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# Smart System For The Management Of Municipal Solid Waste And Recycling

[1]Shivangi Srivastava, [2]Aaryan Gupta, [3]Siddharth Gaur
[1]B.Tech Student, [2]B.Tech Student, [3]B.Tech Student
Computer Science and Engineering Department
SRM University, Delhi NCR, India

***Abstract:*** Effective waste management is crucial for the sustainability of the environment, where rapid urbanization has led to increasing waste generation and inadequate recycling practices. Traditional systems often fall short due to inefficiencies and lack of public engagement. This research introduces a user-friendly waste sorting gadget designed specifically for Indian urban contexts, which categorizes waste into recyclable, non-recyclable, and compostable materials. The gadget utilizes a machine learning-based system powered by a deep learning convolutional neural network (CNN). Users can place their waste items into the device, which scans and analyzes them using advanced image recognition technology. The design of the gadget emphasizes user-friendliness, featuring an intuitive interface with clear visual indicators. When waste is sorted, users receive immediate feedback on whether the item was categorized correctly. This real-time interaction not only enhances the sorting experience but also educates users on proper waste disposal practices, fostering a greater sense of responsibility. By addressing specific waste management challenges, this innovative gadget aims to enhance recycling rates, reduce landfill waste, and promote greater environmental responsibility among citizens. The integration of technology into waste sorting can significantly contribute to a more sustainable urban environment in India, encouraging community engagement and effective waste management solutions

***Index Terms*** **– Waste Management, Machine Learning, Artificial Intelligence, CNN algorithm etc.**

## I. Introduction

Municipal solid waste (MSW) refers to the trash or rubbish collected by local municipalities [1-3]. It is made up of commonplace goods that we use every day but subsequently discard, like product packaging, grass clippings, furniture, clothing, bottles, food scraps, newspapers, appliances, paint, batteries, etc. [4] Household garbage accounts for the majority of municipal solid waste, but waste from businesses, trade, offices, and institutions is also included.

Most human activities generate some type of waste. That being said, production of waste is still a major cause of worry, as it has been since prehistoric times. In recent times, both the amount and rate of garbage produced has been steadily increasing. With the increase in the amount of waste, the variety of waste generated has also increased. Shifts in population are leading to a higher concentration of waste in urban areas [5]. Population growth, urbanization, and prosperity all tend to increase the output of waste. The population of the world is growing, but it is changing more drastically in terms of distribution. The majority of the world's urbanization is taking place in small and medium-sized cities in low-income countries, and it is happening at a rate and scale never seen before [6]. The places that are most affected by urbanization trends are also home to a billion new consumers.

India is one of the top 10 nations in the world for producing municipal solid waste (MSW) because of its quick urbanization, strong economic growth, and higher rates of urban consumption. The Energy and Resources Institute (TERI) said that India produces more than 62 million tons (MT) of trash annually. Of the total garbage created, only 43 MT are collected; the remaining 31 MT are just dumped in wasteyards, and 12 MT are treated before being disposed of [7-8]. The majority of waste produced is not even accounted for or treated. Inadequate waste management, including collection, transportation, treatment, and disposal, is now a major national environmental and public health hazard. The 62 MT of garbage produced annually, according to a study published in the Journal of Urban Management (December 2021), includes 7.9 MT of hazardous waste, 5.6 MT of plastic waste, 1.5 MT of e-waste, and 0.17 MT of biological waste [9]. According to a recent projection by the Central Pollution Control Board (CPCB), India's annual trash generation is expected to reach 165 MT by 2030 [10]. It is anticipated that the amount of hazardous, plastic, e-waste, and biomedical waste produced will rise correspondingly [11].

Based on the source, origin, and type of waste, the Ministry of Urban Development has divided solid waste into fourteen categories: household, municipal, commercial, institutional, trash, ashes, bulky, street sweepings, dead animals, construction and demolition waste, industrial waste, hazardous waste, and sewage waste [12]. Commercial and residential garbage produced in a notified municipal area, in either solid or semi-solid state, is referred to as municipal solid waste (MSW). This category does not contain industrial hazardous waste, although it does include treated biomedical waste. The processes involved in a solid waste management system are waste collection, segregation, transportation, processing, and disposal [13].

