TrashVision: Dry Waste Assortment using Machine Learning and Deep Learning

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Abstract

These days, as the population grows, garbage production rises dramatically, which causes a spike in plastic manufacture that has a negative environmental impact. Because of the size of trash accumulation, manual waste segregation is ineffective and unfeasible. We suggest TrashVision, an advanced waste sorting system that makes use of deep learning and machine learning techniques, as a solution to this problem. Our method ensures accurate and effective waste sorting by combining YOLO (You Only Look Once) for real-time object identification with Inception-ResNet for high-accuracy image classification. This project makes use of both custom photos and a publicly accessible dataset. To enhance model performance and generalisation, preprocessing and data augmentation approaches are used. The system's efficacy in trash classification is assessed using important metrics like accuracy, precision, recall, and F1-score. According to the findings, deep learning greatly increases the effectiveness of garbage sorting, opening the door for automated smart waste management systems. In order to enable real-time garbage segregation and encourage sustainable recycling behaviours, future work intends to implement this concept in IoT-enabled smart bins.

Keywords: Deep Learning, Deep Neural Network, Convolutional Neural Networks (CNN), Image Classification, Transfer Learning, Artificial Intelligence, Data Augmentation

<H1> Introduction

Serious environmental risks, such as greenhouse gas emissions, contamination of land and water, and threats to human health, are presented by this increasing volume. Decomposing trash releases greenhouse gases like carbon dioxide and methane, which contribute significantly to the escalation of air pollution and global warming, as stated in reference [2]. According to a study [3], 33% of trash worldwide is not managed in an environmentally safe manner, frequently as a result of open dumping and insufficient landfilling, making environmental security a serious worry. Reducing these problems requires efficient waste management, especially through waste segregation. Sorting garbage into categories such as hazardous, recyclable, and biodegradable allows for proper processing and lessens reliance on landfills. However, manual segregation is ineffective and prone to mistakes, particularly when done on a large scale, highlighting the need for clever, automated solutions to improve accuracy and lessen reliance on humans. By developing a novel classification model that combines YOLO and Inception-ResNet, this research aims to reduce human effort in waste sorting through automation.

Rest of the paper is structured as follows. Section 2 discusses existing research on automated waste classification. Section 3 details the proposed approach, covering dataset preparation, model architecture, and training procedures. Section 4 shares the experimental findings, followed by Section 5, which provides result interpretation and analysis. Finally, Section 6 concludes the study and outlines potential directions for future work.

<H2> Related Work

A summary of earlier studies and contributions by researchers who created methods akin to the waste segregation system this study proposes is given in this section. In an effort to decrease manual labour and increase accuracy, a number of studies have investigated machine learning (ML) and deep learning (DL) methods for trash classification automation. Deep convolutional neural networks (CNNs) trained on datasets like TrashNet were the mainstay of early waste classification research. A DenseNet201-based model was presented in a work by Hossen et al. [4], which used data augmentation, normalisation, and cross-validation approaches to achieve 95.01% accuracy. In a similar vein, ConvoWaste, a smart trash segregation system [5], achieved 98% accuracy by combining IoT-based automation for real-time waste sorting with Inception-ResNetV2 for image classification. Early waste classification research relied heavily on deep convolutional neural networks (CNNs) trained on datasets such as TrashNet. Hossen et al. [4] reported a DenseNet201-based model that achieved 95.01% accuracy through data augmentation, normalisation, and cross-validation techniques. Similarly, ConvoWaste, a smart garbage segregation system [5], combined Inception-ResNetV2 for image classification with IoT-based automation for real-time waste sorting to reach 98% accuracy.

