A Project Work - Phase I on

WASTE SEGREGATION USING DEEP LEARNING

Submitted in partial fulfillment of the requirements for the award of the

Bachelor of Technology

in

Department of Computer Science and Engineering
(Artificial Intelligence and Machine Learning)

by

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CERTIFICATE

This is to certify that the Project Work - Phase I entitled "**Waste Segregation using Deep Learning**" is submitted by **Dogga Sree Naga Sreeja (20241A6613), Mummadi Krishnamai (20241A6637) and Baswa Ramya Sri (21245A6601)** in partial fulfillment of the award of degree in Bachelor of Technology in Computer Science and Engineering (Artificial Intelligence and Machine Learning) during Academic year 2023-2024.

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DECLARATION

We hereby declare that the Project Work - Phase I titled **"Waste Segregation using Deep Learning"** is the work done during the period from **18th July 2023 to 22nd November 2023** and is submitted in the partial fulfillment of the requirements for the award of degree of Bachelor of Technology in Computer Science and Engineering (Artificial Intelligence and Machine Learning) from Gokaraju Rangaraju Institute of Engineering and Technology (Autonomous under Jawaharlal Nehru Technology University, Hyderabad). The results embodied in this Project Work - Phase I have not been submitted to any other University or Institution for the award of any degree or diploma.

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ABSTRACT

Waste disposal is a major issue in today's world. Due to ongoing economic expansion, industrialization, and urbanization, the rapid increase in the amount and the type of solid and hazardous garbage is becoming a significant concern for local and national governments to ensure effective and sustainable waste management. To combat this issue, a smart and effective waste management solution is proposed. The objective is to segregate the waste into two categories: biodegradable and non-biodegradable. The proposed approach uses a robust deep learning model such as CNN, VGG-16, and Resnet50 pre-trained on a diverse waste image dataset. The Waste Image dataset is taken from Kaggle which consists of 15,150 images belonging to 12 different classes. The accuracies achieved by CNN, VGG-16 and Resnet50 are 76.07%, 88.83%, 97.47% respectively. These results underline the superior performance of ResNet50 in waste classification, emphasizing its potential for accurate and reliable predictions compared to the other models.

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MSW	Municipal Solid Waste
CNN	Convolutional Neural Network
VGG	Visual Geometry Group
IOT	Internet of Things
RELU	Rectified Linear Unit
UML	Unified Modelling Language

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CHAPTER 1
INTRODUCTION

1.1 Introduction to the Project

Garbage classification is the process of sorting garbage into different categories, such as biodegradable, non-biodegradable, recyclable materials, compostable materials, and non-recyclable materials. It is important to classify garbage in order to reduce pollution, conserve resources, and improve public health. However, traditional methods of classifying waste are often inefficient and manual. This may lead to errors or inconsistencies in the sorting of waste which, if not addressed, could hinder the effectiveness of waste management systems. To improve the efficiency and accuracy of garbage sorting systems, Deep Learning and Internet of Things technologies can be applied. Deep learning helps to automatically detect and label waste, whereas, the Internet of Things can be used to collect data on waste streams, as well as automate the garbage classification process.

1.1.1 Waste Disposal: A Major Concern

Waste disposal has evolved into a significant global concern in the contemporary era, driven by various factors that underscore its paramount importance. This concern extends beyond local and national boundaries and manifests itself as a multifaceted issue that necessitates immediate attention:

- **Unprecedented Waste Generation:** The world is currently witnessing an unprecedented surge in the generation of waste, primarily stemming from the interplay of population growth, economic development, and urbanization. This surge is characterized by a vast array of waste types and sources, including residential, industrial, commercial, and healthcare-related waste.
- **Environmental Consequences:** Improper waste disposal has far-reaching environmental ramifications. Landfills, incineration, and unregulated dumping of waste materials result in the pollution of air, soil, and water. This pollution can lead to long-term ecological degradation, endangering biodiversity and ecosystems. As the global community grapples with the challenges of climate change and biodiversity loss, the environmental impact of waste disposal has become an increasingly critical concern.
- **Public Health Risks:** Inadequate waste management poses significant public health risks. Contaminated water sources, for instance, can lead to the spread of waterborne diseases,

affecting human populations. Open dumping sites and uncontrolled burning of waste emit pollutants that can have adverse health effects on nearby communities.

- **Economic Burdens:** The economic costs associated with waste disposal are substantial. Governments bear the brunt of these costs in terms of waste collection, management, and cleanup. Additionally, businesses may face legal liabilities and increased costs related to waste disposal practices, while the long-term costs of environmental damage often far exceed the initial savings from inadequate waste management.
- **Resource Depletion:** In a world where non-renewable resources are dwindling, the improper disposal of waste exacerbates resource scarcity. Many materials found in waste, such as metals and plastics, can be valuable resources when properly recovered and recycled. The failure to do so not only leads to the squandering of finite resources but also intensifies resource competition on a global scale.

1.1.2 Different Types of Waste

Various types of waste are generated in today's world, reflecting the diversity of human activities and consumption patterns. Understanding these waste categories is crucial for effective waste management and classification. Here are the different types of waste generated

- **Municipal Solid Waste (MSW):** This is everyday household waste generated by individuals and families. It includes items like food scraps, packaging, paper, clothing, and small appliances.
- **Industrial Waste:** Produced by manufacturing and industrial processes, industrial waste includes materials like chemicals, solvents, heavy metals, and other byproducts of industrial activities.
- **Commercial Waste:** Generated by businesses and commercial establishments, this waste comprises items such as office paper, packaging materials, and discarded office equipment.
- **Construction and Demolition Waste:** Construction sites produce materials like concrete, wood, drywall, and insulation, while demolition waste includes debris from the destruction of structures.
- **Hazardous Waste:** Hazardous waste is potentially harmful to human health and the environment. It includes materials like toxic chemicals, asbestos, radioactive substances, and medical waste.
- **Electronic Waste (E-Waste):** E-waste encompasses discarded electronic devices such as computers, smartphones, and televisions. These devices often contain hazardous materials

like lead, mercury, and cadmium.

- **Biomedical Waste:** Generated by healthcare facilities, biomedical waste includes items contaminated with biological materials, such as needles, syringes, and expired medications.
- **Organic Waste:** This category includes biodegradable materials like food scraps, yard trimmings, and organic matter. When improperly disposed of, organic waste can produce harmful greenhouse gases in landfills.
- **Construction and Demolition Waste:** This type of waste originates from building and demolition activities. It includes materials like concrete, wood, metal, and insulation. Proper disposal is crucial to prevent environmental contamination.
- **Radioactive Waste:** This highly hazardous waste is generated by nuclear power plants, research facilities, and medical institutions that use radioactive materials.
- **Agricultural Waste:** Agriculture produces waste materials such as crop residues, manure, and agrochemical containers. Proper management is essential to prevent soil and water pollution.
- **Economic Waste:** This waste category includes obsolete, unused, or expired products and materials, such as unsold inventory or outdated electronic devices.

Each of these waste categories presents distinct challenges and requires specific disposal and recycling methods to mitigate environmental impact, safeguard public health, and optimize resource recovery. Adequate waste management practices are essential to address the diverse waste streams and their associated complexities.

1.1.3 Consequences of Improper Disposal of Waste

Improper waste disposal carries significant and far-reaching consequences that impact the environment, public health, and socioeconomic aspects of society. One of the most evident repercussions of improper waste disposal is environmental pollution. It results from waste being dumped in unauthorized sites, open dumping, or improperly managed landfills, leading to the contamination of soil, air, and water. Pollutants released from waste can seep into the ground, adversely affecting soil quality and plant growth. Additionally, the act of burning waste, particularly plastics and synthetic materials, releases harmful emissions into the atmosphere, contributing to air pollution. This not only impairs air quality but also poses health risks to nearby communities, leading to respiratory problems and other health issues. Furthermore, water sources are at risk of contamination due to the infiltration of hazardous substances from waste materials. This can result in water pollution, endangering aquatic ecosystems and posing health risks to humans through the consumption of contaminated water.Improper waste disposal practices can have dire consequences for natural habitats and ecosystems. When waste is discarded indiscriminately in environmentally sensitive areas, it can lead to the destruction of natural habitats. Wildlife may be displaced, injured, or killed as a result of habitat alteration or degradation. This disruption can lead to long-lasting ecological consequences, including the potential loss of biodiversity in affected regions. Additionally, the destruction of habitats can have adverse effects on the populations of various species and disrupt the delicate balance of local ecosystems, with repercussions for the broader environment.

One of the less visible but equally concerning consequences of improper waste disposal is soil contamination. Landfills, especially those without proper lining and management, can allow leachate, a liquid produced by the decomposition of waste materials, to percolate into the ground. This leachate may contain hazardous substances that can infiltrate the soil, affecting its quality and potentially harming plants and crops. Contaminated soil can pose health risks to humans who consume crops grown in such conditions, as the toxins can accumulate in the food chain. Thus, improper waste disposal can have both direct and indirect effects on agriculture and the quality of the food supply, impacting human health.

