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An AI- and IoT-Enabled Smart Waste Management Framework for Real-Time Waste Classification and Collection Optimization

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Abstract

The amount and variety of municipal solid trash have expanded due to rapid urbanization and shifting consumption habits, making it challenging for traditional systems to collect and segregate waste in a timely manner. When other containers are getting close to overflowing before the next scheduled visit, fixed collection schedules may cause needless journeys to partially filled bins. In this paper, a framework that combines image-based trash classification, real-time smart-bin monitoring, overflow-risk prediction, priority scoring, and dynamic collection-route optimization with AI and IoT capabilities is proposed. While IoT sensors offer operational data like fill level and optional temperature or weight, a deep-learning classifier is utilized to detect trash categories from photos. To calculate overflow risk, machine-learning models use both recent and past sensor readings.The decision engine then assigns priorities to a route-optimization module based on the urgency of the bins. As complementing computer-vision benchmarks, TrashNet and TACO are suggested, with the former offering photos for controlled classification and the latter offering litter in contextual settings [5], [6]. Results presented in the literature are just used as benchmarks; the suggested system is not claimed to have any artificial experimental precision. For assessing categorization quality, prediction performance, route efficiency, service reliability, and deployment cost, the framework offers a repeatable experimental design. In order to transition waste management from a fixed, reactive process to a predictive and adaptive system, the study offersanend-to-enddesign.
Keywords: Deep Learning, Computer Vision, Artificial Intelligence, Internet of Things, Smart Waste Management, Waste Classification, Smart Bin, Overflow Prediction, Route Optimization, Sustainable Cities.

1. Introduction

The management of municipal solid trash has grown more complicated as cities expand and consumption trends shift. Vehicle deployment is not always in line with the actual state of individual bins because traditional collection systems typically follow predetermined schedules and routes. As a result, research on smart waste management has shifted toward data analytics, sensor-based monitoring, linked garbage containers, and adaptive routing [1, 3, 4]. The infrastructure required to continuously monitor garbage bins is provided by the Internet of Things. Fill level, temperature, weight, and other operational characteristics can be measured via sensors. In order to assess whether a collection action is necessary, these readings might be sent to a municipal platform for analysis. Smart bins, sensors, waste-truck management, route planning, and stakeholder information exchange were highlighted by Sosunova and Porras as key components of IoT-enabled waste management after reviewing 173 primary papers [1].

The sensing infrastructure gains the ability to forecast and make decisions thanks to artificial intelligence. AI has been used in waste forecasting, bin-level detection, process prediction, vehicle routing, and waste-management planning, according to earlier systematic research [2]. While acknowledging data quality, privacy, cost, and real-world validation as significant difficulties, more recent evaluations highlight AI-based classification, predictive analytics, route optimization, and IoT integration [3], [4], [13], and [16].

Another significant issue is waste segregation. Sorting by hand requires a lot of work and is not always reliable. Computer vision based on deep learning is capable of autonomously classifying trash objects and learning visual representations. In addition to moving toward multi-label detection and contextual litter recognition, research has shown CNN-based classification on benchmark datasets [17]–[23]. Because laboratory-style photos can facilitate classification more easily than real-world waste scenarios, dataset selection is crucial. The majority of the 2,527 photos in TrashNet's six classes were taken against white backgrounds [5]. TACO was created especially for contextual litter identification and segmentation; 1,500 photos and 4,784 annotations were included in its initial version [6]. Therefore, these datasets offer comparable environments for contextual robustness testing and controlled classification. Another crucial element is collection optimization. Instead of treating every collection point similarly, dynamic garbage collection systems can react to actual fill levels. In terms of time, pollution, and cost, Abdallah et al. examined GIS-based dynamic collection and contrasted it with traditional methods [10]. Route optimization can be integrated with AI and IoT, according to recent research, albeit simulation-based enhancements shouldn't always be taken as field performance [7], [13]. This study suggests a single architecture that links waste-image gathering, deep learning categorization, IoT monitoring, overflow prediction, collection-priority scoring, and route optimization based on these advancements. The goal is to offer a comprehensive and repeatable framework in which each module can be independently analyzed before being evaluated as an integrated system, rather than to assert an experimentally proven deployment prior to measurements.

