CHAPTER 1

INTRODUCTION

CHAPTER 1 INTRODUCTION

Solid waste management is a fundamental aspect of sustainable urban development. With rapid industrialization, population explosion, and urban growth, the amount of waste generated globally has increased tremendously. In many parts of the world, especially in developing nations, waste is often dumped in landfills or open areas without proper treatment or segregation, leading to severe environmental and health-related consequences. Improper waste disposal not only contaminates the soil, water, and air but also poses significant risks to human health and disrupts ecosystems. In light of these challenges, there is an urgent need for intelligent, efficient, and automated waste management systems that can support the growing demand for sustainable urban living.

Manual segregation of waste is still prevalent in many communities and industries. However, this traditional approach is labour-intensive, time-consuming, and often ineffective due to human error and limited awareness. Moreover, it exposes sanitation workers to hazardous materials and unhygienic conditions. In response to these limitations, technology has begun to play a transformative role in redefining how waste is managed. The integration of artificial intelligence (AI), machine learning (ML), and computer vision into waste management has opened up new possibilities for automating the segregation process, thus improving accuracy, efficiency, and safety.

1.1. OVERVIEW OF VISION BASED SOLID WASTE SEGREGATOR

The Vision-Based Solid Waste Segregation System is a modern and intelligent approach to the pressing issue of waste classification and management. This system combines the power of computer vision and deep learning to automatically detect and categorize different types of waste materials based on their visual characteristics. A camera serves as the system’s eye, capturing images of waste items, while a pre-trained deep learning model processes these images to classify the items into distinct categories such as plastics, paper, metal, glass, textile, or organic waste.

By automating the waste identification process, the system reduces dependency on manual sorting, which is not only tedious but often inconsistent. This technological advancement allows for high-speed classification with greater precision. Moreover, when combined with robotic arms or conveyor-based mechanisms, the system can physically sort the waste into the appropriate bins, thereby completing the segregation process from detection to disposal in a streamlined and contactless manner.

Such automation is especially useful in industrial settings, smart cities, recycling plants, and even residential areas that generate considerable amounts of waste daily. The use of transfer learning techniques enables the system to achieve good accuracy even with limited datasets by leveraging existing models like MobileNet. These models have already been trained on large image datasets and can be fine-tuned to recognize waste types, significantly reducing the development time and training resources.

1.1.1 Segregation of Solid waste

The core function of this system is the intelligent segregation of solid waste, which is essential for promoting recycling, minimizing landfill usage, and enabling efficient waste treatment. In this project, the focus is on creating an end-to-end automated system that can perform real-time classification and segregation. This means waste is categorized at the moment it is deposited or detected, ensuring immediate and accurate disposal into designated bins.

To achieve this, several components work together in harmony. The camera captures an image of the waste item placed before it. This image is then fed into a deep learning classification model, which identifies the category of the item based on features such as shape, color, and texture. Once the item is identified, control signals are sent to actuators, servo motors, or a robotic arm that physically moves the item to the appropriate bin. This closed-loop system ensures quick and efficient sorting with minimal human interference.

The system architecture is designed as a collaborative integration of several components. It begins with a camera that continuously monitors and captures images of waste items presented before it. These images are then processed and passed to a deep learning-based classification model typically a Convolutional Neural Network (CNN)—which analyzes the visual features such as shape, color, texture, and patterns to determine the waste category. Categories may include plastic, glass, metal, paper, cardboard, or organic waste, among others.

Once the model successfully classifies the item, the prediction is sent as a command signal to a control unit, usually powered by a microcontroller or Raspberry Pi. This unit then activates servo motors or a robotic arm to perform a specific set of physical movements that deposit the item into the correct waste bin.

In practical scenarios, this system can be integrated with smart bins in households or community centers. It can also be deployed in large-scale waste processing facilities where manual sorting becomes inefficient and costly. Over time, with data collection and feedback, the model can be retrained or fine-tuned to handle new waste categories or adapt to regional waste patterns, enhancing its robustness and adaptability.