The burning of waste materials, a common practice in some areas, contributes to air pollution, with a range of adverse effects. In particular, the incineration of plastics and synthetic substances releases harmful pollutants into the atmosphere. These emissions can contain toxic compounds and particulate matter, contributing to air pollution and degrading air quality. The consequences of air pollution are not confined to the immediate vicinity of waste disposal sites but can have regional and even global implications, affecting the health and well-being of communities and contributing to climate change and its associated challenges.

One of the more insidious consequences of improper waste disposal is its contribution to climate change. When organic waste is improperly disposed of in landfills, it undergoes anaerobic decomposition, producing methane, a potent greenhouse gas. Methane emissions are a significant driver of the greenhouse effect, trapping heat in the atmosphere and leading to global warming. The release of methane from landfills not only exacerbates climate change but also underscores the missed opportunity for harnessing the energy potential of this gas through proper waste management practices. Thus, improper waste disposal not only contributes to the environmental crisis but also represents a lost opportunity to mitigate it.

Communities residing near improperly managed waste disposal sites face a range of health risks. The ingestion or contact with contaminated water, soil, or air can lead to waterborne diseases, respiratory illnesses, skin problems, and various other health issues. Vulnerable populations, including children and the elderly, are particularly at risk. For instance, waterborne diseases like cholera and dysentery can result from the consumption of water contaminated by waste. Additionally, inhaling airborne pollutants from open burning or improperly managed landfills can lead to respiratory ailments and other health complications. Thus, improper waste disposal poses direct health risks to individuals and communities.

The economic costs associated with improper waste disposal are substantial and can have a profound impact on both governments and local authorities. The expenses incurred in waste collection, disposal, and cleanup can strain public budgets, diverting funds from other essential services such as healthcare, education, and infrastructure development. The need to manage and mitigate the consequences of improper waste disposal comes at a significant financial burden, which, in many cases, could have been minimized or averted through responsible waste management practices. The economic costs extend beyond the immediate expenses associated with waste management and can include long-term costs resulting from environmental damage and healthcare expenditures.

Improper waste disposal exacerbates resource depletion, particularly of non-renewable resources. Many waste materials, such as metals and plastics, have inherent value and can be recovered, recycled, and reused in various industries. Failing to recover and recycle these valuable materials squanders finite resources. Metal ores, for example, require extensive energy and natural resource inputs for extraction and refinement. When valuable materials end up in landfills or are incinerated, it not only leads to their loss but also intensifies resource competition on a global scale. Resource depletion and the associated environmental impacts can be mitigated through responsible waste management practices that prioritize recycling and resource recovery.

Improper waste disposal has profound implications for ecosystems and biodiversity. The pollution and habitat destruction caused by waste can lead to ecosystem degradation, reducing biodiversity and disrupting ecological balance. This disruption can result in adverse effects on plant and animal species, affecting their survival and reproduction. The disruption of ecological interactions within ecosystems can have far-reaching consequences, leading to the loss of biodiversity

1.1.4 Waste Categorization: Biodegradable and Non- Biodegradable

Waste categorization into biodegradable and non-biodegradable is a fundamental aspect of waste management. It involves classifying waste materials based on their ability to decompose naturally and the potential environmental impact they pose.

a. Biodegradable Waste

Biodegradable waste comprises organic materials that can decompose naturally through the activities of microorganisms like bacteria, fungi, and other living organisms. These materials are typically derived from plant or animal sources and include:

- Food Waste: Leftover food, fruit and vegetable peels, and kitchen scraps are common examples of biodegradable waste. When disposed of properly, these materials break down into organic matter, returning nutrients to the soil.
- Yard Waste: Grass clippings, leaves, twigs, and garden debris fall under this category. When allowed to decompose, they contribute to natural soil enrichment and support healthy plant growth.
- Paper Products: Materials like newspapers, cardboard, and uncoated paper are biodegradable. They can be recycled or composted, reducing the need for landfill disposal.
- Wood: Natural wood, untreated with chemicals or preservatives, is biodegradable. It can be composted or used as a carbon source in composting.
- Natural Fabrics: Fabrics made from natural fibers like cotton, silk, and wool are biodegradable. However, synthetic fabrics like polyester are not.

b. Non-Biodegradable Waste

Non-biodegradable waste consists of materials that do not easily decompose in natural environmental conditions. These materials may persist in the environment for extended periods and include:

- Plastics: Plastics are one of the most common non-biodegradable materials. They can persist in the environment for hundreds of years, contributing to plastic pollution. Examples include plastic bottles, bags, and packaging materials.
- Metals: Materials like aluminum and steel do not biodegrade. While they can be recycled and reused, their natural decomposition is extremely slow.
- Glass: Glass containers and products do not biodegrade. They can be recycled, but the recycling process is energy-intensive.

- Synthetic Fabrics: Fabrics made from synthetic fibers, such as polyester and nylon, do not biodegrade. They can break down into smaller plastic particles, contributing to microplastic pollution.
- Electronic Waste (E-Waste): E-waste, which includes discarded electronic devices like computers and smartphones, contains non-biodegradable components like circuit boards, batteries, and plastics. Proper disposal and recycling of e-waste are essential to prevent environmental contamination.
- Toxic Chemicals: Hazardous materials like pesticides, solvents, and heavy metals are non-biodegradable and can contaminate soil and water if not disposed of properly.
- Certain Construction Materials: Some construction materials, such as concrete and asphalt, do not biodegrade naturally. They can be reused or recycled, reducing their environmental impact.

The categorization of waste into biodegradable and non-biodegradable materials is pivotal in waste management planning. It enables the implementation of appropriate disposal methods and recycling strategies for different types of waste. Biodegradable waste can be diverted from landfills and used to create compost, reducing the burden on landfill space and supporting sustainable agriculture. Non-biodegradable waste, on the other hand, requires responsible recycling and disposal practices to minimize its environmental impact and promote resource conservation.

Figure 1. Segregation of Waste (Courtesy: Source[1])

1.1.5 Motivation

The Need for Efficient Waste Management: The motivation behind striving for efficient waste management is rooted in several critical factors. Efficient waste management not only ensures the cleanliness of urban and rural environments but also plays a pivotal role in public health. Inefficient waste disposal can lead to the spread of diseases, as waste provides a breeding ground for pathogens. Moreover, it affects the quality of life for local communities, causing discomfort and health hazards. Therefore, efficient waste management is essential for maintaining a high standard of living and the well-being of society.

The Role of Technology in Addressing Waste Challenges: Technology is increasingly recognized as a promising solution to address waste management challenges. It offers the potential to streamline and optimize waste collection, recycling, and disposal processes. Through the integration of technologies like deep learning and the Internet of Things (IoT), it is possible to automate waste sorting and enhance the accuracy of categorization. This not only improves operational efficiency but also aids in the proper separation of recyclables from non-recyclables, which is essential for resource recovery and minimizing waste's impact on the environment. The role of technology is pivotal in advancing waste management practices into the 21st century.

1.2 Objectives

- **To segregate the waste into biodegradable and non-biodegradable using deep learning.**

The objective is to utilize deep learning to automate the segregation of waste into two distinct categories: biodegradable and non-biodegradable. This technology-driven approach enhances waste management by improving sorting accuracy, reducing manual labor, and promoting recycling efforts. It contributes to environmental protection by preventing the mixing of biodegradable waste, which can produce harmful emissions, with non-biodegradable waste.

- **To Create an Efficient and Smart Waste Categorization System.**

The core objective of this research is to develop a smart waste categorization system that can accurately differentiate various waste materials. This system will reduce the reliance on manual labor, streamline waste collection and sorting processes, and enhance the overall efficiency of waste management.

1.3 Methodology

The world is facing a growing waste management problem with increasing amounts of garbage generated daily. Effective waste sorting is crucial for recycling and minimizing environmental impact. To address this issue, an automated waste classification system is proposed. This system uses deep learning technology to accurately classify waste as either biodegradable or non-biodegradable.

To classify waste, Convolutional Neural Networks (CNN), VGG16, and ResNet50 algorithms are employed in the methodology. These algorithms play a crucial role in automatically learning and recognizing patterns, features, and hierarchical representations within images, allowing for the effective and accurate classification of waste into different classes. The specific strengths of each algorithm contribute to the overall success of the waste classification task.

CNNs are particularly well-suited for image-related tasks, and in the context of waste classification, they excel at recognizing spatial hierarchies of features within images. Given a dataset consisting of 12 different waste classes with a total of 15,000 images, CNNs automatically learn and extract hierarchical representations of features during the training process. This automatic feature extraction is crucial in waste classification, as it allows the model to discern intricate patterns and textures associated with different waste types.

