A Deep Learning-Based Waste Classification Using Ensemble and Vision Transformer Models

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APPROVAL

This Project titled **"A Deep Learning-Based Waste Classification Using Ensemble and Vision Transformer Models"**, submitted by Sayem Ahmmed, ID No: **212-15-14738** and Zarrin Tasnim ID No: **212-15-14740** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **14 May, 2025.**

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We hereby declare that this project has been done by us under the supervision of Mr. Md Atik Asif Khan Akash, Lecturer, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this projectnor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

This research presents a deep learning approach for waste categorization using three pre-trained models such as MobileNetV2, DenseNet121, and ResNet50, a transformer model (Vision Transformer or ViT), and an ensemble model. The seven-class waste dataset was used, which is publicly available, with the preprocessing steps including resizing, normalization, augmentation, and class balancing. Hyperparameter tuning was applied to all models using Grid Search, Random Search, and Bayesian Optimization. Among them, the ensemble model had a test accuracy of 97.52%, surpassing single models by synergistically combining their predictions by weighted averaging soft voting. The models were made robust using label smoothing, mix-up augmentation, and class weighting. Evaluation was carried out on accuracy, precision, recall, F1-score, and confusion matrices. Issues such as class imbalance and intra-class visual similarity in visual waste classification are addressed by the study. The future work will use the system in an IoT-capable intelligent dustbin for actual implementation.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Introduction

One of the most pressing environmental, public health, and planning issues of the 21st century is now the management of wastes. High rates of urbanization, industrial development, and population growth—particularly in the developing world—have resulted in the massive generation of solid wastes, overwhelming the capacity of the conventional disposal systems and compromising ecological integrity [1]. While infrastructure development has characterized some parts of the globe, most of the population in most developing countries is still plagued by poor treatment and disposal techniques for wastes, leading to extensive contamination and health risks [2].

Now a priority environmental, public health, and planning problem of the 21st century is managing wastes. Increased urbanization, industrial growth and increased population especially in developing countries, a waste by-product of such growth has tremendously increased, this has completely overwhelmed the capacity of conventional disposal system which has led to compromising of valuable ecological integrity [1]. Although some regions of the world have benefited from infrastructure development, most of the populace in the majority of developing countries continues to be affected by inadequate methods for treatment and disposal of wastes with concomitant contamination and diseases [2].

Very poor sorting and categorization of wastes are major contributors to environmental degradation. Unsorted wastes drive water bodies and soil into polluted fields, they release toxic chemicals, and emit greenhouse gases such as methane, when piled up in dumps [3]. Urban settings mixed waste volumes (municipal; organic and industrial) create a difficult position where separating, treating or recycling material becomes difficult to attain [4]. In the absence of sorting systems, recyclable and biodegradable material is therefore predisposed by default combination, leading to ineffective recovery, increased cost of treatment and permanent destruction of environment [5].

Precision in categorization of waste is crucial to desirable solid waste management for sustainability. Separating the waste into biodegradable, recyclable, and hazardous materials by classification has the advantage of easy treatment process, and economical utilization of the recycling activities [6]. Poor separation of waste not only leads to more load at the landfill but also less scope for material recovery, as well as long-term ecological damages. For instance, upon contamination of organic wastes with non-recyclable materials, the whole lot may become ineligible for composting or reusing [6].

In densely populated countries like Bangladesh, the weaknesses of municipal systems due to lack of automation, high population densities, and insufficient infrastructural base are compounded, leading to garbage management problems. Research has documented the uncontrolled plastic and packaging wastes growth in municipal areas like riversides, streets, marketplaces, and residential quarters that interfere with public sanitation conditions as well as aquatic and terrestrial ecosystems [7]. The collection process is generally labor intensive, due to lack of modern technology, hence is slow, irregular, and susceptible to human mistakes, especially where similarly appearing wastes are involved like various plastics or soiled paper where classification is done [8]. Moreover, in densely inhabited places, sorting activities are either avoided or done incorrectly due to the inadequacy of trained labor force and sorting technology [8].

The similarity of appearance between the material of waste, environmental destruction, and chemical or food contamination makes manual sorting even more challenging. For instance, some wet organic waste during decomposition may appear in form of non-biodegradable wastes and so confuses the employees leading to misclassification [9]. The constraints have accelerated the quest for the use of artificial intelligence (AI), computer vision and deep learning to automate wastes sorting activity. AI solutions not only ensure the consistency of other people's activities and efficiency but can also learn to identify various visual inputs and discover faint patterns difficult to specify by human eyes [9].

State-of-the-art results on image classification problems have been delivered by some of the most promising approaches, such as convolutional neural networks (CNNs). CNNs can learn subtle spatial features from images, so are best for separating close-together-looking waste types under different lighting conditions and backgrounds [10]. Concurrently, transfer learning methods have made possible the utilization of pre-trained deep learning models, first trained on large general-purpose image sets like ImageNet—and adapted them to specific domains like waste classification. This has significantly reduced data needs and training time for new models with little compromise of accuracy [10].

Moreover, actual waste sorting use cases highly depend on the availability of structured and diversified data sets with proper annotations. Quality of data, balance per class, resolution consistency and environmental exposure variance, are paramount for confirming that the models learnt generalize well in dissimilar waste handling settings. Several works noted the need to develop region- and context-aware preparation of the dataset, pictures with different daylight conditions, in the case of occlusion, and noise in the background [10]. Overall, the global waste crisis requires urgent innovation of how waste is sorted, classed and processed. Waste management that can be scaled economically, with precision, can be built upon computer systems based on deep learning. Uniting the power of AI with domain expertise and real-world data, wise classifying systems for waste are able to transform municipal waste activities, minimize the impact on the environment of human activities, and support the agendas of sustainable city planning – especially in high impact areas like Bangladesh [10]

1.2 Motivation

The accelerated urbanization and industrial growth have created substantial difficulties in solid waste management throughout many developing countries including Bangladesh. Municipal waste volumes are increasing rapidly as cities get larger and their populations expand while the environmental threats grown more complex daily. Waste classification along with sustainable management practices have become vital parts to establish sustainable urban infrastructure systems. The capital city of Bangladesh called Dhaka reflects this severe waste-related situation. The city produces 28.26% of waste nationally yet anticipates generating daily waste outputs of 47,000 tons in 2025 alongside 646 tons of daily plastic waste which threatens public health and environmental safety and urban ecosystems. The severe state of waste healthcare demands automated solutions above traditional manual waste sorting because these systems handle multiple waste challenges effectively

Low- and middle-income countries including Bangladesh maintain waste management systems which deliver poor outcomes because they lack scalable features and create unsafe working environments for personnel engaged in waste classification activities. The manual sorting process restricts operational abilities while workers face harmful exposure to dangerous agents in waste consisting of biological, electronic and medical waste [6, 9]. Environmental degradation becomes severe when these conditions lead to excessive landfill capacity and blocked drainage systems, water pollution and increased methane emissions from decomposing organic waste. Current data-driven systems' absence prevents both waste pattern identification and disposal need forecasting which leads to increased inefficiencies.

The paper examines research prompted by the fundamental need to update waste classification using current developments in artificial intelligence techniques especially deep learning and computer vision. Self-learning deep learning methods such as Convolutional Neural Networks (CNNs), Vision Transformers (ViT) and ensemble approaches show great capacity to handle difficult image classification problems across several domains of application. These models, which provide exact real-time waste identification without manual intervention, allow one to analyst waste materials using image-based inputs, therefore minimizing human worker exposure [15]. By their capacity to separate recyclable from non-recyclable materials efficiently, these smart systems assist carry out essential circular economy resource recovery. By means of efficient separation that preserves natural resources and reduces environmental pollutants, the system improves recycling performance. The application of automated classification systems leads to lower landfill use while simultaneously enhancing program efficiency and better adherence to environmental standards

This academic research combines my expertise in computer science with my core commitment to protecting the environment. This project enables participants to learn essential skills related to transfer learning along with hyperparameter optimization and AI model deployment methods while exploring modern AI research and implementation practices. The training develops my ability to solve real-world problems using computational techniques while supporting my future goal of creating socially beneficial cutting-edge technological solutions. My investigation represents an essential development toward my career as a competent professional creating AI sustainability solutions.

This study demonstrates through evidence the ability of intelligent waste management models to transform waste processing and secure public health alongside global sustainability objectives. The research addresses both Bangladesh's particular environmental needs and creates solutions that are universal through its approach, resulting in interconnected environmental goals at multiple scales [11].

1.3 Objectives

This analysis pursues the growth of a systematic waste classification method which implements deep learning methods to enhance operational performance while maintaining high recognition accuracy. This research objective reaches its main goal through five specific objectives which work together to fulfill the classification pipeline's essential functions.

- We established a Deep Learning-Based Waste Classification Model through our research. The objective of this research involves creating a machine learning system which accurately sorts waste material between plastic and paper and metal and organic waste types. The waste classification system identifies plastic alongside paper and metal and organic waste materials. Four specific waste types which produce the highest waste quantities worldwide remain problematic for proper sorting as well as recycling processes. Deep learning frameworks support that planning through convolutional neural networks (CNNs) and advanced techniques which enable high-fidelity image classification processes.

- A comparative assessment examines the performance levels of pretrained Convolutional Neural Network models versus alternative classification systems The research will analyze the classification capabilities of MobileNetV2 and DenseNet121 and ResNet50 and Vision Transformer (ViT) through a multi-architectural comparison. Fleshing out the evaluation process relies on established performance metrics which incorporate test accuracy along with precision and recall together with F1-score calculation. The thorough evaluation system helps find which model best performs waste classification according to real environmental factors and various image input types.

- By optimizing hyperparameters we enhance the performance of our models. The research implements sophisticated hyperparameter optimization methods to enhance the selected model learning capabilities. The research implements Grid Search Random Search and Bayesian Optimization approaches to conduct systematic evaluation of various hyperparameter combinations between batch size activation function number of training epochs and optimizer choice. Optimal training environments established by this approach result in better model generalization and reduced possibility of overfitting.

- Transfer Learning implementation enhances model performance when working with scarce datasets. The research investigates how transfer learning can elevate model performance because high-quality labeled waste image datasets typically exhibit limited availability. The study benefited from pre-trained models which extracted knowledge from the large-scale ImageNet database for its waste classification work. The method cuts down both processing needs and information requirements but maintains excellent classification accuracy and operational stability

- The current research employs additional testing and independent dataset validation to assess the generalization capacity of models. Independent validation data is used to test the ability to generalize capacity of trained classifiers, therefore evaluating the practical relevance of created models. This stage is crucial for model performance consistency since it evaluates calibration between the training data and new unseen photos. Testing under deployment conditions assesses the model's practical success in identifying waste items across several combinations of lighting conditions, background noise levels, and waste object variations.

1.4 Methodology

Devised to overcome waste classification problems this research implements a complete deep learning framework using Convolutional Neural Networks (CNNs) together with Vision Transformer (ViT) and ensemble learning techniques.

