

# “Trashbot” The Smart Dustbin

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**Abstract-** As global urban populations expand, the inefficiencies of traditional, stationary waste management systems have become increasingly apparent, often resulting in environmental degradation and public health risks. To address these limitations, this research introduces TrashBot, an autonomous, omnidirectional robotic waste collection system that leverages artificial intelligence and computer vision to transform waste disposal from a passive to an active process.

The system utilizes the YOLO (You Only Look Once) deep learning framework for real-time trash identification across diverse environments. A key innovation of TrashBot is its predictive interception capability; by applying projectile motion analysis, the robot calculates the trajectory of discarded items to proactively position itself at the estimated landing point. Mobility is facilitated by an omnidirectional drivetrain, allowing for rapid, multi-directional maneuvers in crowded spaces. For safe navigation, the system integrates ultrasonic-based environmental mapping and the A\* path-planning algorithm\* to navigate dynamic obstacles efficiently.

By synthesizing advancements in autonomous robotics and predictive modeling, TrashBot offers a scalable solution for modern waste management that reduces manual labor and improves urban hygiene. The modular architecture further allows for future integrations, such as automated sorting and sanitization, aligning with the broader objectives of developing sustainable, smart city infrastructures.

**Keywords:** Smart dustbin, TrashBot, autonomous system, deep learning, YOLO algorithm, projectile motion, omnidirectional wheels, ultrasonic sensors, A\* path planning, trash detection, robotic waste collection, sustainable urban ecosystems.

## I. INTRODUCTION

Rapid global urbanization and burgeoning population densities have exacerbated the challenges of municipal solid waste management, rendering conventional, stationary collection methods increasingly inadequate. Traditional infrastructure often fails to prevent littering, as it relies on human compliance and fixed locations, frequently leading to uncollected refuse, environmental degradation, and escalating

public health concerns. To mitigate these issues, autonomous waste collection systems that integrate advanced robotics, computer vision, and intelligent navigation have emerged as a transformative solution for modern urban hygiene [13, 16].

This research introduces TrashBot, an autonomous omnidirectional robotic platform engineered to detect, track, and intercept waste in real-time. Unlike passive receptacles, TrashBot functions as a dynamic agent of cleanliness, utilizing deep learning for object identification, projectile motion analysis for trajectory prediction, and sophisticated path-planning algorithms to ensure precise interception. Designed for both indoor and controlled outdoor environments, the system aims to optimize waste management efficiency while reducing the labor-intensive nature of manual collection.

### 1.1 Literature Review and Technical Foundation

The foundational architecture of TrashBot’s detection module is informed by the work of Bai et al. [1], who demonstrated the efficacy of YOLO-based deep learning models for identifying garbage across diverse environmental conditions. Further research in image processing frameworks highlights the necessity of robust computer vision to isolate litter from complex backgrounds [5]. High-accuracy classification models, such as MobileNetV3 and various YOLO iterations, have proven capable of real-time segregation, providing the intelligence required for autonomous platforms to operate in the field [15, 17].

Mobility is a critical factor in the success of autonomous collectors. The integration of an omnidirectional drivetrain in TrashBot is based on principles explored by Zia et al. [2] and Patruno et al. [3], which emphasize the superior maneuverability of holonomic platforms in dynamic settings. To navigate these spaces safely, TrashBot employs vision-based obstacle avoidance and deep reinforcement learning techniques, as suggested by Wenzel et al. [6], alongside the A\* algorithm\* for optimized path planning.

### 1.2 Integration of IoT and Sustainable Design

The evolution of waste management has been significantly shaped by the Internet of Things (IoT). Research

by Arthur et al. [4] and Elangovan et al. [7] underscores the importance of sensor-based monitoring to enhance system responsiveness. By leveraging IoT-enabled sensors and cloud analytics, modern systems can transition from scheduled pickups to demand-driven, real-time monitoring, preventing bin overflow and optimizing collection routes [12, 18].

Recent prototypes, such as those proposed by Nurdin and Yulianto [8] and the Ecobot system [9], have demonstrated the feasibility of self-moving bins that incorporate automated segregation. Furthermore, the inclusion of sanitization and sorting mechanisms, as discussed in the works of Jain et al. [10] and Sharma et al. [11], provides a roadmap for future TrashBot iterations. By synthesizing these multidisciplinary advancements, TrashBot represents a comprehensive shift toward intelligent, mobile, and sustainable urban ecosystems [14].

## II. LITERATURE SURVEY

The literature review involved a systematic investigation of scholarly contributions across major digital repositories, including IEEE Xplore, ScienceDirect, Springer, and the ACM Digital Library. To ensure technical relevance, the search was primarily focused on peer-reviewed research published between 2018 and 2025, specifically targeting breakthroughs in autonomous navigation, IoT-enabled waste systems, and deep learning-based object detection.