VGG16, a specific architecture within the VGG family of models, plays a key role in this methodology due to its uniform architecture and deep representation learning capabilities. With 16 layers featuring small convolutional filters, VGG16 maintains a consistent structure that facilitates effective feature learning. In waste classification, where the goal is to identify subtle differences between waste classes, VGG16's uniformity proves advantageous. Its depth enables it to learn deep representations of features, capturing complex patterns that may be indicative of specific waste categories.

ResNet50, part of the Residual Network family, addresses challenges associated with training very deep neural networks. ResNet50 introduces residual connections, mitigating the vanishing gradient problem and enabling the effective training of deeper models. In the context of waste classification, where certain waste types may exhibit nuanced characteristics, ResNet50's ability to handle deep architectures becomes particularly valuable. Its deeper architecture allows for the capture of complex features and patterns, contributing to a more profound understanding of waste characteristics.

1.3.1 CNN

- **Spatial Hierarchy Recognition:** CNNs are particularly well-suited for image classification tasks due to their ability to recognize spatial hierarchies of features. In waste classification, where the arrangement and combination of features in an image can be indicative of a specific waste class, CNNs excel at automatically learning these hierarchical representations.
- **Automatic Feature Extraction:** CNNs automatically extract relevant features from images during the training process. This is crucial in waste classification, where distinctive patterns and textures associated with different waste types need to be identified.

1.3.2 VGG-16

- **Uniform Architecture:** VGG16 is known for its simplicity and uniformity in architecture, featuring 16 layers with small convolutional filters. This uniformity allows for ease of interpretation and implementation. In waste classification, where the goal is to identify subtle differences between waste classes, VGG16's consistent structure contributes to effective feature learning.
- **Deep Representation Learning:** VGG16's depth allows it to learn deep representations of features in images, capturing complex patterns that might be indicative of specific waste categories.

1.3.3 Resnet50

- **Deep Learning with Residual Connections:** ResNet50 addresses the challenge of training very deep neural networks by introducing residual connections. These connections help in mitigating the vanishing gradient problem, enabling the effective training of deeper models. In waste classification, where the diversity of waste types may require a deeper understanding of features, ResNet50's ability to handle deep architectures is advantageous.
- **Complex Feature Capture:** The deeper architecture of ResNet50 allows it to capture complex features and patterns, which is valuable in waste classification where certain waste types may exhibit nuanced characteristics that require a deep learning approach.

1.4 Architecture Diagram

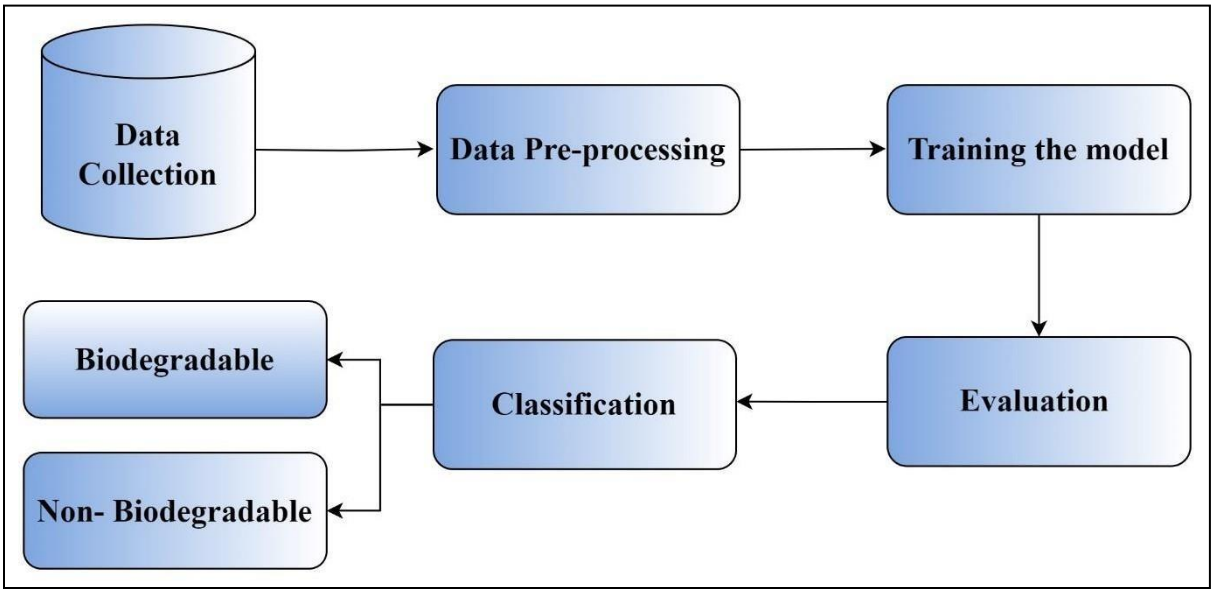

Figure 2. Architecture Diagram

In the initial phase of the waste classification process, a dataset is compiled, consisting of 12 distinct waste classes with a total of 15,000 images. This dataset undergoes a preprocessing stage, where the data is partitioned into training, testing, and validation sets using a 70:15:15 ratio. To enhance the model's ability to generalize, data augmentation methods are applied specifically to the training dataset. These methods involve introducing variations to the existing images, such as rotation, flipping, and zooming. Subsequently, the pre-processed data is utilized to train three different deep learning models: Convolutional Neural Networks (CNN), VGG16, and ResNet50. Each of these models possesses unique architectures and characteristics, making them suitable for image classification tasks.

The training process involves the iterative adjustment of internal parameters to minimize the disparity between predicted and actual waste class labels. After the training phase, the models are subjected to evaluation using metrics like accuracy, precision, and recall. Accuracy provides an overall measure of the correctness of the model's predictions. Precision assesses the accuracy of positive predictions, revealing how many predicted positive instances are genuinely positive. Recall gauges the model's capability to identify all positive instances, indicating how many actual positive instances were correctly predicted.

Once a satisfactory level of performance is achieved, the trained model is considered ready for predictions. Any input image can be fed into the model, and it will classify the image as either biodegradable or non-biodegradable based on the features and patterns it has learned during the training process.

1.5 Organization of the Report

The report is divided into the following chapters.

- **Chapter 1:** Introduction

  In the first chapter, a brief introduction to the project, followed by a proper objective and methodology was provided. An architecture diagram conveying the process of waste classification is provided.

- **Chapter 2:** Literature Survey

  In this chapter, 12 existing approaches are discussed along with the literature review and summary of the drawbacks of the existing approaches.

- **Chapter 3:** Proposed Method

  This chapter consists of the problem statement of the project and then the objective of the project followed by details of the architecture diagram, modules, and its description. Also, the chapter involves hardware and software requirements, functional and non-functional requirements. Additionally, Class Diagrams, Sequence Diagram, Use case Diagrams and Activity Diagram are also provided in this chapter for better visualization of the proposed method.

- **Chapter 4:** Results and Discussion

  The description about the dataset that was used followed for the working of the project followed by the detailed explanation about experimental results and significance of the proposed method is provided in chapter.

- **Chapter 5:** Conclusion and Future Enhancement

  The Summary of project emphasizing objectives, importance, approach that is adapted followed by the results and future enhancement was provided in detail.

- **Chapter 6:** Appendices

  Sample code of the proposed method is provided in the chapter.

CHAPTER 2

LITERATURE SURVEY

The following section describes the study of existing approaches.

2.1 Literature Survey

Sundaralingam and Ramanathan [2] designed an automated household waste sorting system by combining TensorFlow's object detection capabilities with an Arduino platform. They assembled a unique dataset of household waste images for training an SSD MobileNet V2 model. This model demonstrated an impressive 86.5% mean average precision in identifying six waste categories: paper, plastic, metal, glass, organic, and an unclassified class. Utilizing the model's predictions, the Arduino-driven system efficiently separates waste items into their respective bins on a movable platform. This innovative waste segregation system has the potential to significantly reduce the amount of waste destined for landfills, promoting increased recycling efforts and minimizing its environmental impact.

Gunaseelan and team [3] introduced an enhanced image classification and waste sorting system by combining a modified ResNeXt model with ResNet 50. This model demonstrates an impressive 98.9% accuracy in the classification of waste materials into eight distinct categories: biodegradable, non-biodegradable, hazardous, plastic, metal, paper, glass, and cardboard. To power this system, they employed Raspberry Pi, sensors, and IoT technology to facilitate real-time monitoring and data collection from intelligent bins. By analysing historical data, the system enables the creation of predictive models and well-informed decision-making for waste management authorities. This integrated smart bin system, driven by deep learning and IoT enhances operational efficiency, reduces environmental impact, and encourages sustainable waste disposal practices.

Endah and team [4] conducted a study on waste classification, investigating the utilization of pre-trained models, which included VGG16, ResNet-50, and Xception, for the purpose of categorizing garbage. The Xception model achieved an accuracy rate of 88%, while Fu's intelligent garbage classification system attained a higher accuracy rate of 92.62%. The research involved a comparison of various models using classification metrics such as precision, recall, F1-score, and accuracy. The authors emphasized the significance of employing more complex datasets and expanding the range of waste material types in future research. They also suggested the implementation of cameras for real-time waste material detection and classification.

