WASTE CLASSIFICATION AND SEPARATION USING COMPUTER VISION AND DEEP LEARNING

[1]Dr. Kanchana J, [2]Benita Babu, [3]Nihal Koya Thangal N, [4]Mohammed Farhan Hassan K M, [5]R Rahima Afrin
[1]Professor, Department of Computer Science
Younus College of Engineering & Technology, Kollam, Kerala,India.
[1]kanchanasukumar@gmail.com, [2]benitababu0123@gmail.com, [3] nihalthangal16@gmail.com, [4]mohammedfarhanmk@gmail.com, [5]r.rahimaaffrin@gmail.com

Abstract—Waste management is a critical challenge in modern urban environments, requiring efficient and accurate classification and separation of waste to enhance recycling processes and reduce environmental impact. This project presents a novel approach to waste classification and separation using computer vision and deep learning techniques. We propose a system that leverages convolutional neural networks (CNNs) to automatically identify and classify different types of waste, including plastics, metals, paper, and organic materials. The implementation of this system in waste sorting facilities has the potential to significantly improve the efficiency of recycling processes, reduce contamination in waste streams, and contribute to more sustainable waste management practices. This study presents an innovative approach for waste classification and separation utilizing computer vision and deep learning techniques. By deploying a convolutional neural network (CNN) model, we analyze images of waste materials to accurately classify them into distinct categories such as recyclables, organic waste, and non recyclables. This research not only contributes to the advancement of intelligent waste management systems but also promotes environmental sustainability by improving recycling rates and reducing landfill contributions. Future work will focus on real-time implementation and integration with waste collection systems to optimize urban waste management.

I. INTRODUCTION

The global increase in waste production has become a pressing environmental issue, leading to significant challenges in waste management. Traditionally, waste sorting has relied on manual labor, which is time-consuming, labor-intensive, and prone to human error. By leveraging the power of convolutional neural networks (CNNs) and other deep learning models, it is possible to build systems capable of identifying and categorizing different types of waste with high accuracy. We propose a robust system for automatic waste classification that can be integrated into smart waste management frameworks. The system is designed to handle a variety of waste types, including plastics, metals, paper, and organic materials, making it versatile and applicable to diverse waste streams.

To address these challenges, this project explores the application of computer vision and deep learning techniques for automated waste classification and separation. By leveraging advanced image recognition capabilities, we aim to develop a system that can accurately identify and categorize various types of waste materials in real time. This approach not only enhances the efficiency of waste sorting processes but also minimizes the reliance on manual labor, making waste management more effective. Ultimately, this project seeks to contribute to the development of intelligent waste management solutions that can be implemented in urban settings, promoting better recycling practices and reducing the environmental impact of waste disposal. By adopting a data-driven approach, we hope to pave the way for future advancements in automated waste separation technologies, thereby supporting broader sustainability goals.

II. RELATED WORK

Conducting a literature survey on Waste Classification And Separation Using Computer Vision And Deep Learning using hardware module involves reviewing existing research papers, articles, and academic publications in the field. Here's an overview of some key studies and findings:

TABLEI : Literature Review

Name of the Paper	Year	Author(s)	Algorithm	Accuracy
Waste Management Using Machine Learning and Deep Learning Algorithms [?]	2020	Khan Nasik Sami, Raini Hassan	Decision Trees, SVM, Random For-est, CNN	CNN-90%,SVM -85%,RF/DT-55–65%
Intelligent Waste Classification System Using Deep Learning CNN [?]	2021	Olugboja Adedeji, ZenghuiWang	ResNet-50,SVM	87%
Deep Learning for Plastic Waste Classification System [?]	2021	Janusz Bobulski, Mariusz Kubanek	CNN	95%
A Deep Learning Approach for Medical Waste Classification [?]	2022	Haiying Zhou, XiangyuYu, Hui Lu	CNN	85–95%
Intelligent Waste Management Us-ing Deep Learning with IoT [?]	2022	Md.Wahidur Rahman, Ra-habul Islam	AlexNet,VGG16,ResNet 34	95.31%
Waste Classification Basedon Multilayer Hybrid CNN [?]	2022	CuipingShi, CongTan	MLH-CNN	92.6%
Deep Learning for Recyclable Products Classification [?]	2023	Mohammed Imran,Basheer Ahmed	CNN,ResNet50V2	CNN-87.22%, ResNet50V2 -98.95%
Trash Net Dataset ClassificationviaDeep Learning [?]	2018	Rahmi Arda Aral	DenseNet121,InceptionResNetV2	DenseNet121 -95%, IRV2 - 94%
Waste Management of Residential Society via ML and IoT [?]	2020	Sonali Dubey, Pushpa Singh	SVM,Na¨ıveBayes,RF,DT,KNN	KNN-0.77,SVM -0.78,RF-0.85
Smart Municipal Waste Manage-ment with DL and IoT [?]	2021	CongWang, Jiongming Qin	MobileNetV2/V3, InceptionV3,ResNet50-152, Xception	MobileNetV3 -94.26%

