EPJ Web of Conferences **343**, 04004 (2025) https://doi.org/10.1051/epjconf/202534304004
AIMACE-2025

On Comprehensive Review and Simulation Analyses of Intelligent Autonomous Waste Management Systems

Sivaganga Reghu[1*], *Senthil* A Muthukumaraswamy[2], *Girish* Balasubramanian[2] and *Talal* Shaikh[2]

[1]Imperial College, London, United Kingdom
[2]Heriot-Watt University, Dubai, United Arab Emirates

Abstract. Growth in population and consumerism has triggered an unprecedented increase in waste generation. However, the existing waste management systems are outstripped and do not promote sustainable living. An intelligent autonomous waste management system, discussed in this paper, addresses these challenges by integrating swarm intelligence and machine learning. Various object detection models and convolutional neural network (CNN) architectures, including ResNet, and their fusions are analysed for waste classification accuracy. IoT-based waste bin level and gas monitoring are explored for effective waste tracking. Various swarm intelligence algorithms, including particle swarm optimization (PSO), are reviewed for optimized waste collection. Image classification models such as You Only Look Once (YOLO) and Faster R-CNN are evaluated for accuracy and speed in waste classification. From the simulation results, it is demonstrated that YOLOv8 is the best-suited real-time waste classification model, achieving an accuracy of 95.8%. Further, the proposed PSO algorithm is assessed for effective waste collection routes by reducing environmental impact. From the simulation results obtained through the proposed PSO-based waste collection algorithm, it has been proven to outperform standard PSO. This study demonstrates the efficacy of integrating swarm intelligence, machine learning, and IoT in waste management and their potential to transform the waste management process.

1 Introduction

By 2030, it is estimated that approximately two-thirds of the global population will reside in urban areas. Thus, it is necessary to make investments in living in a sustainable and clean environment. However, waste management and disposal have become problematic tasks with tons of waste being generated daily, affecting both the environment and economy [1].

In densely populated urban areas, waste bin levels are checked manually, which is a highly inefficient and time-consuming task. Daily waste collection with high-capacity trucks leads to about 1.8 million litres of fuel consumption every year. A huge part of the fuel

* Corresponding author: sr2025@hw.ac.uk

consumption is due to improper scheduling and confining to a general waste collection schedule for all areas [2]. Waste segregation done manually has low accuracy rates and reduces the use of potential recyclable resources. Waste management processes pose a potential health risk for the workers.

Swarm intelligence technology can be employed to foresee the fastest and most optimal routes for waste collection in complex environments, considering all factors. IoT-based waste monitoring can be used for the detection of hazardous gases and waste, thus reducing overall health risks in waste management. By integrating this approach with machine learning and computer vision for autonomous waste classification, a significant impact on current waste management can be achieved. Implementing smart waste management on a large scale in cities is the first step to creating a pollution-free and sustainable environment. And thus, fostering the development of smart cities.

2 Waste production and management

A huge influx of human population over the years has led to a substantial increase in waste production, with industrial waste being the primary source of waste [3]. Waste management is a complex process as various types of waste are being generated, each of which needs to be treated accordingly. Solid waste can be segregated into municipal solid waste (MSW), industrial waste, e-waste, biomedical waste, and hazardous waste [4]. Waste management consists of several processes: collection and transportation, segregation and characterization, storage, recycling, and disposal [4]. Improving these processes can greatly benefit the environment.

For waste segregation, a detailed sorting procedure sorts wastes into paper, plastic, glass, metals, and miscellaneous manually. It is further sorted into subcomponents for undergoing composting, recycling, or energy recovery [4]. Solid waste is disposed of by using methods such as landfills, incineration, and biogas. Improper segregation during landfill and incineration processes can result in the release of harmful substances into the environment, which can be damaging to the ecosystem [3]. Automating segregation and optimizing the other processes of waste management will increase accuracy, reduce time taken, minimize health risks, and promote recycling.

3 Machine learning and computer vision in waste segregation

Waste can be segregated into categories such as dry or wet, recyclable or non-recyclable, and biodegradable or non-biodegradable, based on disposal methods. Thus, waste segregation must be performed with high accuracy to aid recycling, reuse, and prevent environmental pollution due to hazardous wastes [3]. Machine learning algorithms and computer vision can be used to accurately detect and classify waste effectively.

3.1 Object detection

Object detection algorithms such as You Only Look Once (YOLO) and Faster Regional Convolutional Neural Network (Faster R-CNN) can be used. A high-speed garbage detection and collection model uses YOLO for object detection. The YOLO algorithm has different mutations, but it is mostly recognized for its high-speed real-time object detection and precision.

The YOLO algorithm divides the image into panels and a single forward pass through the algorithm to predict the bounding box regression (centre coordinates, dimensions, and class

of the object). Intersection over union is the overlap between the bounding box identified by the algorithm and the actual bounding box of the object. Fig. 1 shows the three components explained above in the YOLO algorithm [5].