Nafiz and colleagues [5] introduced an automated waste separation system known as ConvoWaste, which employs deep learning and image processing techniques. They curated a unique dataset of waste images to train the ConvoWaste deep learning model, enabling it to categorize various types of waste. The system is equipped with a conveyor belt, a camera module, and servomotors, which work in tandem to capture images of waste and direct them into designated bins. For real-time monitoring, ultrasonic sensors integrated into the bins and GSM communication are employed. Impressively, the ConvoWaste model achieved a classification accuracy of 98% for discerning plastic, metal, glass, organic, medical, and electronic waste materials.

Sharma, Dwivedi, and Singh [6] put forth the idea of employing deep learning models, specifically CNN and YOLOv3, for the automated categorization of waste into six distinct categories. They gathered a dataset of waste images, enhanced its quality through augmentation techniques, and used it to train these models. The CNN model demonstrated a test accuracy of 82.75%, whereas YOLOv3 outperformed it with an accuracy of 85.29%. Notably, YOLOv3 displayed superior performance in terms of both accuracy and recall when it came to identifying multiple waste items simultaneously. This system holds the potential to streamline waste segregation, reducing the need for manual labor and minimizing associated health hazards

Akanksha and team [7] proposed a garbage segregation system using machine learning to classify waste into biodegradable and non-biodegradable categories. The system uses a conveyor belt, camera module, and CNN model trained on a garbage image dataset. Captured images undergo preprocessing and are classified by the CNN model as biodegradable or non-biodegradable. A rotating disk mechanism operated by the classifier output separates the waste into respective bins. The system achieved approximately 95% accuracy in classifying common household garbage types.

Wei Liu along with the team [8] has introduced a garbage classification model named GCNet. This model is a result of a fusion of features from EfficientNetv2, Vision Transformer, and DenseNet through the application of transfer learning and model fusion methods. They used a substantial dataset comprising more than 41,650 garbage images, and data augmentation techniques were applied to improve the dataset's quality. The outcomes of their experiments reveal that the model exhibits favorable traits such as efficient convergence, a high recall rate, accuracy, and rapid recognition times.

Iyyanar and team members [9] have introduced an efficient and intelligent waste categorization system that leverages deep learning. This system makes use of the VGG16 model to distinguish between organic and inorganic municipal waste and identify recyclable waste items. By automating waste management processes and enhancing recycling initiatives, the proposed system aims to tackle the challenges associated with waste segregation and overall management. The system attains an accuracy rate of 87 percent and holds promise for further enhancements and practical implementation in real-world scenarios.

Nnamoko and their team [10] designed a unique 5-layer CNN architecture to classify solid waste images as either organic or recyclable. They trained the model using two different image resolutions, 80x45 and 225x264 pixels, from an augmented public dataset containing 25,077 waste images. Both models outperformed a random guess baseline, with the smaller image resolution achieving a higher accuracy of 80.88%. Additionally, the smaller image resolution resulted in a more compact model, only 1.08MB in size, and reduced training time, taking only 6.4 hours. This research highlights how reducing image size can be an effective approach to develop efficient waste classification models, especially in resource-constrained settings.

Qi and their team [11] introduced the utilization of ConvNeXt as a deep learning model to categorize waste images into four groups: hazardous, dry, wet, and recyclable. They collected and annotated a dataset comprising 1660 waste images, which was used to train the ConvNeXt model in conjunction with the Mask R-CNN framework. Their experiments revealed that ConvNeXt achieved a mean average precision of 79.88%, surpassing the performance of models such as Swin Transformer, YOLOv3, and ResNet-50. Ablation studies were conducted to investigate the impact of various factors, such as activation functions and normalization, on ConvNeXt's performance. The findings underscore the potential of ConvNeXt in accurately classifying waste from images when compared to other deep-learning models.

Zhenhua and team members [12] authored a paper outlining a thorough approach to garbage classification. Their design process encompasses image preprocessing methods and the application of a compact Convolutional Neural Network (CNN). They introduced an image brightening algorithm that autonomously adapts image brightness using a threshold-based brightening principle. The results from their experiments highlight the effectiveness of the optimized CNN model, achieving a high accuracy rate of 96.77% for the Trash-7 dataset and

93.72% for the TrashNet dataset. This study makes a valuable contribution to enhancing the accuracy of efficient garbage classification systems.

Kumsetty and team [13] introduced an innovative quantum transfer learning technique for classifying images of trash into seven distinct categories. They also introduced a novel dataset named TrashBox, which comprises 17,785 images categorized into hazardous, e-waste, glass, medical, metal, paper, and plastic groups. Through experiments with transfer learning models like ResNet, they achieved an impressive 98.47% accuracy on the TrashBox dataset, showcasing its potential. Furthermore, they implemented and optimized quantum transfer learning models using parallelization, resulting in a significant performance improvement of 10.84%. This quantum learning framework holds promise for efficient trash classification when compared to traditional deep learning models.

Table 1. Summary of the Existing Approaches

Ref No	**Methodology**	**Disadvantages**
[2]	Compared the performance of various pre-trained Convolution Neural Networks namely AlexNet, ResNet, VGG-16, and InceptionNet for garbage classification.	The proposed system excelled in classifying high-resolution images with a white background but was less effective in recognizing objects in dull, distorted, or noisy images with different backgrounds.
[3]	VGG- 16	The model can be trained on more realistic garbage images for better accuracy.
[4]	ResNeXt model and ResNet 50 architecture with IoT sensors for real-time monitoring.	The environmental impact of the IoT components, including the production and disposal of sensors and Raspberry Pi devices, is not discussed. It's important to consider the overall sustainability of the proposed solution.
[5]	Pre-trained Inception-Resnet V2 model with additional layers.	After detecting the presence of the waste, the conveyor belt creates a delay for 10 seconds to capture the

		image of the waste using the camera module mounted in the conveyor belt.
[6]	CNN models like AlexNet, ResNet50, ResNet34,VGG-16.	The dataset is limited, it was trained on only five different categories of waste.
[7]	CNN is used to build the model. A physical mechanism, likely consisting of DC-geared motors and a conveyor belt, is employed to physically segregate the waste objects into the identified categories based on the model's classification.	The initial setup and integration of the conveyor belt, camera module, and machine learning infrastructure requires a substantial upfront investment. The system is currently trained to classify a limited range of waste materials.
[8]	The paper combines three pretrained deep learning models, namely DenseNet, Vision Transformer, and EfficientNetV2, to construct the GCNet.	Lack of multitarget garbage detection and the presence of false detections.
[9]	Utilizes a convolutional neural network (CNN) for waste image classification. Explores two image resolutions, comparing their performance(80 × 45 and 225 × 264 pixels).	Overfitting in the small model. Acknowledges potential dataset quality issues and mislabeling.
[10]	ConvNeXt, a CNN-based backbone network, is used for waste classification. A dataset with four waste classes: Hazardous waste, dry waste, wet waste, and recyclable waste was used.	The accuracy achieved was only 79.88% which can be improved.
[11]	Proposed a garbage classification method based on a small CNN. Optimized the neural network based	The method still has a certain false detection rate.

	on the MLH-CNN model to simplify and improve efficiency.	
[12]	A deep learning-based ResNet-50 model was used for trash classification. Integrated the classification module into a Raspberry Pi computer, controlling trash bin slides to sort garbage into the appropriate bins.	A small dataset, binary classification system, and limited experiments and comparisons.
[13]	Four models (DenseNet, MobileNet, ResNetModified, and ResNet50v2) were experimented with, and ResNet50v2 provided the most optimum results (92%).	Accuracy can be improved and the model was trained on a small dataset.

2.2 Drawbacks of Existing Approaches

The system demonstrated proficiency in categorizing high-resolution images against a white backdrop but showed limitations in identifying objects in images with various backgrounds, such as those that are dull, distorted, or noisy. Training the model on more realistic garbage images could enhance its accuracy. The environmental impact of the IoT components, encompassing the production and disposal of sensors and Raspberry Pi devices, is a crucial aspect that remains unaddressed in the proposed system. Evaluating the overall sustainability of the solution is imperative. Following waste detection, there is a 10-second delay in the conveyor belt to capture an image using the mounted camera module. This procedural delay may impact the real-time efficiency of the system. The dataset used for training is limited, encompassing only five distinct waste categories. Expanding the dataset to include a more comprehensive range of waste materials could enhance the model's versatility and accuracy. The initial setup and integration of the conveyor belt, camera module, and machine learning infrastructure entail a substantial upfront investment. The system, as it stands, is designed to classify only a restricted set of waste materials, lacking multitarget garbage detection and exhibiting false detections. Overfitting is observed in the small model, and the acknowledgment of potential dataset quality issues and mislabelling introduces uncertainties in the model's reliability. The achieved accuracy is 79.88%, indicating room for improvement.

