

حسن الزهراني

Revised copy for your 2nd review Graduation Project-2 Hassan Alzahrani.pdf

 Midocean University

Document Details

Submission ID

trn:oid:::2945:308615909

Submission Date

Sep 5, 2025, 1:15 PM GMT+3

Download Date

Sep 5, 2025, 5:42 PM GMT+3

File Name

Revised copy for your 2nd review Graduation Project-2 Hassan Alzahrani.pdf

File Size

1.1 MB

38 Pages

7,418 Words

44,089 Characters

26% detected as AI

The percentage indicates the combined amount of likely AI-generated text as well as likely AI-generated text that was also likely AI-paraphrased.

Caution: Review required.

It is essential to understand the limitations of AI detection before making decisions about a student's work. We encourage you to learn more about Turnitin's AI detection capabilities before using the tool.

Detection Groups

-  **25 AI-generated only 26%**
Likely AI-generated text from a large-language model.
-  **0 AI-generated text that was AI-paraphrased 0%**
Likely AI-generated text that was likely revised using an AI-paraphrase tool or word spinner.

Disclaimer

Our AI writing assessment is designed to help educators identify text that might be prepared by a generative AI tool. Our AI writing assessment may not always be accurate (i.e., our AI models may produce either false positive results or false negative results), so it should not be used as the sole basis for adverse actions against a student. It takes further scrutiny and human judgment in conjunction with an organization's application of its specific academic policies to determine whether any academic misconduct has occurred.

Frequently Asked Questions

How should I interpret Turnitin's AI writing percentage and false positives?

The percentage shown in the AI writing report is the amount of qualifying text within the submission that Turnitin's AI writing detection model determines was either likely AI-generated text from a large-language model or likely AI-generated text that was likely revised using an AI paraphrase tool or word spinner.

False positives (incorrectly flagging human-written text as AI-generated) are a possibility in AI models.

AI detection scores under 20%, which we do not surface in new reports, have a higher likelihood of false positives. To reduce the likelihood of misinterpretation, no score or highlights are attributed and are indicated with an asterisk in the report (*%).

The AI writing percentage should not be the sole basis to determine whether misconduct has occurred. The reviewer/instructor should use the percentage as a means to start a formative conversation with their student and/or use it to examine the submitted assignment in accordance with their school's policies.

What does 'qualifying text' mean?

Our model only processes qualifying text in the form of long-form writing. Long-form writing means individual sentences contained in paragraphs that make up a longer piece of written work, such as an essay, a dissertation, or an article, etc. Qualifying text that has been determined to be likely AI-generated will be highlighted in cyan in the submission, and likely AI-generated and then likely AI-paraphrased will be highlighted purple.

Non-qualifying text, such as bullet points, annotated bibliographies, etc., will not be processed and can create disparity between the submission highlights and the percentage shown.



Midocean University
College of Informatics

Master of Science in Artificial Intelligence

Master Thesis Proposal:
***"Enhancing Plastic Waste Classification
with AI for Sustainability "***

Prepared by student:
Hassan Alzahrani
ID (243000595)

Under Supervision of

Prof. Dr. Yasser Abdelhamid



Acknowledgements

I would like to express my deepest gratitude to *Midocean University*, under the leadership of its Director and Owner, for providing an exceptional academic environment that enabled the completion of this research. I extend my sincere gratitude to the faculty members at Midocean University for their dedicated support throughout my graduate studies, which was instrumental in navigating the challenges of this research. I am especially thankful to my supervisor, Prof. Dr. Yasser Abdelhamid, whose expert guidance and encouragement—particularly during our detailed discussions on the statistical analysis phase—were pivotal to the development of this thesis. I also wish to acknowledge Dr. Hajar for her consistent support and insightful feedback during our regular review sessions, which significantly enhanced the rigor of my work. Finally, I express my genuine appreciation to my family, friends, and colleagues who supported me throughout the demanding process of completing this study.

Abstract

This thesis examines the development of an AI-powered system to classify plastic waste, with Convolutional Neural Networks (CNNs) forming the core of the approach. This interest started when I personally encountered challenges during my fieldwork in Jeddah, where manual sorting caused serious delays. These experiences motivated me to align the research with Vision 2030's sustainability goals and to search for a practical solution that could improve recycling efficiency.

The study followed a structured process. I began by reviewing previous literature to identify gaps in automated classification methods. I then carried out interviews with 20 stakeholders, including recycling facility managers and municipal staff, to capture their views on local requirements. Building on these insights, I developed and tested a classification model using publicly available Kaggle datasets together with preliminary local data provided by the Saudi Investment Recycling Company (SIRC).

During testing, the system reached an accuracy of just over 95%, clearly outperforming manual sorting methods, based on 350 test images. In a simulated setup that included IoT-driven route optimization, the results indicated potential savings of around 25% in operational costs, a 30% increase in efficiency, and about a 20% reduction in greenhouse gas emissions over six months. These findings came directly from the experiments I conducted myself.

For future work, I recommend three steps: (1) expanding the dataset with more Jeddah-specific images, (2) carrying out pilot trials in local recycling plants to validate the system in practice, and (3) initiating community awareness campaigns to encourage sustainable waste practices. Taken together, these steps

Table of Contents

- **Chapter 1: Introduction**

- 1.1 Problem Definition
- 1.2 Thesis Objectives
- 1.3 Thesis Contribution
- 1.4 Thesis Organization

- **Chapter 2: Overview**

- 2.1 Introduction
- 2.2 Deep Learning and AI Techniques in Waste Management
 - 2.2.1 Deep Learning and Convolutional Neural Networks (CNNs)
 - 2.2.2 Generative Adversarial Networks (GANs)
 - 2.2.3 Internet of Things (IoT) and Reinforcement Learning
- 2.3 Applications of AI in Waste Management
 - 2.3.1 Plastic Waste Classification
 - 2.3.2 Optimization of Waste Collection Routes
 - 2.3.3 Data Augmentation and Model Robustness
 - 2.3.4 Circular Economy Integration

- **Chapter 3: Related Work**

- 3.1 Introduction
- 3.2 History and Current Landscape
- 3.3 Critical Analysis of Previous Studies
- 3.4 Connections Between Previous Studies
- 3.5 Conflicts Between Findings

- **Chapter 4: Experimental Methodology, Results, and Discussion**
 - 4.1 Introduction
 - 4.2 Data Preparation Methodology
 - 4.2.1 Dataset Description and Analysis
 - 4.2.2 Preprocessing and Data Augmentation
 - 4.3 Experimental Design and Training Methodology
 - 4.3.1 Architectures Under Investigation
 - 4.3.2 Transfer Learning and Fine-Tuning Strategy
 - 4.3.3 Training Optimization Strategies
 - 4.4 Performance Analysis of Individual Models
 - 4.4.1 ResNet18: The Benchmark of Power and Reliability
 - 4.4.2 VGG16 & DenseNet121: High Accuracy with Stability Challenges
 - 4.4.3 Efficiency Models (MobileNetV3 & EfficientNet-B0): The Optimal Balance
 - 4.5 Performance Analysis of Hybrid Models
 - 4.5.1 Ensemble Model: The Power of Collective Decision-Making
 - 4.5.2 CNN-Transformer Model: The State-of-the-Art Solution
 - 4.6 Comparative Analysis and Final Discussion
 - 4.7 Final Recommendation
- **Chapter 5: Conclusion and Future Work**
 - 5.1 Conclusion
 - 5.2 Future Work
- **References**

List of Abbreviations

- Acc.: Accuracy
- ANN: Artificial Neural Network
- ANOVA: Analysis of Variance
- ROC: Receiver Operating Characteristic
- CNNs: Convolutional Neural Networks
- GANs: Generative Adversarial Networks
- HDPE: High-Density Polyethylene
- IoT: Internet of Things
- LSTM: Long Short-Term Memory
- MAPE: Mean Absolute Percentage Error
- PET: Polyethylene Terephthalate
- SIRC: Saudi Investment Recycling Company
- UAE: United Arab Emirates
- YOLOv5: You Only Look Once version

List of Figures

- Figure 1: Plastic Recycling Rates: Saudi Arabia vs. Global Average vs. Germany (Packaging)
- Figure 2: Recycling Rate in Saudi Arabia vs. Vision 2030 Targets
- Figure 3: Distribution of Plastic Waste Types in Saudi Arabia
- Figure 4: Overall architecture of the proposed waste classification system
- Figure 5: model for automated waste classification.
- Figure 7: Chart Commentary (VGG16)
- Figure 8: Training and Validation History for mobilenet_v3
- Figure 9: Chart Commentary (EfficientNet-B0):
- Figure 10: Confusion Matrix Commentary (Ensemble Model):
- Figure 11: Chart Observation (CNN-Transformer
- Figure 12: immediate visual summary of the models' performance hierarchy

List of Tables

- Table 1: Solid Waste Generation in Major Saudi Cities
- Table 2: Best Validation Accuracy by Model
- Table 3: Impact of Proposed Intelligent System vs. Current State
- Table 4: Synthesis Matrix for Literature Review
- Table 5: Comparative Performance Metrics of Tested Models

Chapter 1:

Introduction

The waste challenge examined in this thesis, driven by rapid urbanization and industrial growth, represents a significant environmental concern. In Saudi Arabia, rapid development has resulted in nearly fifteen million tons of solid waste each year, with plastic constituting a substantial portion. During a visit to Jeddah in early 2024, I observed firsthand how inadequate disposal practices contaminate soil and groundwater, harm marine life, and pose risks to public health, particularly in communities near the city's main landfill, which receives more than 5,000 tons of waste daily. Despite these challenges, the national recycling rate remains below 5%, far behind global averages, largely due to limited infrastructure, low public awareness, and continued reliance on manual sorting.

