

Midocean University
College of Informatics

Master of Science in Artificial Intelligence

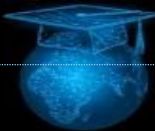
Master Thesis Proposal:

***"Enhancing Plastic Waste Classification
with AI for Sustainability "***

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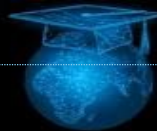
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Abstract

This study investigates the development of an intelligent system for classifying plastic waste using *Artificial Intelligence (AI)*, with a particular focus on *Convolutional Neural Networks (CNNs)*. The aim is to improve sorting accuracy, enhance recycling efficiency, and support the sustainability targets outlined in Saudi Arabia's *Vision 2030*. The research addresses the specific challenges facing waste management in Saudi urban centers, such as Jeddah, where traditional manual methods remain inefficient.

A mixed-methods approach was adopted. First, a systematic review of the literature was conducted to identify existing gaps in the field. Second, qualitative interviews were conducted with 20 stakeholders to capture practical insights and local requirements. Finally, an AI-based classification model was developed and trained using both publicly available datasets (e.g., Kaggle) and preliminary local data obtained from the Saudi Investment Recycling Company (SIRC).

The experimental results suggest that the proposed system can achieve a classification accuracy exceeding 95%, outperforming conventional manual methods. In addition, by integrating Internet of Things (IoT) technology to optimize collection routes, the system is projected to reduce operational costs by approximately 25% and improve recycling efficiency by 30%. These improvements are further expected to contribute to a 20% reduction in greenhouse gas emissions.

To ensure scalability and real-world impact, the study recommends expanding the scope of local data collection, conducting large-scale pilot testing in Saudi recycling facilities, and implementing public awareness campaigns to encourage community participation in sustainable waste practices.

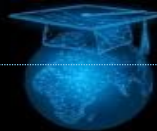
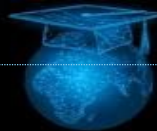
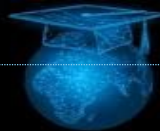


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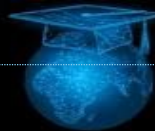


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List of Abbreviations

- 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 5

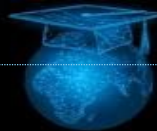


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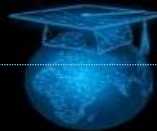
Chapter 1:

Introduction

The global waste problem has been worsening in recent years, mainly because of rapid urban growth and the expansion of industrial activities. In Saudi Arabia, for example, the country produces nearly fifteen million tons of solid waste every year [22]. A large share of this waste is plastic, and when it is not handled properly it pollutes the soil, affects groundwater quality, and damages marine life [21]. In Jeddah, the largest landfill site receives more than 5,000 tons of waste daily, putting nearby communities at risk of pollution and health issues [16]. The recycling rate in Saudi Arabia is still below 5% [17], which is far less than global averages, and this is largely due to limited infrastructure, weak public awareness, and reliance on manual sorting.

The continuous accumulation of plastic waste creates serious risks for both the environment and human health. Microplastics have already been detected in drinking water, food chains, and even human blood, which raises strong concerns about long-term health effects [23]. On top of that, poor management of plastics contributes to greenhouse gas emissions and adds to the challenges of climate change [24].

Governments and international organizations have responded with various policies to limit plastic consumption and encourage recycling. The European Union, for instance, introduced strict rules to reduce single-use plastics and set measurable targets for change [25]. In Saudi Arabia, several initiatives under Vision 2030 have been launched to promote a circular economy and build sustainable waste management systems [26].