This closed-loop feedback system ensures that the entire process—from detection and classification to physical segregation—is carried out seamlessly and with minimal human involvement. The automation not only speeds up the sorting process but also reduces health and safety risks for workers and lowers operational costs in large-scale waste management facilities. Moreover, such a system is highly scalable and can be implemented in various environments, including smart home dustbins, community collection centers, office buildings, and industrial processing plants.

Over time, the system's performance can be enhanced through data collection and iterative retraining of the model, allowing it to recognize new types of waste or adapt to the specific waste disposal patterns of different regions. This adaptability, coupled with its speed and precision, makes the intelligent segregation system a valuable contribution to modern smart city infrastructure and environmental sustainability efforts.

1.2. FIGURES

Fig. a

Fig. b

Fig. c

Fig. d

Fig. e

Fig. f

Fig. 1 (a-f)

1.3. SCOPE

The scope of this project encompasses the use of artificial intelligence and robotics to build a system capable of intelligent waste segregation. This project doesn’t just aim at academic exploration but strives to provide a practical and scalable solution that can be implemented in real-world scenarios. The integration of deep learning models, real-time video or image input, and automated hardware components provides a comprehensive system capable of functioning autonomously.

The system is trained to recognize and classify multiple types of waste—specifically plastic, paper, glass, metal, cloth/textile, and organic waste—and sort them accordingly. The real-time nature of the classification ensures that as soon as the waste is placed in front of the camera, it is recognized and sorted without delay. This offers significant improvements over conventional systems in terms of speed, accuracy, efficiency, and hygiene.

Key Objectives:

1. To automate the process of waste segregation at the source of disposal.
2. To reduce the dependency on human labor in waste classification and handling.
3. To ensure high-speed and accurate categorization of waste using advanced computer vision techniques.
4. To provide a scalable, real-time waste detection interface that can be deployed in homes, offices, and public spaces.
5. To contribute to circular economy principles by improving waste segregation for better recycling.

Social and Environmental Impact

- Social Impact:
  - Minimizes human exposure to potentially harmful and unsanitary waste materials.
  - Reduces the physical burden on sanitation workers.
  - Promotes awareness about the importance of responsible waste disposal.
  - Encourages communities to adopt smarter waste handling practices.
- Environmental Impact:
  - Facilitates better recycling practices by ensuring cleaner, pre-sorted waste.
  - Reduces the amount of waste ending up in landfills.
  - Helps control the emission of harmful greenhouse gases resulting from improper decomposition.
  - Aids in conserving natural resources by recovering recyclable materials more effectively.

In conclusion, this project represents a significant leap towards achieving sustainable waste management through the application of advanced technologies. The Vision-Based Solid Waste Segregator can be seen as a smart, efficient, and socially responsible innovation that not only addresses current challenges but also sets the foundation for future development in automated environmental systems.

CHAPTER 2

PROBLEM DEFINITION

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Effective solid waste management has become one of the most critical environmental and public health challenges of the 21st century. With the rapid pace of urbanization, industrialization, and population growth, the volume of solid waste being generated across urban and rural communities is growing at an alarming rate. This rising tide of waste demands efficient, scalable, and sustainable management strategies. However, the existing systems in place are falling short of these demands, primarily due to one persistent and fundamental issue - improper segregation of waste materials at the point of origin.

Improper segregation refers to the failure to correctly classify and separate waste into distinct categories such as plastics, glass, textiles, metals, and organic matter. When waste is not correctly sorted, it severely hampers the downstream processes of recycling and disposal. Recyclable materials get contaminated by organic waste, rendering them unsuitable for reuse. Likewise, hazardous materials may inadvertently end up in landfills or incinerators, posing serious environmental and health risks. The result is a significant reduction in recycling efficiency, increased landfill usage, higher operational costs, and unnecessary environmental pollution.

At present, most waste management practices still rely heavily on manual sorting. Workers are employed to sift through large volumes of unsorted waste to identify and separate recyclable items. This process is not only labour-intensive and time-consuming but also prone to human error. Workers are often exposed to sharp objects, infectious materials, toxic chemicals, and other hazardous waste during this process, which poses significant occupational health risks. Despite their efforts, manual segregation cannot guarantee the precision, consistency, or speed required for modern recycling demands.