2. Literature Review

2.1 IoT-enabled smart waste management

IoT technologies facilitate connectivity between bins, municipal platforms, and collection vehicles and offer ongoing trash container monitoring. The literature demonstrates that the technological foundation of many smart waste-management systems consists of sensors, smart bins, route planning, and stakeholder information exchange [1]. Similar suggestions for sensor-driven alerts and route optimization for municipal operations have been made in a recent architecture assessment [4].

2.2 AI for waste management

AI has been used in trash generation forecasting, bin level detection, process variable prediction, collection vehicle routing, and other general planning tasks [2]. This includes automated sorting, monitoring, recycling, and predictive management, according to recent reviews [3], [13], and [16].

2.3 Image-based waste classification

CNNs can develop helpful representations for recyclable garbage, according to early deep learning research. While Aral et al. looked at deep-learning models on TrashNet [18], RecycleNet assessed deep architectures for intelligent garbage sorting [17]. Later, Mao et al. obtained 99.6% accuracy on TrashNet after optimizing

DenseNet121 utilizing augmentation and classifier tuning based on evolutionary algorithms [19]. These findings highlight the potential of deep learning but also reveal that field robustness and controlled benchmark accuracy are not the same thing.

2.4 Contextual waste detection

Detecting waste in chaotic scenes is not the same as classifying an isolated waste object. TACO was developed for contextual litter identification and segmentation [6]. While later comparison work assessed TACO for deep-learning-based litter identification [20], Pro Rodríguez and Simič stressed the necessity of photographs of litter in realistic environments. A multi-task architecture for concurrent garbage location and recognition was also suggested by Liang and Gu [21].

2.5 Lightweight and deployable models

Computational resources may be limited in practical smart-bin systems. While EfficientNet developed compound scaling to balance depth, width, and resolution [27], MobileNetV3 was created for mobile CPUs and hardware-aware efficiency [28]. Due to its comparatively low storage and inference requirements, MobileNetV3 has also been tested in an integrated municipal system in waste-management research [22].

2.6 IoT, cloud, and integrated systems

Wang et al. presented a proof of concept for intelligent urban garbage management that combines IoT, cloud computing, and deep learning. Their system supported adaptive collection and vehicle-routing decisions through picture classification and sensor-based monitoring [22]. Because it shows that categorization and collection management can be viewed as components of a single operational system rather than as separate research issues, this work is very pertinent.

2.7 Forecasting and overflow prediction

Planning can be enhanced by accurate trash generation forecasting. Abbasi and El Hanandeh showed that AI models can learn temporal waste-generation patterns by comparing SVM, ANN, ANFIS, and kNN for municipal waste-generation forecasting [24]. A different case study conducted in New Delhi found that a GA-ANN model performed the best out of six AI configurations [25]. The use of historical temporal data as an input for predictive collection systems is supported by these studies.

2.8 Dynamic route optimization

When bin circumstances change, dynamic collection adapts. In order to evaluate dynamic and traditional collection tactics, Abdallah et al. created a GIS-based smart collecting approach [10]. IoT-enabled routing optimization and its impact on collection distance have also been the subject of recent systematic research [7]. The suggested framework's routing component is motivated by these investigations.

2.9 Research gap

Strong evidence for individual AI, computer vision, IoT, forecasting, and routing components may be found in the literature; nevertheless, thorough integration and validation are still necessary for an end-to-end solution. This is addressed by the suggested paradigm through multi-level evaluation, explicit priority formulation, and the definition of a shared data pipeline. Therefore, the systematic integration and validation of the entire decision chain—rather than the development of each particular technology—is the primary research gap.

