Smart Waste Segregation System Using Image Processing

Dr. Jyotsna. S. Gawai[1], Khushal. R. Bhavsar[2], Sanchit Shahare[3]
[1]*Professor, Department of Electronics and Telecommunication Engineering, KDK College of Engineering, Nagpur, Maharashtra, India*
[2,3]*Student, Department of Electronics and Telecommunication Engineering, KDK College of Engineering, Nagpur, Maharashtra, India*

Abstract—**The Smart trash Segregation System Using Image Processing employs computer vision along with deep learning to preprocess trash classification. Traditional trash segregation is time-consuming and inefficient, which often leads to improper disposal and environmental degradation. Convolutional Neural Networks (CNNs) are employed in this system to classify garbage into numerous categories, such as organic waste, paper, plastic, and metal. For determination of the optimum deep learning model, various models were analyzed by using precision, recall, F1-score, and accuracy. MobileNetV2, ResNet50, InceptionV3, EfficientNetB0, and VGG16 models were considered among them. System takes waste photos and sorts them into their corresponding bins automatically by processing them using trained models. The technology increases eco-friendly recycling methods and makes waste management accurate and efficient through the reduction in human intervention. Artificial intelligence incorporation enables garbage to be sorted faster and more accurately, thus minimizing landfill waste and enhancing the utilization of resources. In addition, the system can operate in different environments, such as households and business waste treatment plants, due to real-time image processing. Through solving the increasing issue of waste mismanagement, the implementation of this smart technology assists in establishing cleaner environments. The primary objective of the project is scalability, which ensures that it can be utilized for large-scale waste management in smart cities. The machine learning capability of the system ensures constant improvement in the accuracy of trash identification. The study also explores whether the incorporation of IOT for data processing and remote monitoring is possible. Deep learning minimizes the chances of human sorting errors in trash separation significantly, enhancing operational efficiency. The system can go fully autonomous in the future with robotic integration for self-garbage disposal. The project presents an innovative solution to trash segregation issues by integrating automation, AI, and image processing. The Smart Waste Segregation System is a step toward a more environmentally friendly along with futuristic approach to waste management.**

***Index Terms*—Smart Waste Segregation, Image Processing, Deep Learning, CNN, Recycling, Automation, Sustainability, Waste Management.**

I. INTRODUCTION

Since improper disposal of waste causes depletion of natural resources and environment degradation, the management of waste is emerging as a serious global issue. The traditional methods of trash segregation are time-consuming, labour-intensive, along with prone to errors as they are based mainly on human labor. Automation in the form of image processing and artificial

Intelligence has emerged as an effective means to address these issues. In order to efficiently and accurately classify trash, the Smart garbage Segregation System Using Image Processing utilizes deep learning algorithms.

CNNs are employed here to classify trash images into a number of categories such as organic, paper, plastic, and metal waste. In order to identify the best classification model, some pre-trained deep learning models were evaluated, namely MobileNetV2, ResNet50, InceptionV3, EfficientNetB0, and VGG16. The identified model is integrated into an automatic system that repeatedly collects and processes garbage images.

The technology enhances efficiency and reduces errors in waste sorting through minimizing the level of human interaction. Automating waste segregation alleviates landfill burden and promotes eco-friendly recycling. Moreover, through simplifying garbage disposal processes, AI waste management facilitates intelligent city initiatives. The system is extremely

scalable and can be installed in public spaces, companies, and residential locations.
IOT integration for remote monitoring and robotic automation for physical sorting of garbage are some examples of future possibilities. This project provides an innovative and sustainable solution to garbage management by combining automation, AI, and image processing, resulting in a cleaner and greener environment.