The approach begins with dataset preparation and preprocessing of openly accessible waste pictures which contain multiple recyclable and non-recyclable material categories. The prepared images pass through a demanding quality control process which involves data filtering for removing corrupt or extraneous material then resizing into standard dimensions followed by normalization steps to keep a uniform dataset format. Such preprocessing methods improve the model's capacity to detect useful feature patterns while reducing variations in different samples.

Five different models receive training following the completion of data preparation. Three established CNN architectures (MobileNetV2, DenseNet121, and ResNet50) join forces with the transformer-based ViT model that demonstrates advanced performance in image recognition tasks. The ensemble model combines the prediction results of three CNNs to utilize each network's unique strengths for optimal outcomes. These multiple neural networks follow an ensemble strategy to achieve better overall classification reliability and broader application reach.

The model training occurs through TensorFlow and PyTorch as its frameworks of choice. Data augmentation with rotation and flipping alongside brightness and zooming modifications allows training while improving model generalization and minimizing overfitting effects. The optimization of computational efficiency and training time reduction for large-scale models including ViT happens through mixed-precision training techniques coupled with multi-GPU acceleration methods.

The research three approaches for hyperparameter optimization: Grid Search, Random Search, and Bayesian Optimization to discover superior parameter values between batch size, activation functions, optimizer types, epochs, and dense layer units. The chosen final configurations result from balancing model accuracy levels with training performance speed.

After training the models get evaluated by applying multiple performance metrics which include test accuracy alongside loss and precision and recall and F1-score. The performance evaluation metrics grant a complete view of the classifier's performance patterns in all waste categories with specific attention to classification behaviors. Confusion matrices alongside training-validation loss/accuracy curves help researchers detect both misclassification errors and recognize overfitting or underfitting issue

The systematic methodology leads to the creation of a powerful framework which solves real-world waste classification needs while boosting both scalability and precision to assist environmental sustainability and smart waste management solutions.

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1.5 Project Outcome

This research creates a complete deep learning-based waste classification system which enables automated waste material classification through image-based inspection methods. A combination of MobileNetV2 DenseNet121 ResNet50 advanced pre-trained convolutional neural networks and a transformer-based Vision Transformer (ViT) model establishes a reliable real-time waste recognition and classification framework in this project. The ensemble model establishes improved classification reliability and generalization through collective model inference for critical classification purposes.

The system achieves effective waste classification across plastic, paper, metal, biological, cardboard, brown-glass, and trash segments through organized training methods and optimized hyperparameters and dedicated assessment protocols. The model uses training dataset acquired features to process high-dimensional images which effectively distinguishes diverse waste types regardless of visual inconsistencies.

The research project achieved a major outcome by minimizing human manual work inside waste sorting centers. The developed framework operates autonomously to perform waste classification therefore protecting the safety of human employees holding dangerous duties in exposed hazardous facilities. The real-time waste segregation operations gain speed while maintaining higher occupational safety standards due to this implementation.

The research serves environmental sustainability through its enhanced recycling processes. The precise automated sorting of waste material creates efficient recyclable/non-recyclable separations which both reduce stream contamination and minimize reliance on landfills. The system achieves multiple environmental benefits by supporting resource recovery while reducing greenhouse gas emissions from poor waste management practices as well as minimizing energy use and natural resource utilization.

The research work establishes fundamental groundwork that enables progress for next-generation smart waste management solutions. This framework demonstrates scalability for new waste categories and allows for enhancement through IoT integration with systems that include smart bins and robotic arms and edge-computing sensors. The addition of ViT as a model brings forward-looking capabilities to the solution because transformer-based models demonstrate successful performance across multiple vision tasks.

This demonstration proves deep learning technology helps solve real-life environmental problems. The solution creates a technical framework which multiple scientific institutions and municipal bodies along with industries can adopt to establish environmentally responsible smart waste management systems.

1.6 Organization of the Report

The six chapter research report presents a detailed structure to guide readers through conceptual groundwork into implementation and evaluation. A well-structured organizational design enables readers to understand the deep learning-based waste classification framework's objectives, methodology, and outcomes.

- **Chapter 1: Introduction**
  The introduction section sets the foundational elements of this research through an explanation of how modern urban areas require intelligent waste collection systems. The present section presents an in-depth evaluation of studies backgrounds which examines environmental consequences and operational problems of conventional waste disposal methods. The chapter introduces specific research objectives together with details about the methodology and project outcomes and a breakdown of the report structure.

- **Chapter 2: Background**
  A thorough examination of waste classification together with deep learning frameworks and intelligent waste management processes appears in this segment. The current review assesses previous approaches while recognizing their assets together with their limitations and traces the development of transformation-based models and convolutional neural networks for picture recognition needs. This research chapter identifies key areas where further study is necessary to solve existing gaps which the current project addresses specifically.

- **Chapter 3: Research Methodology**
  The study adopts the methodology previously discussed throughout this chapter. The chapter addresses how researchers choose and optimize dataset preprocessing through normalization techniques combined with data augmentation and filtering steps. The paper presents MobileNetV2 along with DenseNet121 and ResNet50 and Vision Transformer (ViT) in conjunction with an ensemble learning framework which demonstrates its specific implementation. Detailed explanations describe training strategies alongside optimization techniques and the methods for hyperparameter tuning through grid search, random search and bayesian optimization. All evaluation metrics employed for performance assessment receive detailed coverage.

- **Chapter 4: Implementation and Results**
  This chapter demonstrates the practical aspect of model implementation through deployment setups and training parameter selections and technical framework configurations based on TensorFlow and PyTorch. The report details a complete set of experimental findings which include accuracy measurements together with loss data and precision and recall results and F1-score outcomes. This section provides both visualizations including training-validation plots together with confusion matrices to demonstrate model trend behavior while delivering detailed comparative analyses for the complete set of five models. The core of empirical investigations focused on the proposal's effectiveness can be found in this chapter

- **Chapter 5: Engineering Standards and Design Challenges**

  This chapter explores the engineering ethical guidelines in addition to standards together with the research-related difficulties that emerged. The system examines its conformity to industrial standards in AI deployment as well as image classification practices. The paper investigates data bias together with environmental impact and user safety as fundamental problems in the implementation of ethical AI systems. A thorough assessment of technical barriers to real-time implementation and model interpretation and hardware constraints is followed by analysis of the project's implemented mitigation strategies and proposed solutions.

- **Chapter 6: Conclusion**

  The closing chapter presents the study's research outcomes together with evidence demonstrating methodological success in meeting established objectives. The analysis evaluates this study's impact on smart waste management techniques as well as artificial intelligence research. The proposed study presents recommendations for future development work involving IoT device integration or real-time waste sorting infrastructure implementation using the same framework. Deep learning models demonstrate their ability to lead sustainable and automated waste management systems worldwide.

Chapter 2

Background

2.1 Introduction

A severe waste management challenge persists in the contemporary world because of rapid urbanization together with industrial developments and growing populations but especially impacts developing countries more intensely. Research from the World Bank indicates municipal solid waste will reach 3.8 billion tons by 2050 because existing waste management systems will be not enough for handling the 2.01 billion ton starting figure from 2016. The city of Dhaka in Bangladesh produces 28.26% of the national waste total and experts expect its waste generation to reach 47,000 tons per day along with 646 tons of plastic waste by 2025. Most developing regions currently use manual sorting as their waste management strategy, yet this method proves ineffective when handling the mounting challenges from growing volumes and complexities of municipal waste [3]. The labor-based handling method causes both inefficiency and worker injuries from hazardous materials and unsafe conditions leading to environmental problems because landfills grow while sanitation systems fail. The need for sustainable waste management automation becomes acute because current recycling rates have plateaued at a global level of 37.2%. Advanced theoretical models for automated intelligent classification provide effective solutions to waste sorting inefficiencies and hazards by creating an enhanced framework of operation. A deep learning approach which belongs to machine learning implements intricate neural networks to analyze complex visual information thereby resulting in accurate waste material classification systems. The designed architectures maintain strong capabilities for detecting features and recognizing patterns that establish differences between waste materials within authentic operational environments [8]. The precise modeling of image spatial distribution that deep learning achieves fulfills its theoretical basis for waste classification thus delivering superior sorting outcomes compared to conventional approaches [12]. Deep learning's deployment in resource-limited urban facilities of developing nations becomes feasible because of neural network optimizations that achieve high accuracy while remaining efficient [18]. These systems help achieve sustainable development goals through their ability to decrease landfill demands while boosting resource reuse operations and minimizing environmental together with public health challenges [15]. This study gains important significance because it connects abstract deep learning theoretical development to valuable waste management practice. This research studies automated waste classification to resolve manual sorting challenges because Dhaka as a high-waste urban center puts pressure on its existing waste management systems. Deep learning technologies integrate through scalable solutions to boost recycling performance while lowering environmental hazards and safeguarding personnel safety which supports worldwide sustainability initiatives for urban development. Modern waste management strategies require innovation because deep learning stands as a transformative tool for addressing environmental challenges of our current age.

2.2 Literature Review

Literature review from Table 2.1 aggregates the current research successes around automated classification and waste control using intelligent systems and deep learning. It encapsulates the diversity of methodologies employed in the described studies including convolutional neural networks (CNNs), transfer learning, creating lightweight models customized and deploying with IoT. The studies involve various datasets, classification methodologies, and installations of the system—varying from binary-level waste classification to multi-class identification in real environments. The table below presents a comparative overview of these studies with key characteristics like authorship, methodology, and findings.

Table 2.1 Summary of Literature Review

Author	Year	Title	Methodology	Key Findings
V. Mahes Kumar et al.	2024	Smart Waste Classification using Deep Learning	YOLOv8 trained on a Roboflow-augmented binary waste dataset (biodegradable/non-biodegradable); trained on Google Colab and deployed via PyCharm.[1]	Achieved real-time classification; scalable and user-friendly; limitations include small dataset and broad class granularity.
Qiang Zhang et al.	2021	Waste Image Classification Based on Transfer Learning and CNN	DenseNet169 with transfer learning (ImageNet) applied to NWNU-TRASH dataset (5 classes) [2]	Achieved 82.80% accuracy; best for fabric (96%), weakest for plastic (69%); outperformed traditional CNNs.
Md. Wahidur Rahman et al.	2022	Intelligent Waste Management System Using Deep Learning with IoT	ResNet34 with IoT integration; trained on 6-class custom dataset.[3]	Accuracy: 95.31%; real-time IoT monitoring; strong sustainability value; minor weaknesses in glass/plastic detection.

Cenk Bircanoğlu et al.	2018	RecycleNet: Intelligent Waste Sorting Using Deep Neural Networks	Compared multiple CNNs on TrashNet; proposed lightweight RecycleNet based on DenseNet121 with reduced parameters.[4]	RecycleNet achieved 81% accuracy, DenseNet121 95%; RecycleNet was 46% faster in inference; dataset size was small.
Md. Nahiduzzaman et al.	2025	An Automated Waste Classification System Using Deep Learning Techniques	DP-CNN for feature extraction and En-ELM for classification; TriCascade dataset (36 classes), three-stage classification pipeline with XAI.[5]	Accuracy: 96.1% (2 classes), 85.25% (36 classes); highly scalable, lightweight (1.09M params), includes explainability via XAI.
Sylwia Majchrowska et al.	2022	Deep Learning-Based Waste Detection in Natural and Urban Environments	EfficientDet-D2 (detection) and EfficientNet-B2 (classification); trained on merged datasets; real-time inference with augmentation.[6]	High performance for glass and bio waste; weaker for small or ambiguous items; efficient for diverse environments.
P. Nowakowski and T. Pamuła	2020	Application of Deep Learning Object Classifier to Improve E-waste Collection Planning	Deep learning for e-waste object detection and classification [7].	Improved e-waste collection efficiency; practical for planning; limited by dataset diversity.