III. MATERIALS AND METHOD

A. Dataset

The dataset, sourced from Roboflow, contains 6,688 an- notated images of various trash types in YOLOv8 format, making it directly compatible with the YOLO object detection framework all resized to 640×640 pixels in RGB format. The dataset is categorized into three distinct waste types:

1. Metal Waste
2. Organic Waste
3. Inorganic Waste

This dataset plays a crucial role in training the YOLOv8 model for waste classification, enabling efficient and accurate trash detection for improved waste management.

B. Hardware Components

1. Rapsberry pi 4 model B

The Raspberry Pi 4 Model B (8GB RAM) serves as the system's main processor, handling image processing, sensor input, and actuator control. Its quad-core ARM Cortex-A72 CPU and ample memory support real-time waste classification. With GPIO pins for easy hardware integration and compatibility with machine learning frameworks, it provides a flexible, efficient platform for deploying computer vision tasks.

2. Webcam as Camera Module

A standard 1080p webcam (1920 × 1080 resolution) serves as the primary imaging device for the robotic waste management system. Positioned to capture a clear view of the conveyor belt or sorting area, the webcam provides high-resolution video input for accurate detection and classification of waste materials. Its ability to capture detailed features—such as color, shape, and texture—enables effective differentiation between various waste types. The video feed is processed in real time using OpenCV and other computer vision libraries on the Raspberry Pi, allowing machine learning algorithms to accurately identify and classify recyclable and non-recyclable materials.

3. Actuator

The system uses a 4-DOF 3D-printed robotic arm for precise waste sorting. It features a bionic design with three MG996R servo motors for joint and base movement, and an SG90 servo motor as a gripper. The base rotates up to 180°, and all movements are controlled via software-driven PWM signals. This actuator setup ensures smooth, accurate handling, enhancing the efficiency and reliability of automated waste segregation.

4. PCA9685 Servo Driver

The PCA9685 is a 16-channel PWM driver that enables efficient control of multiple servos via I2C, minimizing GPIO usage on the Raspberry Pi. It ensures smooth, precise motion—ideal for accurate robotic arm movements in waste handling.Key features of the PCA9685 servo driver include:

• 16 independent PWM channels: Allows expansion for additional actuators if needed.

• 12-bit resolution per channel: Enables fine-grained control over servo positioning.

• I2C communication: Reduces the number of Raspberry Pi GPIO pins required.

• External power support: Prevents excessive current draw from the Raspberry Pi. By integrating the PCA9685 servo driver, the system achieves more reliable and scalable actuator control, optimizing the waste sorting process while maintaining efficient power management.

5. Power Supply

The servo motors are powered by two 3.7V 3000mAh Li-ion batteries connected in series, providing 7.4V, which is regulated to 6V using a buck converter. This stable output is ideal for high-torque servos like the MG996R. The Raspberry Pi and PCA9685 servo driver operate on a separate 5V power supply. All grounds are connected to maintain a common reference, ensuring reliable and stable system operation.

C. Algorithm Description

1. Deep Learning

Deep learning has significantly enhanced automation in waste classification and sorting through convolutional neural networks (CNNs). These networks extract spatial features from images, enabling accurate classification of waste materials such as plastic, metal, glass, and organic matter.

By leveraging large labeled datasets, CNNs can generalize well to real-world waste classification tasks, ensuring high precision. Modern waste management integrates deep learning models with robotic systems for realtime sorting on conveyor belts. Object detection models such as YOLO (You Only Look Once) and segmentation networks like Mask R-CNN are particularly effective in identifying and segmenting waste items even in cluttered scenes. These models ensure low contaminationin recycling streams by precisely categorizing waste materials, thereby improving efficiency in recycling plants.