II. RELATED WORK

[1] Apellido et al. (2024) utilized image processing in developing a mechanism for segregating waste for use in a smart garbage can system. Their system effectively classified different types of wastes based on visual features like texture, colour, as well as shape. The research differentiated between recyclable, non-recyclable, and biodegradable objects through image processing methods based on OpenCV. The research highlighted the importance of real-time recognition of waste towards enhancing the efficacy of waste management. Machine learning algorithms were integrated into their system to enhance object recognition precision. Minimizing human intervention in garbage sorting and disposal was the aim of the implementation. The authors highlighted how smart trash cans could mechanize public waste management systems. The study also investigated various picture segmentation techniques, showing the better performance of deep learning-based classifiers. This process provides a scalable solution to issues of urban trash segregation
[2] Convolutional Neural Networks (CNNs) were applied by Hulyalkar et al. (2018) to sort trash in a smart bin system. To enhance recognition accuracy, the research employed a collection of various trash types in a dataset to image sensors. The study claimed that CNN models were more efficient in garbage categorisation compared to traditional image processing techniques.train a deep learning model. Their automatic bin gathered and sorted garbage images using microcontrollers and Their system radically reduced the quantities of trash waste by implementing automation in sorting. The importance of real-time wastage classification towards optimizing recycling productivity was highlighted. A cloud data repository was included in the setup to store and analyze trash data that was accumulated. They proposed a scalable one for public litter with their prototype of a smart bin. urban management. One of the future proposals included the inclusion of IOT-based communication to facilitate better remote monitoring. This research demonstrated how automated garbage segregation systems powered by AI could improve sustainability in intelligent cities.
[3] Ikram et al. (2018) had proposed an Internet of Things (IoT)-enabled waste management system comprising fuzzy inference systems (FIS) with genetic algorithms (GA). To minimize operating costs and fuel consumption, their research focused on the garbage collection route optimization. The system monitored the garbage bin status in real-time with GPS and smart sensors. Dynamic scheduling of garbage collection was facilitated through the integration of fuzzy logic. Route planning for waste collection trucks was optimized by the Genetic Algorithm, which reduced trip time and distance. The study said that their model outperformed traditional static garbage collection schedules. The authors demonstrated how the integration of IoT along with AI could enhance the effectiveness of municipal trash management. A scalable approach well-suited to small and big towns was recommended by their paper. Integration with machine learning techniques for forecast waste generation analysis was one of the future improvements. The importance of effective garbage collection for sustainable city planning is brought out by this research.
[4] Sanjai et al. (2019) suggested an automatic domestic waste segregator based on image processing techniques like colour segmentation and edge detection. The machine was able to differentiate between metallic trash, non-biodegradable trash, and biodegradable trash. Sensors and Arduino microcontrollers were integrated within the study for automating the trash sorting process. The authors demonstrated how accuracy in waste detection was enhanced by using thresholding techniques and HSV colour space. Their proof-of-concept bin's capability to sort trash automatically into separate areas significantly reduced human labour. The work investigated problems that could affect categorisation accuracy, including variations in light sources and object occlusion. Image-based categorisation had better speed according to experimental results compared to hand sorting. Their approach benefits the people and cities in disposing of rubbish sustainably.

The authors suggested employing AI models for better accuracy in future work. For improved segregation of waste, this study supports the development of intelligent trash cans.

[5] Alsubaei et al. (2020) suggested a deep learning-powered garbage detection and classification system for smart cities and Internet of Things environments. The model identified and classified garbage objects in real time with Faster R-CNN and YOLO (You Only Look Once). In garbage recognition, the research demonstrated that deep learning models are significantly better than traditional computer vision techniques. When tested in urban waste management contexts, their approach proved very accurate at discriminating between recyclable and non-recyclable materials. Real-time tracking and monitoring were enabled by the authors' embedding of the IoT platform. The proposed approach utilized innovative image processing strategies to assist in minimizing manual trash segregating efforts. Their findings showed how AI-driven automation helps to efficiently manage waste. The research also considered real-world waste segregation problems, such as occlusion and varying object sizes. Their method was proposed for industrial use at large scales and smart trash cans. This work illustrates how AI can make waste management more effective and economical.