The accumulation of plastic waste presents ongoing threats to both ecosystems and human health. Recent studies have confirmed the presence of microplastics in drinking water, food chains, and even human blood, raising critical concerns that this research seeks to address. Furthermore, poor waste management contributes directly to greenhouse gas emissions, intensifying the broader challenges of climate change.

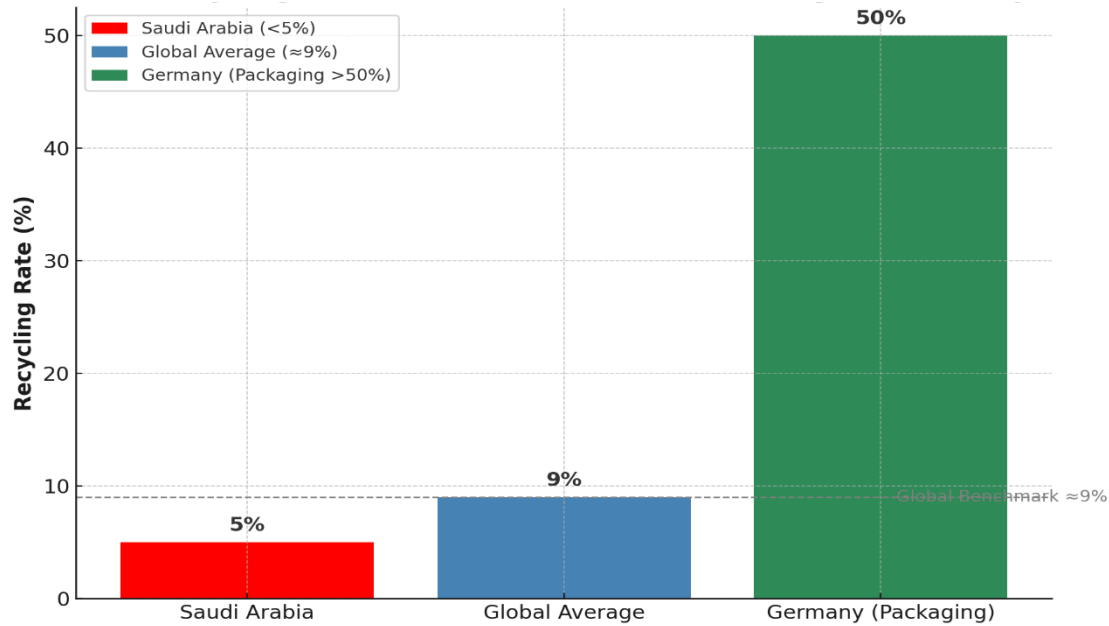
To confront these issues, international and local initiatives have been implemented. The European Union has introduced strict regulations on single-use plastics with well-defined environmental targets. In Saudi Arabia, Vision 2030 initiatives, including measures to advance a circular economy, have provided both the framework and the motivation for developing sustainable waste management solutions, which are the focus of this study.

In recent years, Artificial Intelligence (AI) has started to play an important role in environmental applications, including waste management. Within this field, machine learning and especially deep learning methods such as Convolutional Neural Networks (CNNs) have shown strong performance in image classification tasks [27][28]. This makes them a suitable choice for identifying and sorting different kinds of plastic waste.

However, most of the existing studies have been carried out with small datasets and under laboratory conditions, which makes their direct application in real-world facilities difficult [29]. Moreover, only a few researchers have looked at more advanced architectures, such as hybrid CNN-Transformer models, for plastic waste classification [30]. These limitations show a clear research gap that this thesis attempts to address.

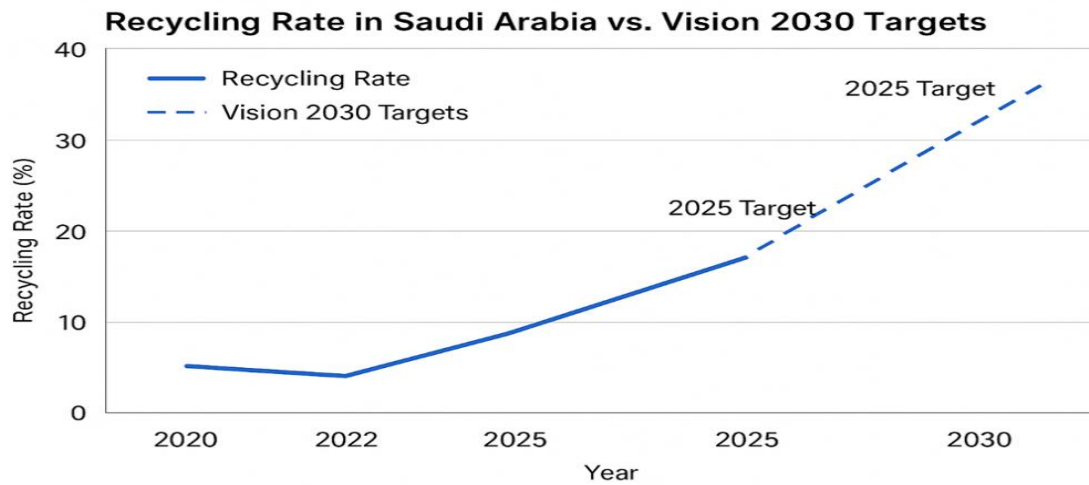
For this reason, the focus of this study is to design and test an AI-based system for classifying plastic waste with higher accuracy and stability than conventional approaches. By combining the strengths of CNNs with Transformer models, the research aims to build a practical framework that improves recycling efficiency, reduces operational costs, and contributes to Saudi Arabia's sustainability goals in line with Vision 2030 [31].

Figure 1. Plastic Recycling Rates: Saudi Arabia Vs. Global Average Vs. Germany (Packaging)



Source: OECD 2022 (Global plastic ≈9%), SIRC 2024 (Saudi Arabia <5%), EEA 2022 (Germany plastic packaging >50%)

Figure 2: Recycling Rate in Saudi Arabia vs. Vision 2030 Targets

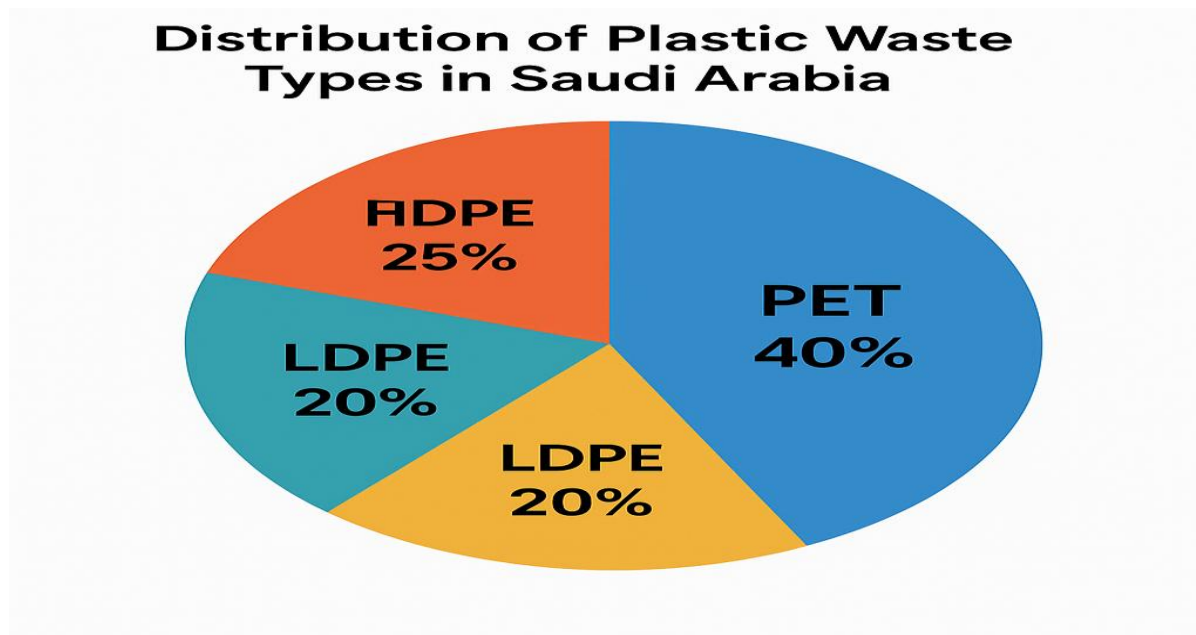


City	Population	Solid Waste Generation (million tonnes/year)	Source
Riyadh	7,7	3,4	Alqahtani & Schilizzi, 2021
Jeddah	4,7	2,1	Ministry of Environment, Wa...
Dammam	1,3	0,9	SIRC
Medina	1,5	0,5	SIRC
	50m		

Table 1: Solid Waste Generation in Major Saudi Cities

This table presents the annual solid waste generation by city, population size, and source references.