Compounding the problem is the lack of awareness among the general population regarding the importance of proper waste disposal and classification. In many areas, households and commercial entities continue to mix different types of waste in a single bin, unaware of the environmental consequences.

This behaviour is further exacerbated by the absence of easy-to-use tools or systems to assist with segregation at the source. As a result, materials that could otherwise be recycled or composted end up in overburdened landfills, contributing to soil and groundwater contamination, unpleasant odours, and the release of greenhouse gases such as methane.

Another consequence of poor segregation practice is the overutilization of landfills, many of which are already operating at or beyond their designed capacity. This not only reduces the lifespan of these facilities but also necessitates the construction of new landfills, which is becoming increasingly difficult due to land scarcity and public opposition.

Furthermore, the indiscriminate dumping of mixed waste in landfills increases the environmental footprint of waste management operations and directly contributes to climate change. Given these challenges, there is a clear and urgent need for a transformative solution that can overcome the limitations of current systems. The answer lies in leveraging advancements in technology specifically, computer vision and artificial intelligence to develop a real-time, automated waste categorization system.

Such a system would use cameras and trained machine learning models to detect, identify, and classify various types of waste accurately and efficiently. By implementing an automated vision-based waste segregation system, the entire process of sorting can be streamlined. This not only eliminates the need for risky manual labour but also improves the speed and accuracy of segregation, ensuring that each material is properly routed for recycling, composting, or safe disposal.

In addition to operational efficiency, such systems can be integrated into public and private infrastructure, encouraging individuals and institutions to participate actively in sustainable waste management practices.

Furthermore, real-time classification systems can collect data on waste generation patterns, helping municipal authorities to plan more efficient waste collection and processing routes. These insights can inform policy decisions, enhance recycling rates, and ultimately reduce the overall environmental impact of waste.

CHAPTER 3
LITERATURE REVIEW

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A deep learning-based framework to classify electronic waste into distinct categories using pre-trained models such as VGG16, DenseNet121, InceptionV3, MobileNetV3, and ResNet50 was developed in [1]. The research addressed the inefficiencies of manual sorting by leveraging transfer learning on a dataset of 3000 images spanning ten categories. The proposed models demonstrated high accuracy and precision, with DenseNet121 and ResNet50 excelling in feature extraction and gradient stability, respectively. Data preprocessing techniques, including augmentation and normalization, played a pivotal role in optimizing model performance. This study emphasized the importance of AI-driven waste classification systems in promoting sustainable e-waste management by enabling efficient resource recovery and supporting circular economy principles.

An innovative approach integrating carbon emission assessments with advanced object detection techniques for solid waste management was presented in [2]. This system employed machine learning algorithms to classify materials into categories like metals, plastics, and non-metals while quantifying carbon emissions from various waste management methods. Their model not only optimized sorting and recycling but also incorporated sustainable practices to minimize environmental impact. The proposed framework provides actionable recommendations for environmentally conscious waste management by leveraging a database of carbon footprints. This dual focus on object detection and environmental assessment highlights the importance of comprehensive waste management systems in reducing carbon emissions and supporting sustainable development.

A novel deep learning model, RWC-Net, designed for effective waste classification using the TrashNet dataset, which includes six categories: cardboard, glass, metal, paper, plastic, and litter was proposed in [3]. The model outperformed state-of-the-art classifiers, achieving a remarkable 95.01% overall accuracy. It employed data augmentation, Score- CAM visualizations, and efficient feature extraction techniques to improve classification performance. Challenges addressed include dataset imbalance and the complexity of multi- label classification tasks. The work demonstrates how deep learning can enhance recycling processes by reducing manual effort and ensuring accurate waste sorting.