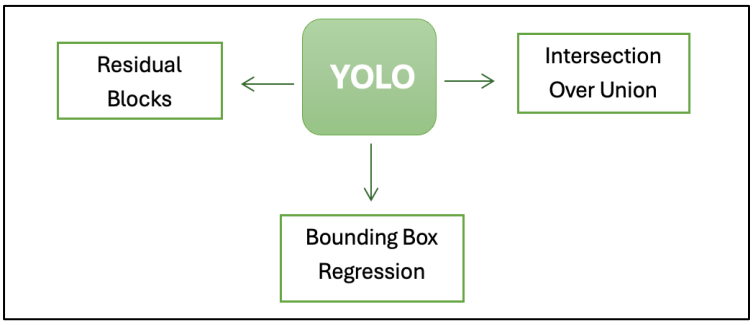

Fig. 1. Components of *YOLO* [5].

YOLO and Support Vector Machine (SVM), when compared for the detection of waste, YOLO exhibited an accuracy of 85.7% and SVM of 57.8%. Table 1 shows the results of waste detection classified into three categories: positive for correctly detected waste, negative for no waste detected, and false positives for detecting objects other than the ones provided in the waste dataset [5].

Table 1. Comparison of *YOLO* vs. *SVM* [5].

Result	**YOLO**	**SVM**
Positive	257	154
Negative	42	112
False Positive	4	84
Accuracy	85.7%	57.8%
Frames Per Second	48 fps	4 fps

A model for smart street detection uses faster R-CNN to detect street litter. It detects vegetation, leaves, litter, branches, plastic cups, and plastic bags. R-CNN consists of a convolutional neural network that detects the edges and shapes of litter. It is then processed by a Region Proposal Network (RPN), this layer then forms regions of interest (ROI) where litter could be present. This confines the areas of the image to be processed.

The ROIs are passed through a pooling layer, where the litter is resized and prepared for image processing. As the steps or iterations are increased, the accuracy improves. Faster R-CNN exhibited an average accuracy of 84.05% [6].

3.2 Image classification

A waste segregation and management system used a convolutional neural network (CNN) classification model with 11 layers (4 convolution, 4 max-pooling, 1 flattened layer, and 2 fully connected layers) to segregate waste into recyclable, organic, and non-recyclable as shown in Fig. 2 [7].

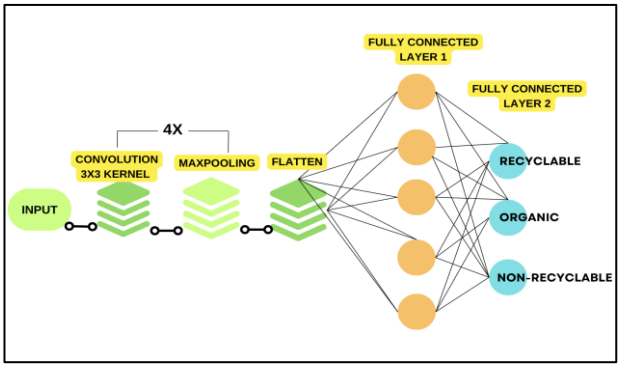

Fig. 2. Architecture of *CNN* model used [7].

The dataset used for training this CNN model was obtained from Kaggle. It showed the highest accuracy of 81.25 % when trained with 10 epochs and a batch size of 50. When compared with ResNet, VGGNet, MobileNet, and various other algorithms, MobileNet resulted in the highest accuracy of 92.65% as shown in Fig. 3 [7].

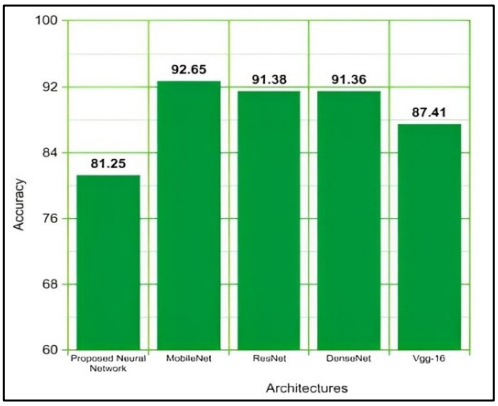

Fig. 3. Bar chart representation of the accuracies of various *CNN* architectures [7].

The fusion of these algorithms can provide even higher accuracies. An improved waste classification model was created using the fusion of different CNN architectures. GoogleNet, ResNet, VGGNet, and AlexNet were tested for their accuracy in sorting waste into cardboard, glass, metal, paper, and trash. ResNet performed the best overall, but GoogleNet performed much better in classifying the trash class, and both VGGNet and GoogleNet performed better in sorting the paper class [8].

