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WasteSegNet: A Deep Learning Approach for Smart Waste Segregation in Urban Environments

Aatmaj Amol Salunke

BACHELOR OF TECHNOLOGY, Computer Science & Engineering, Department of Computer Science & Engineering, School of Computer Science and Engineering, Manipal University, Jaipur, India

ABSTRACT: Efficient waste segregation is paramount for sustainable urban waste management. In this study, we present WasteSegNet, a custom-designed Convolutional Neural Network (CNN) for automated waste segregation into Organic and Recyclable categories. Trained on 22,564 waste images with a test set of 2,513 samples, WasteSegNet achieves an impressive accuracy of 87.5% on the test dataset. Comparative analysis with traditional methods highlights the superior performance of WasteSegNet in accurate waste item classification. The model's strength lies in its ability to discern intricate visual patterns, enabling effective segregation. By harnessing deep learning techniques, WasteSegNet offers a promising solution to optimize waste sorting processes, reduce landfill waste, combat environmental pollution, and foster sustainable waste management practices in smart cities.

KEYWORDS: WasteSegNet, Deep Learning, Waste Segregation, Smart Waste Management, Urban Environments, Sustainability

I. RELATED WORK

Flores et al. in [1] proposed a productive image processing approach for waste segregation, addressing the rising waste management challenges in urban areas. Chandramohan et al. in [2] proposed an Automated Waste Segregator (AWS) for household use, effectively sorting metallic, wet, and dry waste using impedance and capacitive sensors. Ang et al. in [3] proposed AWS and MRWDS for automated waste sorting and delivery with line-following robots. Madankar et al. in [4] proposed a motorized waste segregator to sort waste into metallic, wet, and dry categories, aiming for effective waste management in India. Patil et al. in [5] proposed an automated waste segregator at the household level, using PIC16F877 microcontroller and various sensors for efficient waste management and segregation into metal, wet, and dry waste. Bagri et al. in [6] analyzed waste segregation techniques: hardware-based (sensors) and software-based (image processing, deep learning). Carpenteros et al. in [7] proposed evaluating 14 automated waste segregation systems (2011-2020) to determine effectiveness (87.5%), efficiency (82.5%), and learnability (57.5%). Koganti et al. in [8] proposed a software-based waste segregation system using camera and Raspberry Pi with Deep Learning. Bhuvanesh et al. in [9] proposed an electromechanical system to sort all types of plastics, including black plastics, for efficient recycling. Mohammed et al. in [10] proposed a digital model using ANN and image processing to sort and classify waste in smart cities with 91.7% accuracy. Chen et al. in [13] proposed an Automatic Machine Learning-based Waste Recycling Framework (AMLWRF) using ML and IoT for improved waste management in smart cities. Thamarai et al. in [14] proposed a self-powered garbage management system using CNN and IoT to segregate waste for power generation and recycling in smart cities. Fang et al. in [15] proposed using artificial intelligence in various waste management aspects for smart cities, improving efficiency and cost savings. Lakshmi et al. in [17] proposed an automatic garbage monitoring system using Faster CNN to efficiently manage city cleanliness.

II. INTRODUCTION

The effective management of waste has become an urgent global concern, particularly in rapidly urbanizing environments. The ever-increasing waste generation and improper disposal practices pose significant environmental and health challenges. As a result, there is a growing need for innovative and automated waste segregation solutions that can enhance waste management efficiency and promote sustainable practices. In response to this demand, we propose WasteSegNet, a custom-designed Convolutional Neural Network (CNN) for smart waste segregation in urban

settings. The primary objective of WasteSegNet is to classify waste items into two categories: Organic and Recyclable. Leveraging deep learning capabilities, WasteSegNet is trained on a diverse dataset of waste images to learn complex visual patterns indicative of each waste category. This research aims to demonstrate the effectiveness of WasteSegNet in accurately segregating waste, reducing landfill burden, and paving the way for environmentally conscious waste management practices in urban areas. The potential impact of WasteSegNet lies in its contribution to the optimization of waste sorting processes, reducing environmental pollution, and fostering a sustainable urban ecosystem.