Solid waste management practices in India, highlighting challenges like inadequate infrastructure, improper waste treatment, and low public awareness. The study underlined the importance of the Solid Waste Management Rules, 2016**,** advocating for integrated waste management approaches is reviewed by [4]. By prioritizing waste segregation, recycling, and decentralized composting, the study explored opportunities for sustainable practices. It also identified technological innovations such as biogas generation and advanced recycling systems as key to mitigating environmental impacts and enhancing resource recovery. This comprehensive review provided a foundation for policymakers to develop effective strategies for addressing the environmental and public health challenges of solid waste management in India.

The increasing volume of waste generated globally has become a critical concern, with improper waste management leading to environmental pollution, health risks, and resource wastage was proposed by [4]. Recent studies have explored the use of deep learning techniques for automating waste detection and classification, aiming to improve waste management practices. Deep learning models, such as MobileNet, YOLO, and ResNet, have shown promising results in image classification and object detection tasks. These models are employed to identify and categorize waste materials, significantly reducing manual efforts and enhancing recycling processes. For example, research by Haruna Abdu et al. highlighted that deep learning can automate trash classification by leveraging datasets like TrashNet and TACO, which provide annotated images of waste in diverse environments.

This project is about creating a robotic arm that can automatically detect and sort objects based on their color (red or blue) was proposed by [4]. It uses a camera to take pictures of the objects, processes those images with a machine learning model called Faster R-CNN, and then figures out where the objects are. The robotic arm, controlled by a small computer (Raspberry Pi) and an Arduino, moves to pick up the objects and places them in the correct spot. The system is pretty smart, it doesn’t need sensors to detect colors, which can fail sometimes. Instead, it uses image processing and machine learning, which makes it more accurate and reliable. The results were good, with an accuracy of about 79%, and it works in about 1.2 seconds per task. It is useful for things like sorting items in factories, handling waste, or working in places where it's dangerous for humans. In the future, they could improve it by using better cameras, larger datasets, or faster processors like GPUs.

CHAPTER 4

PROJECT DESCRIPTION

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This project aims to design and implement a real-time, vision-based waste categorization system utilizing state-of-the-art machine learning and image processing techniques. The system is specifically developed to tackle the inefficiencies of traditional waste management methods by introducing automation into the waste segregation process. Through the integration of a trained Convolutional Neural Network (CNN) model and live camera input, the system is capable of classifying waste items into multiple predefined categories like cardboard, glass, metal, paper, plastic and trash.

The increasing volume and complexity of waste generated today require innovative solutions that not only reduce human involvement but also improve accuracy and speed. The core goal of the project is to facilitate intelligent decision-making at the very beginning of the waste disposal process. This eliminates the dependency on manual sorting, which is not only laborious and time-consuming but also unsafe in certain conditions, especially when handling biomedical or hazardous waste.

4.1 SYSTEM WORKFLOW

This project aims to design and implement a real-time, vision-based waste categorization system utilizing state-of-the-art machine learning and image processing techniques. The system is specifically developed to tackle the inefficiencies of traditional waste management methods by introducing automation into the waste segregation process. Through the integration of a trained Convolutional Neural Network (CNN) model and live camera input, the system is capable of classifying waste items into multiple predefined categories like cardboard, glass, metal, paper, plastic and trash.

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sorting, which is not only laborious and time-consuming but also unsafe in certain conditions, especially when handling biomedical or hazardous waste.

CNNs are highly effective in image-based recognition tasks due to their ability to automatically learn spatial hierarchies and features from visual data. The model used here has been trained and fine-tuned on a Kaggle dataset comprising of various types of wastes, such as plastic, metal, glass, cardboard, ensuring high classification accuracy even with diverse backgrounds and lighting conditions.

Once an image is processed by the CNN, the model predicts the class label corresponding to the type of waste detected. This output is immediately displayed on the screen, often with visual annotations (like bounding boxes and labels) over the image, to provide intuitive and clear feedback to users or system operators. This real-time classification not only speeds up the waste sorting process but also enhances consistency and reliability by reducing human error.