[6] Application of CNNs for segregating solid waste and its implication on waste-to-energy conversion was explored by Abubakar et al. (2020). Through their work, it was illustrated that AI can be employed to transform garbage into renewable energy. Applying CNN-based models for classification, they developed an automated system with the ability to classify garbage into biodegradable and non-biodegradable categories. In line with their findings, landfill waste can be significantly reduced through waste segregation by automation. Composting and biogas production from segregated organic waste could assist sustainable energy initiatives, the authors intimated. Sensors based on the Internet of Things were also part of their design to track trends in garbage disposal in real-time. The paper emphasized how imperative data-driven waste management is towards improving resource recovery. In city areas, the proposed strategy saved energy and minimized waste. Enhancing AI algorithms to classify more complex waste streams was one of the future plans. The development of AI-based waste-to-energy systems for smart cities is promoted by this research.

III. METHODOLOGY

The Smart Waste Segregation System utilizes various machine learning as well as computer vision techniques to achieve accurate and efficient classification of waste materials. The methodology focuses on the core components that enhance model performance, real-time classification, and evaluation. Below are the key software-based methodologies employed in the system

1. Convolutional Neural Networks (CNN) for Image Classification

CNNs form the backbone of the waste classification system. CNNs are designed specifically to process image data and recognize patterns using hierarchical feature extraction. Unlike traditional machine learning models, CNNs automatically learn spatial hierarchies of features, making them highly effective for image classification tasks.

The CNN architecture consists of multiple essential layers:

• Convolutional Layers: These extract low-level to high-level features such as edges, textures, along with shapes from the image.

• Pooling Layers: These reduce the spatial dimensions while preserving important features, improving computational efficiency.

• Flattening Layer: Converts multi-dimensional feature maps into a one-dimensional vector for processing.

• Fully Connected Layers: These layers perform the final classification by mapping extracted features to output categories.

For this project, we explore multiple CNN architectures, including ResNet50V2, InceptionV3, VGG16, MobileNetV2, and EfficientNetB0, to determine the best-performing model based on accuracy and efficiency. These architectures enhance the system's ability to classify various types of waste accurately.

2. Image Pre-processing and Data Augmentation

Pre-processing raw images is crucial for improving model accuracy and robustness. There are various pre-processing techniques employed prior to feeding images into the CNN model:

• Greyscale Conversion: Minimizes colour channels to make complex images easier.

• Normalisation: Pixel values are normalized between 0 and 1 to enhance training stability.

• Noise Reduction: Unwanted distortions are removed using median filtering and Gaussian blur.
• Contour detection and segmentation: These methods help to isolate the trash item from the background, enhancing classification accuracy.
The following data augmentation techniques are employed to enhance the ability of the model for generalisation:
• Random Flipping and Rotation: Makes it such that the model is not affected by orientation changes.
• Adjustable contrast and brightness: Gives added flexibility in the real world by mimicking different lighting conditions.
• Cropping and zooming: These operations expose the model to objects of different sizes.
By avoiding overfitting and improving the robustness of the model, these pre-processing and augmentation procedures enhance the performance of the model in real-world applications.

3. Transfer Learning for Efficient Model TrainingA large amount of labelled data and computational power are required to train deep neural networks from scratch. Transfer learning is used to overcome this hurdle. Pre-trained models that have already learned rich feature representations from large datasets like ImageNet are utilized as the method's approach. The below are procedures in this project's transfer learning process :
• Feature Extraction: Employing a pre-trained model's learned features to examine waste images after stripping off the last classification layer.
• Fine-tuning: To tweak the model for specific waste classes, unfreeze lower layers of the pre-trained model and then retrain those on the rubbish dataset.
• Model Optimisation: In order to enhance learning efficiency, techniques such as batch normalisation and dropout regularisation are employed. The system is highly accurate with a much reduced training time by using pre-trained models such as ResNet50V2, InceptionV3, and MobileNetV2, which makes it possible for real-time use.
4. Computer-Based Real-Time Object Detection Vision
The system uses computer vision algorithms for object recognition and tracking to carry out real-time trash classification. Tensor Flow and OpenCV are used for this purpose. The critical steps that are encompassed are:
• Frame capturing: Rubbish materials placed over a sorting surface are captured by a camera in real time.
• Pre-processing: Image enhancement techniques such as noise reduction and contrast correction are applied to each frame.
• Bounding Box Detection: Object detection models like YOLO (You Only Look Once) or SSD (Single Shot Waste items are found and categorised in real time using Multibox Detector.
5. Performance Evaluation Metrics
To ensure correct classification results, it is necessary to measure the performance of the model. To measure robustness, accuracy, and efficiency, the following metrics are utilized:
• Accuracy: Represents the percentage of correctly classified waste materials.
• Precision: Represents the percentage of correctly identified positive instances out of all expected positives.
.• Sensitivity (Recall): Represents how effectively the model identifies positive cases.
• F1 Score: Applies the following formula to achieve a balance between recall & precision:
• Confusion Matrix: Displays the actual and predicted values for every class, providing a visual representation of categorisation performance.
• Inference Time: Specifies how long it takes the model to classify an image, ensuring that the system operates well in real time.