3. Proposed Framework

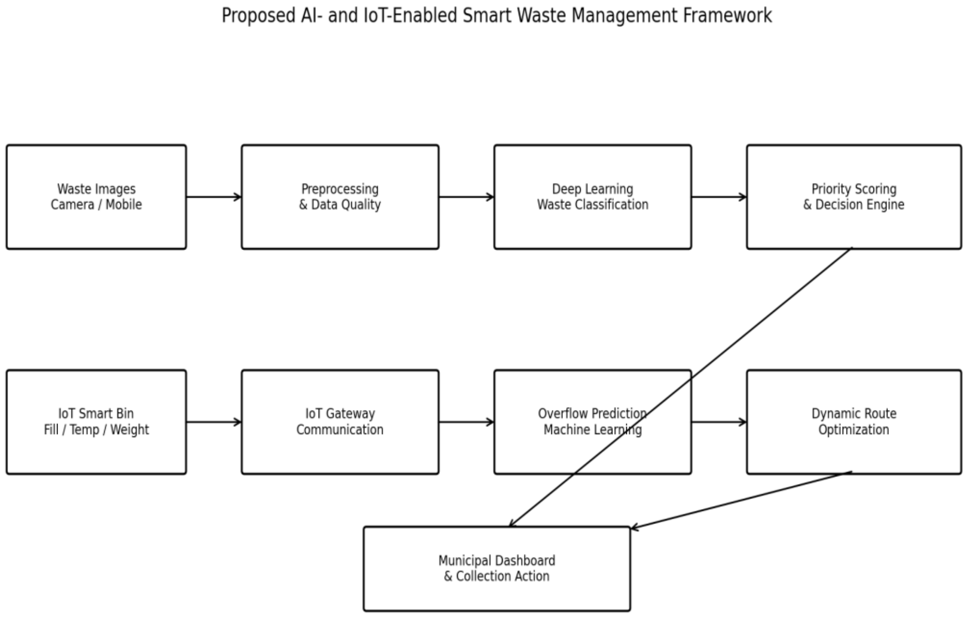

Fig. 1. Proposed AI- and IoT-enabled smart waste-management architecture.

There are five logical layers in the architecture. Smart-bin sensors and cameras are part of the sensing layer. Sensor observations are sent to an edge or cloud platform via the communication layer. The AI layer predicts overflow and classifies images. Predictions are transformed into collection priorities and optimum routes by the decision layer. Municipal employees and collection vehicles receive operational data from the application layer. The more general AI-IoT direction described in recent reviews [1], [4], and [13] is in line with this layered structure.

4. Methodology

4.1 Data acquisition

Bin-mounted cameras, mobile devices, or stationary cameras are used to take waste photos. Bin identification, timestamp, position, fill level, and optional temperature or weight should all be included in sensor records. In order to create future overflow labels without temporal leakage, each observation is associated with a collection event.

4.2 Image preprocessing

During training, images are normalized, scaled to a fixed resolution, and optionally enhanced. Small rotations, horizontal flips, translations, controlled cropping, and slight brightness adjustments are suggested augmentations. Test and validation pictures should continue to be deterministic. Before dividing the data, duplicate or nearly duplicate photos should be eliminated.

4.3 Deep-learning classification

Because EfficientNet-B0's compound-scaling technique strikes a balance between processing cost and accuracy, it is suggested as the main classifier [27]. MobileNetV3 can serve as an edge-oriented baseline [28] and ResNet50 as a deeper residual baseline [26]. A softmax layer completes the classifier. $P_i = exp(z_i)/ {}_j exp(z_j)$ is the expected probability for class I. Argmax(P_i) is the anticipated category. For optimization, categorical cross-entropy is employed. Because Adam employs adaptive first- and second-moment estimates, it is an appropriate optimizer [29].

4.4 Explainability

Image regions that contribute to a prediction can be visualized by applying Grad-CAM to the trained classifier [30]. This is helpful in determining whether the model concentrates on the actual object instead of background artifacts. For controlled datasets, where background can become a shortcut feature, such checks are especially crucial.