MSW composition in India is approximately 40%–60% compostable, 30%–50% inert, and 10%–30% recyclable [14 -16]. According to the National Environmental Engineering Research Institute (NEERI), Indian waste consists of 0.64% +- 0.8% nitrogen, 0.67% +- 0.15% phosphorus, and 0.68% +- 0.15% potassium, and has a 26 +- 5 C:N ratio [17]. Recycling is the process of converting waste materials into reusable resources, helping to conserve natural resources, reduce pollution, and minimize landfill waste. By collecting, processing, and transforming materials like paper, glass, plastic, and metals, recycling not only lessens our environmental impact but also supports a circular economy where products are designed for longevity and sustainability [18]. Embracing recycling practices in our daily lives contributes to a healthier planet and promotes responsible consumption.

This report explores the use of region-based convolutional networks (R-CNN) for analyzing and sorting waste. When users sort their waste, they receive immediate feedback on whether their items were categorized correctly. This real-time interaction not only improves the sorting experience but also educates users on proper waste disposal practices, fostering a sense of responsibility. By tackling specific waste management challenges, this innovative technology aims to boost recycling rates, reduce landfill waste, and promote environmental responsibility among citizens. By integrating advanced technology into waste sorting, we can significantly enhance sustainable urban development in India, encouraging community engagement and effective waste management solutions.

## II. Literature Reviews

### 2.1 An Internet of Things Based Smart Waste Management System Using LoRa and TensorFlow Deep Learning Model (Sheng, T.J., Islam, M.S., Misran, N. and Baharuddin, n.d., 2020)

Traditional waste management system operates based on daily schedule which is highly inefficient and costly. The existing recycle bin has also proved its ineffectiveness in the public as people do not recycle their waste properly. With the development of Internet of Things (IoT) and Artificial Intelligence (AI), the traditional waste management system can be replaced with smart sensors embedded into the system to perform real time monitoring and allow for better waste management. This research aimed to develop a smart waste management system using LoRa communication protocol and TensorFlow based deep learning model. LoRa sends the sensor data and TensorFlow performs real time object detection and classification. The bin consists of several compartments to segregate the waste including metal, plastic, paper, and general waste compartment which are controlled by the servo motors. Object detection and waste classification is done in TensorFlow framework with pre-trained object detection model. This object detection model is trained with images of waste to generate a frozen inference graph used for object detection which is done through a camera connected to the Raspberry Pi 3 Model B+as the main processing unit. Ultrasonic sensor is embedded into each waste compartment to monitor the filling level of the waste. GPS module is integrated to monitor the location and real time of the bin. LoRa communication protocol is used to transmit data about the location, real time and filling level of the bin. RFID module is embedded for the purpose of waste management personnel identification [19].

**2.2 Intelligent waste management system using deep learning with IoT ( Rahman, M.W., Islam, R., Hasan, A., Bithi, N.I., Hasan, M.M. and Rahman 2022)**

Recent innovations in deep learning and the Internet of Things (IoT) provide advanced solutions for waste classification and monitoring which is crucial for minimizing environmental impact through recycling and landfilling. This paper discusses a novel architecture that employs a convolutional neural network (CNN) for the classification of digestible and indigestible waste, highlighting the strengths of deep learning in image recognition tasks. The design incorporates a smart trash bin equipped with a microcontroller and various sensors, leveraging IoT for real-time data management. Bluetooth connectivity facilitates short-range monitoring via an Android application, enabling users to manage waste efficiently. Studies have shown that IoT enhances operational efficiency by providing remote access to waste data, while the CNN model achieves a classification accuracy of 95.3125%, indicating high efficacy. Additionally, a System Usability Scale (SUS) score of 86% reflects the user-friendliness of the system. This architecture not only optimizes waste sorting but also adapts to household activities, promoting sustainable waste practices. The integration of these technologies signals a significant advancement in smart waste management systems, contributing to more efficient recycling processes and increased public engagement in waste reduction efforts [20].