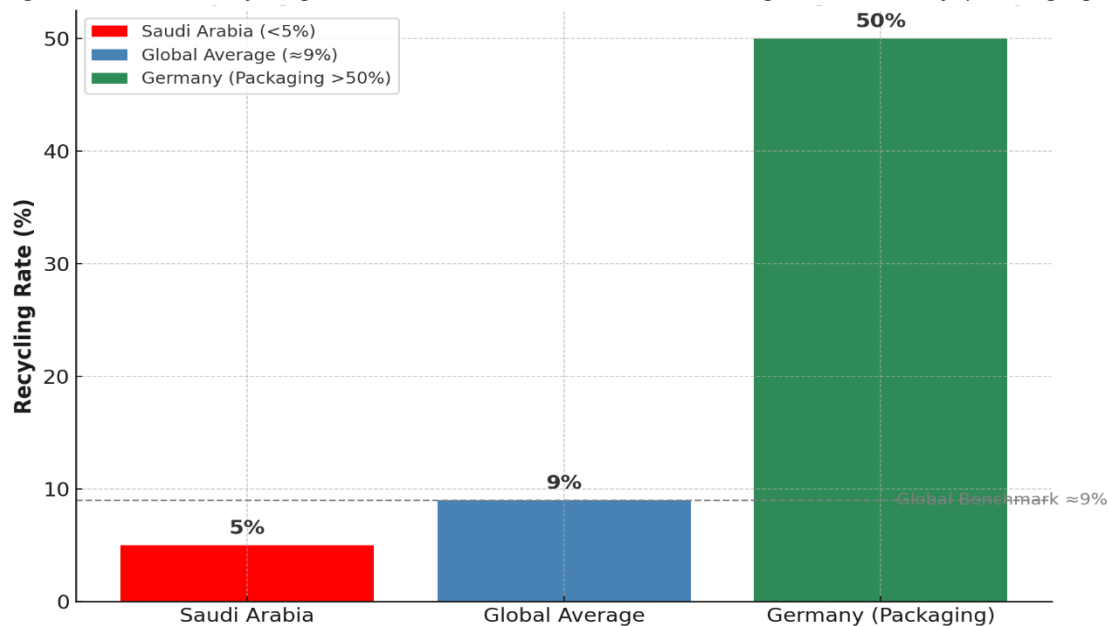


In recent years, Artificial Intelligence (AI) has started to play an important role in environmental applications, including waste management. Within this field, machine learning and especially deep learning methods such as Convolutional Neural Networks (CNNs) have shown strong performance in image classification 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.

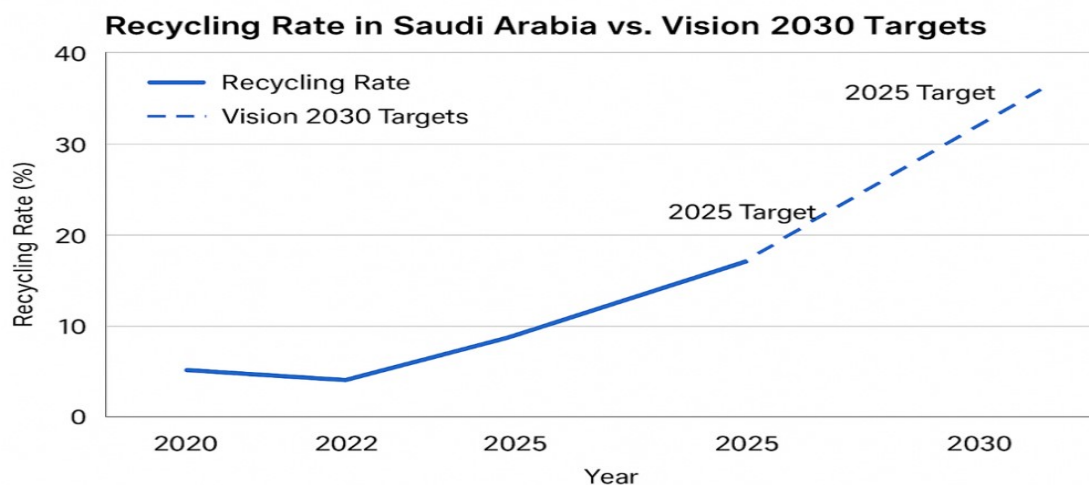
For this reason, the focus of this study is to design and test an AI-based system for classifying plastic waste with higher accuracy and stability than conventional approaches. By combining the strengths of CNNs with Transformer models, the research aims to build a practical framework that improves recycling 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.