4.5 IoT monitoring

Fill percentage for a bin with measured waste height h_t and useable height H can be expressed as $F_t = 100h_t/H$. It is necessary to establish a local calibrated sensor threshold. In order to minimize transitory sensor noise, readings are timestamped and filtered. Instead of being silently replaced, missing values should be explicitly noted.

4.6 Overflow prediction

When the anticipated fill level at a future horizon Δ surpasses a predetermined threshold, like 90%, a binary target is defined as $Y=1$. Current fill level, recent growth rate, time since collection, day of week, historical averages, and local location data are some examples of features. XGBoost, random forest, and logistic regression are examples of candidate models [31]. Since future prediction is the operational goal, temporal train-test splitting is advised.

4.7 Priority scoring

Fill level, overflow risk, time since collection, and service relevance can all be combined to get a useful priority score: $P_i = w1F_i + w2R_i + w3T_i + w4S_i$. Validation trials or operational requirements should be used to determine the weights. Even if their fill level is not yet critical, high-risk bins should be given more priority.

4.8 Route optimization

A graph $G=(V,E)$ with bins serving as service nodes and road segments as edges can be used to express the routing problem. While penalizing unserved high-priority bins and honoring vehicle capacity and service limitations, the goal can reduce journey distance. Heuristics, metaheuristics, mixed-integer programming, and traditional vehicle-routing algorithms can all be assessed. The dynamic-routing idea comes after earlier studies on smart collecting [10].

5. Dataset and Experimental Protocol

5.1TrashNet

Glass 501, paper 594, cardboard 403, plastic 482, metal 410, and rubbish 137 are the six types that make up TrashNet's 2,527 photos [5]. Because of the significant class imbalance, accuracy should be reported along with macroF1 and perclass recall.

5.2 TACO TACO

offers item annotations and contextual litter photos. There were 1,500 photos and 4,784 annotations in the original version [6]. Because waste can be found in a wider range of surroundings than in controlled TrashNet photos, it can be used as a robustness or detection benchmark.

5.3 Internet of Things data

Timestamped observations from several bins over long enough time periods should be included in the IoT dataset in order to capture daily and weekly patterns. The fill-level trajectory should be reset at each collection event. For prediction experiments, the dataset should be split chronologically.

5.4 Protocol for training

When there are enough samples, a stratified split like 70:15:15 can be utilized for classification. Chronological splitting is better for time-dependent sensor prediction. Only validation data should be used for choosing hyperparameters. Until the model selection process is finished, the final test set should not be altered.

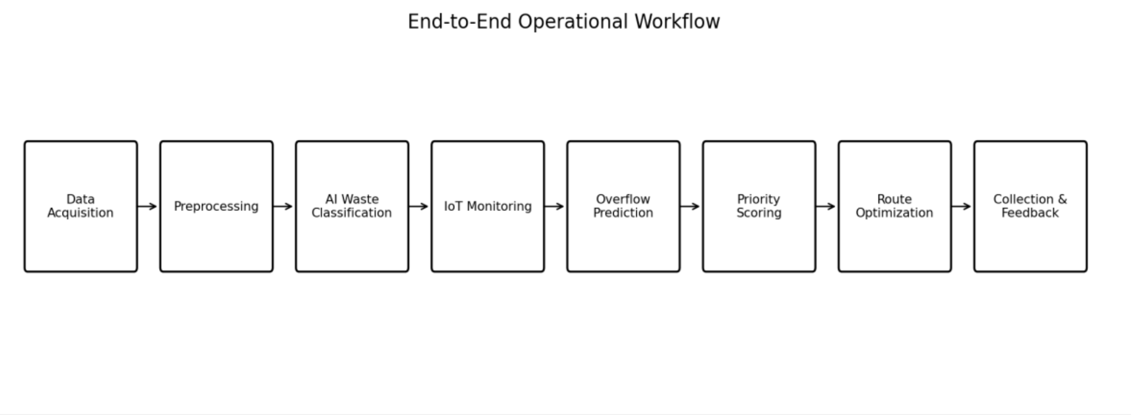

Fig. 2. End-to-end operational workflow.