According to the research paper [8], the author proposed the Query2Label (Q2L) framework, leveraging Vision Transformers (ViT-B/16) to classify municipal waste images with 92.36% accuracy, outperforming ResNet-101. However, after careful research it was found that when waste items are densely packed or not well-represented in the training dataset, the model struggles with accurate classification, potentially reducing its effectiveness in real-world scenarios with diverse and complex waste compositions Additionally, a drone-based waste classification system [9] employed CNNs and YOLO for multi-object detection, achieving 95% classification accuracy and 87.4% mean average precision but the limitation of this research is that the model relies on image-based classification, which may struggle with waste items that are deformed, overlapping, or partially visible in an image. The author in research paper [10], has developed a Smart Waste Management System that uses IoT technology integrated with sensors to automate the monitoring and collection of waste. It consists of Ultrasonic sensors which detects the level of waste, a microcontroller (Arduino) that processes the sensor data, a GSM module to end real-time alerts when the bin is full, and a mobile application that displays the bin status, helping authorities prioritize waste collection. One limitation of the system is that it only detects the fill level of the bin and does not differentiate between types of waste (e.g., recyclable vs non-recyclable), which is crucial for sustainable waste management practices like segregation at the source. Lastly the author in research paper [11] has developed a waste classification system using Convolutional Neural Networks (CNNs), trained on the TrashNet dataset to identify and categorize waste into types such as plastic, metal, cardboard, and glass. The model achieved an accuracy of approximately 87%, demonstrating the effectiveness of CNNs in automating waste segregation through image-based classification. This approach aims to reduce manual efforts and support efficient recycling practices. Although the model performs well under controlled conditions, it lacks adaptability to dynamic environments where lighting conditions, waste deformation, or background noise can significantly affect prediction accuracy.

<H3> Architecture and Structure

The proposed system adopts a two-stage deep learning architecture designed for efficient and accurate waste classification in real-world environments. This architecture integrates object detection and image classification techniques to identify and categorize various types of waste from images, aiming to support smarter and more scalable waste segregation solutions. The depicted block diagram in Fig.1 shows the overview of the waste assortment model

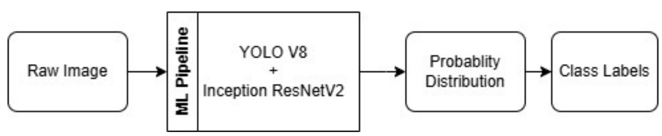


Fig.1 Architecture of the Proposed System

A custom-trained YOLOv8 object detection model receives the raw input image in the initial stage of the model pipeline. This model is in charge of identifying and locating specific waste items inside the image. It was trained using an expanded version of the TrashNet dataset with extra annotated samples. Bounding boxes and corresponding confidence levels that indicate the certainty of detection are produced by the YOLOv8 model for things that are detected. Even in chaotic or real-world settings, this phase aids in separating several trash items from a single image.

After detection is finished, the image is pre-processed and sent into a refined Inception-ResNet V2 model, which serves as the pipeline's second stage. Each waste material found is categorised by this approach into one of six groups: cardboard, glass, metal, paper, plastic, or trash. The system can identify and categorise several trash items in a single image because to this two-stage architecture. In order to analyse the overall composition of waste in the image, the system additionally computes and displays the % distribution of each waste type found at the conclusion of the process.

<H 3.1> **Data Collection**

The TrashNet dataset serves as the foundation for this project's garbage classification model. Cardboard, glass, metal, paper, plastic, and garbage are the six primary kinds of common waste that may be found in the well-known public dataset TrashNet. Since the photos were first taken in controlled indoor settings, they are clean and reliable, which is ideal for preliminary model training. The TrashNet dataset is a good place to start, but it has certain drawbacks, most notably an uneven distribution of photos per class and a lack of diversity in environmental circumstances. In order to improve sample size and environmental diversity, more manually gathered photos were added to the collection. These new images included waste items photographed in real-world scenarios under different lighting, background clutter, and orientations to better reflect practical deployment conditions. The total number of pictures used for training and testing is given in table I.

A variety of data augmentation approaches were applied to the training set in order to further improve the model's robustness and performance. These comprised small translations, brightness tweaks, random rotations, and horizontal flipping. This helped avoid overfitting by artificially expanding the dataset. To ensure a consistent input distribution, all photos were also scaled and normalised before being fed into the model. In order to provide a trustworthy assessment of the model's performance and aid in its development, the dataset was finally divided into training, validation, and testing sets. Fig. 2 below shows a selection of sample photos from our dataset.