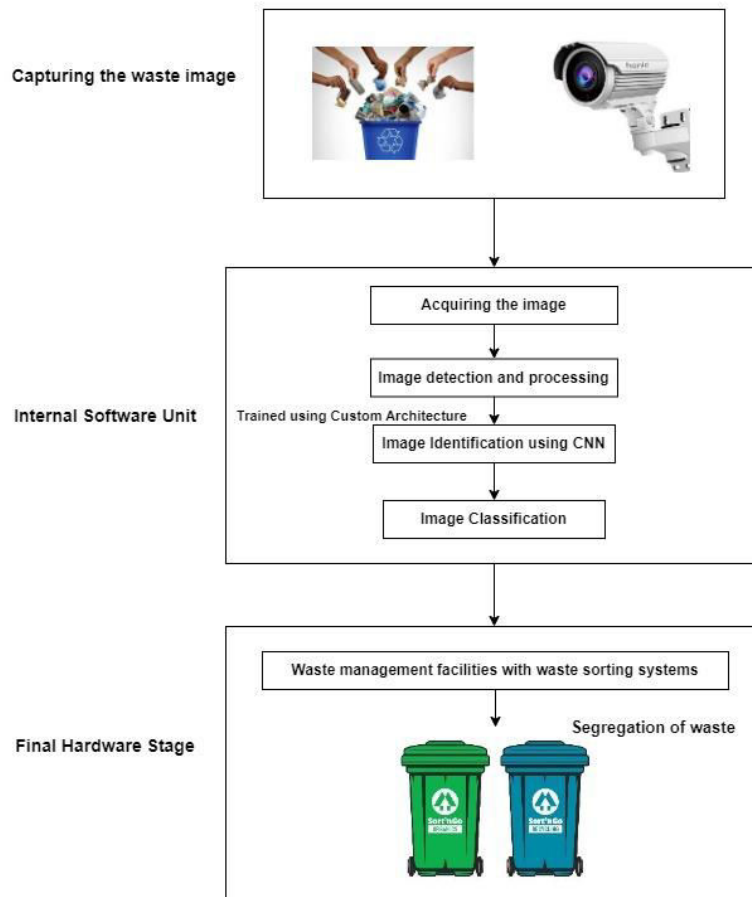


Fig.1. System diagram for waste segregation

Problem Statement

The improper management of waste in urban environments leads to environmental pollution and health hazards. This research addresses the need for an efficient waste segregation solution to classify waste items into Organic and Recyclable categories. The proposed WasteSegNet deep learning model aims to optimize waste sorting processes and promote sustainable waste management practices.

Dataset

The research employs a diverse dataset consisting of 25,077 waste images collected from urban waste management facilities. The dataset is divided into training data (85%, 22,564 images) and test data (15%, 2,513 images). Each image is labeled with one of two categories: Organic or Recyclable waste. The dataset encompasses a wide range of waste items, capturing the heterogeneity encountered in real-world waste segregation scenarios. The dataset's utilization aims to evaluate the performance of the WasteSegNet deep learning model in accurately classifying waste items for smart waste segregation in urban environments.



