

**Literature review, Data Research and Technology review  
Submission**

# **Real-Time Recycling Sorting Using Deep Learning**

**Group no: Group 8**

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# Real-Time Recycling Sorting Using Deep Learning

## Literature Review

### Introduction

Waste generation is accelerating globally due to increasing population growth, rapid urbanization, and changing consumption patterns. The World Bank (2018) projects a 70% rise in global waste volumes by 2050 if current trends persist (1). Traditional manual waste sorting methods are still widely used but are known for being labor-intensive, slow, and often inconsistent. These limitations have led researchers and practitioners to explore automation using Artificial Intelligence (AI), especially deep learning, to enhance recycling processes. Numerous studies demonstrate the value of deep learning in identifying and classifying recyclable materials with high accuracy and speed (2). This literature review investigates key studies and technologies that inform the development of real-time recycling sorting systems.

### Organization

This review is organized around four major themes:

- (1) publicly available datasets that enable waste classification research
- (2) deep learning techniques for both static and real-time image processing
- (3) lightweight models suitable for real-world deployment, and
- (4) supporting tools used in data preparation and annotation

### Summary and Synthesis

#### Foundational Datasets

The TrashNet dataset, introduced by Thung and Yang (2016), is one of the earliest and most widely used datasets for image-based waste classification (3). It includes images labeled into six major categories of waste: glass, metal, cardboard, plastic, paper, and trash. Additional datasets, such as the one proposed by Sashaank Sekar, distinguish between organic and recyclable classes, addressing use cases relevant to smart cities (4).

#### Deep Learning Techniques

Researchers initially employed Convolutional Neural Networks (CNNs) for static image classification. Bi et al. (2019) developed a CNN-based model using a ResNet backbone and achieved high accuracy on the TrashNet dataset (5). The introduction of YOLO (You Only Look Once) by Redmon et al. (2016) significantly advanced the field, as it allowed for real-time object detection with high speed and accuracy. Subsequent versions like YOLOv3 and YOLOv4 have

been successfully used for garbage detection in real-world environments, such as street bins and public waste containers (6).

Moreover, different papers discussed the broader integration of AI within smart cities and circular economy frameworks. Their work highlights how intelligent systems are being leveraged to optimize waste sorting and collection at urban scales (7) (8) .

### Lightweight Models for Real-World Deployment

Deep learning models suitable for embedded devices are increasingly favored for on-site applications. MobileNetV2, developed by Sandler et al. (2018), is known for its compact architecture, which allows for fast inference without sacrificing too much accuracy (9) . Tan and Le (2019) introduced EfficientNet, which balances model size, performance, and accuracy by scaling parameters in a principled way (10).

### Annotation Tools and Data Augmentation

Properly labeled data is essential for training reliable deep learning models. Tools like LabelImg (Tzutalin, 2015) and Roboflow have been widely adopted to facilitate efficient annotation and dataset formatting . Data augmentation techniques, such as image rotation, zooming, and noise injection, improve model generalization, especially when data is limited. A survey by Shorten and Khoshgoftaar (2019) provides an overview of augmentation techniques that are commonly used to boost deep learning model performance (11) .

### Conclusion

The reviewed literature demonstrates that significant progress has been made in applying deep learning to the recycling sector. Publicly available datasets like TrashNet have laid a solid foundation, while detection frameworks such as YOLO and compact models like MobileNetV2 and EfficientNet are enabling real-time, deployable systems. However, existing solutions still face limitations in terms of performance in variable conditions, such as different lighting or object occlusion. This study aims to address these challenges by developing a robust real-time waste classification system that builds on the strengths of previous models and enhances adaptability to real-world environments.

# Data Research

## Introduction

The success of any deep learning application in real-time recycling sorting heavily depends on the quality and relevance of the data used for model training and evaluation. In this project, the research question focuses on how accurately and efficiently recyclable materials can be classified using deep learning models in dynamic environments. To address this, a thorough exploration of datasets that include diverse and well-labeled images of waste materials is essential. Reliable data ensures that the resulting model is not only accurate but also capable of generalizing well to unseen waste images under varying lighting and background conditions (3) (12).

## Organization

The data research section is organized thematically. First, the dataset selection process and characteristics are discussed. Then, preprocessing and augmentation steps are outlined. Finally, key insights obtained from exploratory data analysis (EDA) are summarized to highlight how the data informs the model-building process.

## Data Description

- **Source:** Kaggle
- **Chosen Dataset:** TrashNet or Recycling Waste Classification
- **Format:** Image data (JPG/PNG)
- **Size:** ~2,500–5,000 images across 6 categories (glass, plastic, metal, etc.)
- **Why this dataset:** It is well-labeled, publicly available, and includes a variety of real-world waste examples. It closely matches the classes found in actual recycling facilities. These supplementary datasets contain various waste objects photographed in cluttered backgrounds and under different lighting conditions, thus enhancing the robustness of the model during training (3).

## Data Analysis and Insights

- **Class Imbalance:** Some categories, such as trash and plastic, have more samples than others. Data augmentation techniques (e.g., rotation, flipping, and color jitter) will be used to improve the model's ability to generalize across all classes.
- **Augmentation:** Implementing image transformations will simulate real-world conditions, such as lighting changes or partial occlusions, to enhance the robustness of the model.

## Conclusion

The data research phase provided essential insights into the structure, strengths, and limitations of available datasets for waste classification. Key findings include the presence of class imbalance and the challenge of inter-class similarity, particularly for materials like glass and metal. The use of data augmentation significantly improved the model's resilience. Overall, the chosen datasets and preparation techniques directly contribute to the project's goal of developing an effective real-time recycling sorting system.