Additionally, there is a notable false detection rate that needs to be addressed to enhance the model's precision. The method relies on a small dataset, employs a binary classification system, and has undergone limited experiments and comparisons. These factors suggest avenues for further research and development to enhance the system's robustness and effectiveness. The accuracy of the model, currently at 79.88%, is identified as an area for improvement. The method still incurs a certain false detection rate, emphasizing the need for refinements in the model's performance. The system relies on a small dataset, employs a binary classification system, and has undergone limited experiments and comparisons. Addressing these limitations is crucial for expanding the system's applicability and reliability.

CHAPTER 3
PROPOSED METHOD

3.1 Problem Statement and Objectives

The problem statement and the objectives of the project are discussed in this section.

3.1.1 Problem Statement

The increasing volume of waste generated globally poses significant challenges for effective waste management and environmental sustainability. One critical aspect of this challenge is the need for efficient and automated waste classification systems. Manual sorting of waste is labor-intensive, time-consuming, and prone to errors. As a result, there is a growing demand for automated solutions leveraging machine learning and computer vision to classify waste into distinct categories, such as biodegradable and non-biodegradable materials. The problem at hand is to develop a robust waste classification model capable of accurately identifying and categorizing diverse waste types based on visual characteristics extracted from images. This involves addressing issues related to the variability in waste compositions, the need for real-time classification, and the optimization of deep learning algorithms to ensure high precision and recall in waste categorization. The successful implementation of an automated waste classification system holds the potential to streamline waste management processes, enhance recycling efforts, and contribute to a more sustainable and environmentally conscious future.

3.1.2 Objectives

- To segregate the waste into biodegradable and non-biodegradable using deep learning.
- To create an Efficient and Smart Waste Categorization System.

3.2 Detailed Explanation of Architecture Diagram

The architecture diagram of the propose method is shown in Figure 2. The waste classification process begins with the acquisition of a comprehensive dataset comprising 15,000 images representing 12 different waste classes. To enhance the model's performance, the dataset undergoes preprocessing, a critical step in preparing the data for effective training. This preprocessing involves the division of the dataset into three subsets: training, testing, and validation, following a 70:15:15 ratio. The purpose of this split is to provide sufficient data for the model to learn during training while maintaining separate sets for unbiased evaluation.

As a crucial augmentation step, data augmentation methods are applied exclusively to the training dataset. These methods introduce variations to the existing images, such as rotation, flipping, and zooming. Data augmentation serves to diversify the training set, augmenting the model's ability to generalize and recognize different variations of waste materials.

Subsequently, the pre-processed data is employed to train three distinct deep learning models: CNN, VGG16, and ResNet50. Each of these algorithms is known for its effectiveness in image classification tasks. The training process involves adjusting internal parameters iteratively to minimize the disparity between predicted and actualwaste class labels. Following the training phase, the performance of the trained models is evaluated using metrics such as accuracy, precision, and recall. Accuracy provides an overall measure of correct predictions, while precision assesses the accuracy of positive predictions and recall gauges the model's capability to identify all positive instances. These metrics collectively offer insights into the model's effectiveness and reliability in waste classification.

Once the trained models demonstrate satisfactory performance, they are ready for predictions. Any input image can be fed into the models, and the system classifies it as either biodegradable or non-biodegradable based on the features and patterns learned during the training process.

3.3 Module Connectivity Diagram

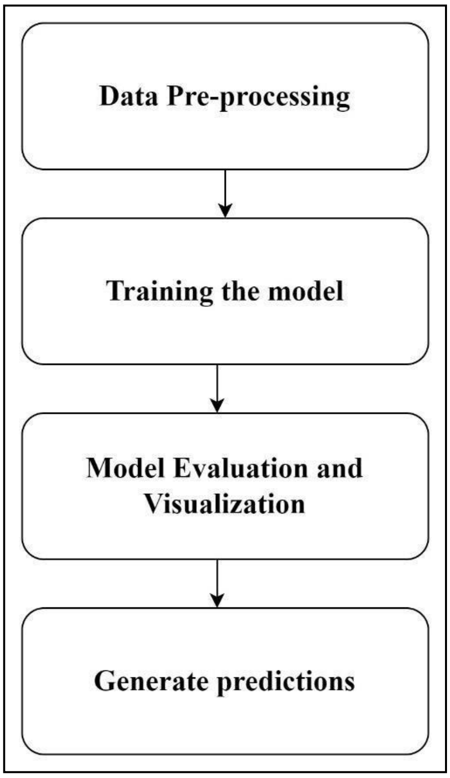

Figure 3. Module Connectivity Diagram

Figure 3 represents the module connectivity diagram of the proposed method. A module connectivity diagram illustrates the flow of data and processes between different modules in a system. The proposed method consists of four modules namely, data pre-processing, Training the model, Model evaluation and visualization, and generating predictions.

- **Data Preprocessing:** This module is responsible for preparing the raw dataset for training and evaluation. It includes tasks such as resizing images, normalization, and, critically, splitting the dataset into three subsets: training, testing, and validation. The output of this module is the pre-processed dataset, which is then fed into the training module.
- **Train the Model using CNN, VGG16, and ResNet50:** The pre-processed data is directed into this module, where three deep learning models are trained: CNN, VGG16, and ResNet50. Each model undergoes an iterative training process, adjusting its internal parameters based on the training dataset. The trained models learn to recognize patterns and features in the waste images associated with specific waste classes. Once the training is complete, the trained models are ready for evaluation.
- **Model Evaluation and Visualization:** This module takes the trained models and assesses their performance using evaluation metrics such as accuracy, precision, and recall. The evaluation phase involves utilizing the testing and validation datasets to measure how well the models generalize to unseen data. Additionally, visualization tools are employed to gain insights into the model's decision-making process. This module provides valuable feedback on the model's effectiveness and any potential areas for improvement.
- **Generate Predictions:** After successful evaluation, the trained models move to the prediction module. This module is responsible for taking new or unseen images as input and utilizing the trained models to generate predictions. The predictions include the classification of waste as either biodegradable or non-biodegradable. The output of this module is the model's predictions for each input image, providing a practical solution for automated waste classification based on the learned features and patterns.

3.4 Software and Hardware Requirements

3.4.1 Software Requirements

- Python with the following packages:
    - NumPy
    - Sklearn
    - Tensorflow

- OpenCV
- Jupyter Notebook

3.4.2 Hardware Requirements

- Processor: Intel Core I5 and above
- RAM: 4GB

3.5 Modules and their Description

The entire workflow of the project is divided into four modules.

1. Data Pre- processing.
2. Train the Model.
3. Model Evaluation and Visualization.
4. Generate Predictions.

Each module plays a distinct role in the waste classification process. The output of one module, be it the pre-processed data or trained models, seamlessly serves as the input to the subsequent module in a sequential and interconnected workflow.

3.5.1 Data Pre- processing

The data preprocessing phase in the waste classification project is a crucial step that involves transforming raw data into a format suitable for training a deep learning model. This process aims to organize the dataset, apply necessary augmentations, and set up data generators for efficient model training.

The project begins by establishing directory paths to manage the data effectively. The main data directory (main_data_dir) points to the location of the raw dataset, while the training (train_dir), testing (test_dir), and validation (val_dir) directories are created to store the preprocessed data. These directories follow a structured approach, ensuring that the data is organized based on the classes of waste. To facilitate class-wise organization, the code identifies subdirectories within the main data directory, each corresponding to a specific waste class. The directories within train_dir, test_dir, and val_dir are created to accommodate the different classes, laying the groundwork for a systematic division of data.

The dataset is then processed by splitting the images into training, testing, and validation sets. This split is achieved using the train_test_split function, ensuring a representative distribution of each class across the subsets. Images are subsequently copied from the original class directories to their designated locations in train_dir, test_dir, and val_dir. This step is pivotal for creating balanced datasets for model training, evaluation, and testing. The training set, test set and validation set are split in the ration 70:15:15.

Data augmentation is a critical component of the preprocessing pipeline, particularly for the training set. Augmentation techniques, such as shearing, zooming, and horizontal flipping, are applied to the training images. This introduces variations in the data, preventing the model from overfitting to specific patterns and enhancing its ability to generalize to unseen examples. The use of the ImageDataGenerator class from TensorFlow's Keras API facilitates this augmentation process.

Generators are employed to dynamically generate batches of augmented data during model training. These generators, created using the flow_from_directory method, significantly optimize memory usage and streamline the training process. For instance, the train_generator generates batches of augmented data from the training directory, while the val_generator and test_generator handle validation and testing data, respectively. These generators are configured to resize the images to a specified width and height, maintaining uniformity in the dataset.

Defining the dimensions of the images and the input shape expected by the pre-trained models is a crucial aspect of the preprocessing phase. In this project, the image dimensions (img_width and img_height) are set to 224x224 pixels, aligning with the requirements of the chosen models. The input shape (input_shape) is established as (224, 224, 3), reflecting the width, height, and color channels of the images.