Categories	The Total quantity of pictures		
	Training	*Validation*	*Total*
Glass	800	100	900
Paper	755	100	855
Cardboard	800	100	900
Plastic	800	100	900
Metal	800	100	900
Trash	755	100	855
Total	3910	600	4510

Table.1 The total quantity of the pictures

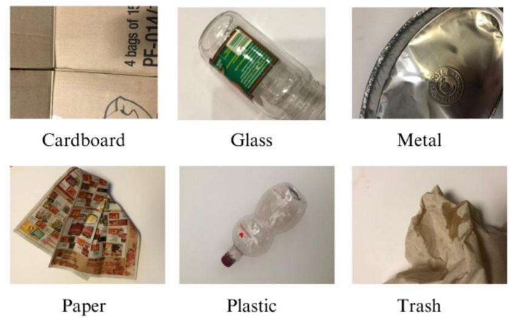


Fig. 2 Sample waste images extracted from the dataset

<H 3.2> **Transfer Learning with TrashVision**

The YOLOv8 (You Only Look Once Version 8) model is used for real-time object recognition in the pipeline's initial stage. The photos were saved in YOLO format, annotated with bounding boxes, and shrunk to 640x640 pixels as required by the model's design. The model was trained using a bespoke dataset. YOLOv8 analyses the entire picture and finds several waste objects in the scene. It generates a bounding box, a class label, and a confidence score for every detection. using a precision of 86%, recall of 82.9%, and mAP@50 of 90.3%, the model demonstrated accurate and dependable object detection after being refined using better and more varied images. The cropped regions extracted from YOLOv8 serve as focused inputs for the next stage of the pipeline, eliminating irrelevant background and improving downstream classification accuracy.

Each detected item is cropped, shrunk to 224x224 pixels, and pre-processed for subsequent steps after the object detection step is finished. The foundation of our classification pipeline was the Inception-ResNet V2 architecture, which was used to extract pertinent features from segmented waste item images. The ImageNet dataset, which has 1,000 object categories and more than 1.4 million photos, was used to pre-train this model. In this instance, transfer learning was used to make use of the pre-trained weights and modify the architecture to fit the waste classification task into six distinct categories. The top classification layers of the initial Inception-ResNet V2 model were eliminated during the transfer learning procedure. In order to maintain the learnt parameters, the previous layers that were in charge of feature extraction were first kept and frozen. A collection of specially designed fully connected layers was then added. In order to prevent overfitting, these featured a Global Average Pooling layer, dense layers with 512 and 128 neurones each that used the ReLU activation function, and dropout layers (0.5) in between. The final output layer was a dense layer with 6 neurons and a Softmax activation function, corresponding to the six waste categories: plastic, paper, glass, metal, cardboard, and trash. The Softmax activation function in Eq. 1 is used to transform the model's raw output (logits) into class probabilities:

$$\sigma(z)_i = \frac{e^{z_i}}{\Sigma_{j=1}^{K} e^{z_j}}$$

where,

– zi is the predicted logit (raw output) for class i

– C is the total number of categories

– σ(zi) represents the probability assigned to class i

After YOLOv8 identification, the cropped and pre-processed photos were scaled to 224 by 224 pixels and normalised before being fed into the model. With the exception of a partial fine-tuning of the final 50 layers, the Inception-ResNet V2 base remained mostly unchanged while the custom layers included 3,682,310 trainable parameters. With a batch size of 16, a learning rate of 1e-5, and category cross entropy as the loss function, the model was assembled using the Adam optimiser. ReLU was selected as the activation function because it avoids the vanishing gradient problem and is computationally efficient. The final classification probabilities for each of the six categories are guaranteed by the SoftMax function at the output. Fig. 3 provides a graphic representation of this full workflow.

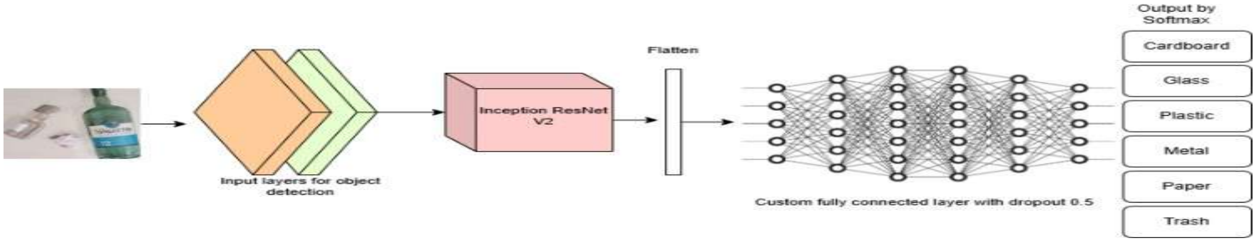


Fig. 3 Detailed workflow of the TrashVision model pipeline

<H4> Model Evaluation

Comprehensive assessment criteria were used at both the detection and classification stages of the proposed two-stage waste classification pipeline to evaluate its performance and dependability. This assessment guarantees the robustness of the integrated system in addition to validating the efficacy of each model separately.