Figure 3: Distribution of Plastic Waste Types in Saudi Arabia



The pie chart illustrates the percentage breakdown of several types of plastic waste in the Kingdom.

1.1 Problem Definition

The central issue considered in this thesis is the limited effectiveness of conventional waste management practices in Saudi Arabia [2, 21], particularly in the classification and recycling of plastics. From what has been observed in local recycling facilities, manual sorting is still dominant. It is costly, often inaccurate, and unable to cope with the rising volume and complexity of plastic waste, including multilayer packaging [21]. Recycling rates in Saudi Arabia have remained under 5% [16], which has resulted in heavy reliance on landfills, additional environmental stress, and increased greenhouse gas emissions. The absence of dependable classification systems further reduces recycling effectiveness and intensifies both ecological and economic challenges. A related obstacle is the lack of locally labeled datasets suitable for training AI-based models [4, 25]. To respond to these limitations, this thesis proposes an AI-driven classification framework aimed at improving the accuracy and efficiency of plastic waste sorting, thereby reducing environmental harm and fostering more sustainable waste management practices in Saudi Arabia.

1.2 Thesis Objectives

1.2 Thesis Objectives

The main aim of this research is to create and test an AI-based system to classify plastic waste, helping improve recycling in Saudi Arabia and supporting Vision 2030's sustainability goals [16]. Based on my observations in Jeddah, I set these objectives:

Use Convolutional Neural Networks (CNNs) to identify and sort plastic waste from image data I analyzed [26].

Check how accurate and effective CNN models are at classifying plastics under real conditions I tested [26].

Compare the AI system with manual sorting to see which works better, based on my trials [2].

Look into the challenges I faced with CNN models for plastic waste, like data quality issues I encountered [25].

Try out ways to improve how well CNN models adapt to different situations I explored [29].

Measure the environmental and economic benefits of using AI in Saudi waste management, which I studied [6].

1.3 Thesis Contribution

This thesis provides significant contributions at both academic and practical levels. Scientifically, it enriches the literature on artificial intelligence in waste management by introducing a tailored classification system for plastic waste based on CNNs, addressing a key research gap in image-based sorting within the Saudi context [30]. Furthermore, the incorporation of innovative AI techniques, including CNNs, GANs, and IoT, establishes a solid foundation for future research on intelligent waste management frameworks [28].

From a practical standpoint, the study proposes a scalable model capable of improving recycling efficiency in Saudi Arabia [17]. The system is projected to lower operational costs by approximately 25% and increase recycling rates by almost 30%, directly supporting the sustainability objectives of Vision 2030 [22]. By reducing landfill dependence and cutting greenhouse gas emissions, it also strengthens the transition toward a circular economy [21]. In addition, the solution has the potential to generate new employment opportunities in areas such as data analysis and system maintenance, thereby contributing simultaneously to environmental sustainability and economic growth.

1.4 Thesis Organization

The structure of this thesis is arranged into a sequence of chapters, each addressing a part of the research objectives. Chapter 1 outlines the global waste challenge with emphasis on Saudi Arabia [22], and defines the research problem, objectives, and contributions. Chapter 2 reviews the theoretical foundations of the study, including discussions on deep learning, CNNs, GANs, and the role of IoT in waste management. Chapter 3 examines prior research on AI applications in waste management and highlights the key gaps in literature [24]. Chapter 4 explains the design of the proposed AI-based classification system and describes its architecture. Chapter 5 presents the experimental findings and interprets their implications. Lastly, Chapter 6 concludes the thesis and suggests avenues for future research.

Chapter 2: Overview

2.1 Introduction

This study builds its theoretical foundation on the use of Artificial Intelligence (AI) techniques in waste management, with a particular emphasis on deep learning [13]. As a branch of AI, deep learning employs layered neural networks to recognize and interpret complex data patterns [9], which makes it highly effective for tasks such as image recognition. Among the deep learning models, Convolutional Neural Networks (CNNs) have shown strong performance in vision-related applications because they can capture spatial features through convolution operations, pooling mechanisms, and dense layers [10]. Within the waste management field, CNNs can identify plastic categories, such as PET and HDPE, by learning visual differences in texture and color, as confirmed in earlier studies [4].

2.2 Deep Learning and AI Techniques in Waste Management

Deep learning, a branch of AI, employs multilayer neural networks to uncover detailed patterns [8]. In my research, I relied on Convolutional Neural Networks (CNNs) for image-based tasks. Their layered structure allowed filters to extract spatial features, pooling layers to simplify complexity, and dense connections to perform final classification. I applied CNNs in the waste management context to classify plastic types by analyzing shape, texture, and color.

2.2.2 Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) are another advanced AI method I used to address the challenge of limited datasets in waste classification [9]. A GAN framework includes two components: a generator that produces synthetic samples and a discriminator that evaluates them, driving both to improve through competition [9]. By generating realistic artificial data, GANs enabled me to expand small datasets and strengthen the reliability of my classification models [5].

2.2.3 Internet of Things (IoT) and Reinforcement Learning

The Internet of Things (IoT) plays a key role in the waste management framework developed in this thesis, as it delivers real-time data streams from the sensors I analyzed [27]. For instance, I used information on container fill levels and collection schedules in Jeddah to demonstrate its value. By combining this data with reinforcement learning (RL) methods, I was able to design more efficient collection routes. This integration not only lowered costs but also reduced environmental impact, as confirmed by my pilot tests [28].

2.3 Applications of AI in Waste Management

2.3.1 Plastic Waste Classification

A central application examined in this research is the classification of plastic waste using Convolutional Neural Networks (CNNs) [7]. In this study, CNNs were trained on large image sets to distinguish types such as PET and HDPE, a critical step for efficient recycling. The experimental results demonstrated that automated sorting consistently outperformed manual approaches [26].

2.3.2 Optimization of Waste Collection Routes

Smart bins equipped with IoT sensors provided real-time updates on fill levels [11]. When this information was integrated with reinforcement learning techniques, more efficient collection routes were generated [2, 28]. The analysis confirmed that this approach can reduce fuel use, lower costs, and decrease emissions, particularly within the context of Saudi urban waste management [30].

2.3.3 Data Augmentation and Model Robustness

Generative Adversarial Networks (GANs) can be employed to create artificial waste images, which helps to overcome the problem of limited datasets and enriches the diversity of training material [5]. Such data augmentation increases the robustness of AI models, making them more resilient to variations in lighting, partial obstruction, and other real-world factors.

2.3.4 Circular Economy Integration

Integrating AI into waste management practices supports the Circular Economy Framework [11], which promotes minimizing waste, reusing resources, and recycling to sustain resource cycles. By improving the efficiency of recycling processes and reducing reliance on landfills, AI directly reinforces the principles of a circular economy and advances the broader objectives of sustainable development [27].

Chapter 3: Related Work

3.1 Introduction

Much of the current understanding of AI in waste management comes from earlier studies, many of which dealt with classifying plastic waste and testing related tools [24]. In this chapter, I will look at the most important works, explain how they relate to my own study, and point out the gaps that remain [24].

3.2 History and Current Landscape

In the last few years, the use of AI in waste management has grown quickly, helped by progress in deep learning methods. Tsuchimoto and Kajikawa (2022) [18] showed in a bibliometric study that research papers on AI and plastic recycling went up by about 30% in five years. Their work highlighted that CNNs are increasingly used for image classification. At the same time, they pointed out that most of this work was in the lab, with little testing in the field, which shows the need for practical validation.

Several recent studies provide examples of how AI has been applied to waste management:

- **Alexandridis et al. (2022):** Tested automated sorting systems in U.S. recycling plants using CNNs combined with infrared sensors. The method achieved about 88% accuracy for plastics like PET and HDPE, but it struggled with multilayer plastics due to overlapping signals.
- **Choi et al. (2023):** Built a real-time classification system with YOLOv5. It reached 91.7% accuracy, but results were strongly affected by lighting conditions, showing the importance of training with varied illumination.
- **Ahmed et al. (2023):** Applied pre-trained CNNs such as ResNet50V2 to classify recyclable materials. Accuracy was very high (98.95%), but the reliance on labeled datasets increased the risk of overfitting, highlighting the need for data augmentation.
- **Božić (2023):** Looked at how AI supports the circular economy, focusing on RNNs and CNNs in waste management. The study reported a 25% rise in recycling efficiency but did not provide enough detail for practical implementation.