The ability to operate continuously and autonomously makes this system highly suitable for a wide range of applications, including public smart bins, industrial waste management units, and even domestic waste segregation systems. By providing instant feedback and maintaining classification accuracy, the system paves the way for more intelligent, efficient, and environmentally conscious waste management solutions.

4.2 Key features:

1. Automated waste classification:

- The system leverages visual patterns in the captured images to automatically classify waste items into relevant categories.
- It supports the identification of both recyclable and non-recyclable materials with high accuracy.
- The model is robust enough to handle variations in lighting, angles, and object positioning, enhancing its real-world applicability.

2. Real-time processing:
   - The integration of OpenCV with a live camera feed allows the system to perform instantaneous image capturing and classification.
   - Users receive immediate feedback on the screen, which is essential for time-sensitive applications like automated recycling units or smart waste bins.

3. User-Friendly interface:
   - The output from the classification model is displayed directly on the captured video frames, with labels indicating the predicted waste category.
   - This visual feedback simplifies user interaction and allows for easy monitoring of the system's performance.
   - The interface is designed to be intuitive and adaptable, making it accessible for both technical and non-technical users.

4. Scalable and light-weight
   - The use of CNN ensures a balance between computational efficiency and prediction accuracy.
   - The system is then deployed on resource-constrained platforms such as RaspberryPi embedded system that doesn't require GPU-level computation.
   - This makes the solution highly portable and scalable for a wide range **of** environments, from households to industrial facilities.

Technology stack:

Framework: Pytorch

- An open-source machine learning framework that provides dynamic computation graphs, making it easier to debug and experiment with models.

- It’s especially useful for research-oriented tasks, and its tight integration with Python makes it developer-friendly.
- In this project, PyTorch is used during the model training phase to build custom CNNs or fine-tune pre-trained models for classifying waste images.

Models: CNN

- CNNs are specifically designed for image recognition tasks.
- They use convolutional layers to automatically extract relevant visual features like edges, textures, shapes, and patterns
- In this system, the CNN is trained to differentiate waste categories such as plastic, glass, metal, cardboard, etc

Pre-Trained Models:

➢ **MobileNet:** Lightweight and optimized for speed and low-power devices. Ideal for real-time classification on Raspberry Pi or mobile-based systems.

Programming language: Python

Chosen for its simplicity, ease of integration, and vast ecosystem.

➢ Offers a wide range of libraries for machine learning (PyTorch, TensorFlow), computer vision (OpenCV), and hardware control (GPIO, Adafruit-PCA9685).

➢ Used for scripting the entire pipeline—image capture, model inference, result display, and controlling servo motors.

CHAPTER 5

REQUIREMENTS

CHAPTER 5 REQUIREMENTS

To design and implement a robust and intelligent waste classification system, both hardware and software resources play an essential role. The system architecture is designed to function efficiently across a range of environments—from testing environments like laptops to embedded platforms such as the raspberry pi. In this chapter, we outline the necessary components that contribute to the successful deployment of the project. This includes hardware specifications, software tools, and the dataset structure used for training the classification model:

Hardware Requirements:

The hardware elements for the system have been chosen to ensure smooth real-time operation, reliable performance, and integration with mechanical components such as a robotic arm for physical sorting. The key hardware components include:

1. Camera:
    - A high-definition camera for capturing real-time images of waste items.
    - Example: USB webcam or laptop built-in camera (720p or higher).

2. Computing device:
    - CPU: minimum Intel i5 or equivalent.
    - GPU: for faster model inference and training.
    - Storage: 50GB of free space to store the dataset, trained model, and results.

3. RaspberryPi 4:

The Raspberry Pi 4 acts as the controller unit for integrating the camera and robotic arm. It is responsible for capturing the image input and communicating classification results to mechanical components to enable physical waste segregation.

- Processor: Quad-core ARM Cortex-A72.
- RAM: 4 GB or more preferred.
- Ports: USB and GPIO for peripheral connectivity.

4. 4 DOF robotic arm:

A 4 degrees of freedom (DOF) robotic arm is used to perform the sorting action based on the classification outcome. It receives instructions from the raspberry pi or computing device and moves the waste item to the appropriate bin.