<H 4.1 > ***YOLOv8 Detection Evaluation***

The YOLO F1-score curve in Figure 4 showed an increasing trend until stabilising at a high value, demonstrating the model's capacity to strike a balance between recall and precision when detecting objects. This step greatly improved the quality of input supplied to the classification model by precisely segmenting the raw waste photos into discrete objects.

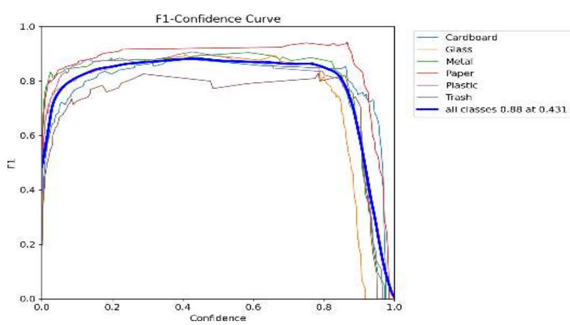
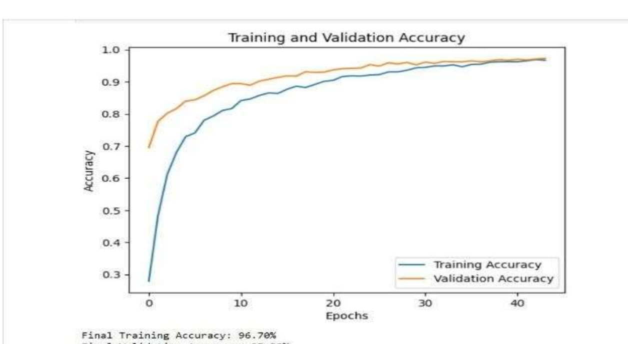


Fig.4 (a) Comparison of model training and validation loss

<H 4.2> ***Inception-ResNet V2 Classification Evaluation***

The Inception-ResNet V2 model's training and validation accuracy plots in Figure 5(a) showed a significant rising trend throughout the training phase. The validation accuracy reached roughly 97%, while the training accuracy rose progressively to above 95%. The model's excellent generalisation performance is seen in this high degree of validation accuracy. The lack of overfitting was further supported by the convergence of training and validation loss.The Inception-ResNet V2 classifier's training and validation loss charts in Fig. 5(b) demonstrated convergence with no overfitting. The model achieved a high validation accuracy, indicating its capacity to generalise well on new data.



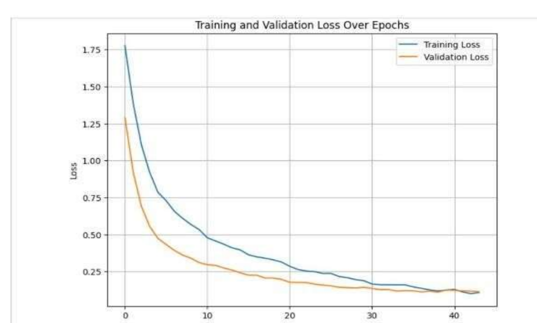


Fig.5 (a) Comparison of model training and validation accuracy Fig.5 (b) Comparison of model training and validation loss

<H 5> Result and Analysis

The end product of the suggested two-stage waste classification pipeline shows how successfully YOLOv8 for detection and Inception-ResNet V2 for classification can be integrated in real-world scenarios. As shown in Fig. 6, the system uses YOLOv8 to process a raw waste image, identifying and labelling each waste item with bounding boxes. The Inception-ResNet V2 model then crops these identified segments and assigns them to one of six categories: plastic, paper, metal, cardboard, glass, or rubbish. This pipeline's capacity to precisely identify and classify waste materials as well as determine the percentage composition of each type is a major benefit. Even in difficult situations including different illumination, busy backgrounds, and overlapping objects, the output image displays high-confidence labels.

Using an NVIDIA RTX 3060, the model achieves an average inference time of 352.1 ms per image, making it appropriate for real-time applications.

With a final training accuracy of 96.70% and a validation accuracy of 97.28%, the classification model Inception-ResNet V2 demonstrated excellent model performance and generalisation skills. YOLOv8's F1-score for the detection task was 0.82, indicating a respectable trade-off between recall and precision.