In conclusion, the data preprocessing steps in the waste classification project are multifaceted and meticulously designed to ensure that the dataset is appropriately formatted for model training. From directory setup to image splitting, copying, data augmentation, and generator configuration, each step plays a pivotal role in creating a robust and well-organized dataset. This processed data is then ready to be fed into deep learning models, facilitating the training of accurate waste classification systems.

3.5.2 Train the Model

Training is a critical phase in developing machine learning models for waste classification. It involves teaching the model to recognize patterns and features in labelled data, enabling it to accurately classify unseen waste items. Training is essential for the model to learn discriminative features, adapt to specific waste characteristics, generalize to new data, optimize its parameters, and incorporate domain knowledge. The iterative process of training includes evaluating the model's performance, fine-tuning it, and continuously improving its ability to classify waste accurately in real-world scenarios.

- **CNN**

The CNN model used in the waste classification project is a simpler architecture compared to VGG16 and ResNet50. While it may not have the depth and complexity of the other models, it provides a lightweight alternative for certain scenarios. The CNN architecture consists of convolutional layers with Rectified Linear Unit (ReLU) activation and max-pooling layers. Theselayers are fundamental for feature extraction, capturing hierarchical representations of input images. A flattening layer is then employed to transform the two-dimensional output into a vector, followed by dense layers for classification. The final layer uses softmax activation to produce class probabilities. Despite its simplicity, the CNN model is effective for certain imageclassification tasks and can be computationally more efficient, making it a viable choice basedon specific project requirements.

The layers involved in the CNN model

1. **Input Layer:** The input layer accepts images of shape (224, 224, 3) representing the width, height, and color channels.
2. **Convolutional Layers:** Two convolutional layers with ReLU activation are applied for feature extraction. Max-pooling layers follow each convolutional layer to reduce spatial dimensions.
3. **Flatten Layer:** The flattening layer transforms the two-dimensional output from convolutional layers into a vector.
4. **Dense Layers:** Two dense layers with ReLU activation are added for classification. The final dense layer with softmax activation produces class probabilities.

- **VGG-16**

The VGG16 model is a convolutional neural network architecture known for its simplicity and effectiveness. In the context of waste classification, it serves as a powerful feature extractor. The model consists of multiple convolutional layers, each followed by max-pooling layers, creating a deep hierarchical structure. In the training process, the VGG16 model utilizes pre-trained weights from the ImageNet dataset, a massive dataset containing millions of images across thousands of categories. This pre-training imparts a general understanding of visual features to the model. By excluding the top classification layer, the model is adapted for the specific task of waste classification.

Batch normalization is incorporated to normalize the activations of the convolutional layers, which helps in stabilizing and accelerating the training process. The model's architecture includes a flattening layer, converting the multi-dimensional output from convolutional layers into a one-dimensional array. Dense layers with dropout are added for classification, and the final layer employs softmax activation to produce class probabilities. Fine-tuning is applied to the model by selectively allowing the last few layers to be trainable while keeping the pre-trained weights fixed for the earlier layers. This allows the model to adapt to the nuances of waste classification while retaining the valuable knowledge gained from ImageNet.

The layers involved in the VGG-16 model

1. **Input Layer:** The input layer accepts images of shape (224, 224, 3) representing the width, height, and color channels.
2. **VGG16 Base:** The VGG16 base consists of a series of convolutional blocks, each comprising convolutional layers followed by max-pooling layers.
3. **Batch Normalization:** Batch normalization is applied after the convolutional blocks to normalize the activations, promoting stable and efficient training.
4. **Flatten Layer:** The flattening layer transforms the multi-dimensional output from the convolutional layers into a one-dimensional array.
5. **Dense Layers:** Two dense layers with ReLU activation and dropout are added for classification. The final dense layer with softmax activation produces class probabilities.

- **Resnet50**

ResNet50, short for Residual Network with 50 layers, revolutionized deep neural networks by introducing residual learning. The model's architecture includes residual blocks, each featuring skip connections or shortcuts, facilitating the flow of gradients more directly through the network. This design addresses challenges associated with training very deep networks, fostering better convergence and performance. In the realm of waste classification, the ResNet50 model, like VGG16, employs pre-trained weights from ImageNet. Global average pooling is applied to reduce the spatial dimensions of the output, producing a compact representation of features. Batch normalization is introduced for normalization, enhancing the model's stability.

Dense layers for classification, coupled with dropout for regularization, follow the global average pooling layer. The final dense layer utilizes softmax activation to generate class probabilities for waste categories. Fine-tuning concentrates on the last layers of the network, allowing the model to adapt to waste classification nuances while retaining the broader knowledge obtained from ImageNet. Learning rate scheduling, early stopping, and model checkpointing contribute to a robust training process.

The layers involved in the Resnet50 model

1. **Input Layer:** The input layer accepts images of shape (224, 224, 3) representing the width, height, and color channels.
2. **ResNet50 Base:** The ResNet50 base consists of residual blocks, each with skip connections and convolutional layers.
3. **Global Average Pooling:** Global average pooling is applied to reduce the spatial dimensions of the output.
4. **Batch Normalization:** Batch normalization is applied after global average pooling.
5. **Dense Layers:** Two dense layers with ReLU activation and dropout are added for classification. The final dense layer with softmax activation produces class probabilities.

For all three models, the training process involves configuring the model with an optimizer, loss function, and evaluation metric. The Adam optimizer is commonly used for its efficiency in updating model weights. Categorical crossentropy is employed as the loss function, suitable for multi-class classification tasks like waste classification. The models are trained on the preprocessed dataset using data generators that provide batches of augmented data during training.

Learning rate scheduling, early stopping, and model checkpointing are crucial components of the training process. Learning rate scheduling adjusts the learning rate during training, optimizing convergence. Early stopping monitors the validation accuracy and stops training if there is no improvement, preventing overfitting. Model checkpointing saves the best-performing model during training.

3.5.3 Model Evaluation and Visualization

Model evaluation and visualization are crucial aspects of developing and assessing machine learning models, including those designed for waste classification. These components play a significant role in understanding the model's performance, identifying potential issues, and gaining insights into its decision-making processes.

Metrics

- **Accuracy:** Measures the overall correctness of the model's predictions.
- **Precision:** Evaluates the accuracy of positive predictions, indicating how many of the predicted positive instances are actually positive.
- **Recall (Sensitivity):** Measures the ability of the model to capture all positive instances.
- **F1 Score:** The harmonic mean of precision and recall, providing a balanced measure between the two.
- **Confusion Matrix:** A table showing the counts of true positive, true negative, false positive, and false negative predictions.

3.5.4 Generate Predictions

The process of generating predictions for waste classification using a pre-trained ResNet50 model involves several key steps. Firstly, the trained model, which has acquired knowledge from diverse waste images, needs to be loaded. This model serves as a powerful tool for recognizing intricate patterns and features relevant to waste classification. The loading of the model is a foundational step that sets the stage for subsequent predictions. Once the model is loaded, the next step is to create a generalized prediction function. This function is designed to take an image as input and produce waste classification predictions. It encapsulates the logic required to preprocess the input image and utilize the loaded ResNet50 model for predictions. The goal is to create a versatile tool that can be applied to various waste classification scenarios.

Within the prediction function, image preprocessing is a critical step. This involves preparing the input image to meet the expectations of the ResNet50 model. Common preprocessing steps include resizing the image to specific dimensions, converting it into a numerical array, and normalizing pixel values. This ensures that the input image is appropriately formatted for the model's requirements. The model prediction step involves using the pre-trained ResNet50 model to generate predictions for the pre-processed image. The model outputs probabilities for each waste class based on the learned patterns during training. Depending on the application, post-processing steps may be included, such as mapping model class indices to human-readable waste class labels or making decisions based on specific classes.

The final output of the process is the predicted waste class or relevant classification result. This output provides valuable insights into the nature of the waste item based on the patterns learned by the pre-trained model. Importantly, the process is not limited to a single image; the generalized prediction function can be applied to new waste images, demonstrating the reusability of the pre-trained model across different waste classification scenarios.

3.6 Requirements Engineering

In Requirement Engineering, the requirements needed for the project are discussed.

3.6.1 Functional Requirements

It specifies the functions to be performed by the system or software being designed, defining its behaviour in response to a range of inputs. The particular features and functions that the system should have, as well as its behaviour when users interact with it, are described in these requirements. The functional requirements describe the specific characteristics and functions that the system should have.

Functional Requirements for the proposed method

- **The system must accept images of waste items as input for classification.**

This requirement highlights the system's primary input type, images, and emphasizes the need for compatibility with different image formats. Additionally, it suggests the potential for scalability, indicating the system's ability to handle varying volumes of image inputs. Overall, this requirement serves as a foundational aspect, outlining the initial step in the waste classification process and providing clarity on user interactions with the system.