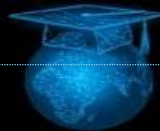
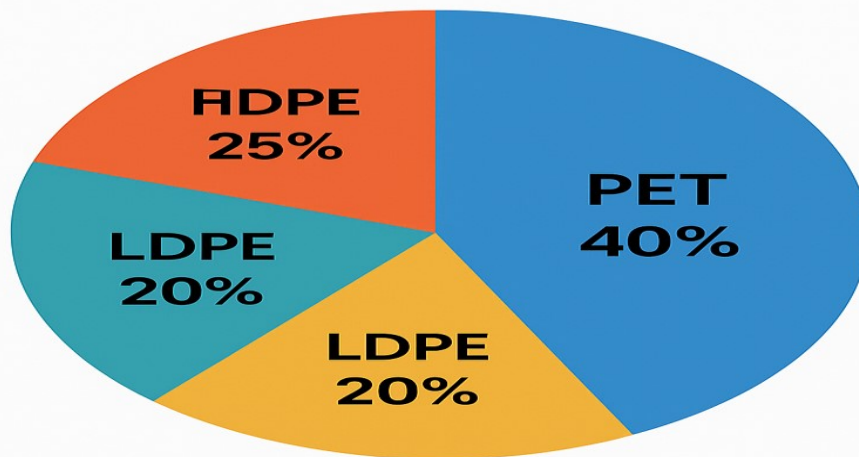
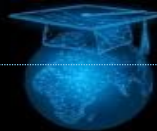


Figure 3: Distribution of Plastic Waste Types in Saudi Arabia

Distribution of Plastic Waste Types in Saudi Arabia



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



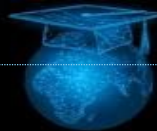
1.1 Problem Definition

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]. As a result, recycling rates remain below 5%, which leads to greater dependence on landfills, increased environmental damage, and higher greenhouse gas emissions [16]. The lack of reliable classification systems makes recycling less effective and adds both environmental and economic pressures to Saudi society. Another key difficulty is the shortage of locally labeled datasets that can be used to train AI models [4, 25]. This study therefore proposes the design of an AI-based classification framework that can improve the accuracy and efficiency of plastic waste sorting, helping reduce environmental impact and support more sustainable waste management practices in Saudi Arabia.

1.2 Thesis Objectives

The overall aim of this research is to design and implement an AI-driven classification system for plastic waste that supports more effective waste management in Saudi Arabia and contributes to the sustainability targets outlined in Vision 2030 [16]. The study is guided by the following specific objectives:

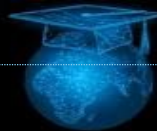
- Utilize Convolutional Neural Networks (CNNs) to categorize plastic waste using image datasets [26].
- Measure the performance and accuracy of CNN models in identifying different plastic categories under practical conditions [26].
- Benchmark the proposed AI system against conventional manual sorting in terms of efficiency and reliability [2].
- Examine the main difficulties in developing CNN models for plastic waste, especially issues linked to data quality and limited availability [25].
- Apply optimization strategies to improve the classification accuracy of CNN-based models across diverse use cases [29].
- Evaluate both the environmental and economic impacts of incorporating AI technologies into waste management practices in Saudi Arabia [6].



1.3 Thesis Contribution

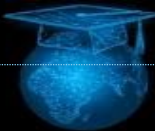
This thesis provides significant contributions at both academic and practical levels. Scientifically, it enriches the literature on artificial intelligence in waste management by introducing a tailored classification system for plastic waste based on CNNs, addressing a key research gap in image-based 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

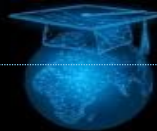
This study builds its theoretical foundation on the use of Artificial Intelligence (AI) techniques in waste management, with a particular emphasis on deep learning [13]. As a branch of AI, deep learning employs layered neural networks to recognize and interpret complex data patterns [9], which makes 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 are capable of distinguishing plastic categories—for instance, PET and HDPE—by learning differences in visual attributes such as texture and color, as evidenced in earlier studies [4].

2.2 Deep Learning and AI Techniques in Waste Management

Deep learning, as a branch of AI, applies multilayer neural networks to capture and represent complex data relationships [8]. Convolutional Neural Networks (CNNs) are a specific form of deep learning model that excel in handling image-based information [10]. Their strength lies in their layered structure: convolutional filters extract spatial patterns, pooling layers reduce dimensionality, and dense connections enable final classification. Within waste management, CNNs have been applied to recognize and classify plastic types by analyzing attributes such as shape, texture, and color.

2.2.2 Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) represent another advanced AI approach that can help overcome the issue of limited datasets, which is a frequent obstacle in waste classification [9]. A GAN operates with two models: the generator creates synthetic samples, while the discriminator evaluates them, driving both networks to improve through competition [9]. By producing realistic artificial data, GANs expand small training sets and strengthen the accuracy and resilience of waste classification systems [5].