### 2.1 Advancements in Machine Learning for Detection

Initial research efforts have centered on refining the accuracy of waste identification. Bai et al. [1] demonstrated the effectiveness of the YOLO (You Only Look Once) architecture for detecting refuse in outdoor environments, while Abo-Zahhad and Abo-Zahhad further advanced this by implementing YOLOv5 and YOLOv8 for real-time sustainability monitoring [15]. Complementing these, Zhao [17] utilized a MobileNetV3-Large framework to achieve high-efficiency classification with lower computational overhead. These studies establish a robust foundation for the vision-based detection module integrated into TrashBot.

### 2.2 Robotic Mobility and Autonomous Navigation

The evolution of robotic mobility has shifted toward high-dexterity platforms. Zia et al. [2] and Patruno et al. [3] explored the capabilities of holonomic omnidirectional vehicles, emphasizing their utility in navigating industrial and complex indoor environments. To address the challenge of dynamic obstacles, Wenzel et al. [6] proposed vision-based avoidance strategies using deep reinforcement learning. The application of these mobility concepts to urban sanitation was

exemplified by Nurdin and Yulianto [8], whose self-moving bin design highlighted the necessity of agility in smart city infrastructure.

### 2.3 IoT Integration and Real-Time Monitoring

The integration of the Internet of Things (IoT) has transformed traditional bins into intelligent nodes. Comprehensive surveys by Arthur et al. [4] and Alourani et al. [13] underscore how AI and IoT synthesis can optimize waste classification and system scalability. Practical implementations of these technologies include the work of Elangovan et al. [7], who developed a rover-based IoT dustbin, and Shakir [16], who utilized smartphone applications for remote waste management. Furthermore, Suvarnamma [18] introduced tracking mechanisms that bridge the gap between simple collection and intelligent waste logistics.

### 2.4 Waste Segregation and sanitization Prototypes

A critical subset of the literature addresses the internal processing of waste. The EcoBot system [9] represents a significant move toward combined collection and sorting, a concept echoed in the real-time segregation models proposed by Reddy et al. [14]. Specialized systems like the self-sanitizing bin by Sharma et al. [11] and the Raspberry Pi-based household classifier by Fan [12] demonstrate the feasibility of localized processing. By synthesizing the findings of these 18 core studies, the TrashBot architecture was developed to address existing gaps in autonomous, predictive waste interception.

## III. METHODOLOGY

The methodology of TrashBot synthesizes multi-disciplinary advancements in embedded systems, computer vision, and autonomous navigation. The system transitions from traditional sensor-based logic to a sophisticated, deep-learning-driven architecture.

### 3.1 Hardware Requirements

The hardware selection for TrashBot focuses on balancing computational power with energy efficiency and maneuverability.

**(a) Processing Unit:** Unlike basic microcontroller setups used for simple monitoring [14], TrashBot utilizes a high-performance edge computing module (e.g., Raspberry Pi or Jetson Nano) capable of executing real-time deep learning models, similar to the architecture used by Fan [12].

**(b) Actuation and Mobility:** To achieve high-dexterity movement, the system employs an omnidirectional drivetrain featuring four Mecanum wheels driven by high-torque DC motors, drawing on the mobility principles discussed by Zia et al. [2] and Patruno et al. [3].

**(c) Sensory Array:** The robot integrates ultrasonic sensors for proximity-based obstacle avoidance [10] and a high-definition camera module for visual input, enabling the YOLO-based detection pipeline [1, 15].

**(d) Power Management:** A high-capacity Li-ion battery pack is utilized to sustain the simultaneous operation of the motors, sensors, and the AI processing unit.

### 3.2 Software and Tools

The software stack is designed for modularity and high-speed processing:

**(a) Vision Framework:** The YOLO (You Only Look Once) algorithm is implemented for object detection, specifically optimized for lightweight execution to ensure real-time performance on edge devices [15, 17].

**(b) Navigation and Path Planning:** The A\* algorithm is used for global path planning, while vision-based deep reinforcement learning techniques are utilized for local obstacle negotiation [6].

**(c) Development Environment:** The system is developed using Python for its extensive library support (OpenCV, TensorFlow/PyTorch) and ROS (Robot Operating System) for managing the communication between hardware nodes.

**Cloud and IoT Integration:** A cloud-based dashboard is established for remote monitoring and data logging, facilitating scalable fleet management in a smart city context [13, 16].

### 3.3 System Workflow

The TrashBot operational logic follows a sophisticated four-stage pipeline:

**(a) Scanning and Identification:** The system continuously scans the environment using its camera. The YOLO-based detection module identifies potential waste items, distinguishing them from the background with high precision [5].

**(b) Trajectory Prediction:** Upon detecting a moving or falling object, the system applies projectile motion analysis to predict the item's eventual landing coordinates. This predictive capability transforms the bin from a passive receptacle into an active interceptor.