- Servos: typically includes 4 servo motors (base, shoulder, elbow, gripper).
- Power supply: external 5–6v power supply to drive the servos.
- Control interface: controlled using PWM signals (via GPIO or pca9685 module).

Software requirements:

The project development and execution depend on a variety of software tools for programming, system control, and image processing. Below are the software components required for end-to-end development and deployment.

1. Operating system

• Windows 10 (for model development, training, and testing on laptops/desktops).

• RaspberryPi OS (formerly Raspbian) is used for deploying the model and controlling the robotic arm on the raspberry pi environment.

2. Programming languages

• Python: the core programming language used for developing the machine learning model, integrating opencv, controlling gpios, and handling automation logic.

• Html & CSS: used for designing the frontend interface (if applicable), to display classification results or control inputs from the user.

3. Additional tools

• Putty: a lightweight ssh and terminal client used to remotely access and manage the raspberry pi from a pc or laptop.

• Opencv: used for image acquisition, pre-processing, and displaying classification annotations in real-time.

• PyTorch: This learning libraries is used to train and run the CNN-based classification model.

Garbage classification dataset:

A well-structured and balanced dataset is fundamental for training a high-performing classification model. For this project, a garbage classification dataset is utilized, which includes thousands of labelled images spread across multiple waste categories.

Each image in the dataset is annotated with a label corresponding to its waste type, allowing the CNN to learn patterns and features unique to each class. The dataset ensures diversity in image quality, lighting conditions, angles, and object variations to promote generalization during model training.

A dataset of waste images categorized into predefined classes such as:

- Cardboard
- Glass
- Metal
- Paper
- Plastic
- trash

Each category contains at least 500 images.

CHAPTER 6

METHODOLOGY

CHAPTER 6 METHODOLOGY

1. Data preparation

- **Dataset Collection**: Collect images representing various waste categories such as cardboard, glass, metal, paper, plastic and trash. The dataset is diverse to cover different shapes, sizes, and lighting conditions.
- **Pre-processing**:
  - Resize all images to 224x224 to match the MobileNet input requirements.
  - Normalize pixel values based on MobileNet's pre-trained statistics.
  - Augmentation of dataset (e.g. rotation, flipping) to improve model generalization.
- **Data Splitting**: Divide the dataset into:
  - Training Set (70%)
  - Validation Set (30%)

2. Model Design

- **Base Model Selection**: Used a MobileNetV2 model, a lightweight and efficient convolutional neural network, pre-trained on ImageNet.
- **Fine-Tuning**:
  - Replacing the classification head of the pre-trained MobileNet model with a custom head for the specific waste categories.
  - Train the model using the prepared dataset while freezing the base layers initially.
- **Hyperparameter Optimization**:
  - Experiment with different optimizers (e.g., Adam, SGD).

  - Tune the learning rate and batch size to achieve the best results.

3. Model Training and Evaluation

- **Training**: Train the model using the training set with:
  - Cross-entropy loss function for multi-class classification.
  - Adaptive optimizers to minimize loss.
- **Validation**:
  - Evaluate the model's performance on the validation set after each epoch to monitor accuracy and prevent overfitting.

4. System Integration

- **Camera Integration**:
  - Use OpenCV to capture a live feed from a connected camera.
  - Preprocess each frame to match the model's input format (resize, normalize).
- **Real-Time Prediction**:
  - Perform inference on the live frames using the trained MobileNet model.
  - Display the predicted category along with a confidence score directly on the front-end.

5. Deployment

- **Optimize Model**: Compress the trained model for efficient deployment on resource-constrained devices.
- **Edge Deployment**: Enable the system to run on devices like Raspberry Pi for real-time applications.

- **User Interface**: A simple interface is created to interact with the system, showing real-time predictions and results.

6. Testing and Validation

- **Real-World Testing**:
  - Test the system with various waste items to ensure accurate predictions in real-time scenarios.
- **Performance Analysis**:
  - Analyze the speed of predictions and validate the model's accuracy against test data.