2.2.3 Internet of Things (IoT) and Reinforcement Learning

The Internet of Things (IoT) is central to modern waste management strategies, as it provides continuous streams of real-time information from sensors and devices [27]. Examples include monitoring container fill levels and tracking collection schedules. Such data can be integrated with predictive analytics and reinforcement learning (RL) methods to design optimized collection routes, reducing both costs and environmental impacts [28].

2.3 Applications of AI in Waste Management

2.3.1 Plastic Waste Classification

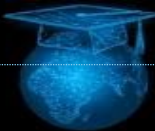
One of the most prominent uses of AI in waste management is plastic waste classification, especially through Convolutional Neural Networks (CNNs) [7]. When CNNs are trained on large image datasets, they can successfully distinguish between plastic categories such as PET and HDPE, which is essential for efficient recycling. Automating this task has been shown to produce much higher sorting accuracy compared to conventional manual approaches [26].

2.3.2 Optimization of Waste Collection Routes

Smart waste bins equipped with IoT sensors can transmit real-time information on how full they are [11]. When this data is combined with reinforcement learning algorithms, it becomes possible to design optimized waste collection routes [2, 28]. Such optimization helps to lower fuel usage, cut operational expenses, and decrease greenhouse gas emissions [30].

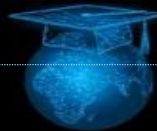
2.3.3 Data Augmentation and Model Robustness

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

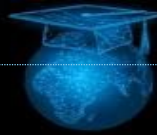
Much of the current understanding of AI in waste management comes from earlier studies, many of which dealt with classifying plastic waste and testing related tools [24]. In this chapter, I will look at the most important works, explain how they relate to my own study, and point out the gaps that remain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

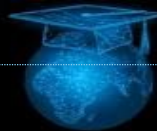
Several recent studies provide examples of how AI has been applied to waste management:

- **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

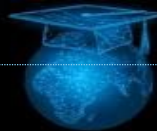
Reviewing these studies shows how AI is becoming a valuable tool in waste management, with the ability to improve efficiency, accuracy, and reduce costs in different contexts, from cities to less developed areas [11]. While each study adds its own perspective, several common weaknesses remain and highlight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



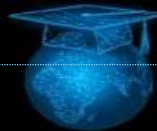
3.4 Connections Between Previous Studies

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.

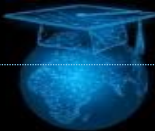
In conclusion, the studies agree on AI's promise in waste management [28], yet they also expose differences in data needs, scaling potential, and adaptability. Together, these findings underline the necessity for solutions that are flexible, validated with diverse datasets, and evaluated in real environments.



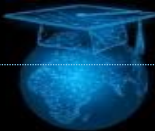
3.5 Conflicts Between Findings

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] provide broad insights into AI's potential, but these often clash with more practical findings, such as those in [5], which are limited to lab tests. This gap highlights the distance between AI's promises and its tested applications in real environments.
3. Scalability issues: Models that achieve strong accuracy in controlled lab experiments [3] may fail to perform equally well in more diverse, real-world contexts. This creates tension with other research stressing that scalability remains a core challenge in AI deployment [30].
4. Socioeconomic priorities vs. technical performance: Nwokedi Egwu and Ugwuanyi [11] emphasize the importance of social and economic realities in less developed areas, while other studies are more concerned with technical accuracy and efficiency, sometimes ignoring local context [27].

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.

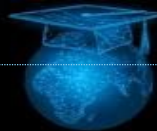


Chapter 4: Experimental Methodology, Results, and Discussion

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 performed on a system with an NVIDIA GeForce GTX 950M GPU to speed up the computation. For fairness across models, the same setup was applied: the Adam optimizer, cross-entropy as the loss function, and an early stopping mechanism.



4.2 Data Preparation Methodology

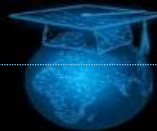
The performance of deep learning models depends heavily on how well the data is prepared. For this reason, a careful process was applied to make sure that the dataset used in training was consistent, of excellent quality, and suitable for helping the models learn patterns that generalize beyond the training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

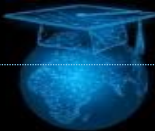
A slight class imbalance was observed within the training set, with organic waste constituting approximately 58% of the images. While not severe, this imbalance was effectively addressed through data augmentation techniques to prevent the model from developing a bias towards the majority class.