Even in difficult situations including shifting lighting, congested scenes, and overlapping objects, the resulting image shows high-confidence predictions. This increases its applicability in real-world deployment circumstances by ensuring consistent and comprehensible outcomes. The captured result is displayed in Fig. 6 The final image displays high-confidence predictions even in challenging circumstances like changing illumination, crowded scenes, and overlapping items. This guarantees consistent and understandable results, increasing its usability in real-world deployment scenarios. Fig. 6 shows the captured result.

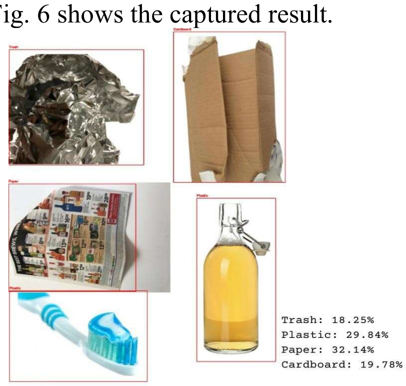


Fig.6. Test results on real-world images using the trained model

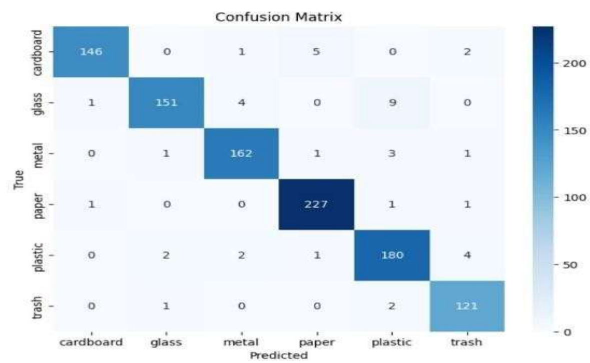


Fig.7. Confusion matrix of the model

<H 5.1> *Comparison with State-of-the-Art Models*

Reference	Model / Method	Dataset	Acc. (%)	mAP @50 (%)	Features / Limitation
Hossen et al. [4]	DenseNet201	TrashNet	95.01	-	Strong classification; no detection
Shankar et al. [5]	Inception-ResNetV2	Custom	98	-	High accuracy; no percentage estimation
Ocat et al. [6]	YOLOv8	Custom	86.67	-	Works well on clean data; weak in real-world scenarios
Priya et al. [7]	Faster R-CNN	Custom	-	-	Classifies biodegradable / non-biodegradable waste
Ours	YOLOv8 + Inception-ResNetV2 (2-stage)	TrashNet + Custom	97.28	90.3	Detection + classification + % estimation

<H 5.2> *Practical Utility and Applications*

The TrashVision system shows great promise for implementation in IoT-enabled garbage segregation systems, especially in smart bins that are connected to conveyor belts. These systems allow for the simultaneous placement of several waste objects on the conveyor belt, usually five or six at a time. Each waste item is identified and localised by YOLOv8's real-time object detection capability, and the Inception-ResNet V2 classifier correctly classifies them into predefined classes including plastic, glass, paper, metal, cardboard, and rubbish. Because of this, the system is ideal for automated trash segregation in municipal waste management facilities, recycling facilities, and industrial waste sorting lines. Scalable and sustainable waste processing infrastructure can be made possible by this IoT connection, which can also facilitate data logging, real-time monitoring, and intelligent decision-making.

<H 6> Conclusion

A dependable and scalable dual-stage architecture for automated trash classification and composition analysis is presented in this work. It delivers great accuracy even on unseen real-world photos by combining the deep feature extraction capabilities of Inception-ResNet V2 with the real-time detection strength of YOLOv8. Through accurate annotation, data augmentation, and transfer learning, the TrashNet dataset was not only enlarged but also improved, resulting in improved performance and generalisation across a variety of trash categories. Our approach determines the relative quantity of each identified garbage kind, unlike other algorithms that just classify waste. This makes it possible to analyse trash composition more precisely, which is essential for streamlining recycling processes and enhancing waste segregation tactics in practical contexts.

This contribution aligns with United Nations Sustainable Development Goal 9 (Industry, Innovation and Infrastructure) by advancing intelligent and automated solutions in waste management through innovative AI technologies. It also supports Goal 11 (Sustainable Cities and Communities) by promoting cleaner and smarter urban waste processing systems. In future iterations, this model could be deployed in intelligent waste bins, integrated into municipal waste tracking systems, or adapted to identify a wider range of materials, further promoting sustainability and technological innovation in urban environments.

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