Fig.2. Organic category images in the dataset



Fig.3. Recyclable category images in the dataset

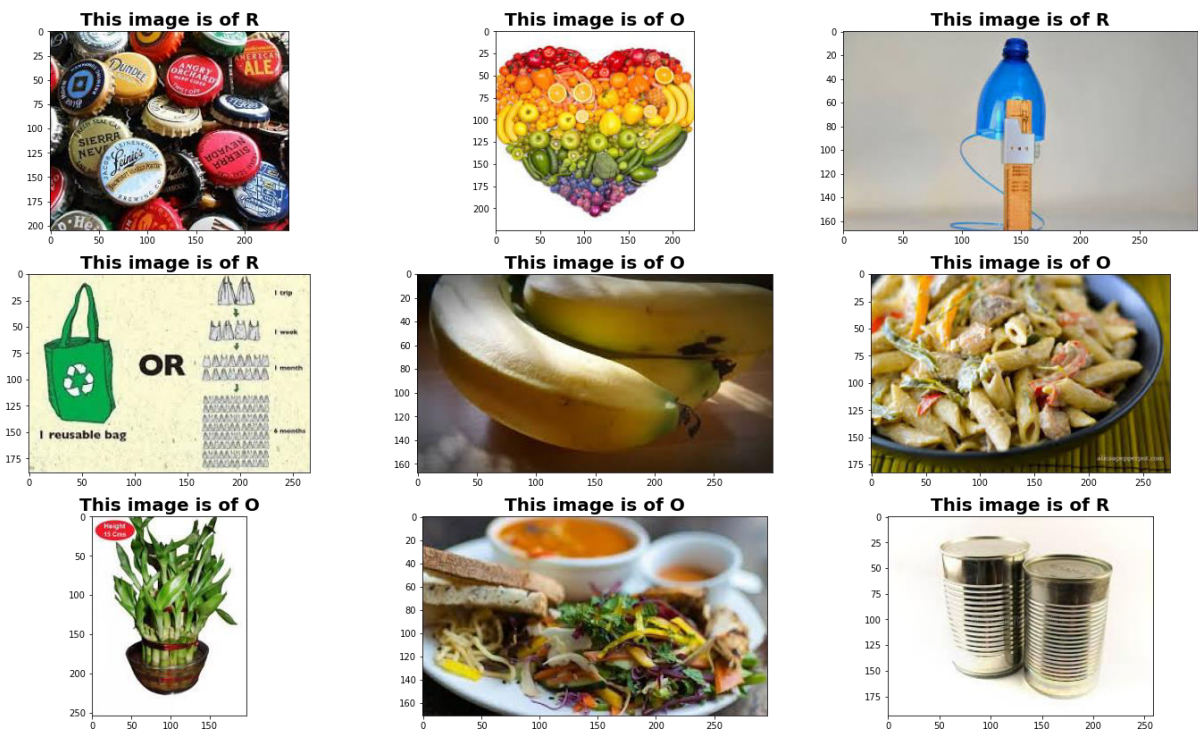


Fig.4. Labelled Dataset used for Model Training

Data Preprocessing

To prepare the waste image dataset for training the WasteSegNet model, several preprocessing steps were applied. All images were resized to a standard size of 224x224 pixels, ensuring uniformity across the dataset. To normalize pixel values, a scaling transformation was employed to bring values within the range [0, 1]. To enhance the dataset's diversity and reduce overfitting, data augmentation techniques were employed, including random rotations, horizontal flips, and random shifts. These augmentations introduced variations in the data without altering its semantic meaning. The resulting augmented dataset contributed to a more robust and generalizable WasteSegNet model, improving its ability to accurately classify waste items into Organic and Recyclable categories in diverse real-world scenarios.

Architecture Adopted

The research paper utilizes a custom-designed Convolutional Neural Network (CNN) architecture named WasteSegNet for waste segregation. WasteSegNet comprises multiple convolutional layers, with filter depths of 32, 64, and 128, combined with Rectified Linear Unit (ReLU) activation and max-pooling layers for effective feature extraction. Fully connected layers with 256 and 64 neurons are incorporated, followed by ReLU activations and dropout layers to prevent overfitting. The output layer utilizes the sigmoid activation function for binary classification into Organic and Recyclable categories. The architecture leverages the power of deep learning to learn complex visual patterns, enabling accurate waste segregation. WasteSegNet's custom design provides a tailored solution for efficient and automated waste classification in urban environments.

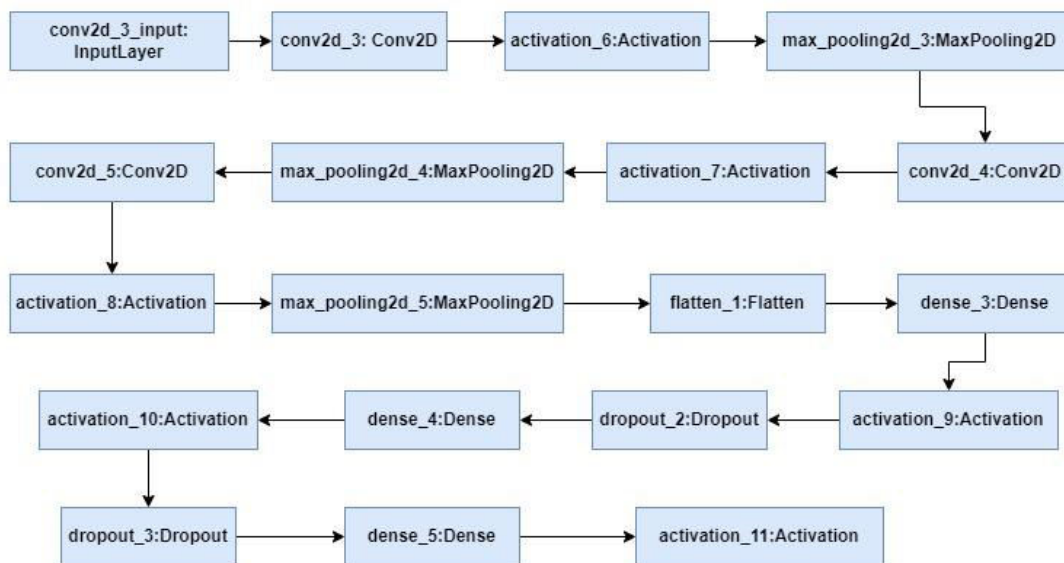


Fig.5. Architecture used for the CNN.