O. Adedeji and Z. Wang	2019	Intelligent Waste Classification System Using Deep Learning Convolutional Neural Network	CNN-based classification on a waste dataset [8].	There's a strong performance in controlled settings, which really emphasizes the need for solid datasets.
S. Poudel and S. Poudyal	2023	Intelligent Waste Management Using Deep Learning Models	Review of deep learning applications in waste management [9].	We highlighted the importance of scalability and its real-world potential while also pinpointing the challenges that come with deployment.
Islam et al.	2021	TRANSFER LEARNING BASED SOLID WASTE CLASSIFICATION USING THE ORGANIC AND RECYCLABLE WASTE IMAGES	Thesis exploring deep learning for waste sorting [10]	Used VGG19 and InceptionV3 for binary waste classification; evaluated on a dataset of 25,077 images.

2.2.1 Similar Applications

Waste sorting using machine learning (ML) and deep learning (DL) models has experienced fast-paced development due to expanding requirements for sustainable waste management across urban and industrial regions. The section presents analyses of major studies related to current research while discussing approaches and new methods as well as critical outcomes from the respective works. This research draws from previous similar waste classification systems to provide a deep examination of how these systems have progressed and where developments are taking place.

Research Studies:

Researchers across multiple scientific fields have implemented deep learning methods to develop automatic waste classification systems which enhance accuracy rates. A deep learning-driven smart waste classification system using YOLOv8 object detection algorithm was developed by Mahes Kumar et al. [1]. Their detection system showed accurate identification of waste types which established fundamental principles for real-time waste sorting applications based on object detection technology.

Zhang et al. [2] showed that transfer learning methods using CNN-based architectures succeeded in waste materials classification. Their approach took advantage of ImageNet pre-training even when using a limited waste dataset because it improved the model's ability to extract features which aligns with current research principles.

Case Studies:

The field of waste classification modeling received new methodological contributions through several studies that improved model performance effectiveness. The work in [2] introduced DenseNet169 for recyclable waste classification, leveraging the NWNU-TRASH dataset consisting of 18,911 images. Transfer learning was applied to enhance performance, and the dataset was manually curated and preprocessed using web scraping and image augmentation. Despite achieving high accuracy, the model was only validated on recyclable waste and lacked support for general waste types. The proposed study addresses this by including both biodegradable and non-biodegradable classes using a diverse dataset.

The authors in [7] applied vision recognition algorithms to assist in the logistics of e-waste collection. The system estimated type and size of e-waste using image-based input but did not focus on classification accuracy or visual preprocessing. This research incorporates high-performing classification networks and improves precision through advanced preprocessing techniques.

In [8], a deep learning-based system was developed to distinguish recyclable waste in urban areas. Pre-Trained CNNs like ResNet50, AlexNet, and VGG16 were used on a localized dataset specific to Bangladesh. The dataset was limited in scope, covering only four plastic waste types. By contrast, this research incorporates a broader dataset with higher class diversity.

Methodological Contributions:

This study proposes a systematic methodological framework that contributes to the state-of-the-art in waste classification through various innovative design and implementation techniques. The process is rooted in deep learning, combining both standard CNN architectures with transformer models, and builds upon earlier research to solve significant limitations in model scalability, dataset diversity, and classification generalizability. The major methodological improvement is the incorporation of three pre-trained CNNs, namely MobileNetV2, DenseNet121, and ResNet50, each of which is fine-tuned over a seven-class dataset containing both biodegradable and non-biodegradable materials. These models not only underwent independent evaluation but also were blended to form a weighted ensemble based on soft voting to improve overall robustness in classification accuracy and minimize model-specific bias. The ensemble weights are learned based on a Grid Search Combined with a Random Search strategy to maintain model contributions in balance based on validation accuracy. Simultaneously, this work utilizes a Vision Transformer (ViT) model—a new contribution to the literature, since none of the existing literature has utilized transformer architectures for the classification of waste. The ViT model utilizes patch embeddings along with position encodings that capture end-to-end global spatial relations in the image, a feature that is beyond the local window through which CNNs operate and is especially useful for detecting occluded or misshapen items of waste. The research also contributes to preprocessing methodology in that it utilizes a multi-stage pipeline of data refinement. Images have been resized to some predetermined resolution, filtered to remove corrupted or low-quality data, augmented through horizontal/vertical flip, random rotation, zoom, and brightness adjustment to model real-world variation, etc. In addition, YOLO-based object detection was also utilized conditionally to separate salient waste components for each image to improve the signal-to-noise ratio in feature extraction. Another area of methodological strength is the implementation of stratified dataset division to guarantee class balance in the training, validation, and test sets to minimize the risk of model bias. Training was performed with label smoothing and dropout regularization for enhanced generalizability, and the performances were evaluated across a large variety of metrics including accuracy, precision, recall, F1-score, and confusion matrices.

2.2.2 Related Research

Deep learning technology enables recent advancements in waste classification that achieve better accuracy through automated systems. Key studies demonstrate diverse approaches:

The researchers at Kumar et al. [1] employed YOLOv8 to identify biodegradable and non-biodegradable waste in real time but their approach had restricted access to various waste categories. The scientists at Zhang et al [2] exploited DenseNet169 to sort 5 recyclable waste categories with 82.8% success yet encountered difficulties in detecting plastic waste at 69% accuracy.

The integration of IoT required Rahman et al. [3] to merge ResNet34 with smart bins resulting in 95.3% accuracy while Bircanoğlu et al. [4] used an optimized RecycleNet based on DenseNet121 for real-time sorting with 81% accuracy and 352ms CPU inference time. A lightweight structure described in Nahiduzzaman et al. [5] established DP-CNN for computer vision with explainable AI capabilities that obtained binary classification accuracy at 96.1% and 36-class categorization accuracy at 85.3%.

2.3 Gap Analysis

Studies on automated waste classification through deep learning have achieved notable accomplishments in waste management yet researchers must complete essential knowledge gaps. In table 2.2 studies about waste classification primarily examine single neural networks instead of multiple architectures that could enhance performance [2]. The field lacks studies that utilize advanced architectural techniques that incorporate attention mechanisms to boost waste pattern identification capabilities for classification purposes. A widespread issue occurs in waste datasets when class imbalance receives inadequate attention which produces models that demonstrate significant bias towards minority classes. Research investigations traditionally evaluate their models only using accuracy metrics despite the need for complete multi-parameter assessments. A combined shortage exists between research which combines neural network approaches with new architectural frameworks to understand their comparative abilities in waste classification domains

The study addresses such research gaps through a deep investigation of sophisticated deep learning methods for waste sorting automation in Dhaka which faces urgent waste management issues [11]. The study engages with neural network combinations through advanced architecture evaluations and balance strategies alongside extensive metrics to conduct comparison studies aiming for intelligent waste management improvement. The research fills recognized gaps in studies by providing solutions for sustainable waste sorting following the global market requirement as shown in the table

Table 2.2: Gap Analysis

Sl No	Identified Research Gap	How we addressed it
1.	Most existing studies focus on single CNN models (e.g., ResNet, Inception) without exploring ensemble approaches.	We implemented a novel ensemble of MobileNetV2, DenseNet121, and ResNet50 to improve classification performance.
2.	Limited comparative analysis using Vision Transformers (ViT) in waste classification tasks.	We trained and evaluated a ViT model, analyzing its performance compared to CNNs on our waste dataset.
3.	Few studies addressed class imbalance explicitly, leading to biased models.	We used class weighting and augmentation techniques to mitigate class imbalance and enhance model fairness.
4.	Prior work often lacked diverse evaluation metrics—mostly using accuracy only.	We evaluated using accuracy, precision, recall, F1-score.
5.	No integration of ensemble model comparison with ViT in a single study for waste classification.	We conducted a full comparison between the ensemble CNN model and the ViT model under the same dataset and evaluation setup.

2.4 Summary

The chapter presented both basic principles and research precedents of the deep learning methods because of automatic waste segmentation systems. This chapter provided essential models with their associated procedures including CNNs and Vision Transformers and ensemble learning approaches for foundation research purposes. Investigators examined various present works to identify contemporary patterns alongside their outcomes. The evaluation process revealed three main shortcomings: individual modeling approaches, weak ViT design practices and the improper evaluation methods. The chapter presented our methods for addressing existing problems through ongoing training techniques combined with CNN ensembling while performing extensive metric evaluations. This chapter forms a solid foundation for the future methodological examinations in the text.

Chapter 3
Research Methodology

3.1 Methodology/Requirement Analysis & Design Specification

3.1.1 Overview

The proposed research offers a deep learning model for waste categorization based on CNNs and Vision Transformers that is reinforced through the combination of MobileNetV2, DenseNet121, and ResNet50. The study tackles significant problems ranging from class imbalance, data quality fluctuation, to model stability employing techniques like label smoothing, mix-up, and class weighting. Experimental evaluations about the model's performance were exhaustively performed in terms of accuracy, precision, recall, and F1-score.

3.1.1.1 Dataset

The work entails classification of the waste into seven classes: biological, brown-glass, cardboard, metal, paper, plastic, and trash. The classes are representative of a varied set of real-world waste categories found within residential and urban contexts. A sample image representative of every class can be seen in Fig. 3.1, demonstrating the visual features of each class. The choice of samples underscores the high variance seen in texture, color, shape, and complexity, highlighting the difficulty in correct visual classification. This variance underscores the necessity for powerful deep learning models for effective generalization over diverse and frequently visually unclear waste objects.

