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Development of a CNN-Based Robotic System for Efficient Household E-Waste Collection and Management in Urban Areas

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Abstract

The rapid technological growth of recent years has made electronic gadgets indispensable in everyday life, but it has also resulted in a large increase in electronic garbage (E-waste). E-waste levels have risen due to the constant development of new products and consumers' need for the most up-to-date technology, with India producing an alarming 3.2 million tons by 2023. Major cities such as Mumbai, Delhi, and Bangalore contribute significantly to this problem. As e-waste continues to increase, proper management and recycling solutions are required to reduce environmental damage and health hazards. While industrial and commercial E-waste management have been highlighted, there is still a severe gap in handling domestic E-waste. This research proposes a novel solution: a mobile robotic system for identifying, collecting, and segregating household E-waste. This robot, which is compatible with municipal garbage trucks, has a robotic arm and a storage mechanism that allows it to collect E-waste in residential areas automatically. E-waste is reliably detected and classified by the system using convolutional neural network (CNN) technology. By reducing human involvement in hazardous material handling, the technology improves safety while saving 20% on collection and disposal costs over five years. This is one of the first applications of such technology in India for domestic E-waste collection. By expediting the collecting process, this solution encourages sustainability through a circular economy, allowing components to be reused and recycled while conserving resources and minimizing waste. This study demonstrates the system's ability to fill a major need in urban E-waste management.
Keywords— F Solid waste segregation, Wastes from electronic and electrical equipment, Deep Learning, Internet of Things (IoT), Transfer learning, Robotics, Convolutional Neural Networks (CNN), Used electronic components.

Introduction

The rapid advancement of technology in recent years has resulted in a significant increase in the number of electronic gadgets manufactured and used. While these advancements have improved how we live and work, they have also created a major issue: managing electronic garbage, or E-waste. E-waste is defined as old or undesirable electronic devices that people discard, such as smartphones, computers, televisions, and household appliances. Every year, the globe generates millions of tons of E-waste, which is only likely to increase. Experts estimate that by 2030, global E-waste will have reached over 75 million tons. Unfortunately, only a small portion of this garbage, approximately 17.4%, is adequately recycled. The rest frequently winds up in landfills or is handled in hazardous ways, endangering the environment and people's health. Electronics contain hazardous elements such as lead, mercury, and cadmium, which can contaminate the ground and water if not properly disposed of. This can have major health consequences, such as lung and nervous system difficulties.

E-waste management presents unique issues for countries such as India. In 2023, India generated approximately 3.2 million tons of E-waste. India is the world's third-largest generator of E-waste, after China and the US. Big cities like Mumbai, Delhi, and Bangalore generate a significant amount of this trash. Consumer electronics and domestic items account for over 56% of the total. Although many businesses have begun to collaborate with specialized recyclers to manage their E-waste, residential E-waste collection and recycling remain limited. One important issue is that many people do not understand how to properly dispose of their old devices. As a result, e-waste is combined with ordinary trash,

[7] which makes recycling more difficult and increases pollution. Workers in informal recycling are frequently exposed to hazardous compounds as they sift through trash in search of valuable resources.

We require innovative technology solutions to address these issues. Robotics, machine learning, and artificial intelligence (AI) can all be used to assist manage e-waste more quickly and safely. Risky manual work is no longer necessary because automated methods are more accurate than humans at sorting and identifying e-waste. Recycling can be made more effective by using AI-based technologies to recognize and separate various forms of e-waste. This article examines the identification and collection of e-waste from homes using a mobile robot system attached to municipal garbage trucks. With the aid of artificial intelligence, this robot can lessen the workload for human workers, increase safety, and guarantee that e-waste is appropriately sent to recycling facilities. By reducing trash and promoting a circular economy, this strategy can assist cities in managing garbage more effectively.