Different algorithms perform better in classifying each type of waste. The double fusion method is used to fuse algorithms by assigning higher weights for better-performing algorithms in the classification of that class of waste. As demonstrated in Fig. 4, the double fusion algorithm performed with much higher accuracy than the overall individual best ResNet with an accuracy of 94.58% [8].

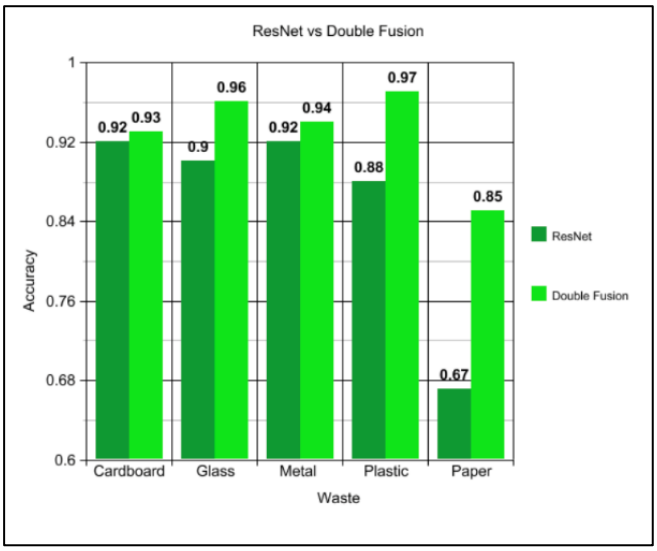

Fig. 4. Bar chart representation of deep model *ResNet* and double fusion model in terms of accuracy per class [8].

4 Swarm intelligence in waste collection

Swarm intelligence (SI) is a branch of artificial intelligence that makes use of multiple agents that interact with each other to achieve a common goal. There are multiple types of swarm intelligence algorithms, bio-inspired swarm intelligence being the most common. These algorithms mimic the behaviour of colonies in nature formed to forage. Some variations of SI are Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and Genetic Algorithms (GA).

Swarm intelligence is used in route optimization for waste collection. ACO and PSO are the most used algorithms. A model of an energy-efficient path-finding robot uses an adapted version of ACO that considers the weight of the waste bins and not just the distance as a heuristic and finds the most energy-efficient route between the waste bins [9]. The routing model represents each trash can as a node, as illustrated in Fig. 5.

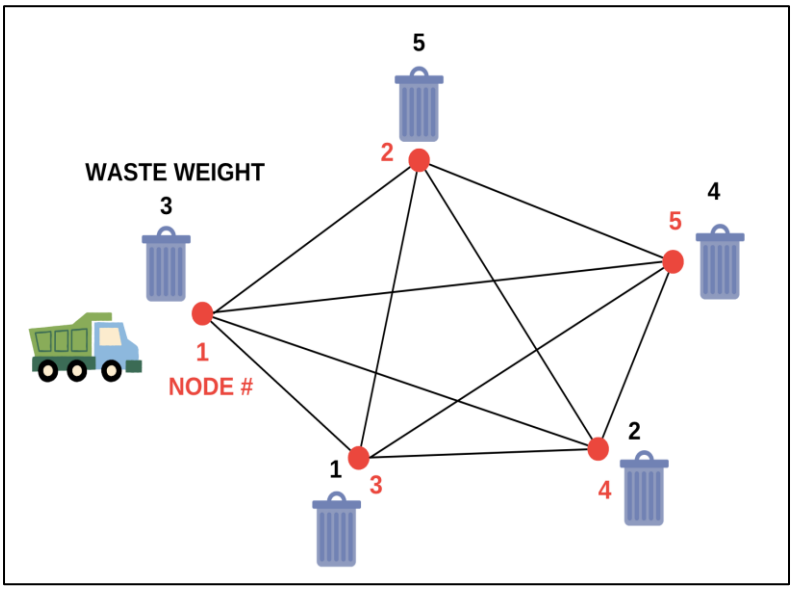

Fig. 5. Weighted graph used for waste collection robot [9].

When compared with conventional ACO for different carrying capacities of the robot, the adapted ACO method outperforms the conventional one by a noticeable amount.

Particle Swarm Optimization (PSO) is an algorithm that mimics the swarm nature in birds and fish. All particles have a fitness value, which gets updated with every iteration. The particles try to find the optimal path by evaluating their personal best and the global best to make decisions. Traditional PSO is hard to use for a discrete problem such as energy-efficient waste collection, so different mutations of it are generally used [10].

The article on energy-efficient dynamic vehicle routing for waste collection uses Q-learning-based hyper-heuristic particle swarm optimization (QLHPSO) to find the best path and schedule for waste collection, considering factors such as waste generation rate, distance, traffic, and vehicle breakdown. Q-learning is a reward-based decision-making algorithm. This is integrated into PSO for better decision-making. QLHPSO allows predictive rescheduling by adapting to low-level heuristics in real-time. It outperforms traditional PSO in terms of rapid responses within dynamic environments [11].

