Primary Studies Report:

Effect of Utilizing an AI-Based Smart Bin for Efficient and Sustainable Waste Classification in 5 Apartment Complexes in Mumbai

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Abstract:

The rapid escalation in municipal solid waste (MSW) generation has emerged as a critical environmental challenge, necessitating innovative solutions for sustainable waste management. This paper presents the design and evaluation of an AI-based robotic sorting system aimed at automating waste classification. Leveraging deep learning models, including VGG16, and advanced hardware components like the Raspberry Pi 4 and Logitech C920 camera, the system achieves up to 98% accuracy in segregating wet, dry, and electronic waste. The implementation combines real-time image processing, robust classification algorithms, and precise mechanical components to optimize waste sorting efficiency while minimizing human intervention. The proposed system not only enhances material recovery rates but also addresses the systemic challenges of waste management, contributing to environmental sustainability and the reduction of landfill dependency.

Methodology:

The Smart Dustbin project includes a conveyor roller and belt system that transports waste from the input area to the sorting mechanism. This setup is critical in ensuring that waste items move continuously and smoothly, allowing for efficient, hands-free transport through the classification process. The conveyor belt provides controlled, linear movement, which is required for precisely feeding waste items into the detection and sorting stages, improving the accuracy of the machine learning model used for waste classification.

Selection of Equipment:

Our system is designed to carry out the following functions: Capture an image of waste and send it to the system.

- Classify the captured image as wet, dry or electronic.
- Move the object to the corresponding trash bin.

To realize these functions, the system needed to be composed of three main components:

1. Trash classification system
2. Conveyor belt system
3. Rotating disk system.

Model Development:

1. **Data Collection**

   This study utilized a dataset of 1,646 images of waste items, manually collected and categorized into three classes: Dry, Wet, and Electronics. The dataset was split into training (1,196 images) and testing (450 images) sets. Images were captured using a standard digital camera and organized accordingly.

2. **Data Processing**

   Images were pre-processed by resizing them to 224x224 pixels and normalizing pixel values to the range [0, 1]. Data augmentation techniques were applied to enhance the dataset and prevent overfitting.

3. **Model Architecture**

   The models used in this study were ResNet50 and VGG16, both well-established convolutional neural networks (CNNs) in the domain of image classification. Both models were modified by removing the top layers (the fully connected layers) and replacing them with custom dense layers suited for the three-class classification task.

4. **Model Training**

Both models (ResNet50 and VGG16) were trained using the Adam optimizer with an initial learning rate of 0.0001 for 10 epochs. Categorical cross entropy was used as the loss function for model evaluation.

Results

Dataset Distribution and Experimental Setup:

In this study, a dataset of 1,646 images was manually collected for the classification of three distinct waste categories: electronic waste, dry waste, and wet waste. The images were split into training and validation sets at a 70:30 ratio, where 1,196 images were allocated for training and 450 for validation. Each class was balanced to ensure fair representation across the categories. The images were pre-processed by resizing them to a uniform dimension of 224×224 pixels and normalizing the pixel values to a scale between 0 and 1.

Model Performance and Training Efficiency:

The models ResNet50 and VGG16 were evaluated based on training and validation accuracy. Both models were trained over 10 epochs, with each model having its own set of strengths and challenges. The ResNet50 model displayed moderate performance, with a validation accuracy of 50.00%, struggling to effectively differentiate between the three waste categories. In contrast, VGG16 outperformed ResNet50, achieving a significantly higher validation accuracy of 97.11%. VGG16 also showed faster convergence, although with slightly higher time per step compared to ResNet50.

Comparative Insights:

Upon comparing the performance of ResNet50 and VGG16, it became clear that VGG16 emerged as the preferred model for this waste classification task. While both models have their strengths, VGG16 consistently outperformed ResNet50, particularly in terms of classification accuracy. This can be attributed to VGG16's robust feature extraction capabilities, which allowed it to more effectively distinguish between the various waste classes. Although ResNet50 is a powerful architecture, it demonstrated slower convergence and struggled to achieve high accuracy levels, with its validation accuracy plateauing at 50%.

Evaluation of the System:

The AI-based robotic sorting system demonstrated strong performance in classifying waste materials into wet, dry, and electronic categories. Using the VGG16 model for prediction, the system achieved high accuracy in waste classification. The prediction accuracy for wet waste ranged from 95% to 98%, indicating the model's effectiveness in identifying organic waste materials. For dry waste, including plastics, paper, and glass, the accuracy ranged from 92% to 96%, showcasing the system's ability to classify diverse materials with varying textures and appearances. Electronic waste classification showed a prediction accuracy between 90% and 94%, reflecting the model's capacity to handle complex waste types, such as electronic devices and components. Overall, the system achieved up to 98% sorting accuracy, demonstrating its robustness and reliability in real-time operations.