6. Evaluation Metrics

6.1 Metrics for classification

Accuracy, macro precision, macro recall, macro F1, per-class recall, confusion matrix, number of parameters, and inference time are all reported. For unbalanced waste classes, accuracy is not enough on its own.

F1 = 2(Precision×Recall)/(Precision+Recall); Precision = TP/(TP+FP); Recall = TP/(TP+FN).

6.2 Metrics for prediction

For overflow prediction, report precision, recall, F1, ROC-AUC, calibration, and confusion matrix. Because missed overflow events can have more operational repercussions than additional alerts, recall is especially crucial.

6.3 Metrics for routing

Report total distance, travel time, number of trips, number of serviced bins, missed high-priority bins, vehicle utilization, and estimated fuel or emission proxy. Compare the proposed dynamic route against a fixed-route baseline.

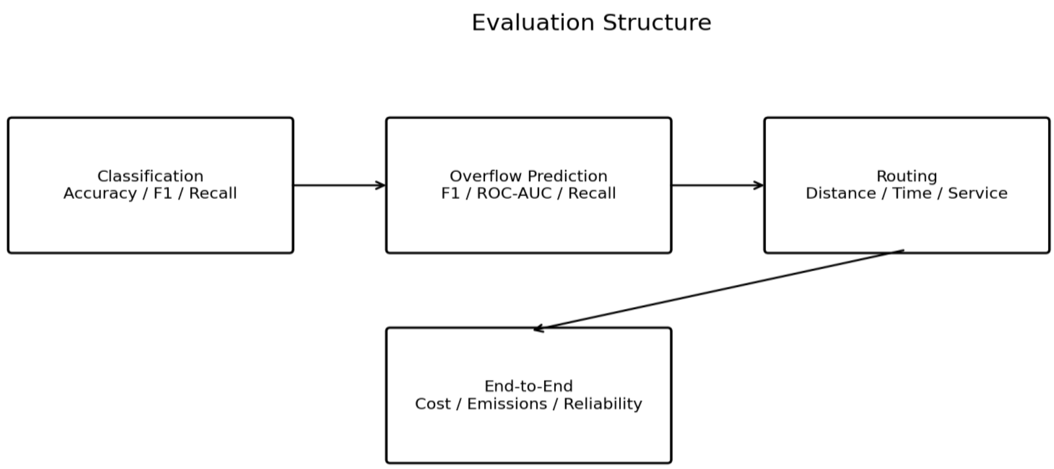

Fig. 3. Multi-level evaluation structure.

7. Results and Benchmark Evidence

This publication does not include any original training runs, municipal sensor datasets, or field trials. As a result, values for initial accuracy, F1, overflow, route-distance, fuel, or cost are not shown as though they were measured. Rather, in order to create a benchmark for the literature, Table I presents a selection of findings from mentioned studies. These values are not outcomes of the suggested framework; rather, they are part of the cited studies.

Study	Dataset/System	Reported result	Interpretation
Mao et al. [19]	TrashNet / optimized DenseNet121	99.6% accuracy	Controlled benchmark classification
Wang et al. [22]	Integrated deep learning + IoT	MobileNetV3: 94.26% accuracy; 261.7 ms	Evidence for deployable integrated architecture
Chen et al. [23]	Self-built waste dataset / GCNet	97.9% average accuracy; ~105 ms on Raspberry Pi 4B	Lightweight classification and edge feasibility
Abbasi & El Hanandeh [24]	Monthly MSW generation	AI models showed useful forecasting performance	Supports temporal prediction
Abdallah et al. [10]	Dynamic collection simulation	Compared time, pollution and cost with conventional practice	Supports adaptive routing concept

These findings from the literature show that each component is feasible, but they shouldn't be merged to provide a single system accuracy claim. To ascertain whether the combination results in quantifiable operational improvement, the suggested approach necessitates a fresh end-to-end experiment.