The article on energy-efficient multi-trip routing for solid waste collection uses contribution-based adaptive particle swarm optimization (CAPSO). This method integrated the Contribution-Based Adaptive learning (CAL) strategy with PSO. PSO blindly searches for optimal routes, whereas this approach makes use of different learning strategies to make decisions. The strategies are chosen according to the needs at each evolutionary stage of the algorithm. For example, in the initial stage greedy learning strategy will perform best, as there is no information to get feedback from. This approach leads to better route planning and convergence when dealing with multiple trips and dynamic requirements, although it is slower than PSO [12].

Conventional ACO can be used for path planning and route optimization, but different adaptations of ACO and PSO perform better.

5 IoT and real-time waste monitoring

Sensor systems and cameras can be used in monitoring waste to check the capacity, composition, and detect hazardous gases and environmental impact.

An intelligent trash bin incorporates the ESP8266 module to detect when the garbage is full. This can reduce carbon emissions during collection as unnecessary trips will be omitted. A combustible gas sensor detects the presence of combustible gases and sends out a warning, helping minimize health risks [12].

A smart solid waste management system uses blockchain to store transactional data and IoT to implement a smart trash can that rewards individuals for proper disposal of waste. This increases awareness and promotes recycling in smart cities [13].

6 Integrated smart waste management systems

Incorporating swarm intelligence, machine learning, and IoT into waste classification, collection, and processing can revolutionize waste management. Current advancements in smart waste management include smart bins, waste sorting robots, sensor-based waste monitoring systems, and predictive models for waste generation [2].

A predictive waste management system using PSO predicts waste generation trends from previously observed patterns to optimize waste collection, monitors the condition of the equipment to predict maintenance requirements, and assists with decision-making regarding management processes. It also uses computer vision and machine learning algorithms for waste sorting and recycling. Fig. 6, given below, depicts the framework of the entire integrated process of the system [14].

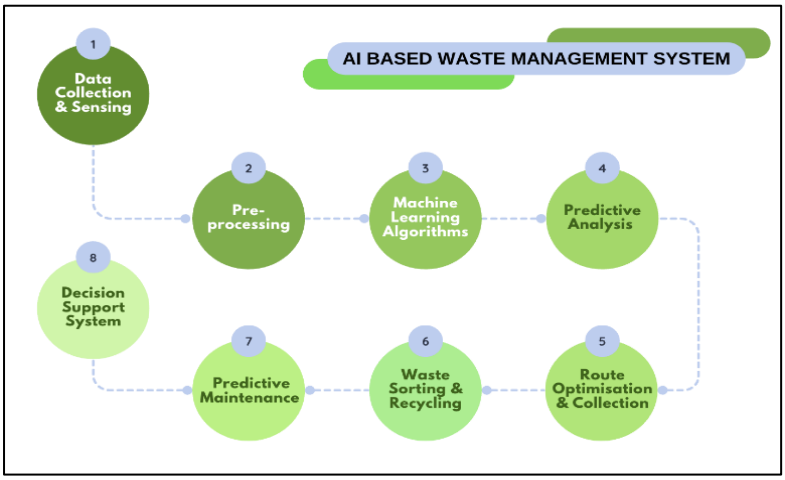

Fig. 6. Framework of proposed *PSO* for AI-based predictive waste management [14].

A proposal for a smart waste management system, using an IoT camera, trains a machine learning model using a dataset from the OpenCV library to detect improper waste collection when trash cans are being serviced in real-time [15].

7 Simulation results

7.1 Waste classification

A simulation was carried out using five pre-trained object detection models on the same COCO dataset consisting of 80 classes: YOLOv8, Faster-RCNN, MobileNet SSD,

EfficientDet D0, and RetinaNet. During this simulation, each of the five models was tested on a simple image of waste 50 times, and the average inference time was calculated along with an analysis of the results. Fig. 7 illustrates the outcomes of the simulation for all five models.

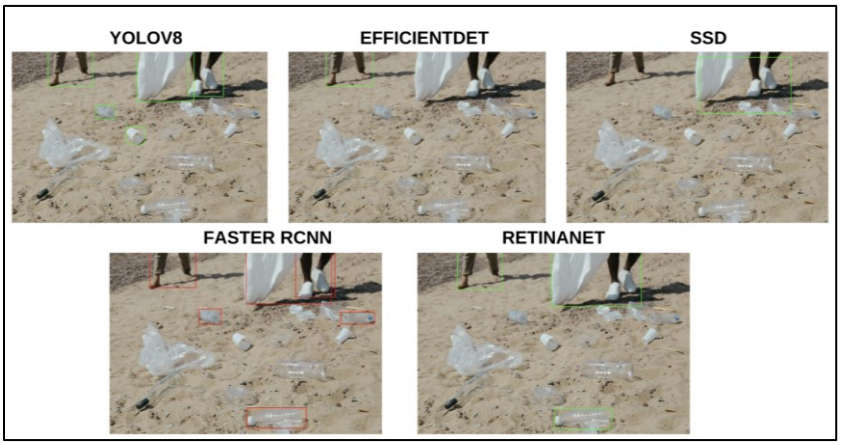

Fig. 7. Result of an image of waste on the beach simulated by the five object detection models.