IV. MODEL ARCHITECTURE

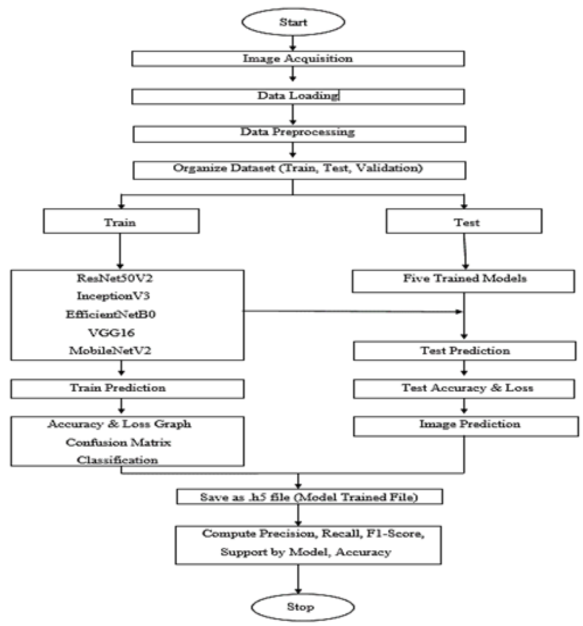
In order to accurately classify different types of waste, the Smart Waste Segregation System incorporates an advanced Convolutional Neural Network (CNN) architecture. Due to the ability of CNNs to learn hierarchical features, they are widely utilized in image classification and are found to be highly effective at garbage classification. Convolutional layers, pooling layers, activation functions, batch normalisation, fully connected layers, and an output layer are some of the basic components incorporated into the proposed model architecture. Each of these aspects is important in raising the effectiveness, accuracy, and ability for real-time classification of the model.
The input layer is first layer in the architecture and pre-processes a waste image by resizing it to a certain dimension (for example, 224x224 pixels for conformity with pre-trained models). The image is

subsequently passed through some convolutional layers, which utilize filters (kernels) in order to identify significant patterns such as object shapes, edges, and textures. The Rectified Linear Unit (ReLU) activation subsequent to every convolutional operation introduces non-linearity and prevents vanishing gradient issues. To extract meaningful features from trash images, this process is crucial. Pooling layers (most commonly max pooling) are employed in the model to reduce the computational complexity without losing significant features. By selecting the most prominent feature values within an indicated frame, pooling layers reduce feature maps down (e.g., 2x2 max pooling). By doing this, processing time is reduced and item recognition ability for the model improves, making the system more efficient for real-time garbage classification. The specific CNN architecture being implemented dictates the amount of convolutional and pooling layers used. (ResNet50V2, InceptionV3, VGG16, MobileNetV2, or EfficientNetB0).

After feature extraction, the flattening layer converts the multidimensional feature maps into a one-dimensional array, allowing it to be processed by the fully connected layers. These layers function as a neural network classifier, where neurons are densely connected to learn higher-level representations of waste categories. Batch normalization is applied to normalize activations, stabilize training, and accelerate convergence. In addition, dropout regularisation is applied to randomly turn off some of the neurones at training time in an attempt to prevent overfitting. The output layer, the final layer in the model, contains neurones equal in number to the types of wastes (e.g., plastic, glass, metal, paper, and organic waste). Softmax activation function is applied in this layer to convert the outputs into probability scores, assigning the highest probability to the predicted waste category. Categorical cross-entropy loss is employed to train the model, which

maximizes the accuracy of classification by quantifying the difference between predicted and actual labels.