**2.3 Hybrid model for the prediction of municipal solid waste generation in Hangzhou, China (Zhang, Zhang, and Wu 2020)**

Accurate forecasting of municipal solid waste (MSW) generation is essential for effective waste management and planning of disposal facilities. A recent study developed a hybrid model that combines ridge regression and GM (1, N) methodologies, significantly enhancing prediction accuracy. This multivariate model incorporates key factors such as urban population, retail sales, per capita consumption, tourism, and college graduation rates. The hybrid approach demonstrated superior performance, achieving a mean absolute percentage error (MAPE) of only 2.59%. By optimizing weight allocation and managing residuals, the model produced a smoother prediction curve that better reflects growth trends. Correlation analyses revealed that demographic, economic, and educational factors play significant roles in waste generation. Focusing on Hangzhou, the model forecasts a steady increase in MSW output, projecting it to reach approximately 5.12 million tons by 2021. These insights are crucial for policymakers, enabling them to design effective waste management strategies that respond to urban growth. This research not only advances understanding of waste generation dynamics but also provides practical tools for urban planners seeking to implement sustainable waste management practices in rapidly developing cities [21].

**2.4 Intelligent Waste Classification System Using Deep Learning Convolutional Neural Network (Adedeji and Wang, n.d., 2019)**

Effective waste management is increasingly reliant on innovative technologies, particularly in recycling and landfilling processes. A recent paper presents a robust architecture for a waste management system that integrates deep learning and the Internet of Things (IoT). This model leverages a convolutional neural network (CNN) to intelligently classify waste into digestible and indigestible categories, enhancing sorting efficiency. The proposed system includes a smart trash bin equipped with a microcontroller and various sensors. This design facilitates real-time data monitoring through IoT connectivity, allowing users to access waste management data remotely. Bluetooth functionality further enables short-range monitoring via an Android application, providing a user-friendly interface for tracking waste classification. Evaluation of the model's effectiveness revealed impressive results: the CNN-based classification achieved an accuracy of 95.31%, and the system usability scale (SUS) score reached 86%. These metrics underscore the potential of the smart waste management system to adapt to household activities, ensuring effective real-time waste monitoring. Overall, this research highlights the promise of combining deep learning and

IoT technologies to optimize waste management practices, paving the way for smarter, more efficient urban waste solutions [22].

### 2.5 Applied Machine Learning for Prediction of CO2 Adsorption on Biomass Waste-Derived Porous Carbons (Yuan et al., 2021)

Biomass waste-derived porous carbons (BWDPCs) represent a promising class of materials in sustainable waste management and carbon capture applications. Their complex textural properties, diverse functional groups, and varying conditions during CO2 adsorption present challenges in understanding the mechanisms involved. Recent research addressed these complexities by compiling a dataset of 527 data points from peer-reviewed sources to explore the relationship between CO2 adsorption and the textural and compositional characteristics of BWDPCs. Utilizing machine learning, the study employed various tree-based models, with gradient boosting decision trees (GBDTs) achieving exceptional predictive performance, exhibiting $R^2$ values of 0.98 for training data and 0.84 for test data. The BWDPCs were categorized into regular porous carbons (RPCs) and heteroatom-doped porous carbons (HDPCs), with GBDT models yielding $R^2$ values of 0.99 and 0.98 for RPCs and 0.86 and 0.79 for HDPCs on training and test datasets, respectively. Feature importance analysis highlighted the critical roles of adsorption parameters, textural features, and compositional properties, guiding the optimization of BWDPC synthesis for enhanced CO2 adsorption. This research underscores the potential of machine learning in advancing the understanding and development of materials for effective carbon capture, paving the way for improved environmental sustainability [23].

## III. Problem Statement

The increasing volume of waste generated in urban areas poses significant environmental challenges. Effective waste segregation at the source is crucial for recycling and waste management. Traditional manual segregation is inefficient and prone to human error, leading to contamination of recyclable materials and increased landfill waste. Thus, we aim at developing an automated waste segregation system to accurately classify and segregate waste items into predefined categories (e.g., plastic, paper, metal, organic, and others). The expected outcomes would be an increase in the efficiency of waste segregation processes, leading to improved recycling rates and reduced contamination of recyclable materials.

