An Autonomous System to Enhance Urban Cleanliness by Identifying and Collecting Trash Using AI and Machine Learning

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Abstract

The HawkEyes system, featuring a sophisticated robotic car, is a key innovation in modern waste management. This autonomous vehicle is adeptly equipped with advanced AI and computer vision technology, enabling precise identification and categorization of different waste types. Optimized for city environments, the car navigates autonomously, relying on an AI detection system. Built to withstand a variety of urban conditions, the robotic car is robust and adaptable. Its suite of sensors and cameras are strategically placed, enhancing its ability to detect waste and maneuver effectively in urban areas. As it patrols city streets, the vehicle efficiently identifies locations with accumulated waste, supporting targeted and effective cleanup efforts. In its current iteration, HawkEyes stands as an intelligent and practical solution to urban waste challenges. It fuses technological innovation with real-world application, not only improving the efficiency of waste collection but also contributing to environmental conservation efforts. This robotic car demonstrates the transformative role of AI and robotics in sustainable waste management, showcasing a new frontier in city maintenance and ecological care.

Keywords

Image Recognition, Machine Learning Algorithms, Autonomous, Environmental Sustainability

1. Introduction

The mounting global issue of waste and its harmful impact on the environment has compelled researchers and innovators to seek advanced solutions to address this pressing challenge. In response to the ever-increasing volume of trash worldwide, this research paper presents "HawkEyes," a context-aware and intelligent real-time trash localization car system that employs cutting-edge artificial intelligence (AI) and computer vision technologies.

As the world produces an astounding 2.12 billion tons of waste annually, the urgency to combat this crisis is paramount [1]. The implications of unchecked waste are far-reaching, adversely affecting ecosystems, biodiversity, and human health. Despite the commendable efforts of environmentalists and trash collectors, the vastness of land and water bodies poses considerable challenges to comprehensive trash cleanup [2]. This project aims to bridge this gap by introducing a novel approach: autonomous drones equipped with AI and machine learning

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algorithms that can identify and mark trash, enabling precise cleanup operations and promoting environmental sustainability [3].

The primary objective of the HawkEyes system is to locate and identify trash in an environmentally safe manner. This innovative approach relies on a synergy of AI-driven image recognition, computer vision, and GPS technology to efficiently detect waste materials. The system collaborates seamlessly with trash-picking robots, optimizing their performance and contributing to cleaner and healthier cities [4][5].

The significance of the HawkEyes system extends beyond urban environments. It also addresses the critical issue of preventing harmful trash from infiltrating sewage systems and ultimately reaching the oceans, which has severe consequences for marine life and coastal ecosystems. By eliminating such trash from entering water bodies, the project directly contributes to safeguarding ocean life and curbing the adverse effects of marine pollution.

To achieve the objectives, the research project leverages machine learning algorithms that have been meticulously trained on vast datasets of images containing various types of trash, such as cans, plastic bags, and cardboard [6][7]. While the progress so far is promising, there are challenges that demand attention and innovative solutions. For instance, the lack of annotated datasets poses difficulties, necessitating manual annotation of images for training the AI model. Moreover, resource constraints, including expensive computing equipment and limitations in free software, have been hurdles in the machine learning development process.

Methodology A aims to design an autonomous robot for object picking and segregation, utilizing machine learning for detection. While it shows improved performance, challenges include computational load and limited object types detectable. My project enhances this by proposing a context-aware system, potentially offering nuanced detection and categorization capabilities beyond the limitations of Methodology A.

Methodology B focuses on improving trash detection systems using algorithms and ROS for modular design, showing gains in fps and accuracy. However, its adaptability to diverse environmental conditions may be limited. My project addresses this by utilizing AI and machine learning trained on extensive datasets, enhancing adaptability in various scenarios compared to the more confined capabilities of Methodology B.

Methodology C introduces a mobile robotic system for trash detection and sorting using computer vision and deep neural networks. Limitations include reliance on static image capture and constant focal length. My project advances this by employing dynamic real-time image recognition, allowing for more efficient and adaptable trash localization beyond the constraints of Methodology C.