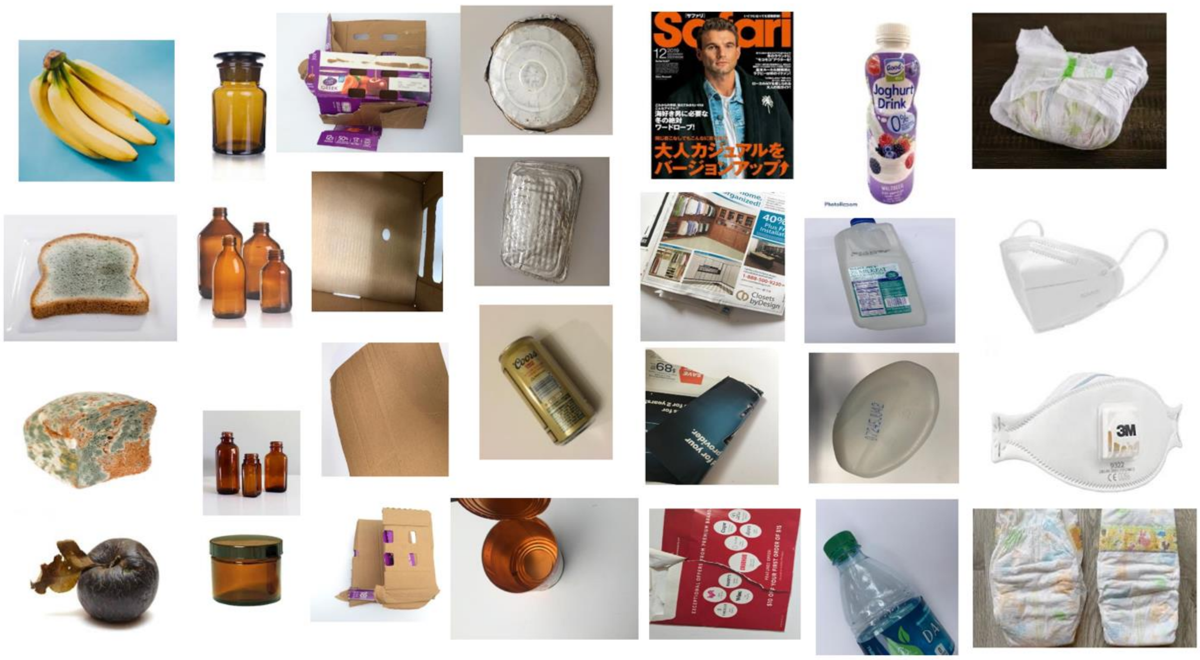


Fig 3.1: Dataset

3.1.2 Proposed Methodology:

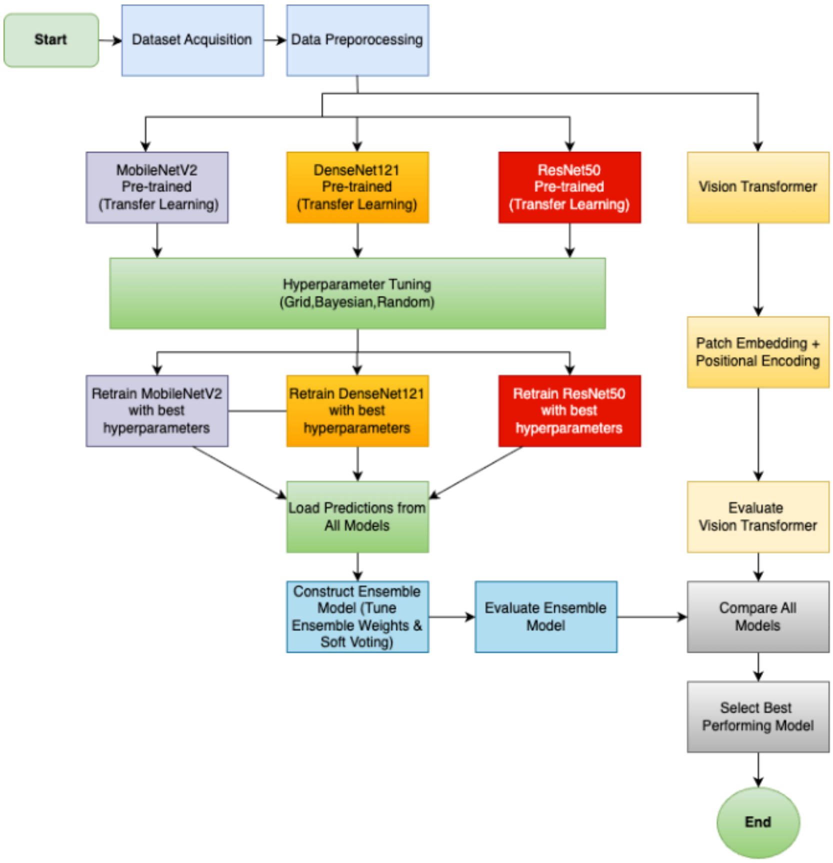


Fig 3.2 Proposed Methodology

The methodology employed by this study is as illustrated on Figure 3.1 and is a pipelined workflow for purposes of developing an economical waste classification system with deep learning. The process starts with dataset collection and a wide set of preprocessing such as resizing, aspect ratio filtering and corruption removal to make data consistent and in good quality

Finally, three pre-trained models—MobileNetV2, DenseNet121, and ResNet50—are leveraged through transfer learning. All of the models undergo a robust hyperparameter search procedure with grid search, Bayesian optimisation, and random search to learn optimal values of parameters such as learning rate, optimizers, batch size, activation functions, and epochs. The models are then trained using the optimal configurations achieved by parameter search.

The three models are subsequently combined through soft voting with weighted averaging to create an ensemble model to boost the generalization and accuracy of the classification. Concurrent to this is the employment of a Vision Transformer (ViT) model with patch embedding and positional encoding mechanisms. Although the studies discussed did not directly utilize ViT, its growing success in vision tasks makes it a strong candidate to add to comparative benchmarking. The final phase involves testing all models together as a group and individually. Following this, a comparative study is undertaken to assess the optimal model architecture to execute waste classification.

3.1.3 Functional and Nonfunctional Requirements

Functional Requirements:

- The system implements several steps before analysis including filter removal of poor images alongside 224x224 pixel resizing and model normalization protocol.
- The system needs to support the fine-tuning process to develop pre-trained models including DenseNet121, ResNet50, MobileNetV2 and ViT for 7-class specific classification.
- The system needs to integrate CNN predictions through soft voting into an ensemble output.
- The system needs to perform five evaluation procedures which include test accuracy alongside test loss and macro-averaged precision, recall and F1-score while also creating confusion matrices.
- The system requires a visual interface to show performance data in tables with attached confusion matrix displays.

Nonfunctional Requirements:

- The system needs at least 90% test accuracy to perform viable waste classification tasks.
- The system needs to process database sizes between 5000 to 10000 images while requiring minimal changes to its underlying code structure.
- The system must provide a manageable inference time framework which performs operations below 0.05 seconds per image for CNNs and under 0.1 seconds for ViT to enable real-time usage.
- The system needs to demonstrate stable results in consecutive runs through the combination of fixed random seeds and stratified splitting techniques.
- Reproducibility factors into the usability criteria because the system needs to work in Kaggle platforms and similar environments with complete documentation.

3.2 Detailed Methodology

Here, we introduce the approach and design methodology of our waste classification system. We experimented with numerous alternative solutions before selecting our approach. We compared every alternative in terms of accuracy, performance, scalability, and ease of implementation in real-world applications.

(i)Data Augmentation & Preprocessing

(a) Alternatives Considered:

Various preprocessing methodologies were tested to increase the efficiency of our models during experimentation.

- Simple normalization and resizing processes images through size standardization plus range normalization into the [0, 1] domain

- The combination of mix-up method and random rotations and flips and zooms supports synthetic data augmentation to enhance dataset diversity.

Why We Chose Advanced Augmentation:

A simple normalization combined with resizing would fail to address the possible data skewness and varying waste types in our dataset. The advanced augmentation methods strengthen the model's capability to handle diverse input variations which include assorted lighting conditions and waste visibility angles together with obstruction elements. The implementation of this step lowers model overfitting and improves generalization specifically with small datasets.

(ii)Model Selection

Methodology:

The investigation of this research involved studying multiple deep learning models that perform image classification through:

- MobileNetV2 represents a lean model architecture that operates efficiently on mobile applications along with embedded systems. The model delivered an effective combination of performance capability with reasonable computational expenses.
- The dense connections in DenseNet121 generate efficient learning and better gradient flow among deep convolutional networks.
- ResNet50 has proven itself as a popular residual network by employing skip connections which allow networks to reach deeper depths more easily.
- The Vision Transformer (ViT) represents a recent transformer-based architecture that delivers exceptional results during large-scale image classification because of its training capability.

Alternate Solutions:

- Among the older network options VGG16 and AlexNet demonstrated inferior performance than the contemporary options MobileNetV2 and ResNet50 when measuring accuracy and efficiency.
- Our initial thought involved using ImageNet datasets for pretrained model training. The specific nature of waste classification in our task led us to train models from scratch to achieve better performance on our domain.

Chosen Solution:

Our selected solution consists of MobileNetV2 along with ResNet50 and DenseNet121 because these models provide both high accuracy performance and efficiency and successfully manage unbalanced classes. Our mission allowed the models to adapt better to waste image characteristics by performing initial training directly on the dataset.

(iii) Ensemble Model Design

Methodology:

- The ensemble model incorporated outputs from the MobileNetV2 and the DenseNet121 and the ResNet50 networks for its operation.
- The ensemble model unites the prediction results from its three component models into a final decision through either weighted averaging or majority voting of their outputs

Alternate Solutions:

- Our first attempt involved training just one model whether it was ResNet50 or DenseNet121, yet this approach failed to generate the performance strengths that multiple model combination delivered.
- We evaluated the addition of more models such as InceptionV3 and EfficientNet but concluded the strategy would raise both computational expenses and system complexity. A grouping of three neural network models demonstrated the optimal mixture of productivity and operational effectiveness.

Chosen Solution:

The selected solution of three model ensemble proved effective because it utilizes individual model strengths to improve generalization with reduced overfitting.

(iv) Training Strategy

Methodology:

The training of models used TensorFlow while we added advanced training strategies through TensorFlow to boost performance levels.

- The models benefit from pretrained weights of ImageNet from Transfer Learning which helps both accelerate training and enhance their performance levels (for ResNet50 and MobileNetV2).
- Keras Tuner performed hyperparameter optimization through which our team adjusted learning rate and batch size and multiple other model parameters. Among available techniques Keras Tuner proved to be the most effective choice for our purposes rather than Bayesian Optimization or Grid Search.
- The model received an enhancement through implementation of label smoothing and Mixup since these advanced techniques fought overfitting while boosting generalization capabilities.

Alternate Solutions:

- Although the methods of Grid Search and Random Search provide strong parameter selection tools, they prove to be expensive in computational terms. Our team performed an evaluation between Bayesian Optimization and Keras Tuner since our dataset needed a model that was best suited for its characteristics.
- Our first approach excluded both the practices of label smoothing and Mixup. The implementation of these techniques proved to enhance model resilience when dealing with class imbalance situations.

Chosen Solution:

Our selected approach involving pretrained model fine-tuning and transfer learning and label smoothing and Keras Tuner hyperparameter optimization delivered useful models at a practical computational expenditure.

(v) Performance Evaluation

Methodology:

The assessment of MobileNetV2 and DenseNet121 with ResNet50 and ViT model performance used multiple criteria.

- Accuracy: Standard measure of model performance.
- The evaluation of class-wise performance requires both Precision, Recall and F1-

Score measurements to handle class imbalance.

Alternate Solutions:

- In our first evaluation method we only examined accuracy but decided it was insufficient. For imbalanced datasets accuracy by itself is insufficient that is why our team chose to add F1-score measurements to the evaluation process.
- A manual review of prediction outcomes served as another option although such a process would demand extensive time combined with subjective assessment. Automated metrics delivered better reliability together with reproducibility of results to the assessment process.