## IV. Proposed Methodology

The proposed model comprises three key components, namely the dataset, the smart bin system, and the waste classification process utilizing a convolutional neural network (CNN). Each of these segments plays a critical role in enabling an efficient and intelligent waste management solution.

### 4.1 Dataset

The dataset forms the foundation, providing the necessary input for training and testing. For this work, we are utilizing a dataset created by Sashaank Sekar [24]. It has been designed for waste classification, focusing on two categories: **organic** and **recyclable** waste shown in **figure 1 and 2** respectively. It contains images of household waste items and is divided into training and test sets, with 85% of the data (22,564 images) allocated for training and 15% (2,513 images) for testing. The purpose of this dataset is to automate the process of waste segregation by leveraging machine learning and IoT technologies, thereby aiding in more efficient waste management. Automation of waste segregation aims to minimize reliance on manual hand sorting. Through extensive research on waste management practices and analyzing the components of household waste, the dataset aims to reduce the amount of toxic waste ending up in landfills by correctly classifying items for recycling or organic processing, helping create a more sustainable environment.


(i) Organic waste


(ii) Recyclable waste

### 4.2 Smart Bin Modelling

Technologies used: Raspberry pi, Servo motor, Infrared sensor, camera. The proposed innovative smart bin system, shown in figure 3.1, aims to address the challenges of waste segregation, featuring a fiber lid as the primary interface through which refuse is sorted. This lid is positioned at the top of the bin and serves as a medium for initial waste classification and is equipped with a servo motor that automatically adjusts its orientation based on the type of waste identified. Figure 3.2 describes how each component has been placed inside the lid of the bin.

Figure 3.1 Smart Bin Model

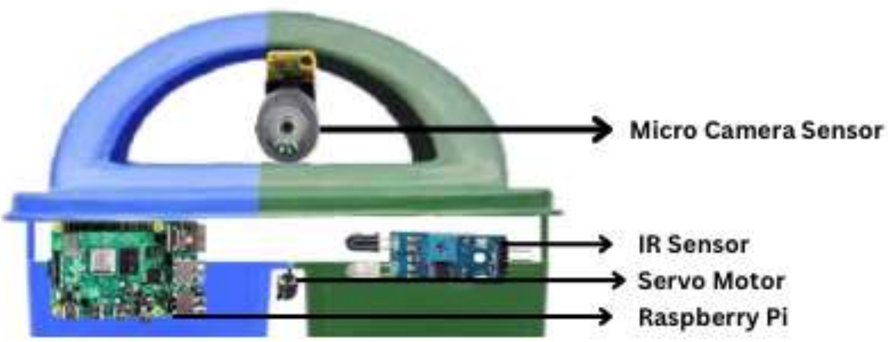


Fig 3.2 Placement of sensors in smart bin lid

The process begins when waste is placed onto the fiber lid, which triggers an infrared sensor. This sensor, sensitive to motion, scans and detects the presence of trash, immediately actuating the next phase of operation. Upon detecting motion, the system obtains a rough waste image, which is quickly followed by the capture of a detailed image using a camera integrated within the system.

These two images, one produced by the infrared sensor and the other by the high-resolution camera, are then fed into an enhanced image processing module for advanced comparison algorithms. The system employs the standard similarity testing based on deep learning architecture known as convolutional neural networks (CNN) for evaluating the similarity between the two images. If the degree of match exceeds a threshold accuracy of 88%, the Raspberry Pi controller processes the data, executing precise commands to activate the servo motor.

The motor then tilts the lid towards the appropriate section of the bin, ensuring that the waste is directed into one of two distinct sections—organic waste or recyclable (inorganic) waste. This autonomous system, driven by the concepts of machine learning and image recognition, enhances efficiency and accuracy in waste management which in turn significantly improves the segregation process.