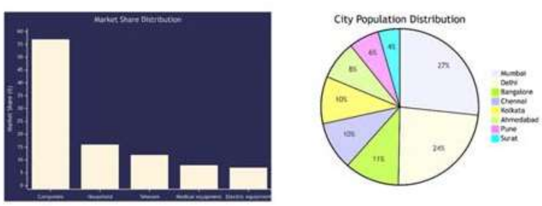

Fig. 1. A Contribution of E-waste in terms of the type of electronic (left) and city (right) in India.

II. Research Objective.

In order to separate e-waste from other collected rubbish efficiently, the goal of this project is to design, develop, and implement a deep learning model for robotics and e-waste classification using Keras and TensorFlow.

Designing, creating, and testing a novel mobile robotic system especially suited for the detection, gathering, and sorting of household electronic waste (E-waste) is the main goal of this study. This method attempts to tackle the crucial problem of man-aging household-level e-waste, which has received less attention than commercial and industrial e-waste.

Advanced convolutional neural network (CNN) technology will be incorporated into the proposed robotic system to precisely identify and categorize a variety of e-waste, including typical electrical devices like cell phones, chargers, and small appliances. By reducing the need for human intervention, this automated system ensures safer handling of potentially dangerous items while increasing the efficacy and economy of e-waste collection [8].

In order to facilitate seamless navigation in residential areas, the research also aims to integrate the robotic system with the current municipal rubbish collection infra-structure, such as garbage trucks. Over a five-year period, the system is anticipated to save overall collection and disposal costs by 20% by automating the collection process and improving trash segregation.

The study will examine the system's contribution to wider environmental and socio-economic objectives, such as the advancement of a circular economy, in addition to its operational advantages. This reduces the environmental impact of urban waste management systems by minimizing waste output and conserving natural resources through component reuse and recycling.

In the Indian setting, where e-waste levels have hit critical thresholds in major cities like Bangalore, Delhi, and Mumbai, the research also attempts to evaluate the technology's

IV. Materials And Methods

A. The robotic component of the system

The four-wheeled, omnidirectional mobile robot has a collection platform and an arm. Inspired by the youBot from Keller und Knappich Augsburg (KUKA) (Bischoff et al., 2011) [4], the arm has five degrees of movement and can carry up to 20 kg of cargo. There is also a platform for keeping the rubbish that has been gathered. In order to provide asymmetric friction for stepping on uneven terrain, the wheels are indestructible and consist of successive rubberized rollers that are fastened to the rim. To capture continuous photographs of the robot's environment, a webcam with Bluetooth is mounted on top of the support. For identification, the acquired imagery is routed to a deep learning recognition system. The arm grabs the item and places it in the robot's collection platform if it is determined to be electronic garbage. The robot operating system (ROS) and embedded personal computer (PC) tiny Information Technology extended (ITX) are compatible with the application programming interfaces (APIs). With the ability to convert to manual remote control, this robot can operate in a semi-autonomous manner. The robot deposits the gathered materials into a special section of the garbage truck designated for E-waste whenever the specified wastes are on the platform or the payload capacity is achieved. A three-dimensional model of the suggested robot is shown in Fig 2.

III. Related Work

TABLE I. Related Work in AI in E-Waste Management.