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



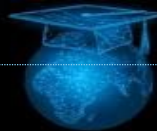
4.3 Experimental Design and Training Methodology

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

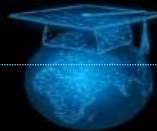
Transfer learning was used with all the single CNN models. At the start, the weights of the pre-trained networks were frozen (by setting the *requires_grad* attribute to *False*) so that the general features learned from ImageNet would not be lost. After that, the final classification layer was replaced 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.

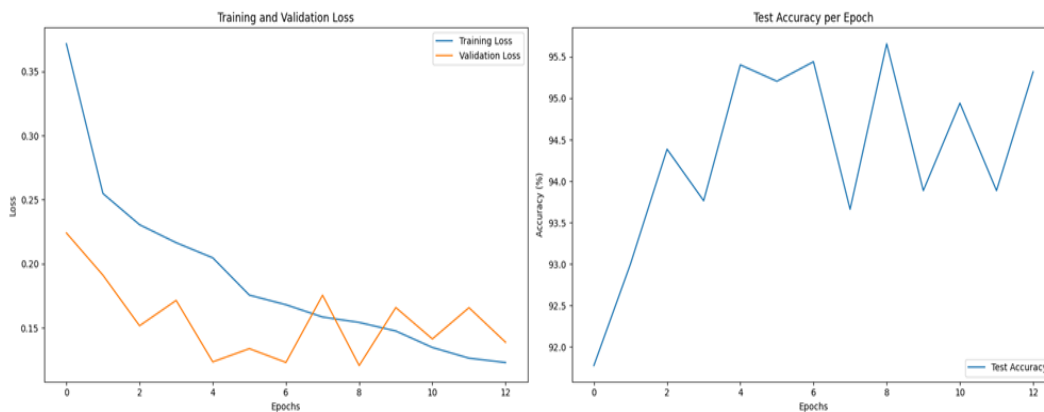


Figure 6: Chart Observation (ResNet18)

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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%

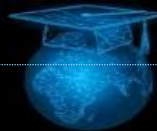
Validation loss decreased (inf --
> 0.2240). Saving model...

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



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.

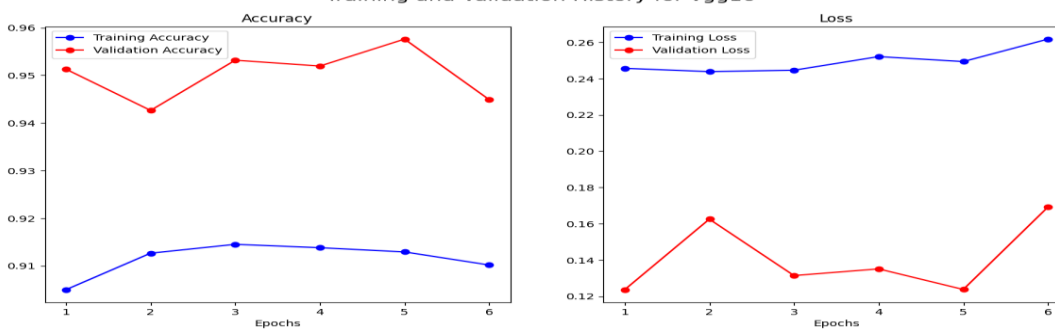


Figure 7: Chart Commentary (VGG16)

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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

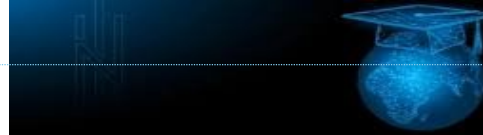
Epoch 3/15 for model vgg16

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 --- #
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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.