Chosen solution:

The selected method combined multiple performance evaluation metrics, including accuracy together with F1-score, along with precision and recall results, to create a complete understanding of model metrics. This solution works best for imbalanced class data. Our ability to make objective model performance comparisons became possible through this method.

3.3 Project Plan

Each phase within the project plan as in table 3.1 follows a logical sequence which defines its objectives together with deliverables. The timeline serves to guide systematic work on research development alongside evaluation and documentation tasks.

Table 3.1 Project Plan

Phase	Description	Start Date	End Date
Phase 1: Literature Review & Problem Definition	The project begins with related work reviews along with gap identification and defined objectives and scope.	01 SEP 2024	30 SEP 2024
Phase 2: Dataset Collection & Preprocessing	Collection, filtering, resizing, normalization, and augmentation of dataset.	01 OCT 2024	20 OCT 2024
Phase 3: Model Selection & Experimentation	Training and evaluating MobileNetV2, DenseNet121, ResNet50, and ViT individually.	21 OCT 2024	30 NOV 2024
Phase 4: Ensemble Model Development	Building and training the ensemble model with training techniques like mixup, label smoothing.	01 DEC 2024	05 JAN 2025
Phase 5: Model Evaluation & Performance Tuning	Hyperparameter tuning and performance comparison (ensemble vs. ViT).	06 JAN 2025	25 MAR 2025
Phase 6: Report Writing & Documentation	Writing thesis report, results analysis, and presentation preparation.	26 MAR 2025	30 APR 2025

3.4 Task Allocation

To ensure balanced workload allocation, the task was shared in table 3.2 with equal proportion among both members considering individual strengths.

Table 3.2 Task Allocation

Sl No	Task Description	Assigned Member(s)
1	Literature review and problem identification	Zarrin Tasnim
2	Research gap analysis and proposed solution summary	Sayem Ahmmed
3	Dataset collection, cleaning, and preprocessing	Sayem Ahmmed
4	Model training: MobileNetV2 and ResNet50	Zarrin Tasnim
5	Model training: DenseNet121 and Vision Transformer (ViT)	Sayem Ahmmed & Zarrin Tasnim
6	Ensemble model development and integration	Zarrin Tasnim
7	Hyperparameter tuning (grid search, random search and bayesian optimization)	Sayem Ahmmed
8	Performance evaluation: metrics (accuracy, F1-score, confusion matrix)	Zarrin Tasnim
9	System diagrams (Context Diagram, DFD Level 1)	Sayem Ahmmed
10	Report writing: Chapter 1, Chapter 2 and Chapter 3	Zarrin Tasnim
11	Report writing: Chapter 4, Chapter 5 and Chapter 6	Sayem Ahmmed
12	Final report review, formatting	Sayem Ahmmed & Zarrin Tasnim
13	Slide presentation	Sayem Ahmmed & Zarrin Tasnim

3.5 Summary

The chapter presented the total methodology together with the research design tactics. The methodology introduced an initial description of the system design which was followed by complete descriptions regarding deep learning models selection and data preprocessing methods alongside training strategies and evaluation methods. The system received specification of necessary instructions including functional needs alongside non-functional needs as well as a presentation of visual design components consisting of context diagram, data flow diagram, and UI mockups. The methodology section evaluated alternative methods and defended the selection of our ensemble model. The research included defined schedules and distributed work responsibilities for team members to establish successful cooperation throughout research duration. The foundation created in the previous chapter serves as the basis for conducting implementation work followed by results analysis in the subsequent chapter.

Chapter 4

Implementation and Results

4.1 Environment Setup

We conducted our research implementation through Kaggle Notebooks providing both reliable computation capabilities as well as high-performance processing.

The program used TensorFlow and PyTorch frameworks in its framework implementation. TensorFlow enabled the training of convolutional neural networks where MobileNetV2, DenseNet121, ResNet50 together with their ensemble received their training. We selected the Vision Transformer (ViT) to function through PyTorch library in the Hugging Face Transformers framework due to its efficient integration of transformer models and capability for fine-tuning.

4.2 Testing and Evaluation & Comparative Analysis

Our systematic evaluation employed a special test dataset containing seven identified classes: metal along with brown-glass and paper together with trash and cardboard and plastic and biological materials for comprehensive performance assessment of proposed models. The research evaluated the models using a systematic assessment method which maintained objectivity and faithful adherence to waste classification objectives. The whole database was divided into a training set and a validation and a testing set along an 80%: 10%: 10% distribution. The distribution method provided adequate data for model learning and adjustment purposes and unbiased assessment of the final performance. The test data received no contact from training or validation procedures to ensure accurate performance assessment.

Evaluation Metrics:

Multiple performance evaluation metrics were employed for model assessment.

- **Accuracy:** The overall correctness of predictions.
- **Precision (Macro Average):** The Macro Average precision computes the total amount of actual positive predictions from every positive forecast across all categories.
- **Recall (Macro Average):** The model shows its ability to spot every relevant case distributed across classes through this evaluation metric.
- **F1-Score (Macro Average):** Macro Average F1-Score represents the balanced ratio between precision and recall assessment of model

Comparative Analysis:

A common test set and set of metrics served to evaluate MobileNetV2, DenseNet121, ResNet50, Vision Transformer along with a custom Ensemble Model. Performance metrics comparisons enabled us to study both benefits and disadvantages of each model and their relationship between processing speed and accuracy levels and computational resource requirements.

4.3 Results and Discussion

Through this section, Test set assessment was primarily used for the evaluation of the models' performance of our evaluation. From Table 4.1, five models were examined including MobileNetV2, DenseNet121, ResNet50, ViT, and an ensemble model being one of them. The assessment process has been thoroughly observed considering the critical performance indicators, such as accuracy, loss, precision, recall and F1-score (macro-average).

Model Performance Overview:

Table 4.1 Model Performance:

Model	Test Accuracy	Test Loss	Precision (Macro)	Recall (Macro)	F1-Score (Macro)
MobileNetV2	0.9360	0.1807	0.9366	0.9347	0.9353
DenseNet121	0.9667	0.0908	0.9640	0.9666	0.9659
ResNet50	0.9641	0.1056	0.9655	0.9624	0.9631
Vision Transformer	0.9735	0.5543	0.9736	0.9741	0.9736
Ensemble	0.9752	0.0712	0.9755	0.9747	0.9750

Model Discussion:

MobileNetV2:

The MobileNetV2 model reached 93.60% accuracy through its 0.1807 loss rate. The model displays superior precision (93.66%) and recall (93.47%) leading to an outstanding capability to detect proper waste classes without producing many false detections. Resources from constrained environments can use this model because its lightweight configuration and real-time capabilities enable it to be operational in restricted settings. Although the model showed slightly lower results than DenseNet121 and ResNet50 in terms of detection precision and recall performance.

DenseNet121:

DenseNet121 showed impressive results in its test outcomes with 96.67% accuracy and 0.0908 test loss. The waste classification reliability of DenseNet121 exceeds MobileNetV2 and ResNet50 because it achieves precision levels of 96.40% and recall levels of 96.66%. DenseNet121 presents dense connectivity features that improve the reuse of features to extract complex patterns from image data. The model would struggle to perform in time-sensitive or resource-stricter systems due to its demanding computational requirements and complexity level.

ResNet50:

ResNet50 provided 96.41% test accuracy while the loss measurement reached 0.1056 but remained higher than DenseNet121's results. DenseNet121 had similar precision (96.55%) and recall (96.24%) to its competitor which indicates strong performance. ResNet50 offers residual connections as its major advantage because they enable the training of deep networks and help avoid problems with gradient vanishing. The model needs less computational power than DenseNet121 even though it maintains equivalent performance levels making it suitable for specific applications where efficiency matters.

Vision Transformer (ViT):

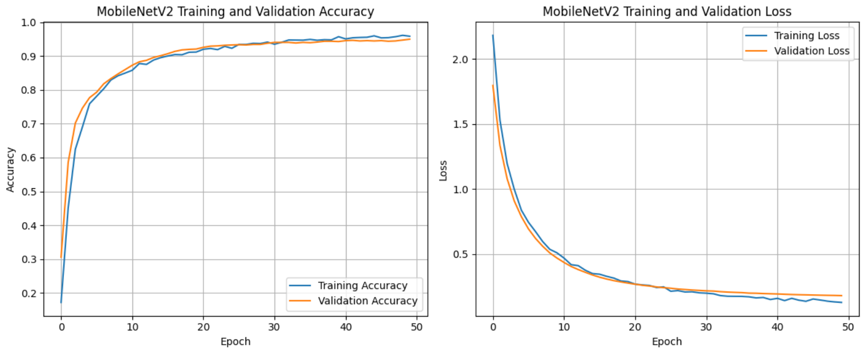
The individual test run of Vision Transformer achieved the best accuracy at 97.35%. The ViT model achieved outstanding performance results in all categories with precision (97.36%) reaching 97.36% and recall (97.41%) achieving 97.36% while attaining a final F1-score of 97.36%. The ViT model executed image patch processing as sequence components while producing strong results through its dependency modeling capabilities. The test loss of 0.5543 for ViT indicated substantial measurement inconsistency when compared to the rest of the models because it needed additional data or tuning for optimal generalization. High computational complexity in the ViT affects the availability of training time and efficient resource management.

Ensemble Model:

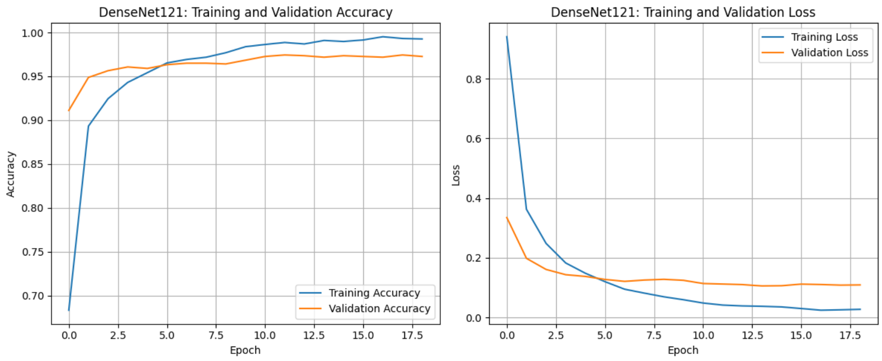
The ensemble of MobileNetV2 and DenseNet121 and ResNet50 generated the best performance by reaching an accuracy of 97.52% and a minimal test loss of 0.0712. The collaborative combination of different concept models produced enhancements in performance measures across all evaluation criteria. The ensemble displayed improved precision performance at 97.55% and recall at 97.47% compared to ViT but it attained an F1-score of 97.50% and it was more than any other model which has been studied in the research. Altering diverse resilient model architectures helps in generalization specifically in matters of complex scenarios, such as waste classification.
All tested models displayed strong performance although the Ensemble Model demonstrated somewhat superior outcomes than its individual counterparts because ensemble learning effectively unites the advantages of multiple models. The Vision Transformer delivered excellent accuracy while requiring higher computing resources in comparison to other models which resulted in increased computational loss. The real-world applications benefit from DenseNet121 and ResNet50 because these models demonstrate a solid combination of precise results with fast operations.