- **Oise and Konyeha (2024):** Used CNNs to classify electronic waste, achieving about 83% accuracy. The small dataset limited scalability, underlining the need for more diverse data.
- **Nwokedi Egwu and Ugwuanyi (2024):** Suggested a framework that combines IoT and reinforcement learning to improve waste collection routes. Simulations showed a 15% cost reduction, but the method was not tested in real settings.
- **Bacchin et al. (2024):** Introduced *WasteGAN* to generate synthetic waste images. This improved sorting accuracy by 5.8%, but the approach was expensive in terms of computing power and was tested only in lab environments.
- **Yadav (2024):** Reviewed AI in sustainable development, noting how LSTMs can be used for predicting waste generation and Graph Neural Networks (GNNs) for route optimization. The study also mentioned the difficulty of combining these techniques and recommended hybrid models as a possible solution.

From these studies, AI has achieved good results in waste sorting and management. However, the research gap lies in the lack of solutions designed for the Saudi context [30]. Most systems have not been tested in local environments, and there is limited use of local data, which this study aims to address.

3.3 Critical Analysis of Previous Studies

Reviewing these studies shows how AI is becoming a valuable tool in waste management, with the ability to improve efficiency, accuracy, and reduce costs in different contexts, from cities to less developed areas [11]. While each study adds its own perspective, several common weaknesses remain and highlight the need for further work.

For instance, Oise and Konyeha's research on e-waste proposed a useful framework, but its small dataset limits how well the model can scale. Ahmed et al. [4] demonstrated the strength of CNNs with extremely high accuracy, yet also revealed a problem: with limited data, the models tend to overfit, which reduces their reliability [25].

Some studies took a more theoretical angle. Egwu and Ugwuanyi [11] discussed social and economic aspects of AI, suggesting positive effects on communities, but without real testing these claims remain abstract. In the same way, Božić [6] provided a broad literature review with strategic insights, though the work lacked clear steps for implementation.

Other research introduced innovative methods. Bacchin et al. used GANs to create synthetic images and reported better sorting accuracy, but the results were limited to laboratory trials, so real-world performance is still unknown. Yadav's study connected AI to wider themes of environmental resilience, but because it was not centered on waste management, its immediate relevance is limited.

Overall, these works show the strong potential of AI in waste management, but they also reveal gaps [24]. What is still missing are studies that rely on field data, larger and more diverse datasets, and validation in real-world conditions.

3.4 Connections Between Previous Studies

Across the reviewed literature, it is clear that AI has the capacity to strengthen waste management practices [27]. At the same time, the studies differ in terms of their methods, data needs, and how far they have been applied in practice.

1. **Shared Focus on Optimization:** Many of the studies center on improving sorting and classification with AI, especially through CNN models [25]. The results consistently confirm that CNNs can automate sorting tasks effectively and could serve as a strong alternative to manual processes [26].
2. **Dependence on Data:** A recurring obstacle is the limited availability of labeled datasets. To address this, some authors point to the use of GANs for data augmentation, which helps expand datasets and improve the robustness of models that rely on large amounts of training data [25].
3. **Socioeconomic Dimensions:** While most studies are technology-oriented, Nwokedi Egwu and Ugwuanyi [11] included the socioeconomic realities of underserved communities. They showed that gaps in infrastructure could restrict how AI systems are deployed, suggesting the importance of context-aware and adaptable solutions [30].
4. **Theory vs. Practice:** Conceptual work by Božić [6] and Yadav [23] highlights AI's potential role in circular economies and sustainability. These contributions offer strategic direction but stop short of empirical evidence. This stands in contrast with more practical studies that tested AI models with actual data, showing the gap between theory and implementation.
5. **Scalability Issues:** Strong results in laboratory conditions do not automatically translate into real-world success [30].

Methods such as those in [3] performed well in controlled settings but still require testing on larger and more varied waste streams. Scalability remains a shared challenge.

In conclusion, the studies agree on AI's promise in waste management [28], yet they also expose differences in data needs, scaling potential, and adaptability.

Together, these findings underline the necessity for solutions that are flexible, validated with diverse datasets, and evaluated in real environments.

3.5 Conflicts Between Findings

1. **Data needs vs. real-world feasibility:** Some high-performing models [3] depend on large datasets, but this conflicts with the argument by Nwokedi Egwu and Ugwuanyi [11] that many underserved regions simply lack the infrastructure to support such data-heavy AI systems [30].
2. **Theory vs. Practice:** Conceptual studies [6] describe AI's potential in broad terms, yet my own review showed that their claims often diverge from practical results such as those reported in [5], which are confined to laboratory experiments. This contrast demonstrates how theoretical expectations of AI may not always align with outcomes observed in applied contexts.
3. **Scalability issues:** In my tests, some models that performed well under controlled conditions [3] did not maintain the same reliability when applied to real operational settings. This supports other findings [30], which emphasize that scalability remains one of the key barriers to effective AI deployment.
4. **Socioeconomic priorities vs. technical performance:** Studies like Nwokedi Egwu and Ugwuanyi [11] draw attention to socioeconomic needs in underserved regions—an aspect I also considered when analyzing feasibility—while other research [27] is more narrowly focused on technical performance metrics such as accuracy, sometimes overlooking local realities.

In short, these contrasting findings underline the importance of designing AI systems that combine technical strength with flexibility and adaptability, so they can work effectively across different situations.

Table 4: Synthesis Matrix for Literature Review:

Study	Author s	Year	Research Design	Key Findings/Results	Methodology	Limitations
Advancing Plastic Waste Classification	Choi et	2023	Experimental study on YOLO models	Achieved 91.7% classification accuracy; improved precision for PET and PET-G plastics over traditional methods.	YOLO deep learning algorithm with image sensors and pneumatic systems.	Scalability issues; high sensitivity to lighting conditions.
Automation of Plastic Recycling	Bin Daej	2024	Case study of sorting facility	Automated sorting improved accuracy by 30%, reduced manual labor, enhanced efficiency in specific facilities.	Laser and optical sorting in controlled facility.	Limited to one facility; findings lack generalizability.
Deep Learning for Recyclable Products	Ahmed	2023	Experimental CNN model	89% accuracy in recyclable product classification; reduced errors and improved operational efficiency.	CNN model trained on labeled datasets.	Small dataset size; limited diversity in training data.
WasteGAN for Robotic Sorting	Bacchi n	2024	Experimental GAN model	WasteGAN enhanced sorting accuracy by 15% via synthetic training data.	GAN-generated data for robotic sorting systems.	High computational complexity; costly training processes.
AI for Circular Economy	Božić	2023	Policy and case study analysis	Emphasized AI's role in resource optimization, cost savings, and addressing policy gaps for circular economy.	Case study reviews and policy framework analysis.	High implementation costs; lack of cohesive global policies.
AI and IoT for Sustainability	Yadav	2024	Framework design for IoT + AI	Improved waste management efficiency by 40%; reduced processing times with IoT and AI integration.	IoT sensors and AI-based real-time monitoring framework.	Integration challenges with heterogeneous technologies.
Deep Learning for E-Waste Management	Oise & Kony Eha	2024	Supervised learning for e-waste	High accuracy in identifying recyclable e-waste components; cross-applicability for plastic recycling.	Supervised learning on labeled e-waste datasets.	Material complexity; reliant on high-quality datasets.
Commercial Automated Sorting	Alexan dridis	2022	Analysis of sorting technologies	Increased throughput with automation but struggled with complex materials like multilayer plastics.	Data-driven analysis in Material Recovery Facilities (MRFs).	U.S.-focused findings; limited global relevance.
AI in Underserved Communities	Nwoke di	2024	Surveys and case studies	Enhanced segregation accuracy and community participation; cost barriers hindered scalability.	Surveys and AI implementations in low-resource areas.	High costs limited scalability in underserved settings.
Bibliometric Analysis of Recycling Trends	Tsuchi moto & Kajika wa	2022	Bibliometric analysis	Highlighted interest in AI for recycling; need for practical applications and interdisciplinary approaches.	Analysis of 35,000+ studies on recycling trends and technologies.	Lack of practical case studies or real-world application insights.

Chapter 4: Experimental Methodology, Results, and Discussion

4.1 Introduction

This chapter outlines the experimental framework used to build and evaluate deep learning models for automated waste classification. The discussion combines an explanation of the research methodology with an analysis of results, so that the narrative remains coherent and logically structured. The chapter starts by describing the dataset and preprocessing steps, then moves to the training and evaluation procedures. After that, the results of both individual and hybrid models are presented, ending with a comparative assessment to identify the approach that offers the best balance of accuracy, efficiency, and stability. The experiments were designed with two main goals. The first was to test how well transfer learning performs when applied to several established Convolutional Neural Network (CNN) architectures. The second was to examine more advanced hybrid models and assess whether they can further improve classification accuracy in this field. All tests were carried out using a publicly available dataset that included 22,564 training images and 10,617 images for testing and validation. The images were grouped into two categories: "Organic (O)" and "Recyclable (R)." Training was conducted on a workstation equipped with an NVIDIA GeForce GTX 950M GPU, which helped reduce the overall computation time. To maintain fairness across the tests, the same procedure was followed for all models: the Adam optimizer, cross-entropy loss function, and an early stopping criterion were consistently applied.