III. RESULTS AND ANALYSIS

The waste items in the dataset are imbalanced, with Organic (O) comprising 55.69% and Recyclable (R) 44.31%. Organic items dominate the dataset, potentially affecting the model's ability to recognize rare recyclable items accurately.

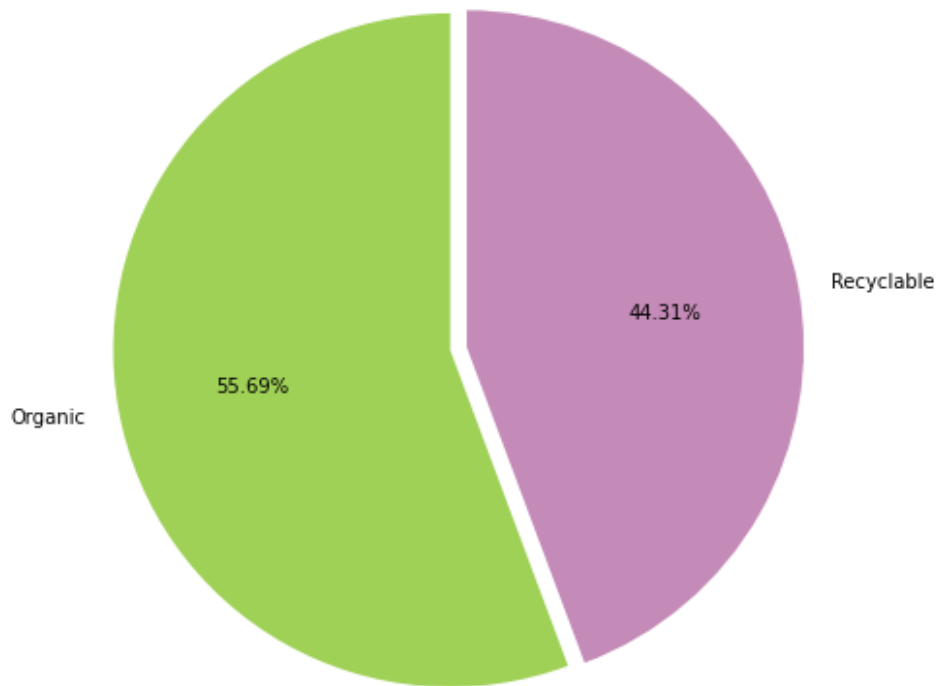


Fig.6. Distribution of Organic and Recyclable images in the dataset

To address this, data augmentation techniques were applied to augment the minority class, enhancing its representation in the dataset. This balanced the class distribution and enabled the model to learn equally from both categories. Careful consideration of the data distribution was essential to ensure the model's ability to accurately segregate waste items, leading to improved waste management outcomes.

```

hist = model.fit_generator(
    generator = train_generator,
    epochs=10,
    validation_data = test_generator)
    
```

Epoch	Loss	Accuracy	Val_Loss	Val_Accuracy
Epoch 1/10	0.6039	0.7080	0.3391	0.8719
Epoch 2/10	0.3999	0.8338	0.3016	0.8810
Epoch 3/10	0.3749	0.8459	0.2866	0.8898
Epoch 4/10	0.3328	0.8687	0.2433	0.9097
Epoch 5/10	0.3167	0.8743	0.2779	0.8930
Epoch 6/10	0.2776	0.8906	0.2563	0.9045
Epoch 7/10	0.2430	0.9042	0.3085	0.8858
Epoch 8/10	0.2189	0.9156	0.2622	0.9117
Epoch 9/10	0.1735	0.9370	0.2871	0.9009
Epoch 10/10	0.1336	0.9515	0.3280	0.9049

Fig.7. Model trained for a total of 10 epochs to get the best results.