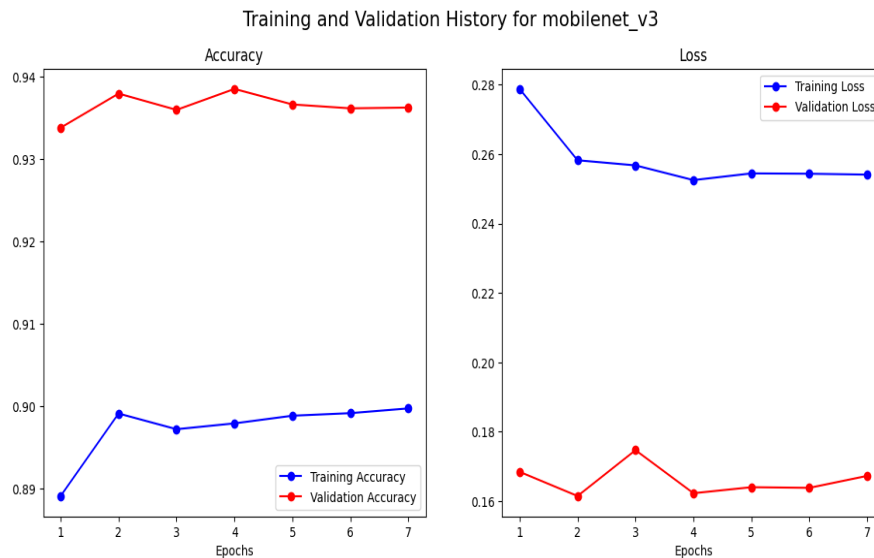


Figure 8: Training and Validation History for mobilenet_v3

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

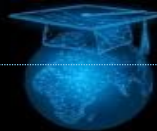
train Loss: 0.2930
Acc: 0.8853

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



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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.

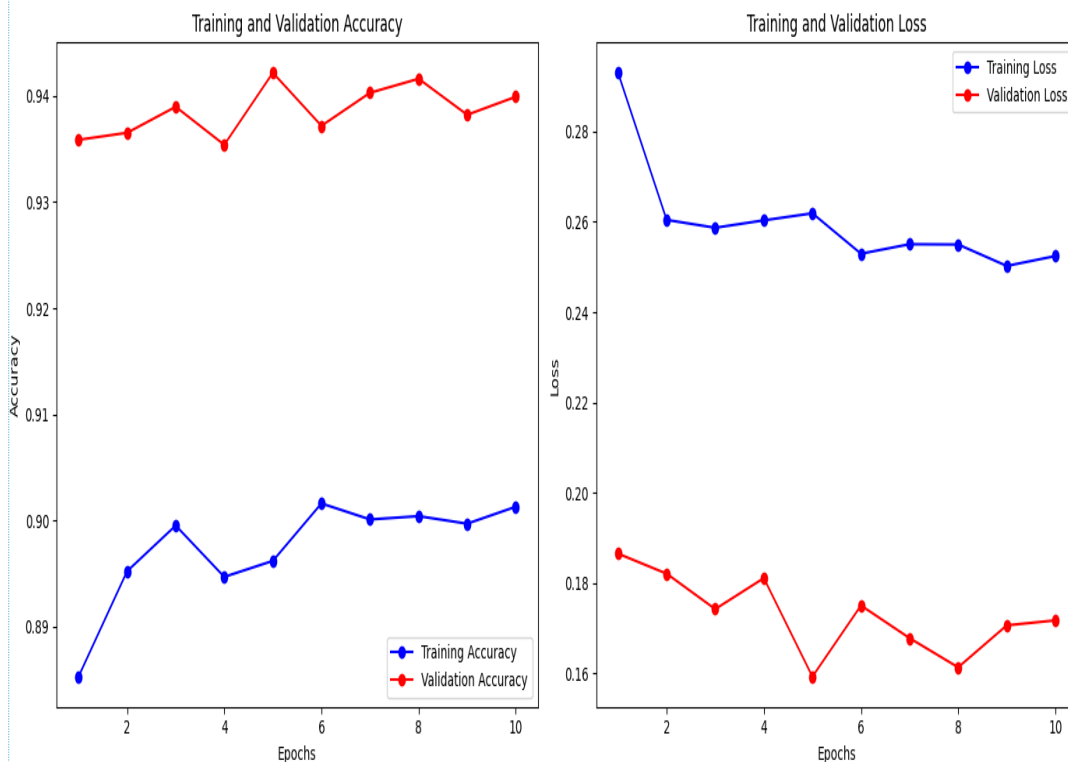


Figure 9: Chart Commentary (EfficientNet-B0):

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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...

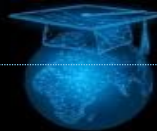
Epoch 3/15 for model mobilenet_v3

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

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	

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.