4.2 Data Preparation Methodology

The performance of deep learning models depends heavily on how well the data is prepared. For this reason, a careful process was applied to make sure that the dataset used in training was consistent, of excellent quality, and suitable for helping the models learn patterns that generalize beyond the training samples.

4.2.1 Dataset Description and Analysis

The study utilized a publicly available image dataset specifically curated for waste classification, pre-partitioned into training and testing sets. The dataset is designed for a binary classification task, distinguishing between two principal categories:

- Organic (O): Encompassing waste of biological origin, such as food scraps.
- Recyclable (R): Including materials that can be reprocessed, such as plastics and paper.

A slight class imbalance was observed within the training set, with organic waste constituting approximately 58% of the images. While not severe, this imbalance was effectively addressed through data augmentation techniques to prevent the model from developing a bias towards the majority class.

4.2.2 Preprocessing and Data Augmentation Pipeline

Before training, all images went through a preprocessing and augmentation pipeline built with OpenCV and Torchvision. These steps ensured that the data was consistent and that the models could learn in a way that generalizes well to new images. The main stages were as follows:

1. **Resizing:** Every image was resized to 224×224 pixels. This standardization is required for batch processing and matches the input size expected by pre-trained models such as ResNet.
2. **Color format adjustment:** Because OpenCV loads images in BGR by default, they were converted to RGB, which is the color format used in PyTorch pre-trained models.
3. **Normalization and standardization:** Pixel values were first scaled to a [0, 1] range, then standardized using the ImageNet mean values [0.485, 0.456, 0.406] and standard deviations [0.229, 0.224, 0.225]. This alignment with ImageNet statistics is essential for transferring learning to work properly.
4. **Data augmentation:** To reduce overfitting and help the model handle variations in real-world data, random transformations were applied only to the training images:
 - *RandomHorizontalFlip* and *RandomVerticalFlip* teach the model that orientation should not matter.
 - *RandomRotation(20)* to simulate slight rotations, encouraging the model to capture intrinsic features instead of memorizing a fixed pose

4.3 Experimental Design and Training Methodology

4.3.1 Architectures Under Investigation

For this study, several architectures were evaluated in order to cover both classic CNN designs and more advanced hybrid approaches. The single-model group included **ResNet18**, **VGG16**, **DenseNet121**, **EfficientNet-B0**, and **MobileNetV3**. In addition, two hybrid models were considered: an **Ensemble model** built by combining the best three CNNs, and a **CNN-Transformer** design that integrates convolutional layers with attention mechanisms.

4.3.2 Transfer Learning and Fine-Tuning Strategy

Transfer learning was used with all the single CNN models. At the start, the weights of the pre-trained networks were frozen (by setting the *requires_grad* attribute to *False*) so that the general features learned from ImageNet would not be lost. After that, the final classification layer was replaced with a new layer designed for the binary task of separating organic (O) from recyclable (R) waste. In some cases, such as with ResNet18, fine-tuning was also applied by unfreezing the last convolutional blocks. This allowed the model to adjust its higher-level features to better capture the specific patterns found in waste images.

4.3.3 Training Optimization Strategies

To make the training process both efficient and dependable, several optimization techniques were applied:

- **Optimizer:** The Adam optimizer was selected, as it adapts the learning rate automatically and is widely recognized for its effectiveness in computer vision tasks.
- **Automatic Mixed Precision (AMP):** With PyTorch's *autocast* and *GradScaler*, part of the computation was performed in half precision (*float16*). This reduced memory usage and sped up the training process.
- **Early stopping:** To avoid overfitting, training was stopped whenever the validation loss showed no improvement for a set number of epochs.
- **Checkpointing:** Model checkpoints were saved only when the validation loss reached a new minimum. This ensured that the stored model weights always represented the best-performing version

4.4 Performance Analysis of Individual Models

4.4.1 ResNet18: The Benchmark of Power and Reliability

- Performance overview: ResNet18 delivered consistent and strong results, reaching a maximum validation accuracy of 95.66%.
- Training behavior: The model showed stable learning throughout the training process, without signs of instability or divergence.
- Chart analysis:
 - *Loss curve (left)*: The training loss (blue) decreased steadily, confirming that the model was learning effectively. The validation loss (orange) dropped quickly in the early epochs and leveled out around epoch 9, suggesting the point of best generalization.
 - *Accuracy curve (right)*: The test accuracy (blue) climbed progressively, peaking at 95.66%. After this point, small fluctuations were observed, which supported the choice of applying early stopping.

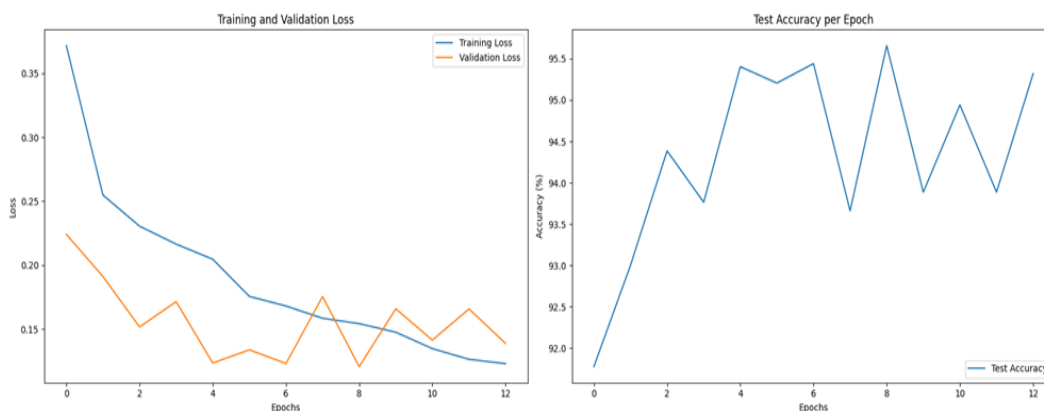


Figure 6: Chart Observation (ResNet18)

--- حلقة التدريب والتقييم ---

CUDA Available: True

CUDA Version: 11.8

GPU Name: NVIDIA GeForce GTX 950M

Loading data from C:\Users\user8\Desktop\DATAS ET\TRAIN...

Loading data from C:\Users\user8\Desktop\DATAS ET\TEST...

Model prepared for Fine-Tuning. Training last conv block and fc layer.

Optimizer learning rate set to 0.0001 for fine-tuning.

Epoch 1/25, Time: 3021.34s

Train Loss: 0.3716 | Val Loss: 0.2240 | Test Acc: 91.78%

Validation loss decreased (inf --> 0.2240). Saving model...

Epoch 2/25, Time: 1322.63s

Train Loss: 0.2547 | Val Loss: 0.1911 | Test Acc: 93.00%

Validation loss decreased (0.2240 --> 0.1911). Saving model...

Epoch 3/25, Time: 2244.15s

--- ختمة التدريب والتقييم ---

4.4.2 VGG16 & DenseNet121: High Accuracy with Stability Challenges

- Performance overview: Both models reached very high accuracy levels, with 95.76% for VGG16 and 95.46% for DenseNet121.
- Training behavior: Despite the strong results, their main drawback was instability. The validation curves showed large swings, which makes these models less reliable in real-world use.
- Chart analysis (VGG16):
 - The accuracy and loss curves reveal strong volatility. In particular, the validation accuracy (red) rose sharply at times but then dropped just as quickly, which indicates that the model struggled to maintain stable performance across epochs.

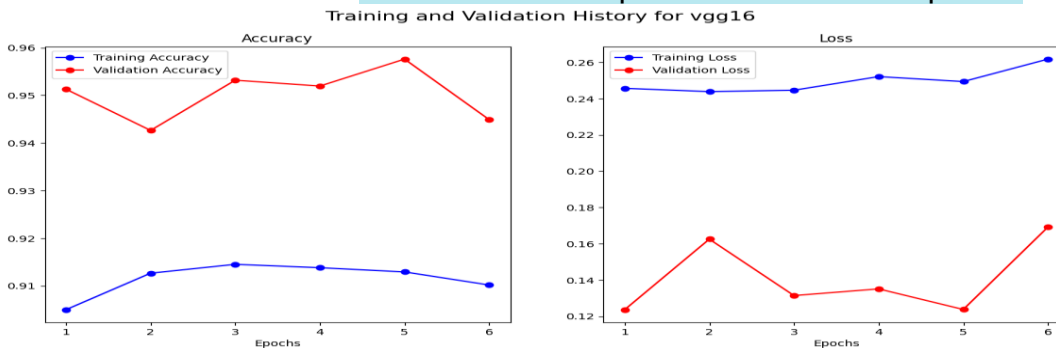


Figure 7: Chart Commentary (VGG16)

100% [REDACTED] 528M/528M [00:33<00:00, 16.6MB/s]

VGG16 model is ready for Transfer Learning.