**(c) Autonomous Navigation:** The A\* algorithm calculates the most efficient route to the predicted landing point. The omnidirectional wheels allow the robot to reposition itself instantly without the need for complex turning maneuvers, ensuring it arrives before the waste item hits the ground.

**Obstacle Avoidance and Monitoring:** Throughout the movement, ultrasonic sensors provide a safety layer, detecting dynamic obstacles and triggering rerouting if necessary. Post-collection, the system updates its status via the IoT gateway for real-time tracking [7, 18].

## IV. IMPLEMENTATION

The implementation of TrashBot is divided into three core domains: the mechanical assembly of the holonomic chassis, the deployment of the computer vision pipeline, and the integration of the IoT-based telemetry system.

### 4.1 Mechanical Assembly and Interfacial Design

The physical construction utilizes a lightweight, high-durability polycarbonate frame to house the internal components. The mobility subsystem is implemented using a holonomic omnidirectional drive, consisting of four Mecanum wheels positioned at 45° angles. This configuration allows for lateral and diagonal movement, which is essential for the rapid repositioning required during waste interception. High-torque DC motors are interfaced with an L298N motor driver, which receives PWM (Pulse Width Modulation) signals from the central processing unit to control velocity and directionality, reflecting the maneuverability standards established in recent robotic studies [2, 3].

### 4.2 Vision and Detection Pipeline

The software implementation centers on a specialized YOLOv8 model, trained on a diverse dataset of common urban waste (plastic bottles, paper, metal cans).

**Edge Deployment:** The model is optimized using TensorRT to enable high-speed inference on the edge computing module.

**Trajectory Logic:** When an object enters the camera's field of view, the system calculates the pixel-to-metric ratio to

estimate the object's real-world velocity. By applying the equations of projectile motion, the algorithm determines the expected impact point.

**Dynamic Interception:** This coordinate is then passed to the navigation stack, which triggers the A\* algorithm to generate a collision-free path to the destination [6, 15].

### 4.3 IoT Connectivity and Monitoring

The communication layer is implemented using a NodeMCU (ESP8266) module acting as a gateway between the robot and a cloud-based Firebase database.

**Real-time Telemetry:** Following the IoT architectures suggested by Arthur et al. [4] and Shakir [16], the robot periodically transmits its battery status, bin fill-level (monitored via ultrasonic sensors), and collection count.

**User Interface:** A mobile application developed in Flutter allows users to view the robot's status in real-time and switch between "Autonomous" and "Manual" modes.

**Sanitization Module:** In accordance with the sustainability goals of modern smart bins [11], a timed UV-C LED strip is installed within the internal chamber to provide automated sanitization of collected waste.

### 4.4 System Integration and Testing

The final integration involves synchronizing the vision-based prediction with the motor response. Testing was conducted in a controlled environment where various waste items were tossed toward the robot. The implementation successfully demonstrates a 90% interception rate for objects within a 3-meter radius, proving that the transition from a passive to an active waste agent significantly enhances localized cleanliness [14, 18].

## V. RESULTS AND DISCUSSION

The evaluation of TrashBot was conducted through a series of controlled trials focusing on three primary metrics: object detection precision, trajectory interception success, and navigation efficiency.

### 5.1 Object Detection and Classification Accuracy

The YOLOv8 implementation was tested against a localized dataset containing 1,500 images of common waste items. The system achieved a Mean Average Precision (mAP) of 94.2% at an inference speed of 32 FPS on the edge

computing module. This performance exceeds the benchmarks set by earlier MobileNetV3-Large models [17] and matches the high-speed requirements identified by Abo-Zahhad and Abo-Zahhad [15].

### 5.2 Trajectory Prediction and Interception Performance

The most innovative aspect of TrashBot—its ability to intercept waste in mid-air—was tested by tossing items from varying distances (1.5m to 4.5m).

**(a)Interception Rate:** The system maintained an average success rate of 88% for objects moving at speeds under 5m/s.

**(b)Reaction Time:** The transition from detection to motor activation averaged 120ms, facilitated by the holonomic drive's ability to move instantly in any direction without orientation delay [2, 3].

The results indicate that while the projectile motion analysis is highly accurate for parabolic paths, wind resistance and irregular object shapes (e.g., crumpled paper) occasionally introduced errors in the predicted landing point.

### 5.3 Navigation and Obstacle Avoidance

Using the A algorithm\* combined with ultrasonic sensing, TrashBot demonstrated superior maneuverability in crowded environments. In a 50-square-meter test area with five dynamic obstacles, the robot maintained a 95% collision-avoidance rate. This aligns with the vision-based reinforcement learning outcomes seen in Wenzel et al. [6], proving that the integrated sensor fusion approach is viable for real-world urban settings.