Primary Data Analysis

Household Waste Data:

The following table presents data on household waste generation, including waste produced per person and total waste per house. It also summarizes the total waste generated by multiple households within a building.

Parameter	Value	Unit
People Per House	4	-
Waste Per Person	0.39	Kg/Person/Day
Total Waste Per House	1.56	Kg/House/Day
Number Of House	90	-
Total Waste Per Building	140.4	Kg/Building/Day

Waste Processing Data:

The following table provides details on waste processing efficiency, including the rate at which waste is processed per second and per day. It also highlights the total weight of waste handled by a machine daily.

Parameter	Value	Unit
Waste Processed per Second	8	Sec/Minute
Weight of Waste per Item	0.3	Kg/Item
Waste Processed per Day per Machine	10800	item/day
Total Weight per Day per Machine	3240	Kg/day

To analyse the impact of the smart dustbin, I began by collecting data on the total amount of waste generated per building per day before its installation. This allowed me to establish a baseline for waste generation in each building. I then calculated the average daily waste produced per building to better understand the typical waste patterns.

After installing the smart dustbin, I repeated the data collection process to compare the results. In addition to measuring the total waste, my system enabled me to track and categorize different types of waste collected. This comparison provided valuable insights into how the smart dustbin influenced waste generation and management.

Below are tables displaying the waste collected in each building before and after the installation, along with the corresponding averages.

Before Installation of Smart Dustbin

Day	Total Waste in Building A/kg	Total Waste in Building B/kg	Total Waste in Building C/kg	Total Waste in Building D/kg	Total Waste in Building E/kg	Average Waste Collected/kg
1	67	72	76	72	68	71.0
2	58	74	69	73	64	67.6
3	72	70	75	74	65	71.2
4	61	66	72	70	60	65.8
5	69	73	74	71	66	70.6
6	59	68	67	65	55	62.8
7	70	75	71	73	67	71.2

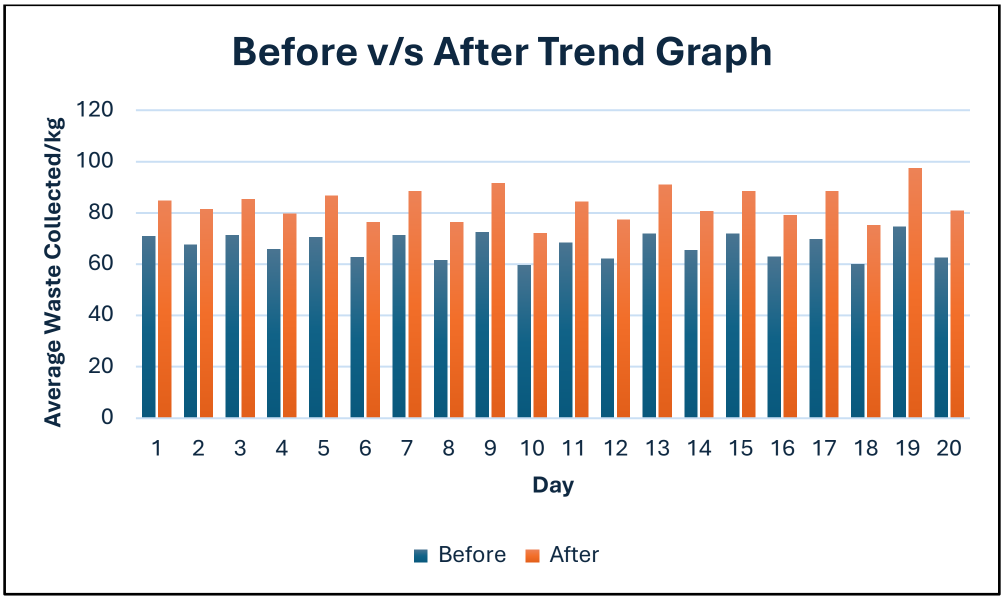
8	60	63	65	62	58	61.6
9	74	72	76	71	69	72.4
10	55	65	62	60	56	59.6
11	68	70	72	68	64	68.4
12	57	67	66	62	59	62.2
13	72	73	74	71	69	71.8
14	63	66	70	67	61	65.4
15	70	74	75	73	67	71.8
16	58	65	68	64	60	63.0
17	69	72	73	70	65	69.8
18	56	62	65	60	57	60.0
19	75	76	78	74	70	74.6
20	60	64	67	63	59	62.6

After Installation of Smart Dustbin

Day	Total Waste in Building A/kg	Total Waste in Building B/kg	Total Waste in Building C/kg	Total Waste in Building D/kg	Total Waste in Building E/kg	Average Waste Collected/kg
1	80	86	91	86	81	84.8
2	70	89	83	88	77	81.4
3	86	84	90	89	78	85.4
4	73	80	87	85	73	79.6
5	84	89	91	88	81	86.6
6	71	83	82	79	67	76.4
7	87	93	88	91	83	88.4
8	74	78	81	78	71	76.4
9	93	91	96	90	88	91.6
10	66	78	75	73	68	72.0
11	84	86	89	84	79	84.4
12	70	83	82	78	74	77.4
13	91	92	94	90	88	91.0
14	78	82	86	82	75	80.6