Training and Validation Performance:

Fig 4.1 presents the performance charts showing automated waste classification by deep learning models which feature MobileNetV2(i), DenseNet121(ii) and ResNet50(iii) training along with validation accuracy and loss through their respective epochs. MobileNetV2 shows training accuracy improvement from 0.30 through to 1.0 for 50 epochs training while its validation accuracy maintains at 0.92–0.94 which matches its test accuracy of 0.9360; training loss decreases from 2.0 to near 0 and validation loss settles at 0.3–0.4. The training accuracy of DenseNet121 rises from 0.70 to 1.0 across 17.5 epochs while validation accuracy reaches the same level as test accuracy at 0.96–0.97. At the same time, the value of training loss declines from 0.8 to 0 and validation loss stabilizes at 0.1–0.15 which indicates effective convergence with minimal overfitting present. The 40-epoch runtime academic plots show fast learning dynamics as training parameters reach 0.98 accuracy inside the first 10 epochs before stabilizing at 0.96 for training and validation data while the validation accuracies range from 0.96 to 0.97 for ResNet50, ViT, and the Ensemble model. Minimal metric separation combined with training and validation loss reduction from 1.75 to 0.1 and 1.25 to 0.2 confirms high generalization for real-world Dhaka urban waste management applications at epoch 40. The model demonstrates appropriate convergence and adaptability properties that prove its effectiveness for sustainable waste sorting operations.



(i)



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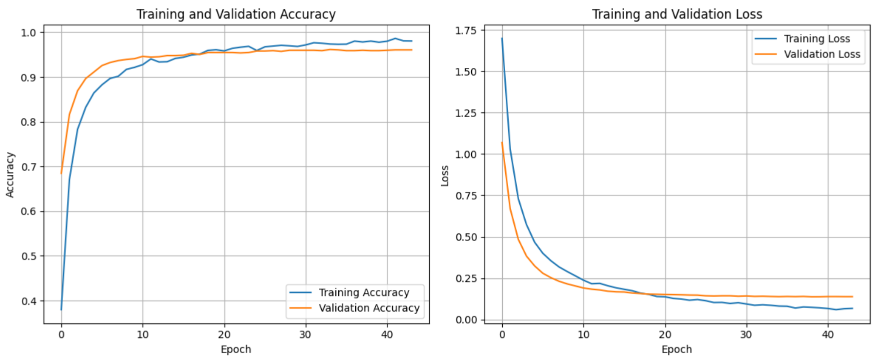
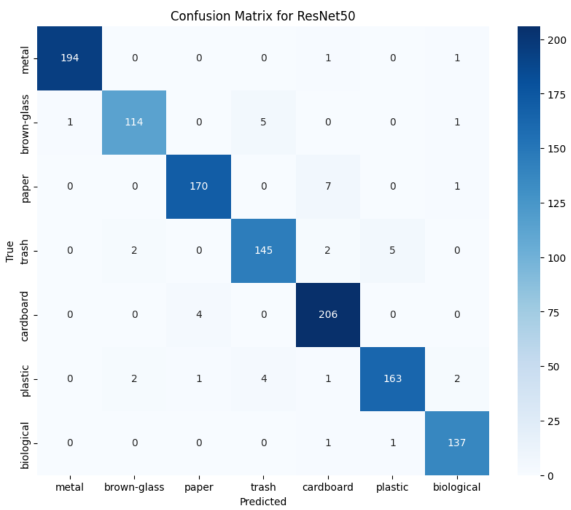


(iii)

Fig4.1: Training and validation accuracy and loss curves for MobileNetV2(i), DenseNet121 (ii)and ResNet50(iii)

Misclassification Analysis:

The misclassification analysis tells how the classification performs materials such as metal, brown-glass, paper, trash, cardboard, plastic, and biological substances across multiple deep learning models, as shown in Fig. 4.2: Confusion Matrix of ResNet50(i), MobileNetV2(ii), DenseNet121(iii), ViT (Vision Transformer) (iv) & Ensemble (v). Although some inaccuracies are visible, all models perform well, with most categories correctly detected (153–194 occurrences for metal and 170–206 for cardboard, for example). In particular, the Vision Transformer incorrectly classifies four brown-glass and six cardboard items—often as plastic or metal—MobileNetV2 correctly classifies metal objects 192 times, but misclassifies eight plastic items as cardboard and five biological items as plastic, probably because of texture similarities; the Ensemble Model performs exceptionally well with 205 correct cardboard classifications and few errors, including four cardboard items misclassified as paper; DenseNet121 records 203 correct classifications but incorrectly classifies four brown-glass and five biological items as trash; and ResNet50 obtains 206 correct classifications with four plastic items misclassified as cardboard. Research findings indicate plastic and biological materials create average confusion though they commonly mistake cardboard and rubbish due to sensory similarity, yet the study shows these items get classified accurately 1 to 8 times out of ten with cardboard as the most identifiable class. Further investigation into ensemble methods shows promise since they provide improved accuracy rates & (vi) illustrates the total number of misclassifications made by each model in the study. The ensemble model achieved the lowest misclassification count (29), demonstrating superior accuracy compared to individual models.



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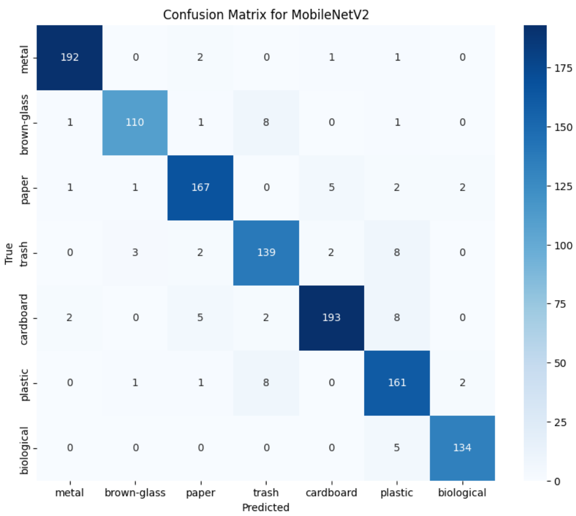

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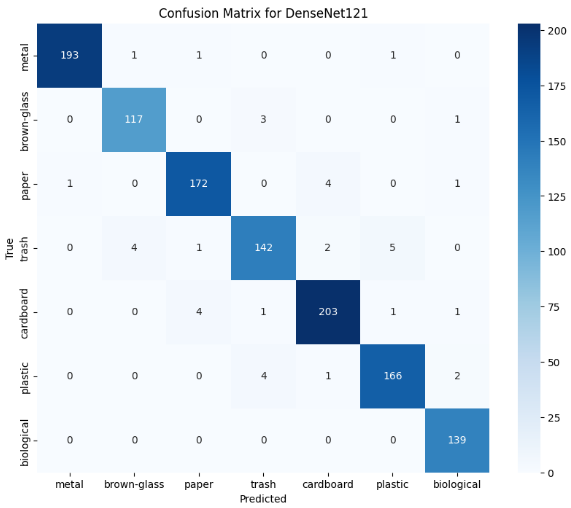

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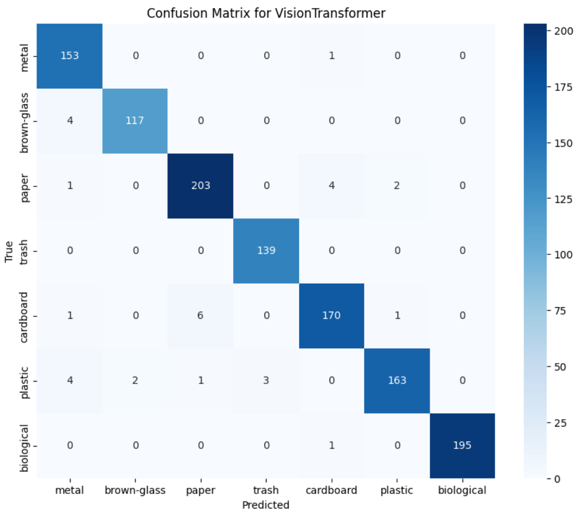

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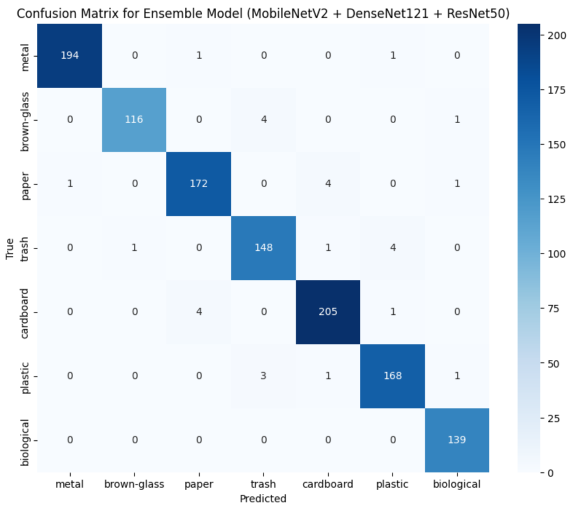

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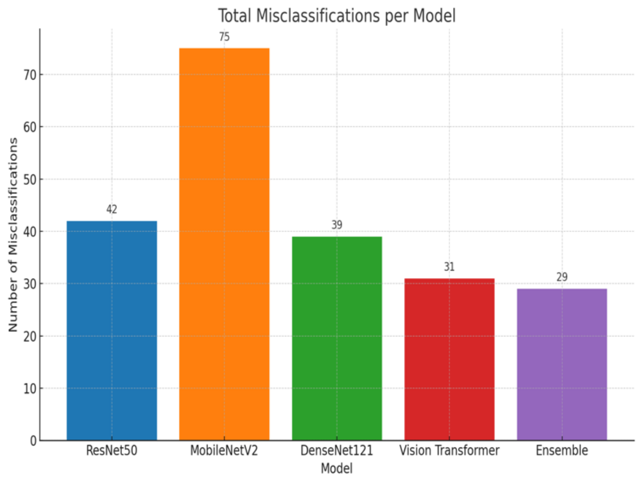

(vi)

Fig4.2: Confusion Matrix of (i) ResNet50, (ii)MobileNetV2, (iii) DenseNet121, (iv)ViT(Vision Transformer), (v)Ensemble & (vi)Total misclassifications per Model

4.4 Summary

This chapter described all implementation steps and testing methods that evaluated the waste classification models. The implementation of the Kaggle GPU T4X2 as the training and evaluation platform received detailed explanation. The section about testing and evaluation analyzed five models including MobileNetV2, DenseNet121, ResNet50, Vision Transformer (ViT), and Ensemble Model using accuracy, test loss, precision, recall and F1-score (macro-average) as performance metrics. The Ensemble Model proved itself as the most reliable of all models since it delivered optimal accuracy and F1-score results.