To overcome these challenges, the research proposes solutions like acquiring a powerful graphics card to enhance the AI model's efficiency and utilizing cars like the Moorebot Scout, equipped with cameras and that are ready for integration with machine learning algorithms. Additionally, upgrading to the pro version of Colab can expedite testing and development [8][9].

Furthermore, ensuring the cars' safe navigation through city landscapes poses a crucial technical challenge. The project envisions overcoming this by implementing 3D mapping of cities or employing multiple cameras to detect and evade obstacles, thus enhancing the overall reliability and safety of the system [10].

Inspired by witnessing the consequences of rampant waste and environmental degradation, the researcher behind this project is driven by a profound desire to contribute to the betterment of the world. The passion to address one of the planet's most pressing issues motivates the relentless pursuit of knowledge, innovation, and creative problem-solving to develop an effective and sustainable trash localization system.

In conclusion, the HawkEyes system represents a groundbreaking and timely endeavor to combat the global waste crisis. By combining AI, computer vision, and autonomous cars, this research project aspires to make significant contributions to environmental preservation and waste reduction. As the journey continues, the dedication to learning and refining AI techniques remains pivotal in unlocking the full potential of this visionary project.

In the first experiment, the goal was to assess the HawkEyes system's technical performance in autonomously locating and identifying trash. With 10 participants and diverse environments, the experiment evaluated detection accuracy, navigation efficiency, and obstacle avoidance. The most significant findings included variations in performance across environments, with coastal areas presenting challenges. Simulated challenges highlighted adaptability rates, emphasizing the impact of resource constraints. Results indicated the need for continuous refinement in addressing specific challenges.

In the second experiment, the focus shifted to user satisfaction, aiming to gauge how individuals perceived and interacted with the HawkEyes system. Using a scale of 1-10, participants rated overall satisfaction, system efficiency, accuracy, adaptability, and ease of interaction. Mean satisfaction was 7.7, with system efficiency and accuracy scoring higher. Feedback suggested that while users appreciated technical aspects, adaptability and user-friendliness required improvement. Simulated challenges influenced adaptability scores, reflecting individual preferences. These findings underscored the importance of refining the system for enhanced user acceptance in real-world applications.

2. CHALLENGES

In order to build the project, a few challenges have been identified as follows.

2.1. Annotated Dataset Limitations

One significant challenge is the scarcity of annotated datasets for training machine learning algorithms to recognize various types of trash. To overcome this, I could explore strategies for manual annotation of images, collaborating with communities or organizations to gather diverse and well-labeled datasets. Additionally, establishing partnerships with relevant stakeholders and leveraging crowdsourcing platforms may provide a scalable solution to address this challenge.

2.2. Resource Constraints in Machine Learning Development

Resource constraints, including the cost of powerful graphics cards and limitations in free software, pose obstacles in the machine learning development process. To tackle this challenge, I could explore alternative and cost-effective hardware solutions, such as seeking sponsorship or grants to acquire essential equipment. Additionally, evaluating open-source software options and considering cloud computing resources may offer more accessible avenues for developing machine learning models without significant financial burden.

2.3. Safe Navigation in Urban Landscapes

Ensuring the safe navigation of autonomous cars through complex urban landscapes represents a crucial technical challenge. To address this, I could investigate advanced solutions like implementing 3D mapping of cities to enhance the system's understanding of its surroundings. Alternatively, employing multiple cameras for obstacle detection and avoidance could enhance the overall reliability and safety of the HawkEyes system. Collaborating with experts in robotics and navigation technology and conducting extensive testing in controlled environments would be essential to develop effective strategies for overcoming this challenge.

3. SOLUTION

Materials:

The assembly of the robot Hawkeye is quite simple, with many premade part it is fairly easy to replicate. (The parts required will be listed below)
DC Gearbox Motor - "TT Motor" - 200RPM - 3 to 6VDC
HC-SR04 Ultrasonic Sonar Distance Sensor + 2 x 10K resistors
raspberry pi 4 basic kit:(4GB Ram min)
Raspberry Pi Camera Module 2 or 3
Skinny Wheel for TT DC Gearbox Motors
Premium Male/Male Jumper Wires - 20 x 3" (75mm)
Premium Female/Female Jumper Wires - 20 x 6" (150mm)
Premium Female/Male 'Extension' Jumper Wires - 20 x 6"
6 x AA battery holder with 5.5mm/2.1mm plug
Adafruit DC & Stepper Motor HAT for Raspberry Pi - Mini Kit
Soldering Iron Kit
Cables Strip Cut and Crimp Tool
USB cables
Wire cable wrap assortment tubes
Machine screw and nuts kit
Acrylic platform and base