By integrating advanced IoT technologies with advanced image analysis using machine learning algorithms, this smart bin represents a leap forward in automated waste sorting systems, offering a streamlined, intelligent solution for environmental sustainability.

### 4.3 Classifying Waste data using CNN algorithm

A classification methodology that employs a convolution neural network (CNN) model dramatically improves the precision and speed of waste classification processes, hence transforming recycling and disposal systems. Since Convolutional Neural Networks (CNNs) are proficient at processing visual inputs, they are the ideal technologies to adopt for waste classification, practice which mainly comprises visual data. The CNN algorithm is enabled to distinguish features such as texture, color, and shape after training on a large dataset consisting of images of different waste types that include plastic, paper, metallic, and organic wastes. Thereafter, the algorithm outlines those particular features found in a different set of images e.g. images of wastes, which she has never seen before and classifies them correctly. This mechanized system control encourages system quenching systems due to less manual sorting and also minimization of the human error aspects.

The ability of CNNs in classification and discrimination of the waste types plays a key role in enhancing the recycling process. When waste is sorted correctly, it can sometimes even be sent for proper recycling or even disposal. This stops individual recyclable materials such as plastics or mixed paper with food waste from being contaminated, for example, which will negatively affect the quality of the materials that are recycled. Further, accurately sorted waste means that more space will be available within landfills and incinerators, therefore more materials will be put into recycling and less into waste generation practices, enhancing the overall waste management strategy.

Besides precision, classifying system based on CNN is scalable and can provide room for total automation in the management of large-scale wastes. These systems can be embedded at waste processing plants which handle large amounts of waste whereby the algorithm is active for materials classification within a short duration. Since it is largely automated, there is optimal use of resources and labor cost is less because there are minimal personnel in the sorting activity. The waste management process can be fully automated by installing modern equipment, for example when CNNs for image classification are used with robotic arms or conveyor belts, and this improves productivity and environmental health.

The application of CNN technologies to radio waste management systems is in line with the current adoption of artificial intelligence and analytics for the efficiency of operations and enhancing green initiatives. It is useful in those scenarios considering the present and future trends of urbanization where smart cities have to incorporate productive and adaptive waste management systems. Waste management companies are turning to cost efficient and ecologically friendly services provision thanks to the ability of the CNN based classification to better recycling rates and reduce the costs of operations. The technology not only helps in improving the systems of recycling but also promotes the change to better waste management that conserves resources and is environmentally friendly.

## V. Results and Discussion

The prototype waste sorting gadget demonstrated significant potential in addressing the challenges of urban waste management in India. Two models were trained differing in input resolution size. Aggregate measures derived from compiling the models were used for evaluation such as training, validation, and testing accuracy and loss. For simplicity, the performance of the two models is reported together in **Table 5.1**.

Table 5.1 Minimum Loss and Maximum Accuracy for both models

| Input Resolution | Epochs | Loss (min) | | Accuracy (max) | |
|---|---|---|---|---|---|
| | | Validation | Testing | Validation | Testing |
| 244 x 244 | 10 | 0.5211 | 0.1566 | 0.7931 | 0.9444 |
| 128 x 128 | 10 | 0.2396 | 0.1878 | 0.9093 | 0.9285 |

However, the visualization of the results is represented separately. **Figure 5.1** shows the training/validation accuracy and loss in function of 10 epochs for the model (trained with 244x244 image resolution). Meanwhile, **Figure 5.2** shows the training/validation accuracy and loss in function of 10 epochs for the model (trained with 128x128 image resolution).