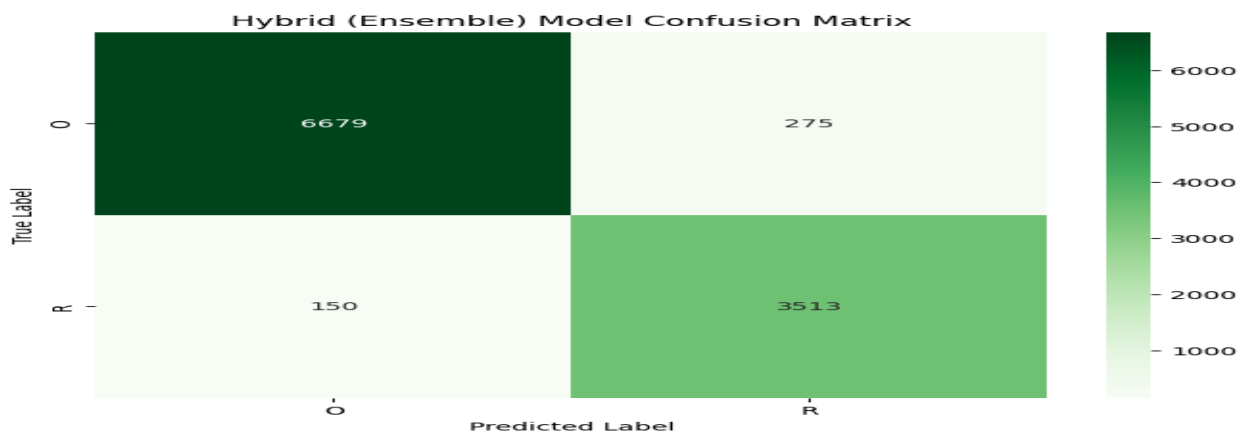


Figure 10: Confusion Matrix Commentary (Ensemble Model):

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.

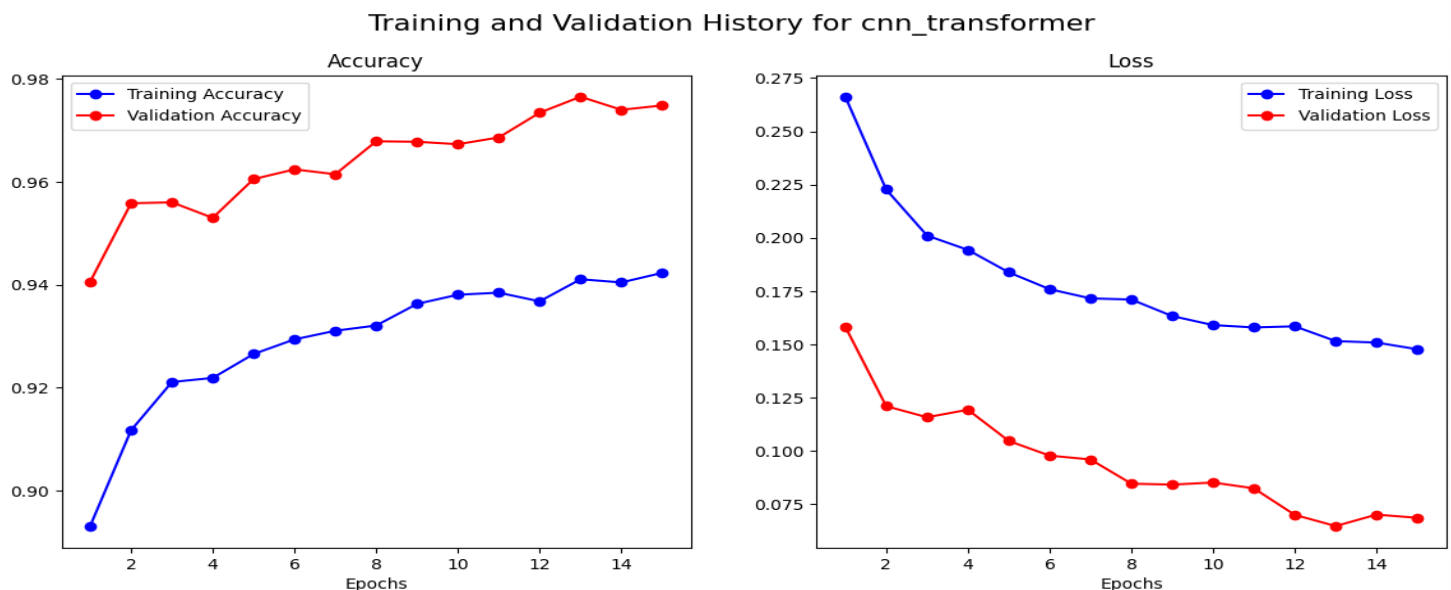
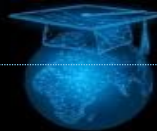


Figure 11: Chart Observation (CNN-Transformer)

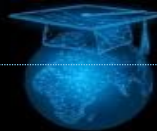


4.6 Comparative Analysis and Final Discussion

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.