- **The system should preprocess input waste images to ensure consistency and compatibility with the deep learning model.**

This requirement implies that the system is equipped with preprocessing mechanisms to standardize and harmonize the format, size, and quality of the input images. By doing so, it ensures that the data aligns with the expectations of the integrated deep learning model. This step is crucial for optimizing the performance of the model, enhancing its ability to accurately classify waste items. Preprocessing may involve tasks such as resizing, normalization, and augmentation, contributing to the overall effectiveness of the waste classification system.

- **The system should provide the waste classification result as output, including the predicted waste class and confidence score.**

This requirement specifies that upon processing an input image, the system is expected to generate a classification result. This result comprises two key components: the predicted waste class, indicating the category to which the item belongs (e.g., paper, plastic), and the associated confidence score, reflecting the level of certainty or probability assigned by the model to the classification. This information serves as valuable output, offering users insights into the system's decision-making process and providing a transparent indication of the model's confidence in its predictions. Users, such as waste management personnel, can leverage this output for informed decision-making based on the system's classifications.

3.6.2 Non- Functional Requirements

Non-functional requirements are a set of standards that describe how a system should operate but have nothing to do with the particular features or operations of the system. They typically focus on the system's overall quality and are crucial to ensuring that it is scalable, reliable, and maintainable. Non-functional requirements make sure the system fulfills stakeholders' demands in addition to the system's intended functionality or features. They aid in making sure the system is scalable and offers a positive user experience while still adhering to performance and security requirements.

Non- Functional requirements for the proposed method

- **The system should process waste classification requests efficiently, with low latency and high throughput, ensuring quick responses to user queries.**

This non-functional requirement emphasizes the need for the waste classification system to efficiently process classification requests, ensuring low latency and high throughput for quick and responsive user interactions. It highlights the importance of optimizing algorithms, resource utilization, and scalability to handle varying workloads. The system is expected to deliver prompt waste classification results, contributing to a seamless user experience and effective decision-making in waste management processes.

- **The system must be highly reliable, with minimal downtime or disruptions, ensuring consistent waste classification services.**

This non-functional requirement places a paramount emphasis on the reliability of the waste classification system, necessitating a consistently dependable service with minimal downtime or disruptions. Users should be assured of the system's ability to provide accurate waste classification services reliably, fostering trust in its capabilities. To achieve this, the system is expected to employ proactive measures, potentially including redundancy and continuous monitoring, to mitigate disruptions and maintain operational consistency. A highly reliable system not only ensures uninterrupted waste classification services but also instils confidence in users, reinforcing their reliance on the system for accurate and dependable results.

- **The system should be easily maintainable, allowing for updates, enhancements, and bug fixes without significant disruptions to ongoing operations.**

This non-functional requirement emphasizes the need for the waste classification system to be easily maintainable, permitting updates, enhancements, and bug fixes without causing significant disruptions to ongoing operations. The system should be designed for simplicity in maintenance activities, enabling efficient implementation of improvements and ensuring adaptability to changing requirements. This flexibility promotes the system's longevity and responsiveness to evolving waste classification needs while minimizing potential disruptions to its regular functioning.

- **The system should be compatible with various platforms, devices, and data formats, facilitating smooth integration with other waste management tools or external systems.**

This non-functional requirement highlights the necessity for the waste classification system to be compatible with diverse platforms, devices, and data formats, enabling seamless integration with other waste management tools or external systems. The system should operate across various devices, support multiple data formats, and facilitate smooth collaboration with external tools, fostering a cohesive waste management ecosystem. This compatibility ensures flexibility and interoperability, allowing the system to adapt to different environments and contribute to an integrated approach in waste management practices.

3.7 Analysis and Design through UML

Analysis and Design in Unified Modeling Language (UML) involves the systematic process of understanding, modeling, and visualizing a system's requirements and architecture. During analysis, UML diagrams such as use case diagrams, activity diagrams, and class diagrams are employed to comprehend the system's functionalities and interactions. In the design phase, UML is utilized for creating detailed models, including class diagrams, sequence diagrams, and component diagrams, to translate the analysis into a structured blueprint for the system's architecture. UML serves as a standardized visual language that aids in communication between stakeholders and ensures a clear representation of the software system's structure and behavior throughout the development lifecycle.

3.7.1 Class Diagram

A class diagram in UML illustrates the static structure of a system by representing classes, their attributes, and relationships, providing a blueprint for the organization of objects and their interactions. It visually depicts the entities in a system, their properties, and the associations between them.

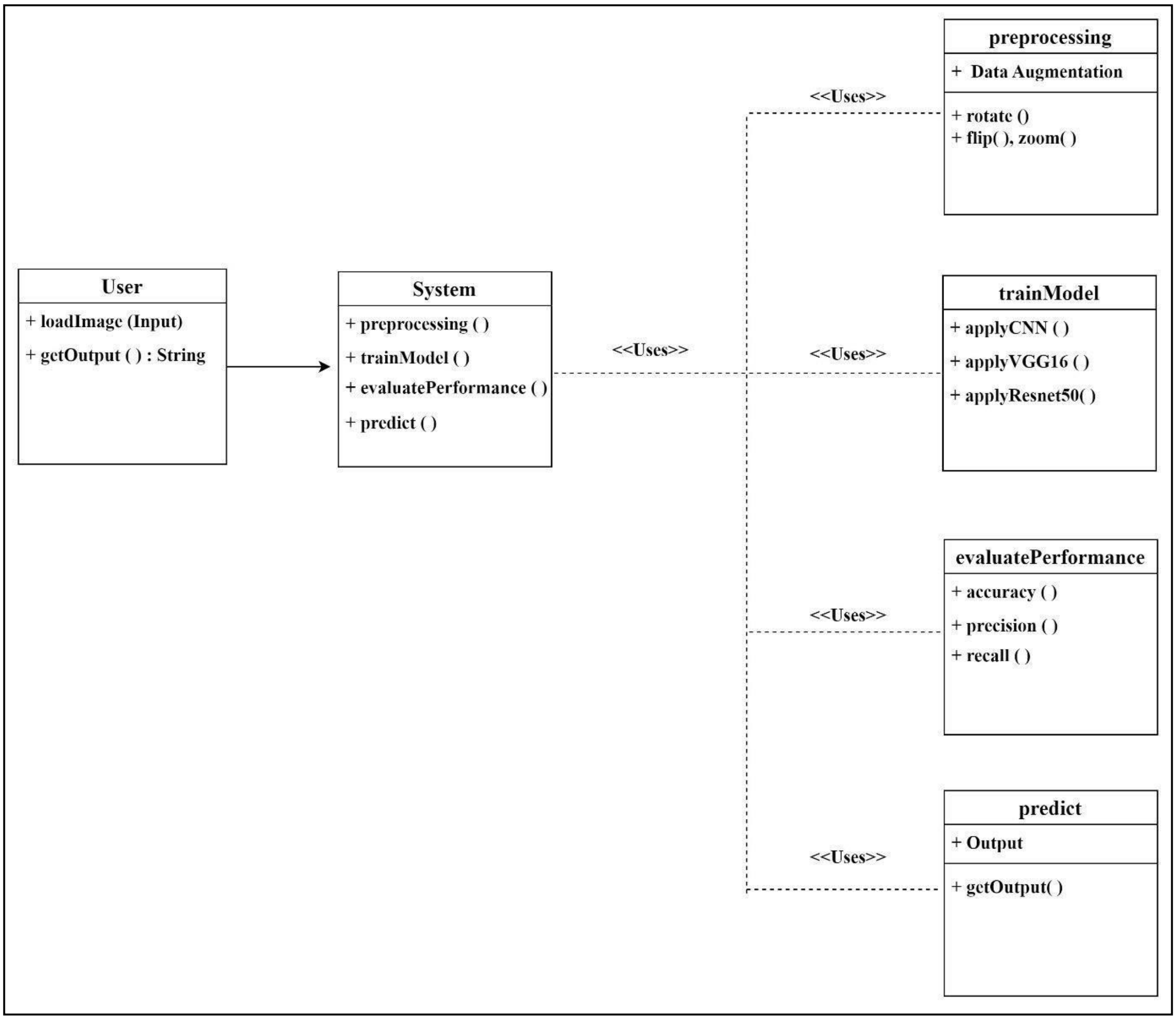

Figure 4. Class Diagram

Figure 4 represents the class diagram for the proposed approach. The class diagram outlines the structural and functional relationships between two main classes in the waste classification system: User and System. The User class represents the end user interacting with the system, and the System class encapsulates the core functionalities of the waste classification system.

1. User class

- Represents the end user interacting with the system.
- **loadImage(image):** Represents the user's action of providing an image to the system for classification.
- **getOutput():** Represents the user's request to receive the classified output from the system.