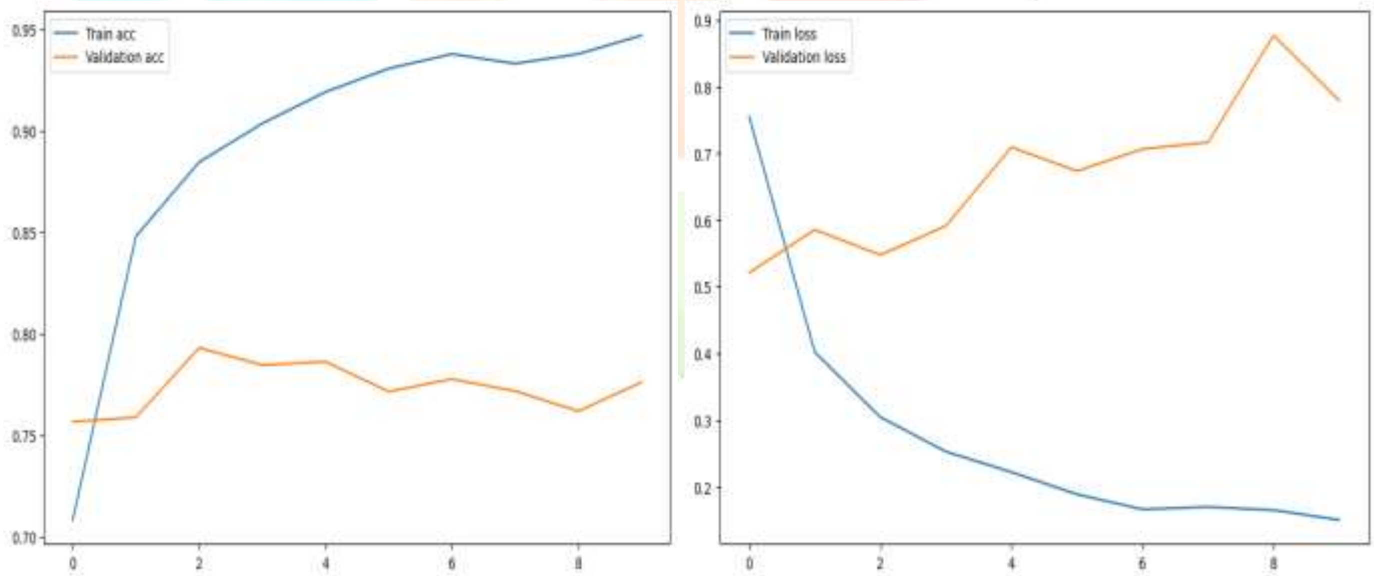


Figure 5.1. Training and Validation Accuracy and Loss (244x244 model)