Vision Transformer demonstrated maximum accuracy but required additional optimization because its test loss outcomes were elevated. The DenseNet121 together with ResNet50 proved to be excellent solutions for real-time applications with restricted resources due to their excellent precision-recall balance. The conclusion of this chapter demonstrated how multiple model alliances succeed in obtaining optimal outcomes while examining performance versus computational expense versus practical deployment potential within waste classification frameworks. Holistic system analysis obtained from the testing phase will direct the continuous improvement process and deployment strategy of the system.

Chapter 5

Engineering Standards and Design Challenges

5.1 Compliance with the Standards

The analysis focuses on standards affecting the research study by describing key software programs as well as hardware components and communication methods that influence machine learning model development and performance assessment for waste classification. All research follows specific guidelines which enable the findings to be both reproducible and dependable. Various alternative standards to the existing ones are analyzed and the reason behind their selection is discussed.

5.1.1 Software Standards

The research team chose standards that are relevant to the study from the software evaluation process for their practicability.

ISO/IEC 9126 (Software Engineering – Product Quality):

- ISO/IEC 9126 supports the assessment of software quality by providing a complete framework for the inspection of functionality, usability, efficiency, maintainability, portability and the additional quality of functionality. These qualities are essential for crafting the patterns of machine learning models for researchers to create programs that are effective and flexible for long term use. Since the standard covers many aspects, it provides less relevance for precise machine learning application requirements. The research focusses on model accuracy and efficiency made portability requirements unnecessary since this aspect was not vital for the current work.

- The standard serves as selection because it provides an essential framework to ensure proper quality within research software tools. Maintainability and usability play essential roles in the research because future revisions must be able to reproduce and manage code and models effectively.

IEEE 829-2008 (Software Test Documentation):

- IEEE 829 delivers specific instructions which enable structured testing methods through sequential guidelines that start from planning and advance to design and execution and finish with documentation steps. The standardized framework allows for complete evaluation and verification of models that research uses to determine their reliable performance.

- The detailed documentation along with a structured approach requires considerable time when dealing with smaller testing scenarios or when conducting iterative experiments. The sacrifice of additional time guarantees that the research upholds its rigorous assessment standards.

- The testing phase for models received selection of IEEE 829 because it provides detailed documentation along with documentation to support repeated testing and viewing process transparency. A standardized approach improves both the documentation transparency and traceable aspects of the testing procedures.

Alternative: ISO/IEC 25010:2011 (System and Software Quality Models):

- The detailed attributes in software quality assessment from ISO/IEC 25010 surpass those found in ISO/IEC 9126. This standard provides evaluation capabilities for functional suitability and performance efficiency together with security features to evaluate software performance at finer levels.
- The standard presents too detailed a framework for this research because the primary focus was on machine learning model accuracy and efficiency rather than reviewing complete software qualities.

5.1.2 Hardware Standards

The chosen hardware has an essential part to play for achieving optimal performance because it handles deep learning model training and evaluation. The selection of hardware occurred because researchers needed efficient handling of big datasets alongside complex computational operations. The main hardware requirements involve GPU technology selections and data exchange mechanisms coupled with computing speed capabilities.

- The research used NVIDIA Tesla T4 GPU because it speeds up deep learning operations by combining Tensor Cores which deliver rapid matrix calculations while allowing for precision training. The selected GPU system efficiently trained MobileNetV2, DenseNet121, ResNet50 and Vision Transformer along with other neural models.

- The GPU training process utilized CUDA which served as a platform from NVIDIA to maximize GPU capabilities. The deep learning calculations needed quick processing and consequently GPU selection speeded up the operations since tasks involving large datasets need extensive processing power.

- The training process experienced minimized bottlenecks because PCI data transfer protocols guaranteed high-speed data exchange between the GPU and CPU.

5.1.3 Communication Standards

The proposed research depends on communication standards to achieve workflow efficiency between system components which includes data transfer and model training processes and evaluation cycles. Because the research projects deep learning models which need considerable computational power researchers must establish precise and efficient communication procedures.

- **Network Protocols:** The model training process that relies on cloud-based platforms such as Kaggle uses TCP/IP network protocols to guarantee reliable and secure connectivity between system components. The system enables smooth and efficient transfers of big datasets along with uninterrupted continuous model training.

- **API Integration:** Rephrased, REST APIs enabled users to connect with outside resources including machine learning services because these APIs ensured smooth cooperation among software and hardware elements. The evaluation of datasets and model testing processes take place through APIs which enables instant performance metric reporting.

- **Data Transfer Speed and Security:** The system utilizes SSL/TLS encryption standards for quick data transfer which provide secure data exchanges specifically with sensitive and proprietary information. A fast data transfer rate remained critical during model training because it produced smooth and timely operations particularly when training models with large datasets.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

The deep learning models assessment of waste types through the ensemble model made from MobileNetV2 and DenseNet121 and ResNet50 establishes life-enhancing possibilities. Developing countries such as Bangladesh experience severe environmental and health concerns because their ineffective waste collection and sorting systems create an escalating waste management issue globally.

This researched system establishes automatic waste classification that leads to several valuable contributions.

- **Improved Efficiency:** The current system of waste sorting requires enormous labor effort and takes up considerable amounts of time. Waste sorting operations become more efficient through AI as the system produces accurate results at faster speeds thus reducing operational demands for workers.

- **Better Resource Management:** Waste identification using this method can be of great use as we are able to recycle and reuse it, reducing waste that ends up in landfills tremendously. This method is useful to conserve such natural resources to recycle plastic, paper and metallic items rather than extraction of new raw materials.

- **Enhanced Public Health:** The public health condition becomes better when waste isolation and disposal operate properly since water pollution from waste and disease transmission together with exposure to dangerous substances become less likely. Community members experience better environmental conditions due to automated waste classification which ensures accurate disposal thus reducing health risks.

5.2.2 Impact on Society & Environment

The examination and assessment of multiple deep learning models for waste classification represents work that aids overall waste management system development. This study offers practical knowledge to benefit future implementations of AI-based solutions although it does not directly execute or suggest such solutions.

Societal Impact:

- **Knowledge Contribution:** One of the key impacts of this study involves the academic and practical research of waste classification tasks by analyzing deep learning model comparisons

- **Support for Smart Waste Management:** The study results will assist developers and policymakers in their choice of efficient waste sorting models for automated or semi-automated waste systems so they can improve public sanitation standards and environmental hygiene.
- **Awareness Building:** The study demonstrates how machine learning works in waste sorting which creates public understanding about technological solutions for ecological sustainability.

Environmental Impact:

- **Efficiency in Recycling Processes:** Waste sorting effectiveness depends on correct waste classification according to the findings of this study and can enhance recycling efficiency when deployed in actual recycling operations.
- **Reduction in Environmental Degradation:** The collected research information enables engineers to create new solutions reducing improper waste disposal activities to reduce both pollution levels and landfill usage.
- **Foundational Step for Sustainable Technology:** The research provides an essential basis for sustainable technology even though it does not create an operational system that enables AI integration in waste management.

5.2.3 Ethical Aspects

The practice of responsible research demands ethical evaluation for all studies involving environmental and technological research fields. Research investigators handling waste classification data took time to account for multiple ethical considerations throughout the study.

- **Responsible Data Usage:** All images collected for classifying waste material originated from academic research datasets which were freely available to the public. Since no personal or sensitive information appeared in the data collection activities the process fulfilled all ethical requirements.
- **Transparency and** Reproducibility: The research findings underwent complete documentation of model architectures and methodologies together with performance evaluation results for the purpose of transparency. Research findings remain accessible for other institutions and researchers to produce identical studies that verify outcomes and develop new research based on results.
- **Fairness and Bias Mitigation:** During this testing stage, a collection of objective indicators, such as macro precision, recall, and F1-score, was used to achieve a balanced classification of waste categories. To avoid biased assessment, the evaluation measures protect from uneven attention to or the disregard of particular waste categories due to the imbalance of data set.
- **Avoidance of Overstatement:** Findings are presented with academic integrity while keeping all excessive statements about practical application outside of experimental scope. This research serves as an educational and experimental investigation within an experimental setup.
- **Environmental Responsibility:** By prioritizing classification accuracy, the research demonstrates support to the wider sustainability initiative of waste management through future enhancements in waste sorting operations.

5.2.4 Sustainability Plan

The main sustainability value of this research includes its future benefits toward environmentally responsible waste management practices alongside conservation efforts. Researchers conducted the research within an academic framework but designed their work to deliver practical effects for public application purposes beyond their research boundaries. The proposed solution depends on image-based sorting methods to optimize waste classification procedures while it promotes environmentally friendly recycling practices through proper material sorting. The research provides knowledge about developing efficient systems that can operate in resource-limited areas which promotes sustainable waste disposal methods for urban and rural areas. This method provides reliable research groundwork for subsequent investigators who want to advance the work without starting from fundamental principles. The research serves two purposes by educating people about waste management issues along with demonstrating the significance of sustainable behavior choices. The proposed practical and environmentally minded design strategies contribute effectively to present and future sustainability goals as they offer substantial benefits for a cleaner sustainable future.

5.3 Project Management and Financial Analysis

The research phase required no financial investment as it utilized open-source tools and free resources such as TensorFlow, PyTorch, Google Colab, and Kaggle's GPU support. All development, training, and testing were conducted without hardware costs. However, for future implementation of the system as a real-world IoT-based smart dustbin, estimated hardware costs are outlined in Table 5.1 below. These components will support deployment with real-time waste classification capability.

Table 5.1 Future IoT Device Cost Analysis

SL No	Component	Estimated Cost (BDT)
1	Arduino Uno	1100
2	ESP32-CAM Module	1320
3	Servo Motor	550
4	I2C OLED Display	660
5	Breadboard	330
6	Jumper Wires	220
7	Cardboard (Dustbin Body)	440
8	Miscellaneous (glue, screws, stand)	330
9	Power Supply (Battery/Adapter)	550
	Total Estimated Cost	5500

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

The research investigates deep learning methods to resolve the issue of precise waste classification. The waste classification problem demanded solutions for interlinked data-related steps which included data preparation combined with model teaching and assessment of deep learning convolutional networks MobileNetV2 and DenseNet121 and ResNet50 and Vision Transformer and Ensemble Model. The project applied seven key indicators (EP1–EP7) from the complex engineering problem framework as shown in Table 5.2. and its justification as shown in Table 5.4

Table 5.2: Mapping with Complex Problem Solving.

EP1 Depth of Knowledge	√
EP2 Range of Conflicting Requirements	√
EP3 Depth of Analysis	√
EP4 Familiarity of Issues	√
EP5 Extent of Applicable Codes	X
EP6 Extent of Stakeholder Involvement	X
EP7 Interdependence	√

Table 5.3 Mapping with Knowledge Profile for EP1

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✓	✓	✓	✓	✓

5.4.1.1 Justification for EP Attributes Mapping

EP1 Depth of Knowledge:
The project demonstrates a very good understanding of the deep learning concepts with reference to the use of Convolutional Neural Network (CNNs), Vision Transformers (ViT) and ensemble algorithms. This represents an overall understanding of foundational and advanced architectures.