8. Proposed Evaluation and Performance Analysis

Waste classification, real-time bin monitoring, overflow prediction, and collection-route optimization are all intended to be evaluated as interrelated components of the suggested AI- and IoT-enabled smart waste management framework. The suggested method takes into account how information produced by one component contributes to later phases of decision-making, as opposed to assessing the image-classification model separately. The goal of this comprehensive evaluation is to ascertain whether the framework can enhance the responsiveness and efficiency of waste collection operations while offering dependable waste recognition.

8.1 Waste Classification Performance

The automatic classification of garbage photos is the main focus of the first evaluation stage. The suggested deep-learning model will be contrasted with well-known designs such as EfficientNet-B0, MobileNetV3, and ResNet50. Accuracy, precision, recall, and macro-F1 score will be used to assess the models. Since the suggested framework is meant to be implemented in an IoT-enabled context, inference time and model size will be taken into account in addition to classification performance.
While precision shows the percentage of anticipated samples that fall into the appropriate class, accuracy gives an overall metric of accurately classified trash samples. While the macro-F1 score offers a fair assessment across classes, recall gages the model's capacity to recognize samples that fall into each waste category. Macro-F1 is very helpful when there are differences in the amount of samples between waste categories.

In order to determine which categories are commonly misclassified, the analysis will also include a confusion matrix. Visually related categories, like paper and cardboard, can be identified by this kind of analysis, which can then direct further data augmentation and model improvement. Furthermore, whether the suggested model concentrates on pertinent waste regions rather than background features can be discovered using Grad-CAM-based visualization. Because regulated waste statistics may include visual patterns unrelated to the actual waste category [5], [17], [18], [30], this is crucial.

8.2 IoT-Based Smart-Bin Monitoring

The second phase assesses the suggested smart-bin system's capacity for real-time monitoring. Information like fill level, temperature, weight, timestamp, and bin position are gathered by IoT sensors. An appropriate communication channel is used to send these measurements to the central processing platform. A constantly updated depiction of each trash container's functioning state is provided by the gathered data. Because it serves as the foundation for deciding whether a bin needs to be collected right away, the fill-level data is especially crucial. The suggested architecture can continuously update the status of individual bins rather than depending solely on pre-established collection schedules. This strategy is in line with earlier IoT-based smart waste management studies, where adaptive collection decisions have been supported by sensor data [1], [4], and [22]. Basic data-quality processes, such as timestamp verification, noise filtering, missing-value detection, and abnormal-value identification, will also be applied to sensor observations. Because erroneous sensor data might spread errors into the prediction and route-optimization stages, these techniques are crucial.

8.3 Overflow-Risk Prediction

Predicting whether a trash container is likely to reach a critical fill level within a certain future time frame is the main goal of the third stage. The suggested methodology estimates future overflow risk using both past and present sensor data, rather than merely reacting when a bin is already full. The present fill percentage, recent filling rate, time since the last collection, day of the week, past filling trends, and other relevant contextual variables are examples of potential input variables. As baseline methods, machine-learning models like Random Forest, XGBoost, and Logistic Regression might be employed [24], [31]. The prediction task can be expressed as a binary classification issue where a non-critical situation is represented by a value of zero and a future critical-overflow event is represented by a value of one. The prediction models will be assessed using precision, recall, F1-score, ROC-AUC, and calibration. Recall will receive special attention because misidentifying a crucial bin as safe could lead to overflow, unpleasant surroundings, and lower service quality. Therefore, rather of choosing a threshold based only on overall accuracy, the prediction threshold can be modified in accordance with municipal service requirements.