These findings were evaluated based on various criteria to determine the most suitable model for real-time waste classification, as detailed in Table 2.

Table 2. Comparison of the five object detection models based on various factors

Model	**Average inference time (seconds)**	**Frames per Second (fps)**	**Accuracy Range (%)**	**Real-time detection**
YOLOv8	0.42849	~2.33	High (**0.86- 0.93**)	**Yes**
MobileNet SSD	0.0601	~16.6	Moderate (**0.42 - 0.79**)	**Yes**, very fast
Faster R-CNN	2.0103	~0.5	Very High (**0.42 - 1.00**)	**No**
RetinaNet	1.9048	~0.5	High (**0.82 - 0.97**)	**No**
EfficientDet-D0	2.0593	~0.49	Moderate (**0.53 - 0.91**)	**No**

Overall, it is proven that YOLOv8 is the best-suited model for waste classification in terms of accuracy, speed, and real-time detection capabilities amongst the remaining methods compared in Fig. 7.

The YOLOv8 model was trained using a dataset that included plastic bottles, plastic bags, and paper. It achieved an overall precision rate of 95.9%. Fig. 8 illustrates the graph displaying the individual precision for each type of waste. The YOLOv8 model was then tested for real-time detection using a video of a plastic bag, a bottle, and paper.

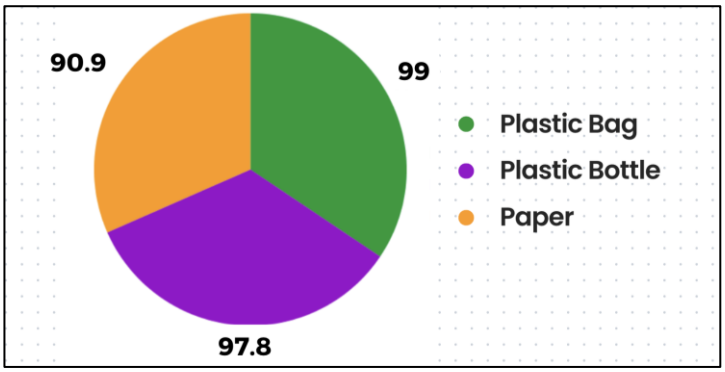

Fig. 8. Pie chart representing the individual precision percentage of each waste component.

The video simulation results of real-time waste detection, using paper, plastic bag, and plastic bottle, are demonstrated in Fig. 9. The outputs show the high accuracy and speed of YOLOv8 in localizing and classifying different waste classes. It outputs the position of the waste in the console while processing each frame in real-time.

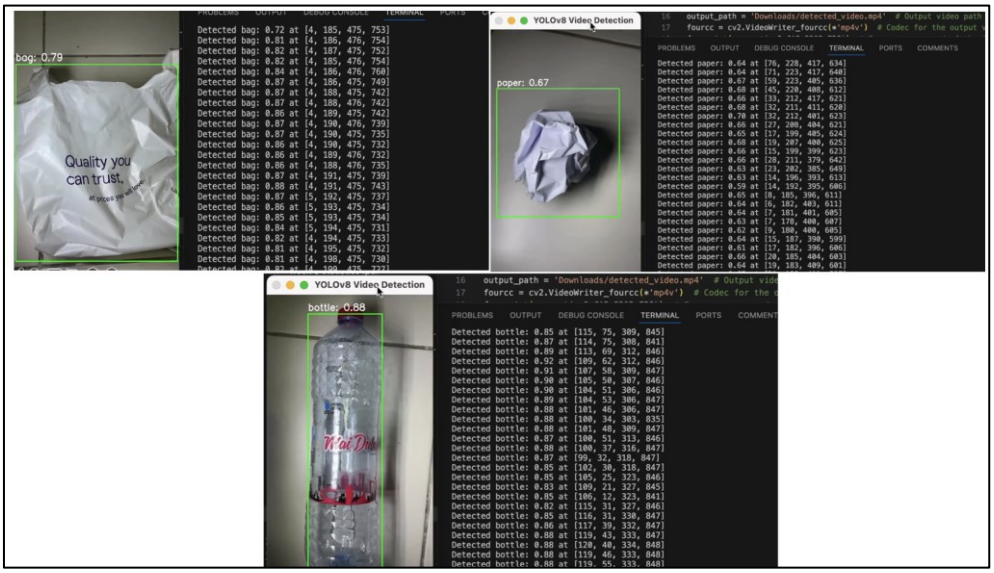

Fig. 9. Images showing the output of real-time waste detection using YOLOv8 of a few waste classes.