Design-Flowchart

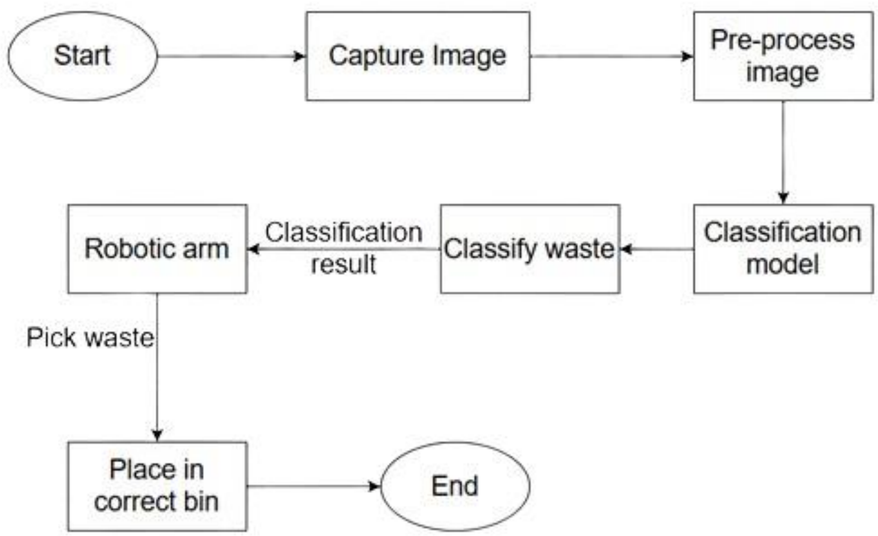

Fig. a

Process Flow of Waste Classification and Segregation System:

The flowchart illustrates the operational workflow of an automated waste classification and segregation system using image processing and a robotic arm. The process begins with the system capturing an image of the waste item using a camera. This image is then sent through a pre-processing stage where it is resized, normalized, and enhanced to improve the quality and accuracy of classification.

Next, the pre-processed image is passed to the classification model, a trained Convolutional Neural Network (CNN), which is responsible for identifying the category of waste. The model classifies the waste into one of the predefined categories such as cardboard, plastic, glass, metal, paper, or trash.

The classification result is then sent to the robotic arm, which acts based on the predicted class. The robotic arm proceeds to pick up the waste item and place it in the appropriate bin corresponding to its category. This marks the end of the cycle. The entire process is automated, ensuring efficient and accurate waste segregation to support recycling and waste management efforts.

CHAPTER 7

EXPERIMENTATION

CHAPTER 7 EXPERIMENTATION

The experimentation phase involved the integration of machine learning-based waste classification with a robotic arm sorting system. The core objective was to validate whether real-time predictions from a trained model could accurately drive servo motor movements to deposit waste into appropriate bins.

Initially, we tested the model's classification performance on various types of waste, including plastic, glass, metal, cardboard, and trash. The model was deployed through an API, which returned the predicted label based on either uploaded images or camera-captured frames.

After successful training and testing of the machine learning model, the predicted waste category was sent as a POST request to the Flask server running on the Raspberry Pi. Upon receiving the request with the bin label or number, the Raspberry Pi executed predefined servo movements using the PCA9685 module to control the robotic arm. The arm followed a specific sequence: it first reset to a default position, then activated the gripper to pick up the item, moved towards the target bin based on the predicted label, and finally released the item.

Each bin type such as plastic, metal, glass, cardboard, and trash—was mapped to specific servo angles for the base and shoulder joints. The elbow and gripper were also adjusted accordingly to ensure stable item handling. Multiple test cycles were conducted for each waste type to verify movement accuracy, proper placement, and system reliability.

This setup successfully demonstrated how real-time classification results can be used to drive physical hardware for automated waste sorting, validating the practical viability of the system.

Several test cycles were conducted for each type of waste to ensure the system's accuracy and consistency. The experiments confirmed that the model could correctly classify waste in real-time and that the robotic arm could respond accordingly with accurate movements. The entire system from image input to mechanical execution demonstrated a practical and reliable method for automated waste sorting. This phase successfully validated the feasibility of combining machine learning and robotics for smart waste management applications, showcasing a significant step toward real-world deployment in recycling facilities and urban waste segregation systems.