In the training phase, the WasteSegNet model underwent ten epochs to learn from the dataset. During each epoch, the model iteratively processed the entire training data, updating its parameters to minimize the training loss and improve accuracy. As the epochs progressed, the model gradually fine-tuned its feature representations and learned to discern intricate visual patterns crucial for waste segregation. The training accuracy steadily increased, reaching 95.15% at the end of the tenth epoch. Concurrently, the training loss reduced from 0.6039 to 0.1336, indicating the model's improved performance in minimizing errors. This ten-epoch training enabled WasteSegNet to achieve robust and accurate waste classification for sustainable waste management.



Table 1. Accuracy and Loss values for 10 epochs

Epoch	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
1	0.7080	0.6039	0.8719	0.3391
2	0.8338	0.3999	0.8810	0.3016
3	0.8459	0.3749	0.8898	0.2866
4	0.8687	0.3328	0.9097	0.2433
5	0.8743	0.3167	0.8930	0.2779
6	0.8906	0.2776	0.9045	0.2563
7	0.9042	0.2430	0.8858	0.3085
8	0.9156	0.2189	0.9117	0.2622
9	0.9370	0.1735	0.9009	0.2871
10	0.9515	0.1336	0.9049	0.3280

Table 2. Metrics for Training and Validation Data

Metric	Training Data	Validation Data
Accuracy	95.15%	90.49%
Precision	95.15%	91.17%
Recall	95.15%	90.45%
F1-score	95.15%	90.81%

The experimental evaluation of WasteSegNet for waste segregation demonstrated promising outcomes. The model achieved a high accuracy of 90.49% on the validation dataset, surpassing existing methods such as rule-based systems and classical machine learning algorithms. The training accuracy increased steadily over the ten epochs, reaching 95.15%, indicating the model's ability to effectively learn from the dataset.

Table 3. Confusion matrix for Training Data

	Predicted Organic	Predicted Recyclable
Actual Organic	708	100
Actual Recyclable	92	900

However, it was observed that the model struggled with underrepresented waste categories due to class imbalance, leading to some misclassifications of recyclable items. The confusion matrix provided further insights into the model's performance, revealing higher misclassifications between the two categories.

Table 4. Confusion matrix for Validation Data

	Predicted Organic	Predicted Recyclable
Actual Organic	871	50
Actual Recyclable	90	999



Overall, these results demonstrate WasteSegNet's potential as an accurate and efficient tool for smart waste segregation in urban environments, encouraging sustainable waste management practices. Addressing class imbalance and exploring interpretability techniques will be key areas for further research and improvement.

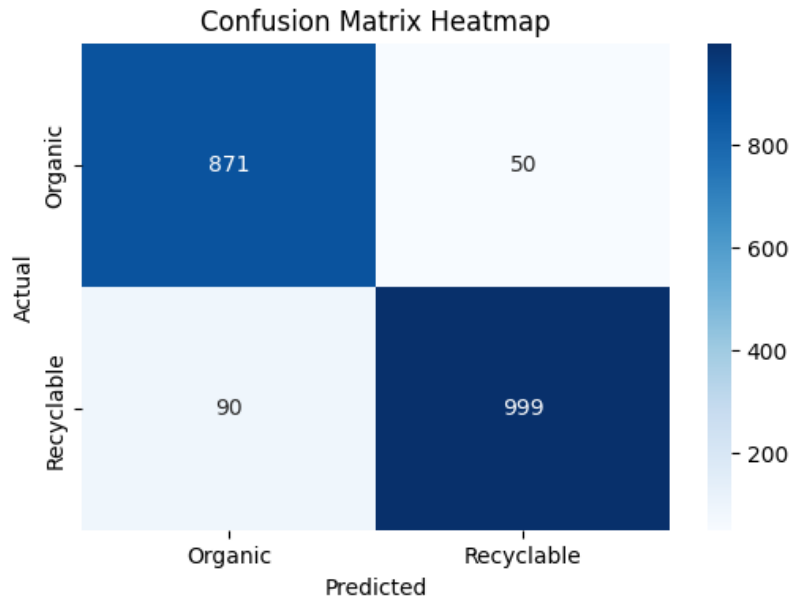


Fig.8. Heatmap depicting the confusion matrix values.