2. Convolutional Neural Networks (CNNs)

CNNs are widely employed in waste classification due to their ability to extract hierarchical features from images. These networks consist of convolutional layers that detect edges, textures, and complex patterns, making them wellsuited for recognizing waste categories.For real-time waste sorting, object detection models such as Faster R-CNN, SSD, and YOLO integrate CNN-based feature extraction with region proposal networks, ensuring accurate object localization. These methods allow automated systems to classify and separate waste efficiently, reducing reliance on manual labor and enhancing sustainability.

3. YOLO

YOLOv8 improves on earlier versions with a refined, architecture, anchor-free detection, and adaptive activation functions. It uses a feature pyramid network (FPN) and crossstage partial networks (CSP) for better feature extraction and reduced computation—ideal for waste classification tasks. Architecture of YOLOv8 YOLOv8 consists of the following major components:

.Backbone: Uses CSPDarknet53 for feature extraction, which improves gradient flow and reduces redundancy.

Neck: Incorporates a modified PANet (Path Aggregation Network) and FPN for better multi-scale feature fusion.

Detection Head: Implements an anchor-free approach, making predictions more adaptable to various object sizes and reducing computational overhead.

Activation Function: Utilizes SiLU (Swish) activation for improved convergence and performance.

Layers: YOLOv8 has a modular architecture with multiple convolutional layers, CSP blocks, and attention mechanisms designed to enhance feature extraction and detection accuracy.

1. Evaluation Metrics

Since YOLOv8 does not directly measure accuracy in the traditional classification sense, the classification model based on YOLOv8 proposed in this study uses the following metrics in the evaluation process: mean Average Precision (mAP), Precision, and Recall [?]. These metrics can be computed from a confusion matrix.

2. Confusion Matrix

The confusion matrix provides a detailed view of the outcomes, showcasing the counts of True Positives, True Negatives, False Positives, and False Negatives for each class.

• True Positives (TP): When the actual value is Positive and the predicted value is also Positive.

• True Negatives (TN): When the actual value is Negative and the predicted value is also Negative.

• False Positives (FP): When the actual value is Negative but the predicted value is Positive. Also known as Type I error.

• False Negatives (FN): When the actual value is Positive but the predicted value is Negative. Also known as Type II error.

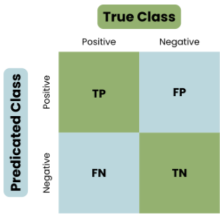

Fig.1:Confusion Matrix Model

3. Precision

Precision is the proportion of correctly identified positive instances among all predicted positive instances. It is calculated using the formula:

$$\text{Precision} = \frac{TP}{TP+FP} \quad (1)$$

4. Recall

Recall measures the proportion of actual positive instances
correctly identified by the model. It is computed as follows:

$$\text{Recall} = \frac{TP}{TP+FN} \quad (2)$$

5. Mean Average Precision (mAP)

mAP provides a comprehensive evaluation of the model’s performance by computing the area under the precision-recall curve. It consists of the following variations:

• Average Precision (AP): Measures the area under the precision-recall curve for a single class.

• Mean Average Precision (mAP): Computes the mean of AP values across all object classes.

• mAP@50: Mean Average Precision calculated at an Intersection over Union (IoU) threshold of

0.50. This metric evaluates model accuracy considering only ”easy” detections.

• mAP@50-95: The average mAP calculated over IoU thresholds ranging from 0.50 to 0.95. It provides a more comprehensive assessment of the model's performance across different detection difficulties.

6. Loss Functions

Loss quantifies the difference between the predicted values and the actual values, with lower values indicating better model performance. YOLOv8 employs several types of loss functions:

• Box Loss: Measures the error in bounding box predictions.

• Classification Loss: Evaluates the correctness of object class predictions.

• Distribution Focal Loss: Enhances the precision of predicted box coordinates.