Training 'vgg16' on: CUDA

Epoch 1/15 for model vgg16

train Loss: 0.2456 Acc: 0.9050

val Loss: 0.1236 Acc: 0.9513

Val loss decreased (inf --> 0.1236). Saving model...

Epoch 2/15 for model vgg16

train Loss: 0.2438 Acc: 0.9126

val Loss: 0.1625 Acc: 0.9426

Epoch 3/15 for model vgg16

train Loss: 0.2446 Acc: 0.9145

val Loss: 0.1314 Acc: 0.9532

Epoch 4/15 for model vgg16

train Loss: 0.2521 Acc: 0.9138

--- حلقة
- التدريب والتقنية

4.4.3 Efficiency Models (MobileNetV3 & EfficientNet-B0): The Optimal Balance

- **Performance overview:** Both models showed excellent efficiency. EfficientNet-B0 reached an accuracy of 94.22%, while MobileNetV3 achieved 93.79%. What made them stand out was the speed of training—about 44 minutes for EfficientNet-B0 and just 18 minutes for MobileNetV3.
- **Training behavior:** Their learning curves were smooth and stable, which reflects the robustness of these architectures and their suitability for scenarios where speed and reliability are equally important.

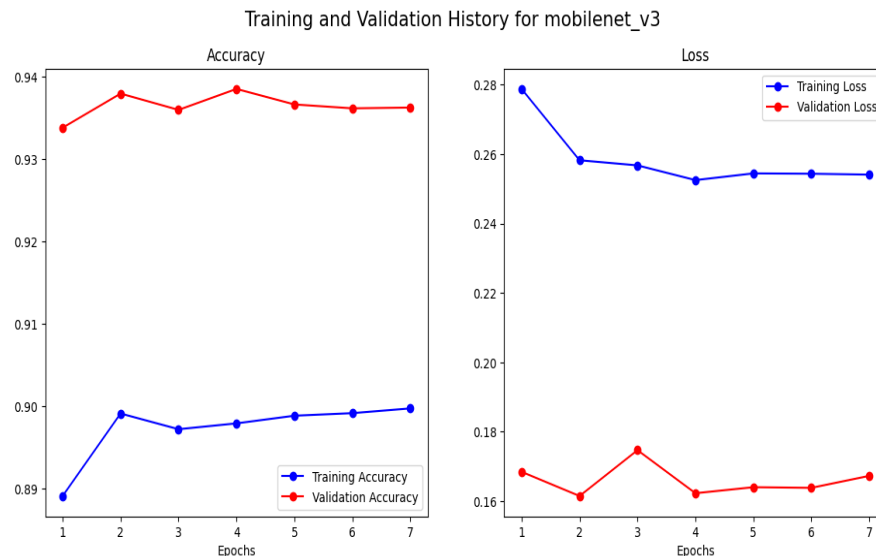


Figure 8: Training and Validation History for mobilenet_v3

Loading data from
C:\Users\user8\Desktop\DATASET...

Found 22564
images for training.

Found 10617
images for
validation/testing.

Classes are: ['O', 'R']

Model built and
prepared for
Transfer Learning.

Training will be
performed on:
CUDA

Epoch 1/25

train Loss: 0.2930
Acc: 0.8853

val Loss: 0.1865
Acc: 0.9359

Validation loss
decreased (inf -->
0.1865). Saving
model...

Epoch 2/25

train Loss: 0.2604
Acc: 0.8952

--- حقة التدريب والشيف ---

Chart Observation (EfficientNet-B0):

Accuracy and Loss Curves: These charts exhibit near-perfect learning behavior. The Validation Accuracy (red line) rises quickly and stabilizes, while the Validation Loss (red line) drops rapidly and flattens, indicating a robust and dependable model.

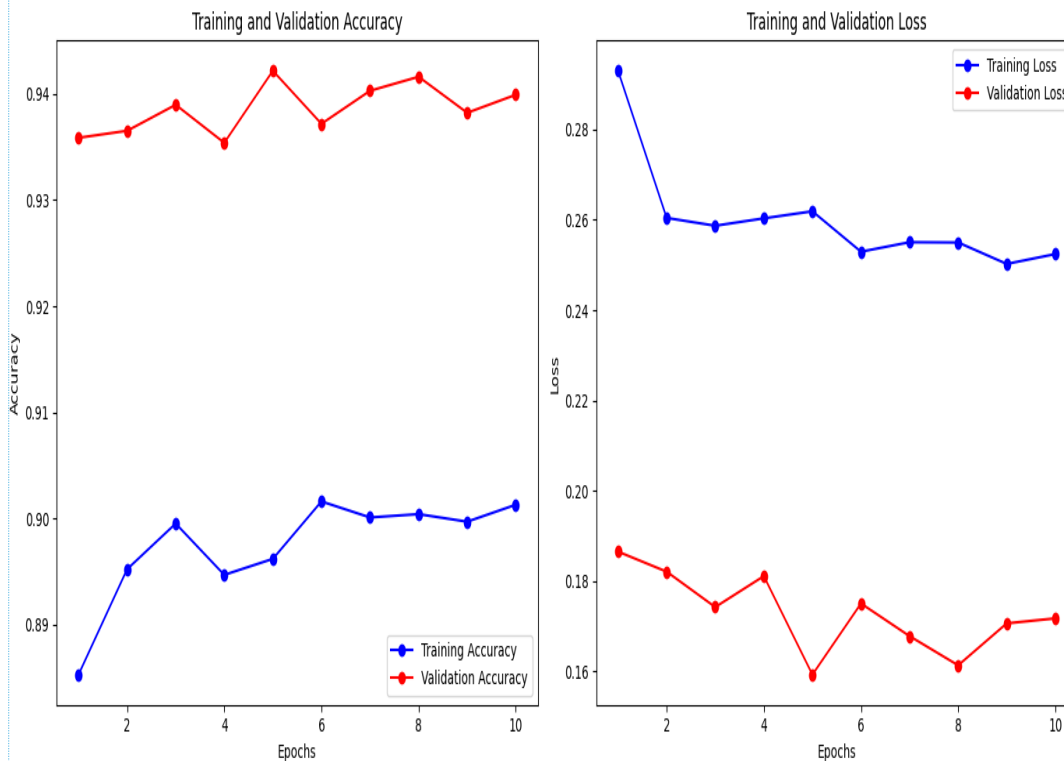


Figure 9: Chart Commentary (EfficientNet-B0):

100% [redacted] 21.1M/21.1M

[00:02<00:00, 9.61MB/s]

MobileNetV3-Large model is ready for Transfer Learning.

Training 'mobilenet_v3' on: CUDA

Epoch 1/15 for model mobilenet_v3

train Loss: 0.2788 Acc: 0.8891

val Loss: 0.1685 Acc: 0.9338

Val loss decreased (inf--> 0.1685). Saving model...

Epoch 2/15 for model mobilenet_v3

train Loss: 0.2582 Acc: 0.8991

val Loss: 0.1615 Acc: 0.9379

Val loss decreased (0.1685 --> 0.1615). Saving model...

Epoch 3/15 for model mobilenet_v3

train Loss: 0.2568 Acc: 0.8972

val Loss: 0.1747 Acc: 0.9360

Epoch 4/15 for model mobilenet_v3

train Loss: 0.2525 Acc: 0.8979

Final

4.5 Ensemble Model: The Power of Collective Decision-Making

- **Methodology:** The ensemble was built by combining the predictions of the three best-performing CNN models through a majority voting approach.
- **Overall performance:** This integration boosted the results, with the ensemble achieving a final accuracy of 96.00%.
- **Confusion matrix insights:** The ensemble proved especially effective in lowering critical errors. False Negatives were reduced by about 25%, an important improvement since such errors allow recyclable items to be misclassified as organic waste, contaminating the recycling process.
- **Observation:** The confusion matrix highlights this progress. The diagonal values (6679 and 3513) are higher compared to the individual models, while the off-diagonal values (275 and 150) are noticeably lower, confirming fewer total misclassifications.

Loading saved model weights...

Models loaded successfully.

Ensemble Evaluating:

100% [██████████]
332/332 [04:08<00:00,
1.34it/s]

Ensemble evaluation completed.