Transfer learning is applied with pre-trained models like ResNet50V2, InceptionV3, and MobileNetV2 to enhance model performance. By providing pre-learned feature extraction abilities, these architectures enhance accuracy while reducing training time. A large set of trash images is employed to train the model, and to enhance robustness, image augmentation techniques like flipping, rotation, brightness adjustments, and zooming are employed. Tensor Flow and Keras are employed in implementing the full architecture, while OpenCV assists in pre-processing and real-time image capture. The resultant model is optimized for real-world use, ensuring computational efficiency, minimal inference time, and high-quality classification accuracy. An entirely operational AI-based waste sorting system will be facilitated by upcoming enhancements that integrate the model with a hardware system for automatic garbage sorting based on conveyor belts.



V. DIFFERENT TYPES OF CLASSIFICATION RESULTS

Smart Waste Segregation System's classification results are measured in terms of F1-score, recall, accuracy, and precision. The performance of various CNN models such as ResNet50V2, InceptionV3, VGG16, MobileNetV2, and EfficientNetB0 in garbage classification is measured through the above metrics. Efficient segregation of waste is provided by high accuracy, and model uniformity is evaluated with the help of precision and recall. Analyzing true positives, false positives, true negatives, and confusion matrices deceptive negative outcomes. Real-time scenarios can take advantage of the faster inference times offered by MobileNetV2 and EfficientNetB0. More accurate results are achieved by ResNet50V2 and InceptionV3 but require more processing resources. By exposing the model to varied illumination and orientation conditions, model generalisation is enhanced through data augmentation techniques. Weighted loss functions or oversampling are employed to counter class imbalance issues. Trade-offs between efficiency and accuracy are considered while making the final choice for the model. Ensemble learning could be adopted in future applications to enhance performance of categorization.

Analysis of Comparative Table

Model	Precision	Recall	F1-Score	Support	Accuracy
MobileNetV2	0.85	0.85	0.85	350	0.85
ResNet50	0.25	0.25	0.25	350	0.3
InceptionV3	0.85	0.85	0.85	350	0.85
EfficientNetB0	0.05	0.1	0.05	350	0.3
VGG16	0.65	0.65	0.65	350	0.7

VI. CONCLUSION

The Smart waste Segregation System successfully integrates computer vision and advanced deep learning techniques to categorize waste in an efficient and accurate way. With the use of transfer learning models and convolutional neural networks (CNNs), including ResNet50V2, InceptionV3, VGG16, MobileNetV2, With EfficientNetB0, the model maximizes computing economy while enhancing classification accuracy. Model robustness and flexibility to diverse waste situations are also improved through the inclusion of image pre-processing, data augmentation, and real-time item detection.

The performance of the system is asserted by factors that measure performance based on accuracy, precision, recall, F1-score, and inference time. The results indicate that transfer learning retains outstanding classification accuracy at the same time that it significantly reduces training time. In addition, the system can be applied in real life in waste management plants because it has real-time categorisation ability.

For efficient garbage segregation, upcoming innovations will focus on integrating the program with an automated conveyor belt system. Scalability and efficiency can be enhanced further by further optimizing the model using advanced approaches such as federated learning and edge AI deployment. With the minimization of human labor and augmentation of environmental conservation efforts, the Smart Waste Segregation System promotes green waste management practices.

REFERENCES

[1] Apellido, P. A. J., Arco, C. D. C., Ayo, E. B., Collado, M. J. T., Cortez, C. D., & Santos, R. D. (2024). Development of Waste Segregation Mechanism Using Image Processing for Kalinisan: A Smart Trash Bin. *International Journal of Innovative Science and Research Technology*, 9(3), March 2024.