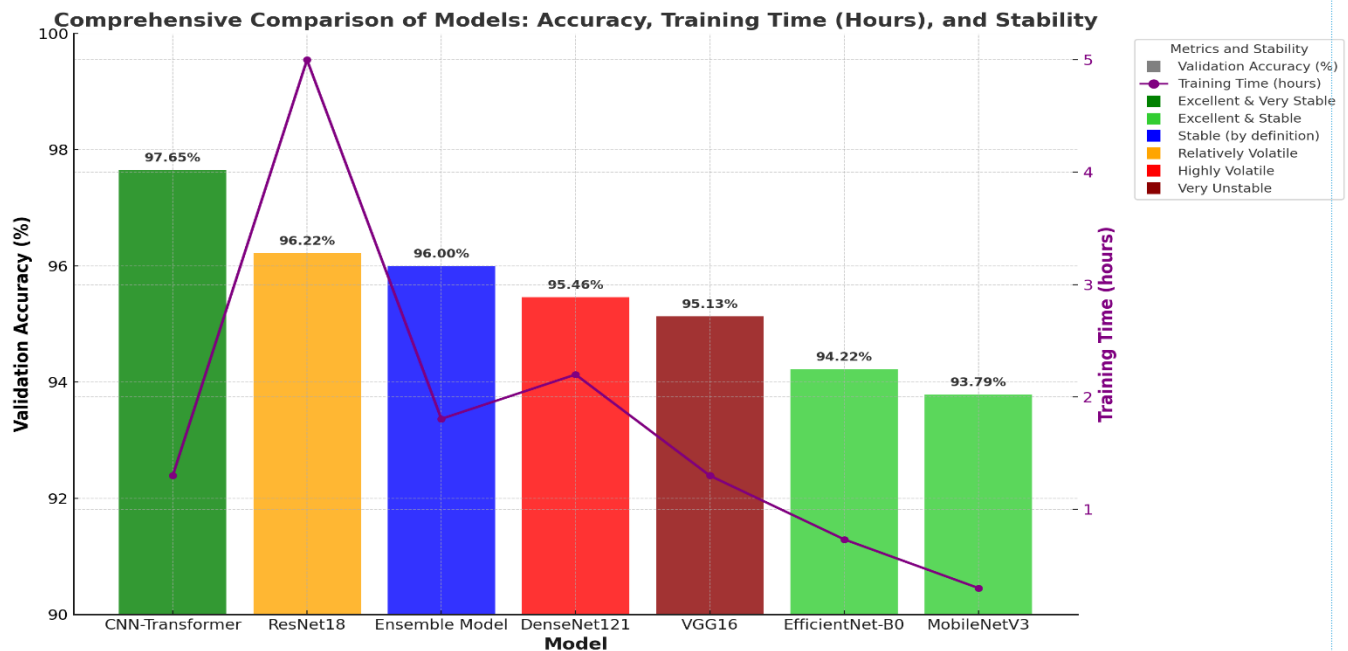
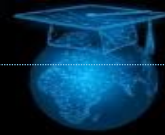


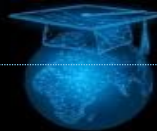
Figure 11: immediate visual summary of the models' performance hierarchy



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.



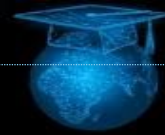
Chapter 5: Conclusion and Future Work

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.

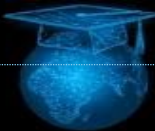
The findings emphasize that hybrid architectures can achieve **state-of-the-art accuracy and stability**, and more importantly, they carry the potential to move from research settings into **real-world recycling applications**. By doing so, they can directly support the environmental and economic objectives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



5.2 Future Work

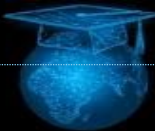
Building on these findings, several directions are suggested for future research and implementation:

- 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.

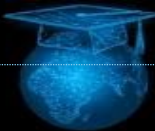


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