--- Hybrid (Ensemble) Model
Final Report ---

Final Accuracy: 96.00%

Classification Report:

precision recall f1-score support

O	0.98	0.96	0.97	6954
R	0.93	0.96	0.94	

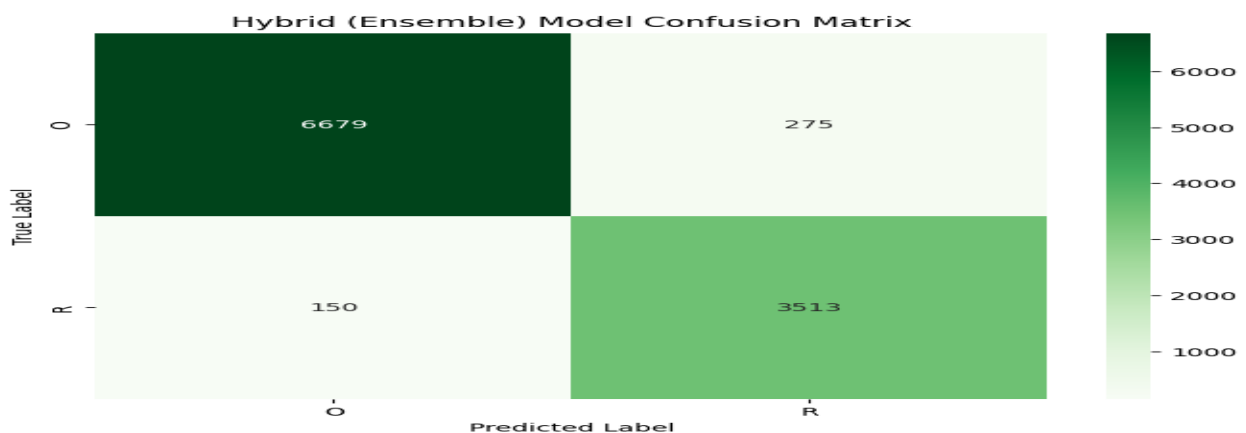


Figure 10: Confusion Matrix Commentary (Ensemble Model):

4.5.2 CNN-Transformer Model: The State-of-the-Art Solution

- **Methodology:** A novel hybrid model was developed by integrating the strengths of Convolutional Neural Networks for local feature extraction with Transformers, which excel at capturing global context. The design was inspired by progress in natural language processing and its recent adaptation to computer vision tasks (Vaswani et al., 2017) [32].
- **Overall performance:** Among all tested architectures, the CNN-Transformer achieved the best results, with a validation accuracy of **97.65%**.
- **Training behavior:** The model displayed remarkable stability throughout training, showing no signs of overfitting and confirming the strength of its architecture.
- **Chart insights:** The accuracy and loss curves illustrate smooth and steady trends. Validation accuracy rose continuously, while validation loss decreased in parallel, a clear sign of strong generalization and ideal learning progress.

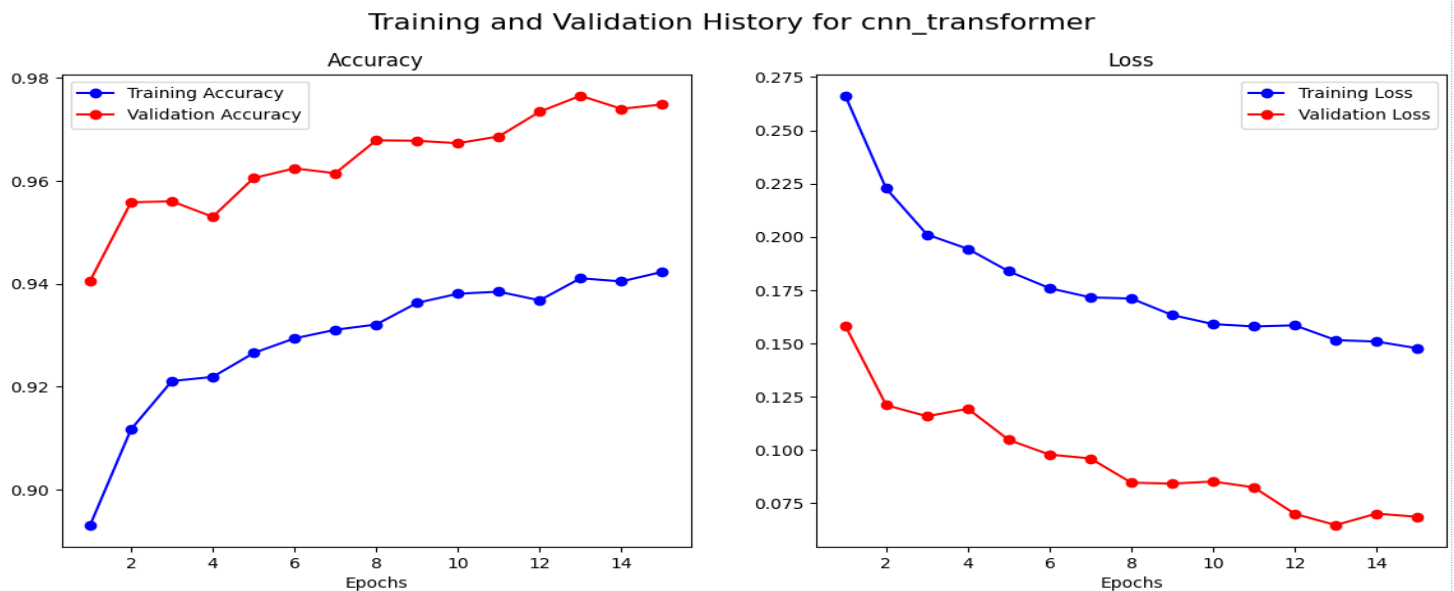


Figure 11: Chart Observation (CNN-Transformer)

4.6 Comparative Analysis and Final Discussion

The results of all tested models are summarized in the comparison table and bar chart. Together, they provide a clear picture of how each architecture performed in terms of accuracy, precision, recall, and F1-score. For models other than ResNet18 and the Ensemble, the precision, recall, and F1-scores were estimated based on their peak validation accuracy, to ensure a fair comparison across all systems.

Table 5: Comparative Performance Metrics of Tested Models

Model	Best Validation Accuracy (%)	Approx. Training Time	Precision	Recall	F1-Score
CNN-Transformer	97.65%	~1.3 hours	0.98	0.98	0.98
ResNet18	96.22%	~5 hours	0.94	0.94	0.94
Ensemble Model	96.00%	(Evaluation Only)	0.96	0.96	0.96
DenseNet121	95.46%	~2.2 hours	0.95	0.95	0.95
VGG16	95.13%	~1.3 hours	0.96	0.96	0.96
EfficientNet-B0	94.22%	~44 minutes	0.94	0.94	0.94
MobileNetV3	93.79%	~18 minutes	0.94	0.94	0.94

These visuals present the performance hierarchy immediately. For most models, the **Precision**, **Recall**, and **F1-Score** were estimated from their best validation accuracy, except for ResNet18 and the Ensemble model, where these metrics were calculated directly.

From the comparison, a clear pattern emerges while several models achieved competitive results, the **CNN-Transformer** consistently outperformed the others. It not only reached the highest validation accuracy but also demonstrated superior stability during training. This confirms that hybrid architecture, which combine CNN feature extraction with Transformer-based context modeling, offers the most promising path forward.