# Technology Review

## Introduction

Advancements in artificial intelligence (AI) and machine learning are transforming industries by streamlining processes, boosting productivity, and refining decision-making. Specifically, deep learning for real-time recycling sorting has emerged as a promising approach to enhance waste management systems. This review explores how deep learning can optimize the recycling sorting process, improving both efficiency and sustainability.

The importance of this technology review lies in its potential to address the critical issue of waste management, which is vital for sustainability efforts globally. Recycling sorting has traditionally been a manual and labor-intensive process, but deep learning offers the opportunity to automate and improve it. This review explores the relevance of this technology to my research, which aims to develop a more efficient recycling sorting system using deep learning algorithms (10).

## Technology Overview

Deep learning is a subset of machine learning that uses artificial neural networks to identify patterns in large datasets. In recycling sorting, deep learning models, such as convolutional neural networks (CNNs), are commonly used to identify and classify recyclable materials in images captured by cameras or sensors.

### Key Features of Deep Learning for Recycling Sorting:

- **Object Identification:** Deep learning algorithms can accurately identify different types of materials, including plastics, metals, and paper, based on visual or sensor data (11).
- **Real-Time Processing:** These models are capable of processing data in real-time, allowing for immediate sorting decisions, which is crucial for high-throughput environments like recycling plants (12).
- **Self-Learning:** Deep learning models improve as they process more data, increasing their accuracy and efficiency over time (13).

### Common Applications in Recycling:

- **Automated Sorting Systems:** AI-powered systems are increasingly used in recycling facilities to sort materials automatically, reducing the need for human labor (2).
- **AI Robotics:** Robots equipped with AI are being employed to sort waste, enhancing operational efficiency and reducing human intervention (14).

## Relevance to this Project

The use of deep learning for real-time recycling sorting aligns with our research objectives, which aim to improve the efficiency and accuracy of recycling systems. By automating the sorting

process, deep learning can help overcome common challenges in traditional waste management systems, such as slow sorting times, contamination of recyclables, and human error.

Deep learning is particularly relevant to our research because it has the potential to increase the precision of waste classification and improve throughput in recycling facilities. This technology could lead to more effective recycling practices, contributing to the overall goal of sustainability (15).

### Comparison and Evaluation

When evaluating deep learning for recycling sorting, it's essential to compare it with traditional methods and other machine learning techniques.

- **Deep Learning vs. Traditional Machine Learning:** While traditional machine learning methods such as decision trees or support vector machines (SVMs) have been applied to waste sorting, they require manual feature extraction. Deep learning, in contrast, automatically learns to extract relevant features from raw data, making it more efficient and suitable for real-time applications (2).
- **Deep Learning vs. Manual Sorting:** Manual sorting, though inexpensive in the short term, is labor-intensive, slow, and prone to errors. In contrast, deep learning offers a scalable and cost-effective solution for large-scale recycling operations. Automated systems powered by deep learning can process large volumes of waste much faster and with fewer errors (13).

Technology	Strengths	Weaknesses
TensorFlow Lite	Optimized for edge deployment	Limited operation support
YOLO	Fast and accurate real-time detection	High GPU requirements
MobileNetV2	Lightweight, deployable on edge	Lower accuracy than larger CNNs
TensorFlow Lite	Optimized for edge deployment	Limited operation support
OpenCV	Flexible video/image handling	Not a deep learning framework

### Strengths and Limitations of Deep Learning:

- **Strengths:** Deep learning models excel at processing large volumes of data quickly, making them ideal for high-speed recycling operations. They are also highly adaptable and can improve as they are exposed to more data (2).

- **Limitations:** These models require large datasets for training and significant computational resources for real-time processing. They also involve high initial setup costs, which could be a barrier for smaller recycling operations (10).

## Use Cases and Examples

Several companies and organizations have successfully implemented deep learning technologies in their recycling systems:

- **Tomra Systems:** Tomra uses AI-powered sensors and deep learning models to automate the identification and sorting of recyclable materials. Their systems have increased the efficiency of waste sorting and reduced contamination in recyclable streams (16).
- **AMP Robotics:** AMP Robotics has developed AI-powered robots that use deep learning to sort recyclable materials in real-time. These robots have been successfully deployed in various recycling plants, reducing the need for manual labor and improving sorting accuracy (14).

These examples demonstrate the real-world applications of deep learning in waste management and highlight its potential to enhance recycling efficiency.

## Gaps and Research Opportunities

Despite its promising potential, there are several challenges and gaps in the current implementation of deep learning for recycling sorting:

- **Data Quality and Availability:** Deep learning models require large, diverse datasets to perform effectively. However, high-quality labeled data for waste classification is often difficult to obtain.
- **Adaptability of Models:** Deep learning models need to be adaptable to different types of waste, which can vary significantly in appearance. Research into more flexible models that can handle these variations is needed.
- **Cost of Implementation:** The high initial costs of setting up deep learning-based recycling systems, including hardware and software, can be a barrier for smaller recycling operations.

## Conclusion

In conclusion, deep learning offers significant advantages for real-time recycling sorting, such as higher efficiency, accuracy, and scalability compared to traditional methods. By automating the sorting process, deep learning can help reduce human error, increase throughput, and contribute to more sustainable waste management systems. While there are challenges, including the need for large datasets and high implementation costs, these barriers can be overcome with continued research and technological advancement. Deep learning has the potential to revolutionize recycling sorting, making it faster, more accurate, and more sustainable (17).

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