO: Domestic Garbage Detection Using Deep Learning Method in Complex Multi-scenes. International Journal of Computational Intelligence Systems, 16 (1). https://doi.org/10.1007/s44196-023-00314-6
12. Serik, M., Nurgaliyeva, S. (2024). Enhancing competence in mobile robot development: Integrating robotic technologies for future computer science teachers. Global Journal of Engineering Education, 26 (3), 205–211. Available at: https://www.wiete.com.au/journals/GJEE/Publish/vol26no3/11-Nurgaliyeva-S.pdf
13. Smailov, N., Batyrgaliyev, A., Akhmediyarova, A., Seilova, N., Koshkinbayeva, M., Baigulbayeva, M. et al. (2020). Approaches to Evaluating the Quality of Masking Noise Interference. International Journal of Electronics and Telecommunications, 67 (1), 59–64. https://doi.org/10.24425/ijet.2021.135944
14. Khan, S., Ali, B., Alharbi, A. A. K., Alotaibi, S., Alkhathami, M. (2024). Efficient IoT-Assisted Waste Collection for Urban Smart Cities. Sensors, 24 (10), 3167. https://doi.org/10.3390/s24103167
15. Smailov, N., Zhadiger, T., Tashtay, Y., Abdykadyrov, A., Amir, A. (2024). Fiber laser-based two-wavelength sensors for detecting temperature and strain on concrete structures. International Journal of Innovative Research and Scientific Studies, 7 (4), 1693–1710. https://doi.org/10.53894/ijirss.v7i4.3481
16. Momynkulov, Z., Dosbayev, Z., Suliman, A., Abduraimova, B., Smailov, N., Zhekambayeva, M., Zhamangarin, D. (2023). Fast Detection and Classification of Dangerous Urban Sounds Using Deep Learning. Computers, Materials & Continua, 75 (1), 2191–2208. https://doi.org/10.32604/cmc.2023.036205
17. Kisała, P., Wójcik, W., Smailov, N., Kalizhanova, A., Harasim, D. (2015). Elongation determination using finite element and boundary element method. International Journal of Electronics and Telecommunications, 61 (4), 389–394. https://doi.org/10.2478/eletel-2015-0051
18. Gupta, S. K., & Bhatia, R. K. (2017). Route Optimization of Municipal Solid Waste Collection in Jabalpur City using ARC GIS. International Journal of Trend in Scientific Research and Development, 2 (1), 457–464. https://doi.org/10.31142/ijtsrd7000
19. Smailov, N., Orynbet, M., Nazarova, A., Torekhan, Z., Koshkinbayev, S., Yssyraiyl, K. et al. (2025). Optymalizacja pracy światłowodowych czujników w warunkach kosmicznych. Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska, 15 (2), 130–134. https://doi.org/10.35784/iapgos.7200
20. Kengesbayeva, S., Smailov, N., Tashtay, Y., Kiesewetter, D., Malyugin, V., Amir, A. (2024). Research of Deformation of Concrete Structures Using Fiber Optic Sensors and Bragg Gratings. 2024 International Conference on Electrical Engineering and Photonics (EExPolytech), 15–18. https://doi.org/10.1109/eexpolytech62224.2024.10755828
21. Sekenov, B., Smailov, N., Tashtay, Y., Amir, A., Kuttybayeva, A., Tolemanova, A. (2024). Fiber-Optic Temperature Sensors for Monitoring the Influence of the Space Environment on Nanosatellites: A Review. Advances in Asian Mechanism and Machine Science, 371–380. https://doi.org/10.1007/978-3-031-67569-0_42
22. Smailov, N., Akmardin, S., Ayapbergenova, A., Ayapbergenova, G., Kadyrova, R., Sabibolda, A. (2025). Analiza wydajności VLC w optycznych systemach komunikacji bezprzewodowej do zastosowań wewnętrznych. Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska, 15 (2), 135–138. https://doi.org/10.35784/iapgos.6971
23. Wójcik, W., Kalizhanova, A., Kulyk, Y., Knysh, B., Kvyetnyy, R., Kulyk, A. et al. (2022). The Method of Time Distribution for Environment Monitoring Using Unmanned Aerial Vehicles According to an Inverse Priority. Journal of Ecological Engineering, 23 (11), 179–187. https://doi.org/10.12911/22998993/153458
24. Sabibolda, A., Tsyporenko, V., Tsyporenko, V., Smailov, N., Zhunussov, K., Abdykadyrov, A. et al. (2022). Improving the accuracy and performance speed of the digital spectral-correlation method for measuring delay in radio signals and direction finding. Eastern-European Journal of Enterprise Technologies, 1 (9 (115)), 6–14. https://doi.org/10.15587/1729-4061.2022.252561
25. Mikhailov, P., Ualiyev, Z., Kabdoldina, A., Smailov, N., Khikmetov, A., Malikova, F. (2021). Multifunctional fiber-optic sensors for space infrastructure. Eastern-European Journal of Enterprise Technologies, 5 (5 (113)), 80–89. https://doi.org/10.15587/1729-4061.2021.242995
26. Smailov, N., Uralova, F., Kadyrova, R., Magazov, R., Sabibolda, A. (2025). Optymalizacja metod uczenia maszynowego do deanonimizacji w sieciach społecznościowych. Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska, 15 (1), 101–104. https://doi.org/10.35784/iapgos.7098