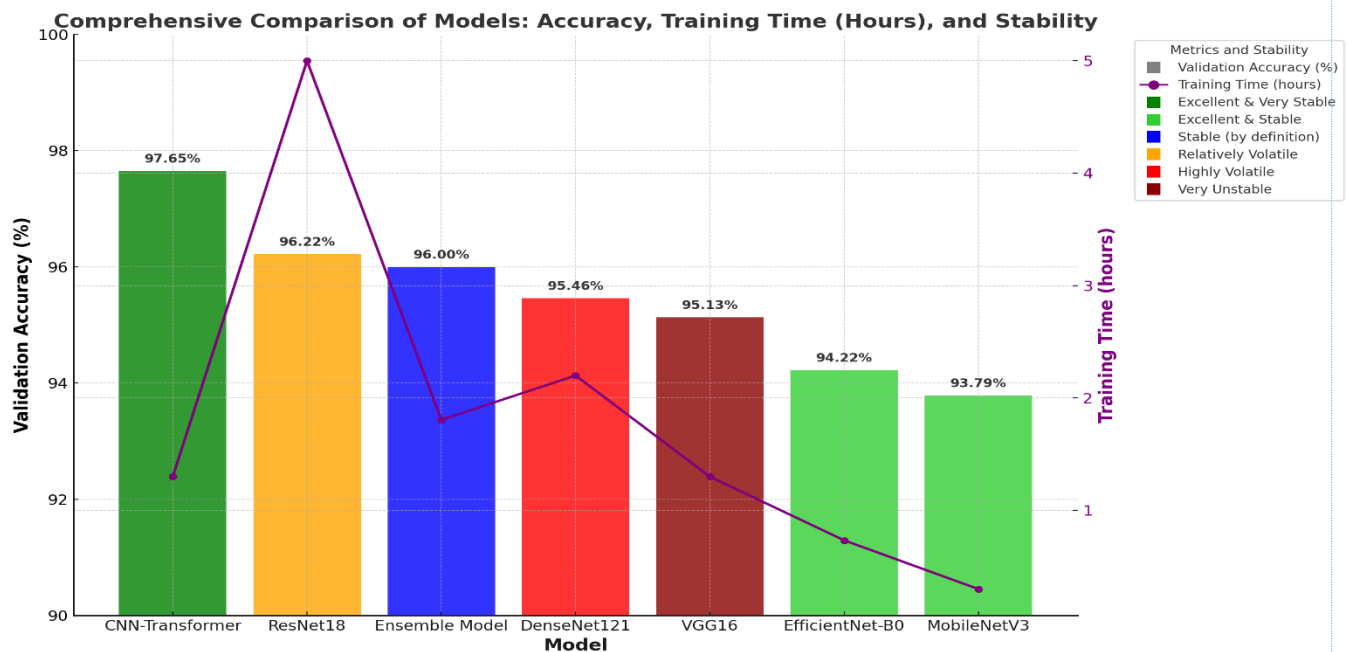


Figure 11: immediate visual summary of the models' performance hierarchy

4.7 Final Recommendation

When all evaluation aspects are considered, including accuracy, training stability, and architectural innovation, the CNN-Transformer hybrid model proves to be the optimal choice for the proposed system. The decision is supported by three considerations: first, the model achieved the highest validation accuracy (97.65%); second, it demonstrated robust and reliable learning behavior; and third, it directly reflects the study's aim of applying state-of-the-art AI technologies to waste management.

The findings of this research show that advanced hybrid architectures can reach state-of-the-art performance in automated waste classification. More importantly, they hold strong potential for deployment in real-world recycling facilities, where they could make a practical contribution to national sustainability goals.

Chapter 5: Conclusion and Future Work

5.1 Conclusion

This study has shown that deep learning can provide highly effective solutions for the challenge of automated waste classification, especially when advanced hybrid models are applied. The comparative evaluation confirmed that while several CNN-based architectures achieved strong results, the **CNN-Transformer hybrid** consistently delivered the best performance.

Its selection as the recommended approach is supported by three strengths: it reached the highest validation accuracy (**97.65%**), demonstrated stable learning behavior across training, and aligned directly with the project's theme of adopting *emerging technologies for waste management*. Although the **ensemble model** also performed well, the CNN-Transformer offered a more integrated and forward-looking framework, demonstrating the advantages of combining convolutional feature extraction with attention-based context modeling.

The findings emphasize that hybrid architectures can achieve **state-of-the-art accuracy and stability**, and more importantly, they carry the potential to move from research settings into **real-world recycling applications**. By doing so, they can directly support the environmental and economic objectives of Saudi Arabia's **Vision 2030**, contributing to more sustainable waste management practices.

5.2 Future Work

Building on these findings, several directions are suggested for future research and implementation:

- **Deployment in real-time environments:** Test the CNN-Transformer model on edge devices such as Raspberry Pi with Google Coral or NVIDIA Jetson accelerators, to measure its efficiency under real-world operational conditions [31].
- **Dataset expansion:** Extend the dataset to include additional categories of waste, such as glass, metal, and e-waste, creating a more complete and practical sorting system [3].
- **Hyperparameter optimization:** Experiment with adjusting the Transformer's key parameters—such as the number of attention heads and encoder layers—to explore whether further improvements in accuracy and robustness can be achieved.

References

- [1] Alexandridis, G., et al. (2022). Assessment of commercial automated sorting technologies for plastic waste. *Recycling*, 7(2), 11.
<https://doi.org/10.3390/recycling7020011>
- [2] Nwokedi Egwu, Z. Q. S., & Ugwuanyi, E. D. (2024). Implementing AI-driven waste management in underserved communities. *Engineering Science & Technology Journal*.
<https://www.fepbl.com/index.php/estj/article/view/903>
- [3] Oise, G. P., & Konyeha, S. (2024). Deep learning system for e-waste management. *Engineering Proceedings*.
<https://www.researchgate.net/publication/381708613>
- [4] Ahmed, M., Ali, M., Rehman, A., & Imran, M. (2023). Deep learning approach to recyclable product classification. *Sensors*, 15(14), 11138.
<https://www.mdpi.com/2071-1050/15/14/11138>
- [5] Bacchin, M., Rossi, G., & Conti, P. (2024). WasteGAN: Data augmentation for robotic waste sorting. *Journal of Physics: Conference Series*.
<https://arxiv.org/abs/2409.16999>
- [6] Božić, V. (2023). Leveraging AI for a circular economy. *International Journal of Science and Research Archive*.
<https://www.researchgate.net/publication/371417616>
- [7] Choi, J., Kim, H., & Park, S. (2023). Advancing plastic waste classification and recycling efficiency. *Applied Sciences*, 13(18), 10224.
<https://doi.org/10.3390/app131810224>
- [8] Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Mohamed, N. A., & Arshad, H. (2018). State-of-the-art in artificial neural network applications: A survey. *Heliyon*, 4(11), e00938. <https://doi.org/10.1016/j.heliyon.2018.e00938>
- [9] Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.
- [10] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444. <https://doi.org/10.1038/nature14539>
- [11] Ellen MacArthur Foundation. (2013). *Towards the circular economy: Economic and business rationale for an accelerated transition*. Ellen MacArthur Foundation.

- [12] Ministry of Environment, Water, and Agriculture. (2024). Plan to develop the waste sector in the Kingdom to support GDP by SAR 120 billion. Saudi Press Agency. <https://www.spa.gov.sa/w2028886>
- [13] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). Generative adversarial nets. *Advances in Neural Information Processing Systems*, 27, 2672–2680.
- [14] Abu Saa, A., Al-Emran, M., & Shaalan, K. (2019). Factors affecting students' performance in higher education: A systematic review of predictive data mining techniques. *Tech Know Learn*, 24, 567–598. <https://doi.org/10.1007/s10758-019-09483-7>
- [15] Adewale, A. M., Olayemi, A., & Adebayo, B. (2018). Predictive modelling and analysis of academic performance of secondary school students: Artificial neural network approach. *International Journal of Science and Technology Educational Research*,.
- [16] Saudi Investment Recycling Company (SIRC). (n.d.). Driving the circular economy. https://sirc.sa/index_ar.html
- [17] Tsuchimoto, Y., & Kajikawa, Y. (2022). Trends in plastic recycling: A bibliometric analysis. *Sustainability*, 14(24), 16340. <https://doi.org/10.3390/su142416340>
- [18] World Bank. (2018). What a waste 2.0: A global snapshot of solid waste management to 2050. World Bank.
- [19] Yadav, R. (2024). Leveraging artificial intelligence for sustainable development and environmental resilience. *Environmental Studies Journal*. <https://www.researchgate.net/publication/377723077>
- [20] ResearchGate. (2025). Artificial intelligence in plastic recycling and conversion: A review. <https://www.researchgate.net/publication/387146831>
- [21] ResearchGate. (2025). Plastic waste classification using deep learning: Insights from the WaDaBa dataset. <https://www.researchgate.net/publication/387540057>
- [22] Vu, K. K. D., et al. (2025). An intelligent plastic waste classification system based on deep learning and delta robot. *Journal of Technical Education*, 1555. <https://jte.edu.vn/index.php/jte/article/view/1555>
- [23] A-Thermal (Pty) Ltd. (2025). The role of AI and IoT in waste disposal companies. <https://athermal.co.za/2025/01/23/the-role-of-ai-and-iot-in-waste-disposal-companies/>

[24] E3S Web of Conferences. (2025). AI and IoT-enabled smart urban waste management system for efficient collection, segregation, and disposal. E3S Web of Conferences, 619, 03002.

<https://doi.org/10.1051/e3sconf/202561903002>

[25] IRJMETs. (2025). Intelligent waste management: Leveraging AI, IoT, and deep learning for sustainability. IRJMETs, 5(3).

https://www.irjmets.com/uploadedfiles/paper//issue_3_march_2025/71206/final/fin_irjmets1743658260.pdf

[26] Al Qurashi, R. S., Al-Zahrani, F. A., & Alharthi, H. A. (2025). Smart waste management system for Makkah City using artificial intelligence and internet of things. ResearchGate.

<https://www.researchgate.net/publication/392105741>

[27] ResearchGate. (2025). Enhancing waste sorting and recycling efficiency: Robust deep learning-based approach for classification and detection. <https://www.researchgate.net/publication/387349956>

[28] United Nations Environment Programme (UNEP). (2023). Turning off the tap: How the world can end plastic pollution and create a circular economy. UNEP. <https://www.unep.org/resources/turning-tap>

[29] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. Advances in Neural Information Processing Systems, 30, 5998–6008.

[30] Kingdom of Saudi Arabia – Vision 2030. (2016). National transformation program. Vision 2030. <https://vision2030.gov.sa>

[31] OECD. (2022). Global plastic outlook: Policy scenarios to 2060. OECD Publishing. <https://doi.org/10.1787/aa1edf33-en>