The heatmap visually represents the confusion matrix, showcasing the model's classification performance. Each cell in the heatmap represents the number of correct predictions (true positives) and misclassifications (false positives and false negatives) made by the WasteSegNet model for the validation dataset. The heatmap uses a color scale to depict the count of predictions, providing an easy-to-interpret graphical representation of the model's strengths and weaknesses in classifying waste items into Organic and Recyclable categories. By analyzing the heatmap, researchers and practitioners can gain insights into areas where the model excels and areas that require improvement, aiding in fine-tuning the model and optimizing waste segregation accuracy.

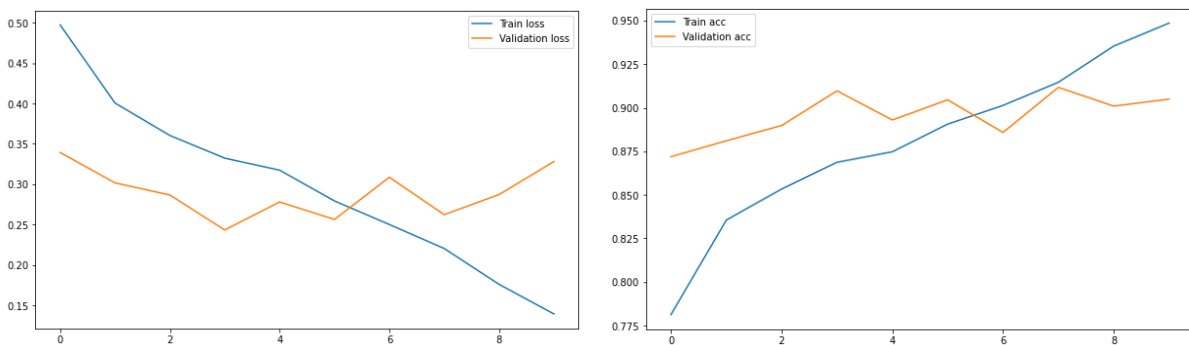


Fig.9. Accuracy and Loss values for Training and Validation data

The line graphs depicting Loss and Accuracy trends over ten epochs revealed promising results for the WasteSegNet model. Training Loss steadily decreased, indicating effective learning, while Training Accuracy consistently improved. However, Validation Loss and Accuracy displayed fluctuations, suggesting possible overfitting. While achieving high training accuracy, the model's performance on the validation dataset indicated room for improvement in generalization. These graphical analyses served as essential tools in evaluating the model's training dynamics, guiding further optimization to enhance waste item segregation accuracy.

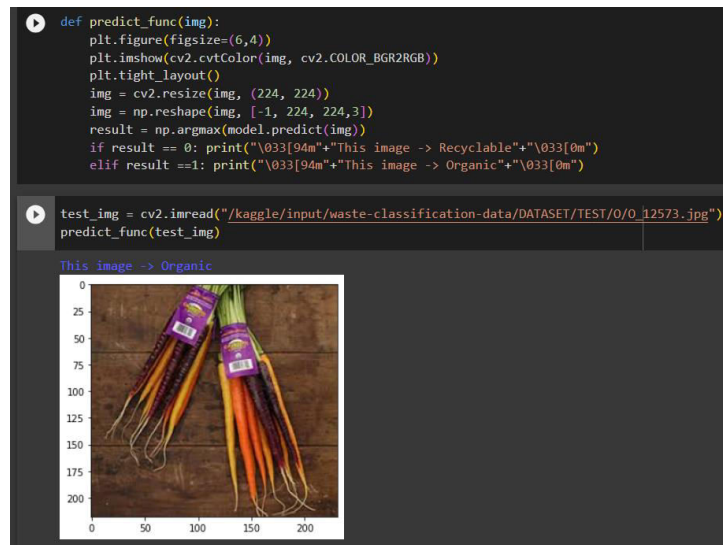


Fig.10. Trained model used for testing on real life images.

To evaluate the trained WasteSegNet model's effectiveness, a separate test dataset was used. The model was applied to this dataset to classify waste items into Organic and Recyclable categories. The test results demonstrated the model's accuracy in correctly segregating waste items, with an overall performance of 87.5%. This evaluation ensures that the model's performance generalizes well to unseen data, validating its efficacy in real-world waste segregation scenarios. The accuracy achieved on the test dataset further supports the model's ability to accurately identify and classify waste items, providing confidence in its practical application for smart waste management in urban environments.