[2] Hulyalkar, S., Deshpande, R., Makode, K., & Kajale, S. (2018). Implementation of Smart Bin Using Convolutional Neural Networks. International Research Journal of Engineering and Technology (IRJET), 05(04), April 2018

[3] Ikram, S. T., Mohanraj, V., Ramachandran, S., & Balakrishnan, A. (2018). An Intelligent Waste Management Application Using IoT and a Genetic Algorithm–Fuzzy Inference System. International Research Journal of Engineering and Technology (IRJET), 05(04), April 2018.

[4] Sanjai, J., Balaji, V., Pranav, K. K., & Aravindan, B. (2019). Automated Domestic Waste Segregator Using Image Processing. International Research Journal of Engineering and Technology (IRJET), 6(4), April 2019.

[5] Alsubaei, F. S., Al-Wesabi, F. N., & Hilal, A. M. (2020). Deep Learning-Based Small Object Detection and Classification Model for Garbage Waste Management in Smart Cities and IoT Environment. Proceedings of the 2nd African International Conference on Industrial Engineering and Operations Management, Harare, Zimbabwe, December 7-10, 2020.

[6] Abubakar, R., Kumar, K. M. S., Acakpovi, A., Ayinga, U. W., Prempeh, N. A., Tetteh, J., & Kumassah, E. S. (2020). Convolutional Neural

Networks for Solid Waste Segregation and Prospects of Waste-to-Energy in Ghana. Proceedings of the 2nd African International Conference on Industrial Engineering and Operations Management, Harare, Zimbabwe, December 7-10, 2020. Agarwal, C., Yewale, B., & Jagadish, C. (2020). Automatic Waste Segregation and Management. International Journal of Engineering Research & Technology (IJERT), 9(06), June 2020.

[7] Mistry, M. (2021). Trash Net Based Waste Segregation Assistive System for Smart Cities. Annals of R.S.C.B., 25(4), 1532-1544.

[8] Salunke, A. A. (2021). WasteSegNet: A Deep Learning Approach for Smart Waste Segregation in Urban Environments. Bachelor of Technology Thesis, Manipal University Jaipur.

[9] Hasan, M. K., Issa, G., & Khan, M. A. (2022). Smart Waste Management and Classification System for Smart Cities using Deep Learning. IEEE International Conference on Big Data and Advanced Technology in Science (ICBATS), February 2022. DOI: 10.1109/ICBATS54253.2022. 9759087.Lu, W., & Chen, J. (2022). Computer Vision for Solid Waste Sorting: A Critical Review of Academic Research. Waste Management, April 2022. DOI: 10.1016/j.wasman.2022.02.009.

[10] Mohammed, M. A., Abdulhasan, M. J., Kumar, N. M., Abdulkareem, K. H., Mostafa, S. A., Maashi, M. S., Khalid, L. S., Abdulaali, H. S., & Chopra, S. S. (2022). Automated Waste-Sorting and Recycling Classification Using Artificial Neural Network and Features

[11] R. Radhakrishnan Nair, L. Sarnot, S. Sutar, P. Prabhu, S. Bhingarkar, M. Annadate, C. Panchal, A. Savyanavar, and N. Mhala, "An Automated System for Waste Segregation Using Deep Learning Algorithms," in Proceedings of the 3rd International Conference for Innovation in Technology (INOCON), 2024, DOI: 10.1109/INOCON60754.2024.10511885.

[12] S. Sundaralingam and N. Ramanathan, "Segregation of Recyclable Plastic Waste with Deep Learning-Based Hand-Eye Coordination," IOP Publishing Ltd., April 22, 2024.

[13] N. Murugan, A. Sivathanu, K. Vaidyanathan, A. Tiwari, and A. Varma, "Automated Home Waste Segregation and Management System," International Journal of Electrical and Computer IJECE Engineering, vol. 13, no. 4, pp. 3903–3912, August 2023, DOI: 10.11591/ijece. v13i4.pp3903-3912.

[14] A. V. S. Madhav, R. Rajaraman, S. Harini, and C. C. Kiliroo, "Application of Artificial Intelligence to Enhance Collection of E-Waste: A Potential Solution for Household WEEE Collection and Segregation in India," Waste Management & Research, vol. 40, no. 7, pp. 1047–1053, 2022, DOI: 10.1177/0734242X211052846.