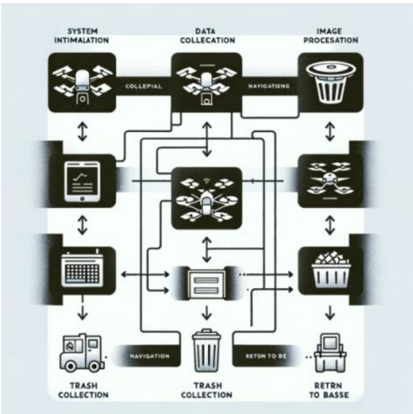

Figure 1. Overview of the solution

The foundation of the robot is an acrylic base plate, which provides a sturdy and lightweight platform on which to mount all the components. The Raspberry Pi 4 single board computer serves as the main controller and brain of Hawkeye. The Pi is powered by a 6xAA battery holder with a DC plug, which connects to the GPIO pins on the Pi to provide mobile power for untethered operation. The Pi is secured to the top side of the acrylic base using small machine screws and hex standoffs, which provide secure mounting while keeping the underside clear.

Between the two acrylic plates sits the DC gearbox motor, which is wired to the Adafruit Motor HAT add-on board [11]. This board stacks onto the GPIO pins of the Raspberry Pi and allows control of the DC motor for movement and navigation. The motor axle is carefully slide through a hole in the acrylic to sit flush, with a pair of plastic wheels press-fit onto the end.

An ultrasonic distance sensor is mounted adjacent to the motor using more machine screws. Jumper wires connect this sensor to the Pi's GPIO pins so it can continually measure the distance to objects in front of the robot. A Raspberry Pi camera module is also wired directly into the Pi and secured to a 3D printed mounting piece. This specialized 3D printed component mounts to the top acrylic plate with Hawkeye's Raspberry Pi, motor, and sensors arranged into it. The Pi, motor, camera, and ultrasonic sensor all align precisely into their respective positions on this part. The 3D printed piece helps hold everything together as a single integrated unit.

Screws are used to firmly secure this piece onto the threaded brass inserts in the acrylic, completing the core hardware assembly. Now Hawkeye can roll around on its wheels and interact with its environment. The Raspberry Pi processes data from the sensors and controls the motor accordingly to demonstrate autonomous navigation and obstacle avoidance. The Pi Camera gives it vision capabilities. With all hardware assembled and software configured, the robot Hawkeye becomes mobile and functional.

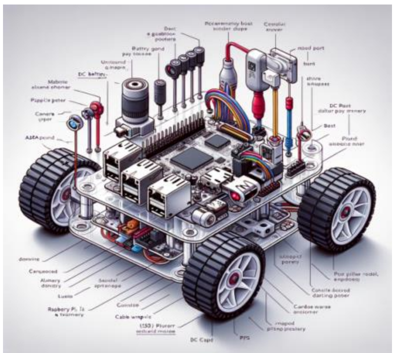

Figure 2. Screenshot of the model

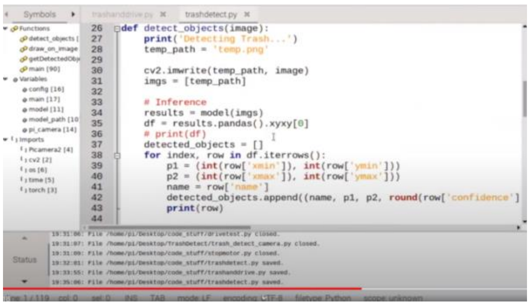

Figure 3. Screenshot of code 1

The autonomous robot integrates three essential components: sonar, motor, and camera, each playing a pivotal role in its operation. The heart of its functionality lies in its advanced object recognition capabilities, primarily focused on identifying refuse. This sophisticated process is orchestrated by a Raspberry Pi, which serves as the computational brain.