Name of Related Work	*Objective*	*Reference*
Automatic Waste Segregator Based on IoT & ML Using Keras model	Develop an IoT-based waste segregation system using machine learning for real-time monitoring and classification of waste materials.	IJISAE [1]
Automated waste-sorting and recycling classification using ANN	Propose a digital model for automatic waste sorting and classification based on artificial neural networks, achieving high accuracy in identifying various waste types.	PMC [2]
Smart Waste Management and Classification Systems Using Cutting Edge Approach	Combine IoT and deep learning to create a smart waste classification model for monitoring and managing waste efficiently, classifying items into biodegradable and non-biodegradable categories.	Sustainability [3]
Conventional Machine Learning Approach for Waste Classification	Introduce a double fusion approach combining multiple deep learning models to enhance waste classification accuracy through feature extraction and score-level fusion methods.	ACM [4]
Waste Management System Using IoT-Based Machine Learning in University	Propose a method for efficient waste management using IoT and machine learning to predict waste levels and optimize collection routes in urban settings.	Wiley [5]
Intelligent waste management system using deep learning with IoT	Implement a deep learning-based system for waste classification using images, aiming to categorize wastes effectively through an intelligent architecture that integrates IoT technology.	Science Direct [6]
Deep Learning Techniques for Waste Classification	Explore various neural network models (including DenseNet121) for classifying recyclable materials using the Trashnet dataset, enhancing dataset size through data augmentation.	Aral et al., 2018 [1]
Image-Based Waste Sorting with IoT Integration	Investigate sensor-equipped bins that utilize image processing for efficient separation of biodegradable from non-biodegradable waste, improving overall waste management efficiency.	Pamintuan et al., 2019 [17]
Microcontroller-Based Smart Bins	Develop microcontroller-based CNN smart bins that provide real-time updates on waste levels and facilitate automated segregation in commercial and residential areas through smartphone connectivity.	White et al., 2020 [24]
Hybrid Deep Learning Methods for Waste Sorting	Utilize hybrid deep learning methods with high-resolution cameras to sort waste into recyclable and non-recyclable categories, enhancing automation in the sorting process.	Chu et al., 2018 [9]
E-Waste Classification Using Thermal Imaging	Classify E-waste materials based on thermal imaging techniques, generating feature vectors for accurate sorting of metallic and non-metallic components, thus improving recycling efficiency.	Gundupalli et al., 2018 [11]
Robotics in Waste Management	Optimize robotic systems for macro-sorting of municipal waste, integrating deep neural networks into autonomous robots to reduce manual labor and improve efficiency in garbage collection processes.	Bai et al., 2018 [3]

B. Image Capture and Data Processing

- Camera Integration: The robot has high-definition Internet of Things cameras that can take close-up pictures of the objects around it. The deep learning model uses the photos as input data.
- Image Feeding to the Model: The trained Deep Learning model receives every image that the robot's camera takes and analyzes it. Using the visual characteristics it has acquired during training, the model analyzes these photos in real time and recognizes items.

Fig. 2. Overview model of the proposed robot.

C.Deep learning-based integrated recognition system

Since deep learning enables the robot to precisely recognize and classify electronic garbage, it is crucial to the proposed e-waste collection system. Convolutional neural networks (CNNs), which are very good at processing visual data, are used in the system. A sizable dataset of e-waste photos, which includes a variety of electronic devices like computers, smartphones, chargers, and other home gadgets, is used to train these networks. This training enables the CNN to recognize patterns, forms, and textures specific to e-waste, allowing it to differentiate between electronic waste and non-electronic things.

The robot in the project has an Internet of Things-enabled camera that takes pictures of its environment in real time. These images are processed using a deep learning model, which categorizes the objects based on the learnt characteristics. The system can assess the image's categorization confidence and determine whether a taken image belongs to a predefined category of e-waste. If the confidence level surpasses a preset threshold, the robot initiates the collection operation with its robotic arm. Transfer learning reduces the requirement for large datasets and significant processing power while increasing the efficiency of the deep learning model by beginning with pre-trained networks such as VGG16 or ResNet50. Additionally,
[7] data augmentation techniques such as rotation, flipping, and scaling improve the model's generalizability and ensure consistent performance in a range of dynamic environments. By using deep learning, the system can identify e-waste with high accuracy, limit human error, and lower the dangers involved in handling hazardous items by hand. This method improves the overall effectiveness and sustainability of waste management by automating the segregation process and guaranteeing that only electronic waste is gathered and sent for recycling.

V. Dataset

A collection of photos depicting various sorts of electronic trash objects is called the E-trash Dataset. The dataset is intended for use in computer vision applications such as object identification and image classification. This dataset attempts to support the creation of technologically advanced solutions for the management and recycling of electronic garbage, or "e-waste," which is an increasing global concern. Three hundred photos of the most well-known consumer electronics, ranging in condition from fully functional to seriously damaged, will make up the dataset. Ten distinct labels—PCB (Printed Circuit Board), Player, Battery, Microwave, Mobile, Mouse, Printer, Television, and Washing Machine Keyboard—are used to organize the complete dataset. Each label includes thirty photos of the relevant equipment. This dataset's photos were gathered from a variety of sources, including private sources, open datasets, and image repositories. An attempt was made to guarantee that the collection of electronic trash items was representative and varied. For the purpose of training and testing our e-waste recognition model, all of the photos will be scaled to 224 × 224. A single image sample from each dataset category is displayed in Fig 3

VI. Proposed System

This article details a simulation using Webots, a popular robotics simulation software, paired with a Python-based.