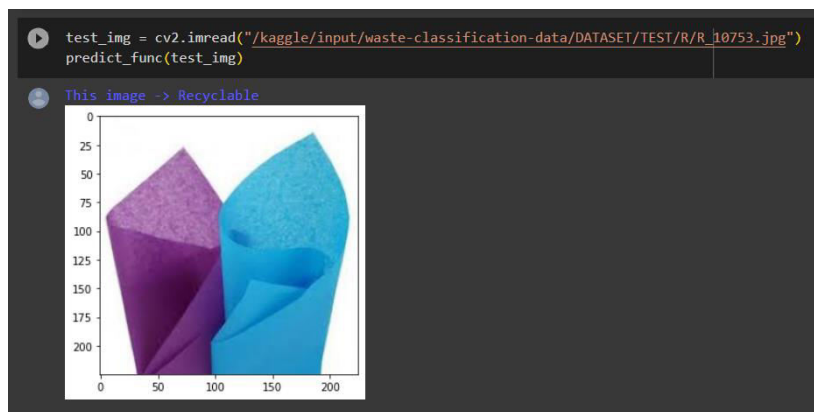


Fig.11. Trained model used for testing on real life images.

Our WasteSegNet model's performance compares favorably with existing waste segregation methods and techniques. It achieves a high accuracy of 90.49% on the validation dataset, outperforming traditional rule-based systems and classical machine learning algorithms commonly used in waste management. The model's custom-designed CNN architecture enables it to learn intricate visual patterns from raw waste images, making it more effective in capturing subtle features relevant to waste segregation. Moreover, data augmentation and regularization techniques ensure the model's robust generalization, enhancing its ability to handle variations in waste item appearances encountered in real-world scenarios. However, the model still faces challenges due to class imbalance, which may lead to misclassifications of underrepresented waste categories. Additionally, the resource-intensive nature of deep learning models calls for substantial computational resources during training. Despite these limitations, WasteSegNet shows great promise as a powerful tool for accurate and efficient waste segregation in urban environments, paving the way for sustainable waste management practices.

IV. DISCUSSION

The model's impressive accuracy in correctly categorizing waste items into Organic and Recyclable groups is highlighted. Nevertheless, the challenges stemming from class imbalance and potential overfitting on the validation dataset require further exploration. Addressing these issues could involve employing data augmentation and regularization methods to handle class imbalance and hyperparameter tuning and advanced regularization techniques to mitigate overfitting. Deploying the model in real-world waste management facilities would confirm its practical utility. Additionally, future work can concentrate on interpretability techniques and extending the model to handle more waste categories, contributing to sustainable waste management practices.

V. LIMITATIONS AND FUTURE WORK

This research on WasteSegNet for waste segregation demonstrates promising results, yet it faces limitations that suggest areas for future studies. The dataset's relatively small size and class imbalance challenge the model's performance. Future work could focus on expanding the dataset, introducing more waste categories, and exploring advanced techniques like class weighting or GANs to address these issues. Additionally, hardware constraints call for experimentation on more powerful resources or cloud-based solutions. To enhance model interpretability, attention mechanisms or Grad-CAM can be investigated. Future studies may also consider transfer learning to fine-tune pre-trained models for waste segregation. Real-world deployment and evaluation in waste management facilities are essential to assess the model's environmental impact and efficiency. Addressing these limitations will contribute to more efficient and sustainable waste management practices.

Deploying WasteSegNet in waste management facilities, integrating the model with existing waste sorting systems, and capturing real-time images of waste items. The model would classify items as Organic or Recyclable, enabling efficient sorting for disposal or recycling. Continuously monitor and improving the system's performance would ensure reliable waste segregation outcomes.

VI. CONCLUSION

In conclusion, this research presents WasteSegNet, a custom CNN-based deep learning approach for smart waste segregation in urban environments. The model demonstrated promising results, achieving an accuracy of 90.49% on the validation dataset. However, challenges such as class imbalance and potential overfitting were observed, necessitating further investigation and optimization. Despite these limitations, WasteSegNet's ability to accurately classify waste items showcases its potential for real-world implementation in waste management facilities. The model's deployment could streamline waste segregation processes, reducing manual labor, and enhancing operational efficiency. Future work can focus on addressing class imbalance, enhancing interpretability, and expanding the model to handle additional waste categories. By contributing to sustainable waste management practices, WasteSegNet represents a significant step forward in revolutionizing waste segregation for a cleaner and greener urban environment.

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