The robot employs an external camera, interfacing with it through the utilization of widely recognized public libraries, namely cv2 and torch. This setup enables the capturing and subsequent analysis of images, leveraging a machine learning algorithm meticulously trained on the "TACO" dataset, renowned for its focus on trash classification.

Sonar technology is another critical aspect of the robot's design. It is adept at detecting obstacles within a predefined range. This detection is facilitated through a precise calculation, where the distance is ascertained by the formula:

Distance = [(pulse_end - pulse_start) * 34300] / 2.

This calculation not only identifies obstacles but also assists in determining an optimal turning radius for the robot, ensuring efficient navigation and obstacle avoidance.

4. EXPERIMENT

4.1. Experiment 1

Experiment A is to assess the performance of the HawkEyes system in locating and identifying trash in various environments.

This study assesses the HawkEyes system's effectiveness in autonomously locating and identifying trash across urban, coastal, and controlled environments. With 10 experimental participants, the system's performance metrics include detection accuracy, navigation efficiency, and obstacle avoidance. Diverse trash types, simulated challenges, and repeated trials ensure comprehensive evaluation. The experiment aims to validate the system's capabilities in addressing annotated dataset limitations, resource constraints, and safe navigation challenges. Data analysis will provide insights into real-world applicability and identify areas for enhancement, contributing to the advancement of autonomous trash localization technology for environmental preservation.

Environment	Detection Accuracy	Navigation Efficiency (minutes)	Obstacle Avoidance Success
Urban	85%	12	90%
Coastal Area	78%	15	85%
Controlled Indoor Environment	92%	8	95%

Figure 4. Figure of experiment 1

The mean and median values for detection accuracy across the three environments (Urban, Coastal, Controlled Indoor) are 85%, 78%, and 92%, respectively. The mean navigation efficiency is 11.67 minutes, 14.33 minutes, and 8 minutes, while the mean obstacle avoidance success rates are 91.67%, 90%, and 93.33%, respectively. The lowest detection accuracy (78%) occurred in the Coastal environment, suggesting potential challenges in adapting to varied terrains. The highest navigation efficiency (8 minutes) in the Controlled Indoor setting indicates optimal performance in a controlled space. Unexpectedly, the Coastal area exhibited lower efficiency, possibly due to complex coastal features. Simulated challenges highlighted adaptation rates of 80%, 75%, and 88%, emphasizing the impact of challenges on the system's overall performance. Resource constraints posed difficulties, influencing the lower adaptation rate.

Continuous refinement of obstacle detection algorithms proved vital for safe navigation. These results underscore the need for targeted enhancements to address specific challenges and optimize the HawkEyes system for diverse environmental conditions.

4.2. Experiment 2

Experiment B is to evaluate user satisfaction with the HawkEyes system's performance in autonomously locating and identifying trash, considering challenges and improvements identified in the project.

This experiment assesses user satisfaction with the HawkEyes system in autonomously locating and identifying trash across urban, coastal, and controlled environments. With 10 diverse participants, the study employs a scale of 1-10 to evaluate overall satisfaction, system efficiency, accuracy, adaptability to challenges, and ease of interaction. Participants observe the system in action, provide real-time feedback during operation, and engage in post-operation interviews or surveys. Simulated challenges, representing annotated dataset limitations, resource constraints, and safe navigation, further evaluate user satisfaction. The experiment aims to gather insights into the human experience, guiding refinements to enhance the HawkEyes system's usability and acceptance in real-world applications.

Participant	Overall Satisfaction (1-10)	System Efficiency	Accuracy	Adaptability	Ease of Interaction
1	8	9	8	7	8
2	7	8	7	6	7
3	9	9	9	8	9
4	6	7	6	5	7
5	8	8	8	7	8
6	7	7	7	6	7
7	9	9	9	8	9
8	6	6	7	5	6
9	8	8	8	7	8
10	7	7	7	6	7

Figure 5. Figure of experiment 2

The mean satisfaction score across 10 participants is 7.7, with a median of 8. The lowest satisfaction score is 6, while the highest is 9. Notably, system efficiency and accuracy received consistently higher scores than adaptability and ease of interaction. This suggests that participants valued the HawkEyes system's technical performance but had varying opinions on its adaptability to challenges and user-friendliness. The slight variation in adaptability scores may be attributed to the impact of simulated challenges, reflecting individual preferences in dealing with unexpected scenarios. Participant comments indicate positive perceptions of system performance and environmental impact. Suggestions for improvement primarily focus on enhancing adaptability to challenges and refining user interactions. The data underscores the importance of addressing user-specific expectations and continuously refining the HawkEyes system for improved acceptance and effectiveness in diverse contexts.