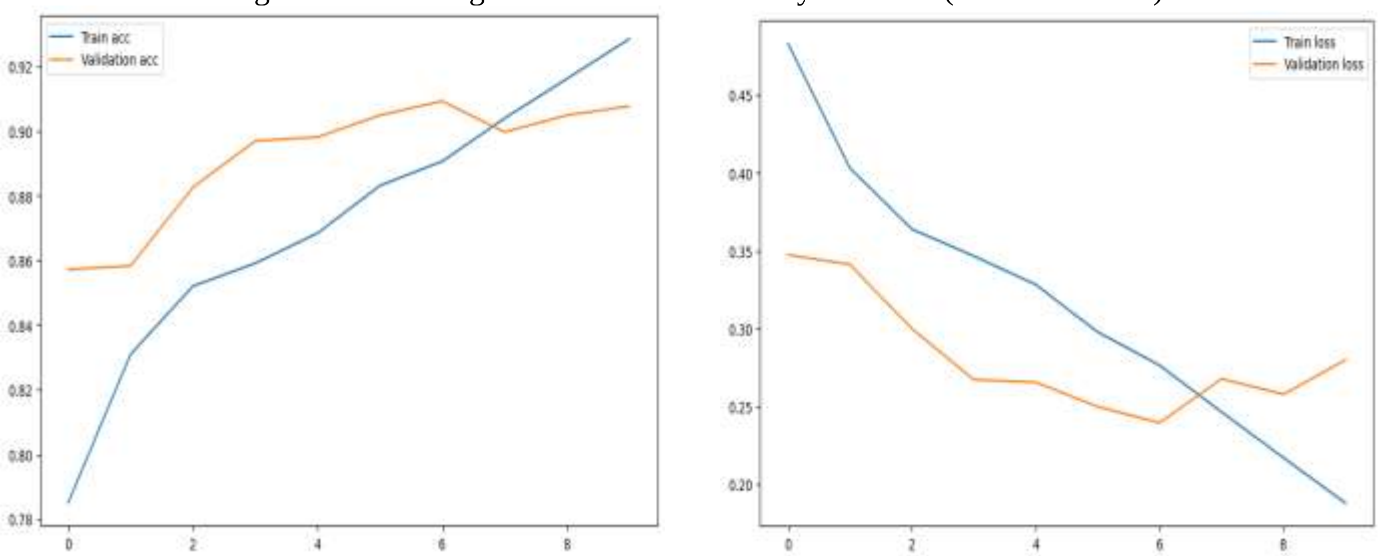


Figure 5.2. Training and Validation Accuracy and Loss (128x128 model)

For the model trained with an input resolution of 224x224 pixels, the results show that the minimum validation loss reached 52.11%, while the minimum testing loss was significantly lower at 15.66%. The model's accuracy in terms of performance reached a maximum validation accuracy of 79.31%, while the maximum testing accuracy was 94.44%. These results indicate that although the model showed good performance on the test set, it was not promising in validation, indicating overfitting or a failure to generalize well from the validation set.

On the other hand, the model trained with the input resolution of 128x128 pixels performed best during validation. The minimum validation loss achieved by this model was 23.96%, substantially lower than that of the 224x224 model, while the minimum testing loss was 18.78%. Furthermore, the model achieved a higher maximum validation accuracy of 90.93%, although its maximum testing accuracy, at 92.85%, was slightly lower than that of the 224x224 model. These results indicate that the 128x128 model performed better during validation and showed a more balanced performance between validation and testing, which could mean that it generalizes better.

In general, the 128x128 model performs better than the 224x224 model in terms of validation metrics, having a lower loss and higher accuracy, which may suggest that the smaller input size helped learn and generalize more efficiently during training. On the other hand, model 224x224 had higher testing accuracy, and this indicates it probably captured much more specific detail during training but at higher validation loss. This comparison outlines the trade-offs between input resolution and model performance, with the 128x128 model providing more consistent results across validations and testing, whereas the 224x224 model provided some signs of potential for a better performance on test data but lacked consistency in validation.

With a classification accuracy reaching a maximum 94% (244x244 model) and 92% (128x128 model) , the machine learning model effectively sorted waste into recyclable and compostable categories, ensuring reliable and efficient waste segregation. The integration of advanced image recognition technology and faster region-based convolutional networks (R-CNN) enabled real-time waste classification, allowing the gadget to identify not only the type but also the size of waste. This advanced capability provides a wealth of valuable data to enhance waste management processes. By offering precise information about waste composition and classification in real-time, the gadget allowed municipalities and waste management organizations to make informed decisions regarding collection and processing.

## VI. Conclusion

In conclusion, this research demonstrates the transformative potential of integrating artificial intelligence and user-centred design in waste management systems. The machine learning-based waste sorting gadget successfully bridges critical gaps in traditional practices by fostering greater public engagement and providing actionable insights to waste management companies. The results highlight the importance of leveraging technology to create sustainable urban environments. For future works, we hope for scaling the gadget for larger communities, incorporating multilingual interfaces, and adding features such as hazardous waste detection. This could further enhance its impact, paving the way for widespread adoption and significant environmental benefits.

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|  | **Shivangi Srivastava**, is an undergraduate student pursuing a Bachelor of Technology (B.Tech.) degree in Computer Science and Engineering at SRM University Delhi NCR. Throughout academic journey, has actively participated in various research projects and technical workshops, honing both theoretical and practical skills. |
|  | **Aaryan Gupta,** is an undergraduate student pursuing a Bachelor of Technology (B.Tech.) degree in Computer Science and Engineering at SRM University Delhi NCR. Throughout academic journey, has actively participated in various research projects and technical workshops, honing both theoretical and practical skills. |
|  | **Siddharth Gaur,** is an undergraduate student pursuing a Bachelor of Technology (B.Tech.) degree in Computer Science and Engineering at SRM University Delhi NCR. Throughout academic journey, has actively participated in various research projects and technical workshops, honing both theoretical and practical skills. |