These loss functions work in tandem to enhance detection accuracy and ensure optimal model performance. However, evaluating a model's effectiveness requires a broader set of metrics, especially in the context of class imbalance. Accuracy, while commonly used, can be misleading when class distributions are uneven. Precision—the ratio of true positives to total predicted positives—is crucial when false positives carry a high cost, such as misclassifying non-recyclable items as recyclable. Recall (or sensitivity) measures the proportion of true positives out of all actual positives, ensuring that recyclable materials are correctly identified and not missed. The

F1-score, the harmonic mean of precision and recall, offers a balanced evaluation, particularly useful in imbalanced datasets.

In object detection tasks, mean Average Precision (mAP) and Intersection over Union (IoU) are widely used to assess the accuracy of both classification and localization. Together, these evaluation metrics offer a comprehensive understanding of model performance, guiding improvements in automated waste classification and advancing sustainability efforts.

METHODOLOGY

This chapter details the methodology used

to design, develop, and evaluate the Waste Management Classification , which utilizes a Raspberry Pi with a Web camera module, Python programming, OpenCV for image processing,

YOLOv8 and google web for prototyping and testing. The approach involves setting up the hardware, capturing and processing images, implementing YOLO algorithms, and testing the system under various conditions.

DEEP LEARNING

Deep learning has revolutionized waste management by introducing advanced automation and accuracy in waste sorting and classification processes. One of the primary applications is in automated waste sorting, where deep learning models—primarily convolutional neural networks (CNNs)—analyze images of waste to identify materials such as plastic, metal, glass, and organic matter. These CNNs are trained on extensive datasets with labeled images of waste items, allowing them to recognize different types of waste with high precision. This image-based classification can be implemented on a large scale by integrating it with robotic systems. For example, robotic arms equipped with cameras and sensors, guided by deep learning algorithms, can perform real-time waste sorting on conveyor belts, quickly separating items for recycling and reducing the need for human labor.

This approach has been especially useful in large waste processing plants, where rapid and accurate sorting is essential for managing vast amounts of waste efficiently.

V.CONVOLUTIONAL NEURAL NETWORK (CNN)

Convolutional Neural Networks (CNNs) are transforming waste management by enabling efficient and accurate image-based classification. Trained on large datasets, CNNs can recognize various waste materials—such as plastics, metals, glass, paper, and organics—with high precision, making them integral to automated sorting systems. Their ability to classify waste into finer subcategories, like distinguishing PET from HDPE plastics or aluminum from steel, supports higher purity in recycling outputs. CNNs also contribute to real-time object detection and localization in cluttered waste streams, where items often overlap or are partially obscured. Advanced models such as YOLO and Faster R-CNN can accurately identify and outline individual items, allowing robotic systems to sort waste with minimal human intervention. This enhances the speed, accuracy, and efficiency of sorting processes while reducing contamination. Overall, CNNs play a crucial role in automating and optimizing sustainable waste management practices.

VI. YOLO

YOLO (You Only Look Once) is a powerful tool for real-time object detection in automated waste sorting systems, offering both speed and accuracy. In waste processing facilities, it can rapidly identify and classify materials such as plastic, metal, glass, and paper on moving conveyor belts. YOLO's single-pass architecture enables instant detection and localization, allowing robotic arms to sort items efficiently—crucial in high-volume environments where continuous operation is essential. Its robustness in cluttered scenes, where waste items often overlap, helps reduce contamination by ensuring accurate classification. Overall, YOLO improves the efficiency, precision, and scalability of waste management operations, promoting a more sustainable recycling process.

VII. YOLOV8

YOLOv8, the latest iteration in the YOLO series, is revolutionizing waste management classification through its combination of high detection speed and accuracy—critical for real-time sorting environments. Its optimized architecture enables rapid identification of waste types such as plastics, metals, glass, and organics on conveyor systems, facilitating immediate action by robotic sorters. YOLOv8 performs well in cluttered scenes, leveraging advanced segmentation to accurately detect overlapping or partially obscured items, thereby minimizing contamination. It also supports granular classification, such as identifying hazardous waste or distinguishing between plastic types, enhancing resource recovery. Overall,

YOLOv8 improves the speed, precision, and scalability of waste management systems, contributing significantly to sustainability goals.