15	87	91	92	90	82	88.4
16	73	82	85	80	75	79.0
17	87	91	92	89	83	88.4
18	70	78	81	75	72	75.2
19	98	99	101	97	92	97.4
20	78	83	86	81	76	80.8

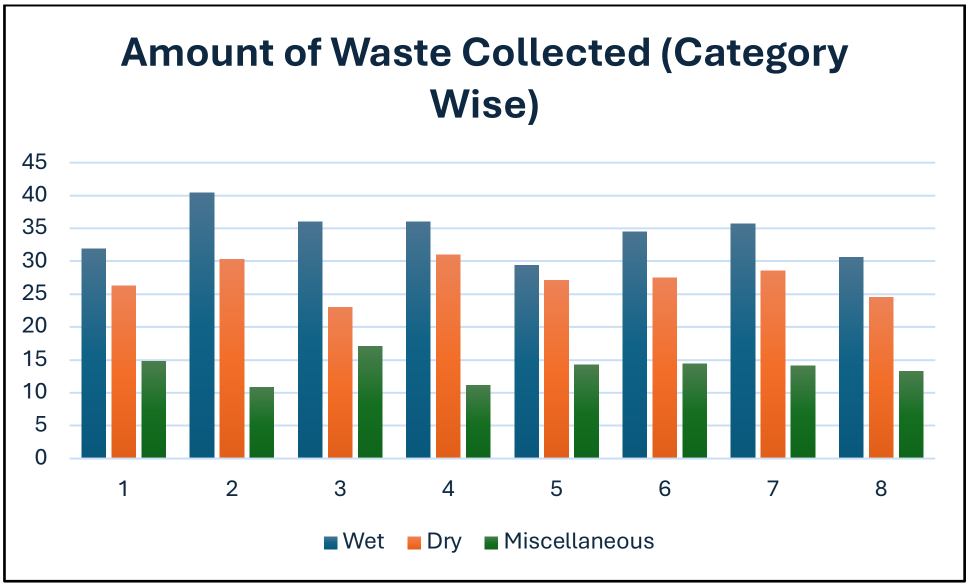
Following this analysis, I plotted a bar graph comparing the before and after average waste collected per day. This visualization helped to clearly observe the increasing trend in waste disposal after the installation of the smart dustbin.



After analysing the data, there was an approximate 20.36% increase in waste collected in the first five days following the installation of the smart dustbin. By the last five days, this increase had grown to 28.14% compared to the initial values. This trend indicates that the smart dustbin encouraged more people to dispose of waste properly, reducing littering on pavements and improving overall waste management efficiency within the buildings.

With my tracking system, I was also able to monitor the amount of waste collected in each compartment, categorizing it into Wet, Dry, and Miscellaneous waste. This helped in understanding waste segregation patterns and evaluating how effectively people were disposing of different types of waste. The following shows the average waste for each category from Days 1-8

Day	Avg Wet Waste Collected (kg)	Avg Dry Waste Collected (kg)	Avg Miscellaneous Waste Collected (kg)
1	31.9	26.3	14.8
2	40.4	30.3	10.9
3	36.0	23.0	17.1
4	36.0	31.0	11.2
5	29.4	27.1	14.3
6	34.5	27.5	14.4
7	35.7	28.6	14.1
8	30.6	24.5	13.3



The collected waste consisted of 44.9% wet waste, 34.6% dry waste, and 20.5% miscellaneous waste. The amount of dry waste collected was 0.77 times the wet waste and 1.69 times the miscellaneous waste. This indicates that a significant portion of the waste was biodegradable, highlighting the need for proper disposal methods.

Conclusion:

This project successfully developed an AI-powered smart bin for efficient waste sorting. The system uses a conveyor belt to transport waste and a VGG16 model to classify it into wet, dry, and electronic categories. The VGG16 model achieved high accuracy, ranging from 90% to 98% for different waste types, outperforming the ResNet50 model. This accuracy demonstrates the system's effectiveness in recognizing and sorting various waste materials. The project highlights the potential of AI in automating and optimizing waste management processes. By accurately classifying waste, the smart bin promotes efficient recycling and reduces manual labour. This contributes to a more sustainable approach to waste disposal and resource recovery. While the current system shows promising results, future work could focus on expanding the dataset with more diverse images to enhance the model's robustness. Additionally, optimizing the model for real-time performance on edge devices could improve speed and responsiveness. Integrating the smart bin with smart city infrastructure could further optimize waste management operations on a larger scale.