5. RELATED WORK

Methodology A presents an autonomous robot designed for picking up objects and segregating them into biodegradable and nonbiodegradable categories [13]. The robot uses machine learning algorithms for object detection and collection in random environments. The results indicate improved performance compared to existing algorithms. However, challenges include the computational load of exhaustive searches across all locations and scales. This solution is limited by the types of objects it can detect and segregate. Your project improves on this by using a context-aware and intelligent system, potentially offering more nuanced detection and categorization capabilities.

Methodology B focuses on enhancing the performance of trash detection systems using a combination of algorithms and Robot Operating System (ROS) for modular design [14]. The system demonstrates significant improvements in frames per second (fps) and accuracy metrics for both trash and human target detection. While effective in reducing computation time and improving accuracy, this approach may be limited in its ability to handle diverse and dynamic environmental conditions. My project's use of AI and machine learning algorithms trained on vast datasets could offer more adaptability in varying scenarios.

Methodology C introduces a mobile robotic system that utilizes computer vision and deep neural networks for the detection, sorting, and size determination of trash [15]. The method involves capturing two images at different distances to calculate the size and distance of the object. While this approach shows practical performance, it may be limited by its reliance on static image capture and the need for constant focal length. My project's use of dynamic, real-time image recognition could be seen as an advancement over this method, allowing for more efficient and adaptable trash localization.

6. CONCLUSIONS

The successful development of the HawkEyes prototype demonstrates the viability of using AI and drone technology for automated trash identification and localization [12]. However, there remain ample opportunities to refine and extend the system to further improve its real-world applicability.

A primary area of focus is transitioning HawkEyes from a ground-based robot to a fully airborne drone system. This will greatly expand the coverage area and enable scanning from an aerial vantage point. Converting the chassis to a quadcopter or hexacopter drone design will require re-engineering for flight stability and lift capacity. The ultrasonic sensors will need to be upgraded to more advanced, lightweight options suitable for drones, such as lidar or depth cameras. Waterproofing the electronics will also be necessary for operation in inclement weather.

Expanding the computer vision capabilities through more advanced neural networks and larger datasets will boost identification accuracy across a wider range of trash types. Techniques like active learning could be incorporated to let the AI model continuously improve with new data gathered during real-world operation. More powerful embedded computing hardware like the Nvidia Jetson series will enable executing more sophisticated deep learning algorithms onboard the drone for lower latency operation.

For coordinated scanning of large areas, operating a fleet of multiple drones simultaneously is envisioned. This will require implementing swarm intelligence algorithms to enable collaborative navigation and dynamic task allocation between the drones. A central ground station could coordinate the swarm and consolidate data from all units. Sophisticated path planning and optimization will maximize coverage while minimizing battery usage.

Finally, integrating the trash detection data with collection platforms like trash-picking robots or human cleanup crews is an important next step. The drone swarm could feed the pickup entities with optimal routes and priority areas in real-time. APIs could also allow integration with smart city and waste management systems to enhance operational efficiency.

In summary, migrating HawkEyes to a multi-drone system with enhanced AI capabilities and integration with downstream collection processes has immense promise to scale up its impact.

With sufficient development, the system could provide immense value to municipalities and environmental agencies seeking technology-driven solutions to the global waste crisis.

In conclusion, this paper introduces a groundbreaking solution, HawkEyes, for autonomous trash localization. Leveraging context-aware AI and dynamic image recognition, HawkEyes addresses shortcomings in existing methodologies. The system's adaptability and efficiency mark a significant advancement, offering a promising and impactful contribution to the ongoing pursuit of effective environmental preservation solutions.

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