VIII. EVALUATION METRICS

In waste classification, evaluating models like CNNs and YOLO is crucial for ensuring accurate and efficient material sorting. Key metrics include accuracy, which gives a general performance overview but may be misleading with class imbalance; precision, which highlights the reliability of positive predictions; recall, which reflects the model's ability to capture all relevant instances; and the F1-score, which balances precision and recall. For object detection tasks, mean Average Precision (mAP) and Intersection over Union (IoU) are used to assess localization and classification accuracy. Together, these metrics offer a comprehensive evaluation framework, driving improvements in automated waste sorting and supporting sustainability efforts.

IX. ENHANCEMENT

Advancements in machine learning and computer vision have significantly enhanced the efficiency and accuracy of waste classification. Deep learning models such as CNNs and object detection frameworks like YOLO enable real-time identification of materials using large datasets of labeled waste images. Techniques like transfer learning accelerate training and adaptation to specific waste streams, while image processing and data augmentation improve model robustness in complex environments. Enhanced segmentation capabilities further increase sorting precision and recycling efficiency.

Additionally, the integration of IoT-enabled smart bins with sensors and cameras supports real-time data collection and dynamic decision-making. These innovations collectively promote a more sustainable and effective waste management system.

X. RESULTS AND DISCUSSION

The evaluation of our object detection model demonstrates its effectiveness in accurately identifying and classifying waste categories. The confusion matrix highlights class-wise precision and misclassifications, while the precision-recall (PR) and F1 score curves illustrate the balance between precision and recall. The model exhibits strong performance, with competitive precision, recall, and mean Average Precision (mAP) scores. Additionally, loss curve analysis provides insights into training stability. This section presents a detailed breakdown of these metrics, outlining the model's strengths and areas for improvement.

XI. MODEL PERFORMANCE

A. Confusion Matrix

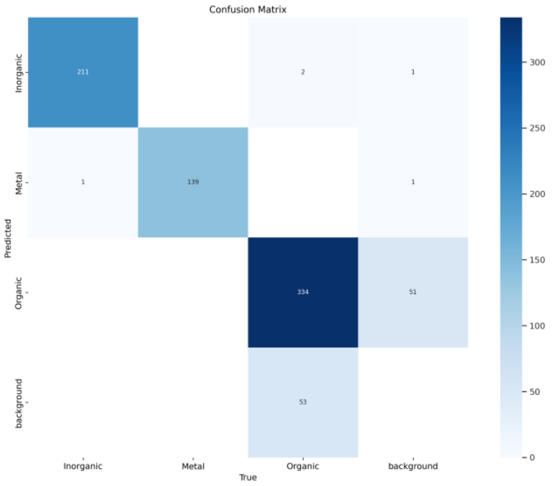

Fig.2:Confusion Matrix

In Fig 5.1 the confusion matrix provides an overview of the model's classification performance across four categories:
Inorganic, Metal, Organic, and Background. The diagonal values indicate correct classifications, with Inorganic (211), Metal (139), and Organic (334) showing strong detection accuracy.
The misclassification between Inorganic and Metal is minimal, suggesting that the model distinguishes these categories well.

B. Key Performance Metrics

To start with the model performance can be summarized by the values of the precision, recall and mAP metrics at the final.

Metric	Value
Precision	0.9696
Recall	0.9370
mAP@50	0.9646
mAP@50-95	0.8123

TABLEII:Key Performance Metricsat Epoch 20

epoch as shown in table 5.1. The key performance metrics at epoch 20 indicate the effectiveness of the trained model:
• Precision (0.9696): The model exhibits a high precision, meaning that when it makes a positive prediction, it is correct 96.96% of the time. This indicates a low false positive rate.
• Recall (0.9370): The recall value of 93.70% suggests that the model correctly identifies most of the actual positive cases, though some false negatives still occur.
• mAP@50 (0.9646): The mean Average Precision at an IoU threshold of 0.5 is 96.46%, reflecting strong detection capability with loose localization criteria.
• mAP@50-95 (0.8123): The lower value of 81.23% across multiple IoU thresholds (0.5 to 0.95) suggests that performance declines with stricter localization requirements, indicating potential room for improvement in precise bounding box placement.
Overall, these metrics suggest that the model performs well in terms of accuracy, with high precision and recall, but there is some decline in performance when stricter localization criteria are applied.