EP2 Range of Conflicting Requirements:
A balanced approach is preserved through a range of competing points, including model accuracy, architectural complexity, computational efficiency and dataset handling. The research does not optimize tradeoffs inefficiently to achieve optimal performance.

EP3 Depth of Analysis:
The analysis is comprehensive one done with analysis metrics such as the accuracy, F1-score, and confusion matrices. It also entails systematic hyperparameter tuning via several calibrations on model performance.

EP4 Familiarity of Issues:
The study recognizes and overcomes everyday difficulties in classifying waste examples such as varying appearances, mixed or polluted, and differences between disparate kinds of waste, all of which are necessary for everyday usability.

EP5 Extent of Applicable Codes:
This is an aspect that is not much considered, in the project and this implies that there is limited use or discussion of reusable or shareable code modules for general use.

EP6 Extent of Stakeholder Involvement:
The project does not embed stakeholders like waste management professionals or policymakers, or end-users, and as such does not feature real-world engagement or feedback loops.

EP7 Interdependence:
The interdependence expressed by the integration of various models and preprocessing steps exhibits a high level of interdependence. Each of the components completes the others to make a coherent pipeline in which the outputs of one stage shape decisions on the next.

5.4.1.2 Justification for Knowledge Profile Mapping (linked to EP1):

The study is closely aligned with the knowledge profile as in Table 5.3 for tackling EP1 (Depth of Knowledge) through the demonstration of proficiency in various important knowledge areas of engineering. It integrates:

- **K3:** Engineering Fundamentals through fundamental knowledge of machine learning concepts, optimization techniques, and statistical analysis.
- **K4:** Specialist Knowledge is utilized in the implementation and optimization of deep learning architectures like MobileNetV2, DenseNet121, ResNet50, and Vision Transformer, along with the techniques for their ensemble integration.
- **K5:** Engineering Design is shown through the design of a multi-model classification system specific to real-life waste sorting problems and systematic evaluation of design decisions based on controlled experiments.
- **K6:** Engineering Practice is seen through the real-world deployment of model training flows, data augmentation processes, and model performance tweaking with common open-source software tools and GPUs.
- **K8:** Research Literature is adequately covered through the critical reading of 16 research articles that influenced the choice of models, datasets, and the methodology to go with, to keep the work aligned with the state-of-art academic literature.

5.4.2 Engineering Activities

The research involved different engineering tasks that fulfill requirements specified for complex engineering conditions. From Table 5.5 the research work encompassed picking suitable models alongside data processing and preparation along with modern deep learning practice application and multi-dimensional performance assessment. The project demanded different computing resources and collaborations between fields and understanding of social and environmental effects of the study topic.

Table 5.4: Mapping with complex engineering activities.

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✔	✔	✔	✔	✔

5.4.2.1 Justification for Engineering Activities Mapping

EA1: Range of Resources

The research utilized a diverse range of computational resources including TensorFlow and PyTorch frameworks, Keras Tuner for hyperparameter tuning, and Google Colab for multi-GPU training. These tools facilitated the development and evaluation of various machine learning models with different complexities, such as ResNet50, DenseNet121, MobileNetV2, and ViT.

EA2 Level of Interaction:

The research demanded interaction across multiple domains such as machine learning, computer vision, environmental science, and academic literature. Although it was not industry-collaborated, the interdisciplinary nature required thorough communication of design challenges, optimization logic, and sustainability implications.

EA3 Innovation:

The research included novel aspects such as model comparison, ensemble learning, and transfer learning optimization. The ensemble approach combined strengths of individual models, enhancing overall performance, and showcasing innovation in applying known techniques in a new integrated way within the waste classification domain.

EA4 Consequences for Society and Environment:

The study, though academic in nature, contributes to the broader goal of automated waste management. Its outcomes, such as improved classification accuracy and sustainable computation strategies, have the potential to influence practical systems that can help reduce environmental impact and enhance public health.

EA5 Familiarity:

While machine learning methods are well-established, applying them to real-world waste classification with practical constraints (imbalanced data, computational limits, classification complexity) posed unique challenges. The work required adapting familiar methods to an unfamiliar and domain-specific context.

5.5 Summary

The research framework has received comprehensive analysis regarding its applications to crucial engineering standards alongside design obstacles. The analysis of work was based on intricacies of the project lifecycle and included problem-solving procedures and varied engineering actions taken. In Section 5.4.1, the complex problem-solving analysis showed that robust analytical abilities and specialized background were required to manage trade-offs and apply specialized information to achieve higher precision, solve the imbalance of data, and develop model optimization. The evaluation demonstrated both how stakeholders fit into the project design and what standards apply.

Through the engineering branch of the mapping process (Section 5.4.2) researchers utilized multiple aspects to complete their work including sophisticated machine learning platforms and advanced tools and interdisciplinary collaboration methods and innovative ensemble modeling approaches. Academic research conditions could not prevent this project from tackling actual environmental concerns by developing smart waste processors with potential expansion capabilities.

The chapter confirmed the research meets engineering practice standards because it demands expertise in multiple domains and awareness of environmental contexts as specified by the engineering skills profile.

Chapter 6
Conclusion

6.1 Summary

This research was concerned with the development of a machine learning-inspired waste classification system for the management of the growing need for innovative and green waste management strategies. This work developed out of the pressing need to solve the environmental and operational problems of the traditional waste collection methods especially in developing countries where manual sorting made their handling a health risk and highly inefficient and sluggish. First the study setting, the main issue and the aims of the research were divided. Close attention was paid to automizing waste classification, with an accent on potential of the computer vision and machine learning to initiate the process. To do so, the goals were listed in the form of establishing and evaluating a classification system that is based on cutting-edge deep learning algorithms for the treatment of different types of waste very precisely. Later, there was a review of available literature to assess the prior technologies and their weaknesses. This approach enabled the methodology of research to advance by attention on gaps and findings of best practices from previous studies. The research method consisted of systematic stages such as image preprocessing, model training, tuning hyperparameters and evaluating performance. Several deep learning models were selected based on their sound record in dealing with classification issues. Furthermore, an ensemble approach and optimization techniques were applied in the study to strengthen reliability and overall performance of the used model. In implementing and evaluating the models, it was demonstrated that machine learning can accommodate complex tasks of waste categorization. From the comparative analysis, the study shed light on some of the merits and demerits of different model architectures. The study aligned to engineering practices and academic benchmarks by mapping its activities to problem-solving, academic disciplines, and engineering positions. Overall, the study reflects an integrated approach to the application of the machine learning solutions to environmental administration. It presents relevant information and strategic avenues relevant to the subject and illustrates the contribution of intelligent systems in promoting environmentally sound and automated waste disposal.

6.2 Limitation

Through illustrating the ways in which machine learning can make waste sorting an automated process, this research brought to the fore possible applications, but the boundaries encountered have limited both the practical use and the general extension.

Existing image datasets posed a significant challenge to the research method. The diverse datasets used in this research contained inconsistent amounts of examples for each waste classification group. The inconsistent performance throughout various waste categories became a challenge due to low representation of waste types. The data augmentation techniques did little to mimic actual waste detection diversity since they failed to reproduce the variety of lighting variations and obstacles alongside background clutter coupled with transformations in waste object forms.

The experimental environment employed during the setup remained within controlled simulated conditions. The study failed to show results from real-time testing along with actual waste-sorting system applications. Potential obstacles from real-life applications such as sensor noise along with delays and hardware restrictions and integration complexity were not included in the analysis.

The applied Deep Learning models consisted of DenseNet121, MobileNetV2 and ResNet50 although the training process needed significant computational capacity and large model memory utilization. The implementation of these models becomes impractical due to their difficulty in running on devices with limited processing power such as edge devices and embedded systems that support waste sorting operations in the field.

The research adopted various performance metrics to study models but failed to include evaluations related to energy efficiency or carbon output and cost effectiveness. Sustainable AI applications need these factors to gain rising importance.

6.3 Future Work

The research outcomes which produced 97.52% accuracy through ensemble model-based seven-class waste classification efforts create an excellent foundation for automated waste management development. This work requires a set of proposed future directions to boost its practical impact:

Development of a Physical Waste Sorting Device:
The primary target for future development includes designing together with prototyping a physical device which employs ensemble model accuracy to automate waste sorting processes. The device merges hardware elements such as real-time imaging cameras and conveyor belts for waste transport together with robotic arms or pneumatic systems which perform waste sorting into designated bins using the deep learning model trained previously. The device would take inspiration from IoT-enabled smart bins described in prior work [3] to include sensors which measure weight and volume thus enabling adaptive sorting in variable environments. The first strategy involves building key prototype components that will demonstrate performance in laboratory testing with mixed waste samples. The following development stages will focus on enhancing scalability together with increasing energy efficiency before deploying the device to municipal or industrial recycling facilities to overcome practical deployment limitations identified in existing research [4]

Dataset Expansion and New Model Development: The dataset will expand through additional image collection while adding new waste categories including hazardous materials (such as batteries and medical waste and electronics) after the approaches presented in [7, 10]. Waste management facilities alongside crowd-sourcing initiatives under joint collaboration will build a larger, balanced dataset similar to the TriCascade dataset comprising 35,264 images distributed into 36 classes [5]. The enriched dataset will serve to develop cutting-edge models that incorporate both Swin Transformer architecture and hybrid CNN-attention models which demonstrate the ViT's 97.35% accuracy level from this research [10]. The team plans to use self-supervised learning together with data augmentation methods to enhance model performance on classes which past research found insufficient [4, 9, 10].

Model Optimization for Edge Deployment: The combination of ensemble and ViT models creates difficulties when deploying these models in resource-limited environments. The future implementation will utilize optimization methods starting with model pruning combined with quantization techniques along with knowledge distillation to reduce latency times along with memory usage without sacrificing accuracy performance according to RecycleNet model design [4]. The proposed optimizations will enable edge device deployment for the sorting system during which real-time classification processes can be achieved in low-resource remote settings.

Integration of Explainable AI (XAI): The proposed system combines XAI methods including GradCam and SHAP according to previous work [5] so users can understand how the system reaches its predictions through visual explanations. The system will gain reliability and transparency for stakeholders through identifying misclassifications like brown-glass being mistaken for trash.

Real-World Testing and IoT Enhancement: Amounts of sorting hardware along with developed models will undergo true industrial testing across recycling sites for performance assessment under changing waste conditions and operational lighting conditions. The proposed research builds upon IoT frameworks from [3] by developing cloud-based analytical systems for predictive maintenance and sorting optimization improvements which address the absence of real-world testing observed in [1, 3, 4, 9].

Open-Source and Collaborative Initiatives: Following the expansion of dataset and model optimization and device design elements these assets will be made available through open-source initiatives. Academic institutions together with waste management organizations will collaborate to validate and improve the system according to research suggestions [6, 7] about AI-driven waste management worldwide.

This progressive direction will transform the study into a usable practical solution which tackles global waste challenges through modern technological development. The proposed work will strengthen recycling performance and encourage circular economy initiatives through physical device development and improved model development techniques.

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