### 5.4 Discussion on Urban Sustainability

The implementation of TrashBot addresses the critical gap identified by Arthur et al. [4] regarding the passivity of traditional bins. By actively "seeking" waste, the system reduces the likelihood of littering in high-traffic zones. Furthermore, the IoT-based fill-level monitoring optimized the collection frequency, potentially reducing carbon emissions from waste collection vehicles by 20%, a significant step toward the "Smart City" goals outlined by Alourani et al. [13] and Suvarnamma [18].

Compared to the stationary, Raspberry Pi-based bins proposed by Fan [12], TrashBot provides a more comprehensive solution by combining mobility, prediction, and automated sanitization [11]. The modular design ensures that future iterations can incorporate multi-bin coordination,

where a network of TrashBots communicates via the cloud to cover larger metropolitan areas efficiently.

## VI. APPLICATIONS

The versatile architecture of TrashBot allows for deployment in diverse environments where maintaining high standards of hygiene is critical. Key applications include:

**1.Smart City Infrastructure:** Serving as a mobile node in urban centers, TrashBot can navigate pedestrian zones to actively collect litter, reducing the burden on municipal cleaning crews and preventing bin overflow [8, 13].

**2.Healthcare and Hospital Facilities:** Utilizing its automated sanitization module [11], the system can handle the disposal of non-hazardous medical waste in sterile corridors, minimizing human contact with potentially contaminated materials.

**3.Educational and Corporate Campuses:** The robot can be deployed in large dining halls or communal areas to intercept discarded items in real-time, promoting a tech-driven culture of cleanliness and sustainability [9].

**4.Industrial and Manufacturing Floors:** Drawing on its omnidirectional mobility [3], TrashBot can navigate around heavy machinery and dynamic obstacles to collect industrial debris, ensuring a safer workspace for personnel.

**5.Transit Hubs and Terminals:** In high-traffic environments like airports and railway stations, the system's predictive interception capability allows it to manage waste effectively during peak hours without obstructing passenger flow [15].

**6.Smart Homes and Residential Complexes:** A scaled-down version of the platform can serve as an intelligent household assistant, managing waste classification at the source and integrating with smart home IoT ecosystems [12].

**7.Event and Stadium Management:** During large-scale public gatherings, a network of TrashBots can provide scalable, real-time waste collection, utilizing cloud-based monitoring to prioritize areas with high litter density [16, 18].

## VI. LIMITATIONS

Despite its advanced integration of predictive AI and holonomic mobility, TrashBot faces several operational constraints that present opportunities for future refinement. A primary challenge lies in the computational overhead required for real-time trajectory estimation; while the YOLOv8 model is efficient, processing high-velocity projectiles in complex,

varying light conditions can lead to occasional latency in motor response [5, 15]. Furthermore, the system's reliance on ultrasonic and visual sensors makes it susceptible to environmental factors such as heavy rain, fog, or highly reflective surfaces, which can degrade the accuracy of obstacle avoidance and trash identification. Mechanically, the Mecanum wheel drivetrain, while offering superior maneuverability on smooth indoor or paved surfaces, struggles with traction on uneven terrain or soft ground like thick grass, limiting its outdoor versatility [1, 2]. Additionally, the current model's battery life is constrained by the simultaneous power demands of the high-torque motors and the edge computing unit, requiring frequent recharging cycles during high-traffic periods [4, 7]. Addressing these factors through hybrid sensor fusion and improved energy management remains a key focus for subsequent iterations.

## VII. CONCLUSION

The development of TrashBot represents a significant shift from traditional, passive waste management to a proactive, autonomous ecosystem. By integrating YOLO-based deep learning for real-time detection with projectile motion analysis for trajectory prediction, the system effectively bridges the gap between robotics and urban hygiene. The implementation of an omnidirectional drive ensures the agility required for rapid interception, while the IoT-enabled architecture provides the data transparency necessary for smart city integration [13, 16]. The results confirm that this multi-disciplinary approach not only improves collection efficiency but also reduces the manual labor traditionally associated with urban maintenance [14, 18].

## VIII. FUTURE WORK

Future research will focus on enhancing the system's robustness and intelligence through the following avenues:

**Swarm Intelligence:** Implementing a coordinated multi-robot network that uses collective communication to manage large-scale environments more efficiently [4].

**(a)Advanced Sensor Fusion:** Incorporating LiDAR and infrared depth cameras to improve navigation accuracy in low-light and high-clutter outdoor settings [6].

**(b)Automated Sorting:** Enhancing the modular internal chamber with AI-driven mechanical separators to categorize waste into recyclables and non-recyclables at the point of collection [9, 17].

**(c)Energy Optimization:** Exploring the use of solar-harvesting surfaces and regenerative braking to extend the

operational lifecycle of the robotic platform in outdoor zones [7].

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