C. Precision-Recall Curve

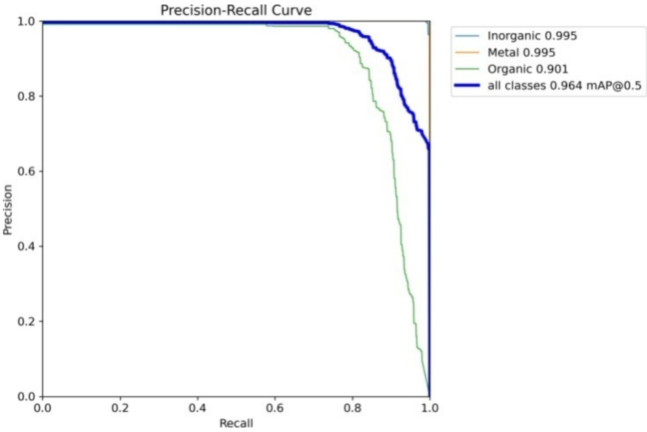

Fig. 3: Precision-Recall Curve

The Precision-Recall (PR) curve illustrates the trade-off between precision and recall across different classification thresholds. Key observations from this curve are:
• Inorganic and Metal Classes: Both exhibit extremely high precision and recall values (0.995), indicating that these classes are well-separated and easily identifiable by the model.

Organic Class: Shows a lower precision-recall performance (0.901), suggesting that it is more challenging to classify correctly, possibly due to greater variation in its features.
• Overall Performance: The model achieves a high mean
Average Precision at 0.5 IoU threshold (mAP@0.5 =0.964), signifying strong detection capabilities with relaxed localization requirements.

D. mAP Curve

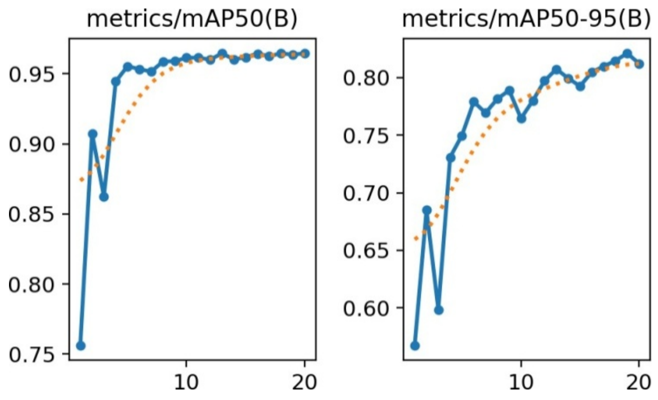

Fig. 4: mAP Curve

The mAP curves provide insight into the model’s detection performance across different IoU thresholds:

• mAP@50: The model achieves a high value, stabilizing above 0.95, indicating strong object detection performance when using a relaxed IoU threshold (0.5).

• mAP@50-95: The model gradually improves and stabilizes around 0.81, showing its ability to maintain good detection accuracy even at stricter IoU thresholds.

• Performance Stability: The curves indicate steady improvement over training epochs, with minimal fluctuation after initial convergence, suggesting a well-trained model with good generalization.

XII. COMPARISON WITH EXISTING SYSTEM

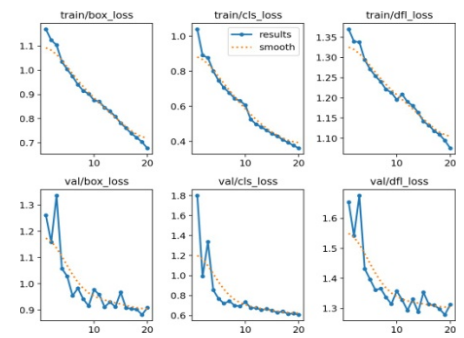

Fig. 5: Train and validation loss curves of the proposed YOLOv8-based system.

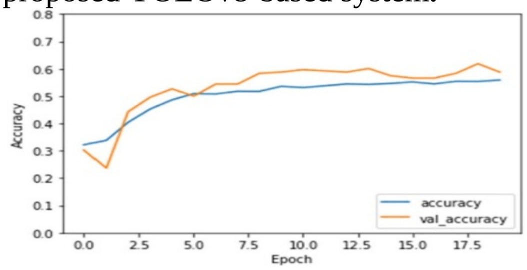

Fig. 6: Accuracy curve of the existing EfficientNet-B0-based system

The performance of the proposed YOLOv8-based system is compared with an existing system utilizing EfficientNet-B0 [?]. The comparison is made using the accuracy curve of EfficientNet-B0 and the loss curves of YOLOv8.