8.4 Collection Priority Determination

A collection-priority system is then integrated with the anticipated overflow likelihood. Each bin is given a priority level by the suggested framework based on its operational significance, time since collection, expected overflow risk, and current fill status. One way to express a conceptual priority score is as follows: $\mathbf{Pi=w1Fi+w2Ri+w3Ti+w4Si}$, where Pi stands for bin i's priority score, Fi for its current fill level, Ri for anticipated overflow risk, Ti for the time-related collecting factor, and Si for service importance. Depending on the deployment environment's requirements, the weighting coefficients can be found experimentally. Bins can be divided into low, medium, high, and critical priority levels based on this score. This enables the collection system to differentiate between bins that need to be attended to right away and those that can continue on a regular basis.

8.5 Dynamic Collection-Route Optimization

The fourth main component assesses whether vehicle-routing decisions may be enhanced by AI-generated collection priorities. Predetermined routes and schedules are typically used in conventional waste collection. This method is simple, but it could lead to needless journeys to partially filled bins while urgent service is needed for other vital bins. By dynamically creating collection priorities based on current sensor observations and anticipated overflow danger, the suggested architecture overcomes this constraint. The location of bins, priority level, truck capacity, trip distance, and other operational limitations are all taken into account by the routing component. Finding a path that minimizes needless travel while serving high-priority bins is the goal. Total journey distance, collection time, number of trips, number of serviced bins, number of key bins missed, anticipated fuel consumption, and possible emission reduction can all be used to assess how well the suggested route-optimization technique performs. The importance of GIS-based optimization and dynamic routing for enhancing waste-collection operations has been shown by earlier studies [10]. Evaluating collection distance and operational efficiency when sensor information is included into routing decisions is further supported by recent IoT-enabled routing research [7].

8.6 End-to-End Framework Evaluation

Instead of evaluating each element separately, the final assessment takes into account the entire AI-IoT pipeline. Waste category information is provided by the waste-classification module's output; real-time container conditions are provided by the IoT layer; future overflow risk is estimated by the prediction module; and collection priorities are determined by the decision engine. These priorities are then used by the route-optimization module to choose a suitable collecting order.
The comprehensive assessment should look at whether advancements at different phases result in significant operational gains. For instance, if sensor malfunctions make it impossible to monitor reliably or if the routing algorithm is unable to adapt to shifting priorities, a highly accurate waste-classification model may not be very useful. In the end, both technical and operational indicators should be used to evaluate the suggested framework.

8.7 Ablation Analysis

To ascertain each component's contribution to the broader structure, an ablation analysis is suggested. IoT monitoring, overflow prediction, and dynamic route optimization can be gradually added to the evaluation starting with the fundamental waste-classification model.
A traditional classification-only strategy will be represented by the baseline configuration. IoT monitoring and overflow prediction will be added in the upcoming configuration. Lastly, dynamic route optimization will be included in the final design. By contrasting various setups, it will be possible to ascertain whether adding more parts results in quantifiable gains in system performance. Because the suggested contribution is not restricted to a single categorization scheme, this analysis is especially significant. Rather, the main contribution is the integration of real-time sensors, predictive analytics, and adaptive collection planning with AI-based waste detection.

8.8 Computational and Deployment Analysis

Computational efficiency will also be taken into account because the suggested framework is meant for smart-city and Internet of Things applications. For any classification architecture, it is necessary to document model parameters, model size, inference delay, and memory needs. While EfficientNet-B0 offers an alternate accuracy-efficiency trade-off, lightweight designs like MobileNetV3 can be a crucial deployment baseline [27], [28]. Communication latency, sensor dependability, energy usage, network accessibility, and edge device processing power should all be taken into account in the final deployment study. Even if the AI model performs well on a benchmark dataset, these factors can have a big impact on real-world performance.