7.2 Waste collection

An adapted particle swarm-based route optimization algorithm for waste collection was developed, considering aspects such as the weight of the waste bin and the shortest distance, to minimize carbon emissions. The algorithm employs standard PSO with a minimizing fitness function that incorporates a decaying weightage factor (first collected bin to last collected bin) for the weights of the bins, as demonstrated in Eq. 1, where 'N' is the total number of waste bins, 'n' and 'n+1' represent the current and next waste bin.

$$Fitness = \sum_{n=0}^{N-1} \left(\frac{n}{N}\right) \times Weight(n) + Distance(n, n+1) \quad (1)$$

The standard PSO algorithm only considers the distance in its minimizing fitness function, while the adapted PSO algorithm considers both weight and distance. Two simulations were conducted using the adapted PSO algorithm and the standard PSO algorithm, featuring three waste bins labelled B, C, and D, along with a single start/drop-off point labelled A for the waste bins.

CASE A: The distances set between A=1, B=2, C=3, and D=4 are as shown in the matrix given below in Eq. 2:

$$Dist\ Between\ ABCD = \begin{pmatrix} 0 & 20 & 50 & 100 \\ 20 & 0 & 100 & 75 \\ 50 & 100 & 0 & 100 \\ 100 & 75 & 100 & 0 \end{pmatrix} \quad (2)$$

The weights assigned to each node/bin are: A=0 kgs (Start/drop off point), B=20 kgs, C=20 kgs, and C=30 kgs. The output of the adapted algorithm and standard algorithm on MATLAB is shown in Fig. 10.

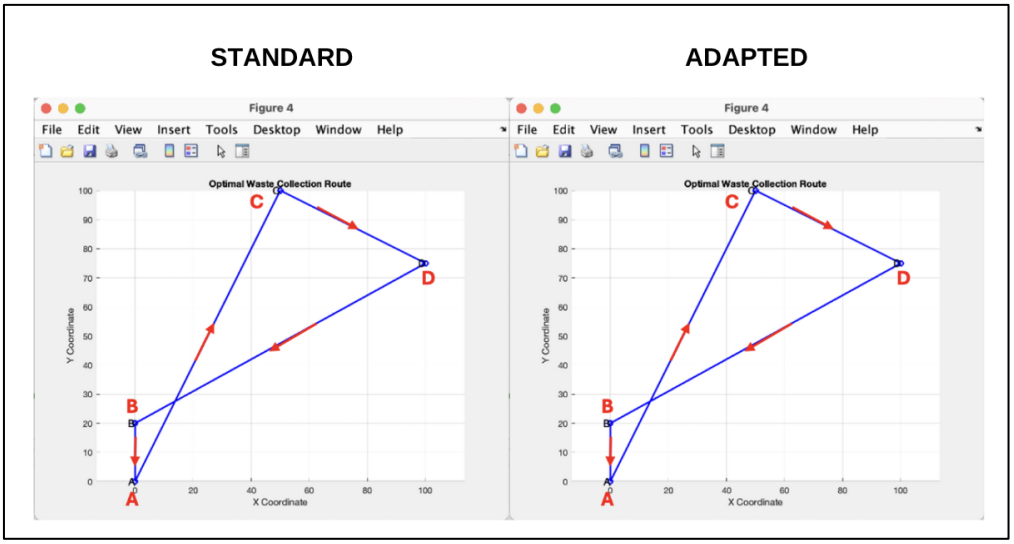

Fig. 10. Optimized route output of both standard and adapted PSO on MATLAB (Case A).

CASE B: The distances set between A=1, B=2, C=3, and D=4 were unchanged. The weights assigned to each node/bin are: A=0 kgs (Start/drop off point), B=300 kgs, C=200 kgs, C=30 kgs. The output of the adapted algorithm now changes with the weight change. In contrast, the standard algorithm remains the same as shown in Fig. 11.