The YOLOv8 loss curves (Figure 5) show a steady and consistent decrease, indicating stable learning. In contrast, the accuracy curve of EfficientNet-B0 (Figure 6) increases gradually but begins to plateau around epoch 10. This suggests that YOLOv8 reaches an optimal state faster than EfficientNet-B0.

The validation loss of YOLOv8 remains low, suggesting strong generalization. Meanwhile, EfficientNet-B0 achieves a maximum accuracy of approximately 60%, which is significantly lower than YOLOv8’s high mean Average Precision (mAP). This indicates that the proposed system is more effective in classification and localization tasks.

EfficientNet-B0’s validation accuracy fluctuates, indicating potential overfitting. The YOLOv8 loss curves, however, show that training and validation losses follow a similar trend without a large gap, suggesting minimal overfitting.

XIII. CONCLUSION

The integration of computer vision and deep learning in waste classification marks a significant advancement in modern waste management. These technologies automate sorting with high accuracy and efficiency, overcoming the limitations of traditional manual methods. By enabling real-time identification of materials like plastics, metals, and organics, they streamline recycling processes and ensure proper waste routing. Their scalability allows implementation across diverse settings without increased labor costs. Ultimately, this approach enhances recycling rates, reduces landfill dependency, and supports sustainable environmental practices.

REFERENCES

1) K. N. Sami, Z. M. A. Amin, and R. Hassan, “Waste management using machine learning and deep learning algorithms,” International Journal on Perceptive and Cognitive Computing, vol. 6, no. 2, pp. 97–106, Dec. 2020.

2) O. Adedeji and Z. Wang, “Intelligent waste classification system using deep learning convolutional neural net- work,” Procedia

Manufacturing, vol. 35, pp. 607–612, 2019, the 2nd International Conference on Sustainable Materials Processing and Manufacturing, SMPM 2019, 8–10 March 2019, Sun City, South Africa.

3) J. Bobulski and M. Kubanek, "Deep learning for plastic waste classification system," Applied Computational Intelligence and Soft Computing, vol. 2021, no. 1, p. 6626948, 2021.

4) H. Zhou, X. Yu, A. Alhaskawi, Y. Dong, Z. Wang, Q. Jin, X. Hu, Z. Liu, V. G. Kota, M. Abdulla, S. Ezzi, B. Qi, J. Li, B. Wang, J. Fang, and H. Hu, "A deep learning approach for medical waste classification," Scientific Reports, vol. 12, 02 2022.

5) W. Rahman, R. Islam, A. Hasan, N. Bithi, M. Hasan, and M. M. Rahman, "Intelligent waste management system using deep learning with iot," Journal of King Saud University Computer and Information Sciences, 09 2020.

6) J. Redmon, S. Divvala, R. Girshick and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 2016, pp. 779–788, doi: 10.1109/CVPR.2016.91.

7) C. Shi, C. Tan, T. Wang, and L. Wang, "A waste classification method based on cumulative hybrid convolution neural network," Applied Sciences, vol. 11, no. 18, 2021. [Online]. Available: https://www.mdpi.com/2076-3417/11/18/8572

8) M. I. B. Ahmed, R. B. Alotaibi, R. A. Al-Qahtani, R. S. Al-Qahtani, S. A. Heteleka, I. A. Al-Matar, N. K. Al-Saqer, A. Rahman, L. Saraireh, M. Youdhana, and G. Krishnasamy, "A deep learning approach to recyclable products classification: Towards sustainable waste management," Sustainability, vol. 15, no. 10, p. 4233.

9) V. A. Aral, R. Keskin, M. Kaymak, and Y. S. Bilge, "Classification of transient dataset based on deep learning models," in 2018 IEEE International Conference on Big Data (BigData), 2018, pp. 2058–2062.

10) S. Dubey, M. Singh, P. Singh, and S. Aggarwal, "Waste management of residential society using machine learning and iot approach," 03 2020, pp. 293–297.

11) C. Wang, J. Qin, C. Qu, X. Ran, C. Liu, and B. Chen, "A smart municipal waste management system based on deep-learning and internet of things," Waste Management, vol. 135, pp. 20–29, 2021.