Fig. 3. Sample image from each category in the dataset.

implementation to bring the proposed E-waste collection system to life. The process begins with the robot moving around its environment and using a camera to capture images. These images are then processed by a trained Deep learning model, which is designed to identify various types of E-waste. For this system, we can implement, convolutional neural networks like VGG16 or ResNet50. These networks are chosen because they are highly effective at learning and classifying visual data. The image captured by the robot is run through one of these models to determine the type of E-waste it represents. If the model classifies the image as one of the predefined categories (e.g., mobile phones, chargers, laptops) and the confidence level of this classification meets or exceeds a set threshold (90% accuracy), the robot proceeds to initiate its collection process. Once an item is correctly identified, the robotic arm is activated to pick up the object and place it on a designated platform. This platform is designed to hold items until they can be properly disposed of or recycled. However, if the robot encounters an item that exceeds its payload capacity (such as a large appliance like a refrigerator), the system's identification function still proves useful. In such cases, the robot's recognition system can alert human garbage collectors to the presence and location of the large E-waste item, enabling them to handle it manually. In essence, this simulation and implementation provide a practical demonstration of how the integration of deep learning models and robotics can automate the detection, classification, and collection of electronic waste, improving efficiency and safety in waste management.

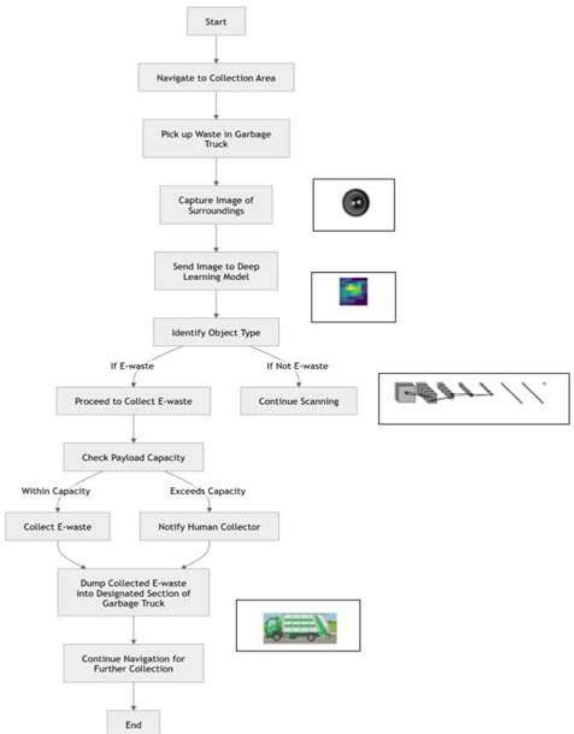

Fig. 4. Flow Chart

VII. Conclusion

Deep learning, particularly CNNs, is central to the success of the proposed system for E-waste collection. By training a model to recognize and classify different types of E-waste, the system can autonomously detect and segregate electronic waste from household environments. The use of image recognition ensures that the model can operate effectively in dynamic, real-world conditions, The deployment of this system will propel the world towards the goal of autonomous waste collection and disposal. The waste identification system used achieves accurate results for electronic wastes and can be implemented as a separate entity at recycling centers. The proposed system combines autonomous robotics and deep learning for electronic waste collection and separation from the general solid waste stream. Further research directions include increasing the payload of the robot and the arm can facilitate the collection of larger appliances like refrigerators and freezers. The addition of more categories of electronic waste items can propel the widespread applicability of the robot in multiple cities.

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