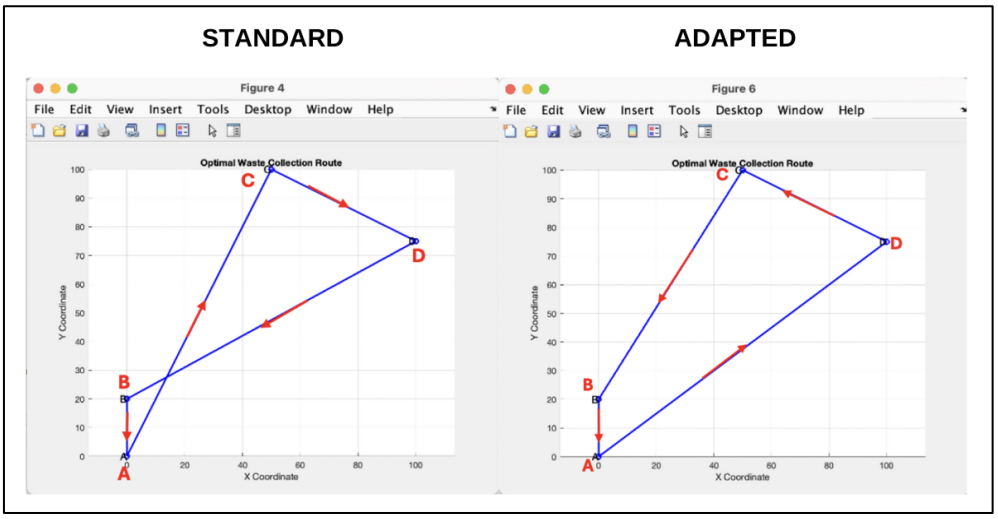

Fig. 11. Optimized route output of both standard and adapted PSO on MATLAB (Case B).

The fuel consumption for each of the cases in litres was calculated using Eq. 3, where the fuel consumption of each segment from bin to bin is calculated separately and summed together. The terms 'i' and 'i+1' refers to the current and next bin the visited by the vehicle. The 'weight factor' represents the weight dependence on fuel consumption, which can be estimated, depending on the vehicle model. The fuel consumption of each segment from bin to bin is calculated separately and summed together.

$$\text{Fuel consumption} = \sum_{i=1}^{n-1} (Distance_{i,i+1} \times (Fuel\ Consumption\ per\ Kilometer\ (Empty) + Weight\ Factor \times \ Weight_i)). \quad (3)$$

Table 3 demonstrates the total distance travelled and fuel consumed for both cases simulated using the standard and adapted PSO algorithm.

Table 3. Comparison of total distance travelled and fuel consumption for cases A and B.

Case	Distance travelled (meters)	Fuel Consumption (litres)
A(Standard)	245	24.475
A*(Adapted)	245	24.475
B(Standard)	245	178.725
B*(Adapted)	320	146.600

From Table 3, it is seen that, with lower weights, the standard PSO (A) and adapted PSO(A*) give the same output, as the weights don't influence the fitness factor much in the adapted algorithm. Hence, the fuel consumption remains the same for both algorithms, as calculated using Eq. 3.

With the weights increased, the standard algorithm(B) travels less distance, but fuel consumption is much higher than the adapted algorithm(B*). This is because the adapted algorithm(B*) takes a slightly longer route but carries lighter bins for most of its journey, hence greatly reducing fuel consumption. Whereas the standard algorithm considers only the

shortest route without concern for the weight of the bins. Thus, it carried heavier bins for most of its journey, increasing fuel consumption.

The adapted PSO gives the optimal route in terms of fuel consumption, considering all factors. Whereas standard PSO is sub-optimal, considering only the distance travelled. Thus, adapted PSO outperforms standard PSO.

8 Discussion

The analysis of multiple proposed or existing waste management models and simulation results obtained demonstrates the performance of swarm intelligence, machine learning, computer vision, and IoT in transforming waste management.

Route optimization for waste collection can be performed using various swarm intelligence algorithms. Performance analysis of conventional ACO and adapted ACO, and PSO methods shows that adapted versions operate with greater accuracy, although it is slower. The simulations using both the standard and adapted PSO-based route optimization algorithms prove the supremacy of the latter in finding the optimal routes for reduced fuel consumption.

Waste Segregation can be automated with machine learning and computer vision algorithms. Simulation results of various object detection models demonstrate the efficacy of YOLO in waste classification in terms of accuracy and speed. The results obtained using the trained YOLOv8 model show that it can detect various types of waste accurately in real-time. With further refinement, training, and the addition of more waste classes, it can classify large amounts of waste with high accuracy. Among multiple CNN architectures, ResNet and MobileNet performed well in various waste classification models. However, CNN architectures fused according to their ability to classify specific waste classes outperformed the individual architectures, as the diverse capabilities of each model in image characterization are combined to provide the best results.

For waste monitoring using IoT, gas sensors can be used to detect and analyse the type of waste, methane levels, and presence of harmful gases. This can immensely reduce health risks and promote the use of renewable sources of energy. Proximity sensors can be integrated to detect waste bin levels to avoid unnecessary waste collection trips and thereby reduce carbon emissions.Analysis of the integration of swarm intelligence, machine learning, and IoT into multiple waste management systems validated significant improvements compared to traditional waste management approaches.

9 Conclusion

This paper shows the importance of implementing smart waste management systems and the ongoing developments in waste management. Various processes in waste management can be transformed using swarm intelligence, machine learning, computer vision, and IoT.