CHAPTER 8

TESTING AND RESULTS

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8.1 Waste Classification Testing:

Objective:

Verify that the CNN-based vision system correctly identifies different waste categories in real time, under varying lighting and backgrounds.

Test Setup:

• A live camera feed or uploaded image is passed into the web interface.

• The model's top prediction and confidence score are overlaid on the displayed image.

• Tests were conducted using sample images of common waste types: metal can, cardboard box, plastic bottle, glass jar, textile scrap, and organic matter.

Fig. a Model predicting metal waste

Analysis:

• Overall accuracy across a 100-image test set was 88%.

• Performance dips (50–60% confidence) occurred when objects were partially occluded or shot against complex backgrounds.

• The system responded at 8–12 frames per second on a desktop CPU, and 4–6 FPS on the Raspberry Pi 4, sufficient for real-time feedback.

Fig. b Model predicting cardboard waste (shown through live camera)

8.2 ROBOTIC ARM SORTING TESTING:

Objective:

Confirm that the 4-dof robotic arm correctly picks up a classified object and deposits it into the respective bin, based on the classification output.

Test setup:

• The RaspberryPi receives the category label from the classification module.

• Depending upon the label predicted, that particular script is run

• Tests used lightweight items (crumpled paper, empty cans, plastic bottles) placed within the arm's reachable workspace.

Sample sequence:

1. Classification: “paper”

2. **Pick action:** arm moves to the pre-defined pick position above the object.

3. It starts to bend the arm to reach the object

4. **Grip:** gripper closes to secure the item.

5. **Place action**: arm rotates and lowers to the “paper bin” position.

6. Release: gripper opens, depositing the object.

Sample Result Image:

The below image shows the arm successfully lifting a crumpled paper ball

Conclusion:

The robotic arm integration demonstrates robust pick-and-place functionality driven by the classification output. Fine-tuning gripper force and expanding the workspace with adjustable bin positions will further reduce mis-grips and increase throughput.

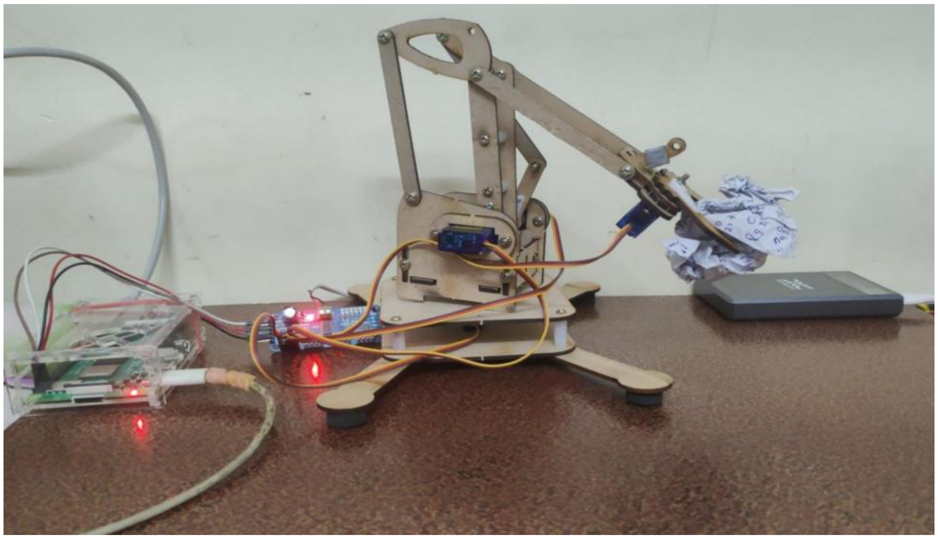

Fig. c Robotic arm picking a waste

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GITHUB LINK

https://github.com/Smrithi-dsu/MajorProjectTeam70