8.9 Expected Contribution of the Proposed Analysis

The overall goal of the suggested evaluation approach is to show that smart waste management should be viewed as an integrated decision-support problem as opposed to only an image-classification task. The framework integrates collection prioritizing, predictive overflow analysis, real-time IoT monitoring, visual waste recognition, and dynamic route optimization. Such integration aligns with the current trajectory of waste management research based on AI and IoT [1]–[4], [13], [22].
Crucially, rather than asserting experimental outcomes, this section outlines the evaluation approach. Only when the suggested models have been evaluated and trained on the chosen datasets and the routing experiments have been carried out can actual numerical performance be disclosed. This distinction guaranties that no unsubstantiated accuracy, F1-score, route reduction, fuel savings, or emission-reduction values are reported as experimental findings in the text.

9. Discussion

The operational goal of the suggested methodology is not just to identify waste, which sets it apart from a traditional image-classification study. A broader decision-making process uses the classification output as one information stream. The routing engine translates those priorities into collection operations after sensor readings identify the bin's present status and the predictive model projects future danger. One of the main concerns is dataset quality. Although TrashNet has a tiny minority class and straightforward acquisition backgrounds, it is useful for controlled benchmarking [5]. Although TACO offers contextual sceneries, its size was initially constrained and it is far more difficult [6]. As a result, if feasible, a model should be assessed using both contextual and controlled data. Additionally, model efficiency is crucial. A little less accurate lightweight model may be more beneficial than a highly accurate network that cannot operate within the computational and latency limitations of a smart-bin or edge gateway. Established architectural choices for striking a balance between accuracy and efficiency are offered by EfficientNet and MobileNetV3 [27], [28]. Both distance reduction and service quality should be taken into consideration while evaluating the routing component. It would not be operationally acceptable to take a path that reduces distance but frequently misses important bins. Similar to this, as real performance might be affected by traffic, road limits, driver conduct, communication breakdowns, and sensor problems, simulation results and field results should be clearly distinguished [7], [10]. The categorization component's confidence can be increased by explainability. Grad-CAM images can show if a model is leveraging backdrops and other false features or utilizing pertinent waste regions [30]. This is particularly helpful when controlled backgrounds are present in the training dataset.

10. Restrictions

1. Public databases could not accurately reflect a municipality's trash makeup.
2. TrashNet is class-imbalanced and under control [5].
3. TACO is still modest in comparison to general computer-vision datasets, but it is more realistic [6].
4. Installation circumstances may impact sensor measurements, or they may be noisy or missing.
5. Real-time responsiveness may be diminished by communication breakdowns.
6. Traffic and operational restrictions cannot be accurately represented by simulated routing.
7. Hardware, connectivity, maintenance, cybersecurity, and employee training are necessary for actual deployment
8. Until the suggested trials are carried out, original system-level performance cannot be claimed.

11. Future Work

Future work should collect municipal smart-bin data over multiple seasons and test the framework in a controlled pilot area. Edge inference can be investigated to reduce communication latency. Object detection and segmentation can be added to handle multiple waste items in one image, using models such as YOLO or Mask R-CNN [32], [33]. Multimodal learning can combine images, sensor readings, historical collection patterns, weather, and traffic. More advanced dynamic-routing methods can also be tested under real traffic conditions. A digital-twin environment could support large-scale scenario testing before physical deployment.

12. Conclusion

This study presented an integrated AI- and IoT- -enabled intelligent waste management system for optimizing garbage collection and sorting in real time. The framework integrates smart-bin sensing, overflow prediction, priority scoring, and dynamic route planning with deep learning-based image recognition. These specific technologies, such as IoT smart-bin systems [1], AI-based trash-management apps [2]–[4], deep-learning waste classification [17]–[23], forecasting [24], and dynamic routing [10], are shown to be feasible by existing research. However, how consistently these parts cooperate under practical circumstances determines system-level effectiveness. Because of this, the suggested paper purposefully distinguishes between original experimental results and benchmark outcomes presented in the literature. The next step is to use the chosen datasets and real or properly labeled simulated IoT data to train and assess the suggested models. The placeholder tables can be filled with measured findings and statistical analysis after those experiments are finished.

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