Swarm intelligence algorithms for route optimization, such as PSO and ACO, can be implemented for predictive rescheduling and routing in waste collection. Machine learning and computer vision algorithms used for automation in waste classification will greatly increase speed and efficiency, as well as play a role in enhancing recycling and waste disposal methods. IoT can be used to monitor waste bins across specific areas for real-time information on capacity and gas levels, which is useful for waste collection and the reduction of health risks in waste management.

Proper handling and management of waste is crucial for a sustainable and safe environment. Smart waste management systems prove to be the best solution for tackling current waste management issues or improving the overall process.

References

1. Omar, M.F. et al. (2016) 'Implementation of spatial smart waste management system in Malaysia', IOP Conference Series: Earth and Environmental Science, 37, p. 012059. doi: 10.1088/1755-1315/37/1/012059.
2. Anagnostopoulos, T. et al. (2017) 'Challenges and opportunities of waste management in IoT-enabled smart cities: A survey', IEEE Transactions on Sustainable Computing, 2(3), pp. 275–289. doi: 10.1109/TSUSC.2017.2691049.
3. Waheeg, S.A., Adesola, R.O. and Garba, S.M. (2022) 'Biochemistry of waste recycling', World News of Natural Sciences, 42.
4. Gour, A.A. and Singh, S.K. (2022) 'Solid waste management in India: A state-of-the-art review', Environmental Engineering Research, 28(4), p. 220249. doi: 10.4491/eer.2022.249.
5. Usha, S.M. and Mahesh, H.B. (2022) 'Accurate and high-speed garbage detection and collection technique using neural network and machine learning', IOP Conference Series: Materials Science and Engineering, 1258(1), p. 012055. doi: 10.1088/1757-899X/1258/1/012055.
6. Ping, P. et al. (2020) 'Smart street litter detection and classification based on Faster R-CNN and edge computing', International Journal of Software Engineering and Knowledge Engineering, 30(4), pp. 537–553. doi: 10.1142/S0218194020400045.
7. Thanawala, D., Sarin, A. and Verma, P. (2020) 'An approach to waste segregation and management using convolutional neural networks', Communications in Computer and Information Science, pp. 139–150. doi: 10.1007/978-981-15-6634-9_14.
8. Ahmad, K., Khan, K. and Al-Fuqaha, A. (2020) 'Intelligent fusion of deep features for improved waste classification', IEEE Access, 8, pp. 96495–96504. doi: 10.1109/ACCESS.2020.2995681.
9. Tomitagawa, K., Anuntachai, A., Chotiphan, S., Wongwirat, O., and Kuchii, S. (2022) 'Adapted ACO algorithm for energy-efficient path finding of waste collection robot', Proceedings of the 22nd International Conference on Control, Automation and Systems (ICCAS), Jeju, Republic of Korea, pp. 469–474. doi: 10.23919/ICCAS55662.2022.10003892.
10. Shen, X., Pan, H., Ge, Z., Chen, W., Song, L. and Wang, S. (2023) 'Energy-efficient multi-trip routing for municipal solid waste collection by contribution-based adaptive particle swarm optimisation', Complex Systems Modelling and Simulation, 3(3), pp. 202–219.
11. Zhao, Y. et al. (2024) 'Energy-efficient dynamic vehicle routing for waste collection by Q-learning-based hyperheuristic particle swarm optimisation', IEEE Access, 12, pp. 56196–56213. doi: 10.1109/ACCESS.2024.3389749.
12. Mohamed, A., ElSayed, Y., Mahasneh, H., Rohouma, W.M. and Otoom, A.A. (2023) 'Intelligent trash bin for smart cities', Proceedings of the 1st International Conference on Advanced Innovations in Smart Cities (ICAISC), Jeddah, Saudi Arabia, pp. 1–4. doi: 10.1109/ICAISC56366.2023.10085313.
13. Paturi, M., Puvvada, S., Ponnuru, B.S., Simhadri, M., Egala, B.S. and Pradhan, A.K. (2021) 'Smart solid waste management system using blockchain and IoT for smart cities', IEEE International Symposium on Smart Electronic Systems (iSES), Jaipur, India, pp. 456–459. doi: 10.1109/iSES52644.2021.00107.
14. Gandhimathinathan, A. (2023) 'IEEE Smart Cities publications journals and magazines special issues', IEEE Smart Cities Newsletter, September. Available at: https://smartcities.ieee.org/newsletter/september-2023 (Accessed: October 2024).
15. V., A., Nithya, B., M., G., M., B.T., Hiremath, A. and Jayaprakash, B. (2024) 'Ingenious waste management: Implementing machine learning in waste segregation', Proceedings of the 2024 International Conference on Emerging Smart Computing and Informatics (ESCI), Pune, India, pp. 1–5. doi: 10.1109/ESCI59607.2024.10497282.