2. System class

The system class encompasses crucial functions that contribute to the waste classification pipeline. These functions are pivotal stages in the process, ensuring the effective and accurate classification of waste items. The key functions within the System class include:

- **preprocessing():** This function manages the preprocessing of input data, a critical step in preparing the images for the classification model. Common preprocessing tasks include resizing images, normalizing pixel values, and applying data augmentation techniques to enhance the model's robustness.
- **trainModel():** Responsible for overseeing the training process of the machine learning model. This function coordinates multiple iterations (epochs) of forward and backward passes, allowing the model to learn patterns and features from the pre-processed data.
- **evaluatePerformance():** This function assesses the performance of the trained model using various metrics, such as accuracy, precision, and recall. Model evaluation is essential to gauge how well the model generalizes to new, unseen data.
- **predict():** The predict() function takes pre-processed data as input and utilizes the trained model to make predictions. It produces the final classification results, determining the category to which each waste item belongs.

3.7.2 Sequence Diagram

A sequence diagram in UML depicts the chronological flow of interactions between objects or components in a system, showcasing the order in which messages are exchanged to accomplish a specific functionality. It provides a visual representation of the dynamic behavior of a system over time.

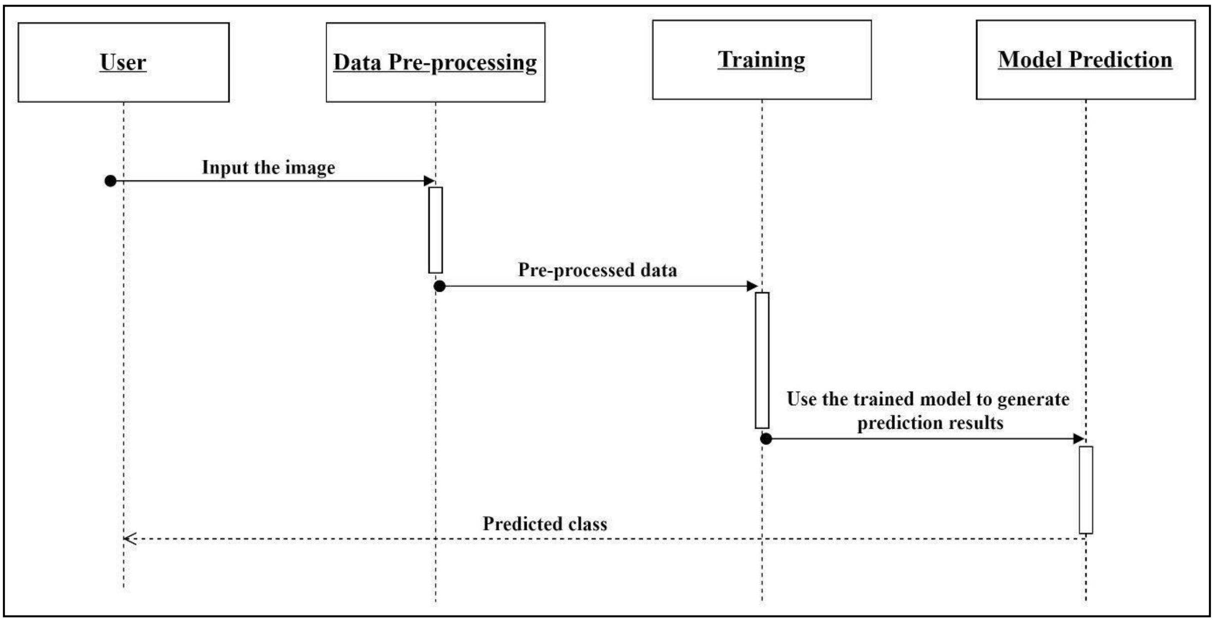

Figure 5. Sequence Diagram

Figure 5 represents the sequence diagram for the proposed method. In the waste classification system sequence diagram, the process begins with the User initiating the classification task by providing an image as input to the system. This input is then received by the Data Pre-processing component, which plays a crucial role in preparing the data for the subsequent stages. Data pre-processing involves various tasks such as resizing, normalization, or augmentation to enhance the quality and suitability of the input data for the deep learning models.

Subsequently, the pre-processed data is directed to the Train the Model component, where deep learning algorithms, such as CNN, VGG16, or ResNet50, are employed. This phase involves training the model on a dataset that consists of various waste classes. The model learns to recognize patterns and features in the input images, enabling it to make accurate classifications.Once the model is trained, the Model Prediction component takes over during the classification phase.

When a user submits an image for classification, the trained model utilizes its learned parameters to predict whether the waste in the image is biodegradable or non-biodegradable. The result of this prediction is then presented to the user, completing the sequence. This sequence diagram encapsulates the dynamic interactions among the key components in the waste classification system, illustrating the flow from user input through data preparation, model training, and finally, the prediction and delivery of the classification results.

3.7.3 Use Case Diagram

A use case diagram in UML visually represents the interactions between actors (external entities) and a system, showcasing the various ways the system can be utilized to achieve specific functionalities. It provides a high-level overview of the system's features and the actors involved in its usage.

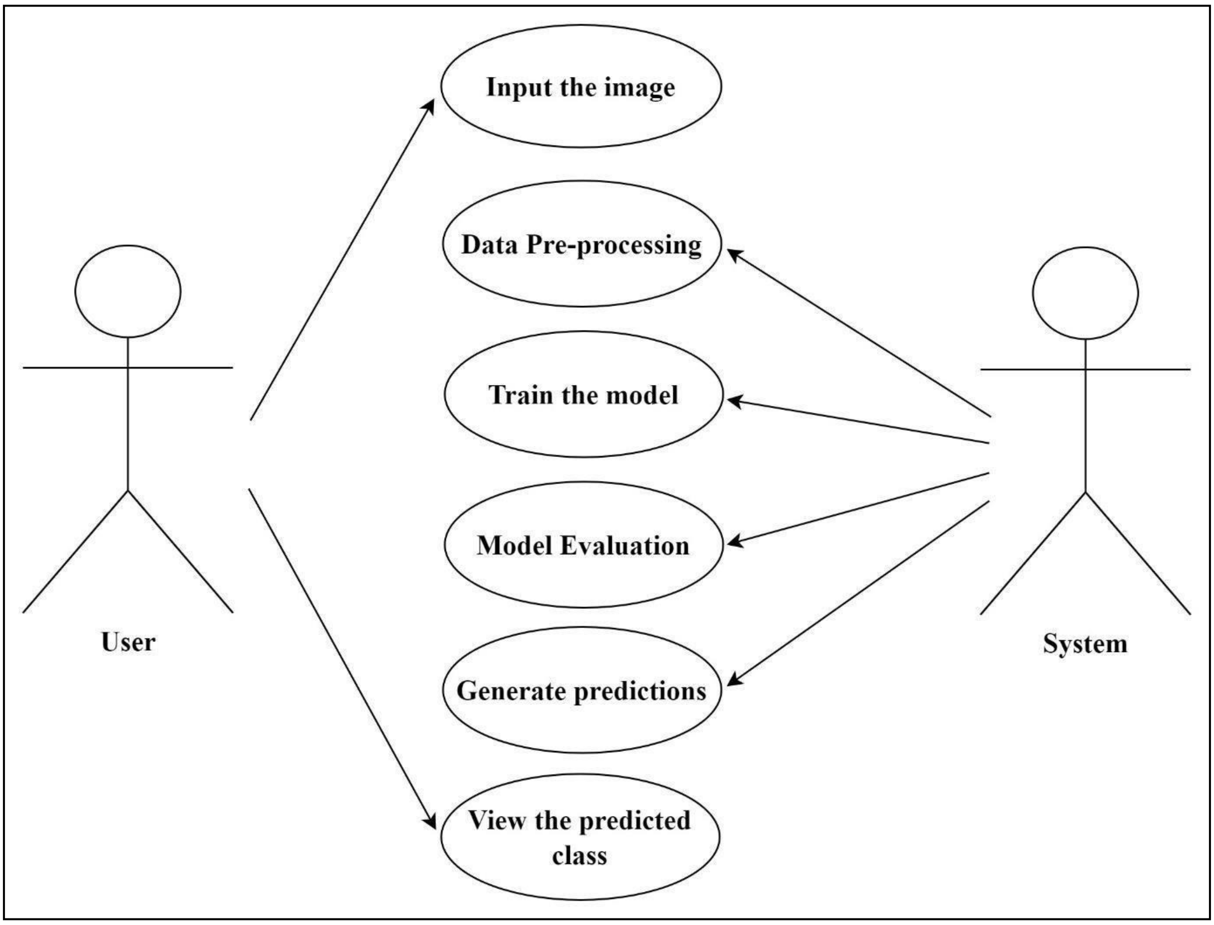

Figure 6. Use Case Diagram

Figure 6 represents the use case diagram for the proposed method. In the use case diagram for the waste classification system, there are two primary actors: the User and the System.

User: The User is an external actor who interacts with the waste classification system. The user initiates various use cases such as "Submit Image for Classification" and "View Classification Results." These use cases represent the primary functionalities the user engages with, highlighting the system's core features from the user's perspective. The "Submit Image for Classification" use case involves providing an image to the system for waste classification, while the "View Classification Results" use case allows the user to retrieve and examine the classification outcomes.

System: The System actor represents the waste classification system itself. It encompasses several use cases that describe the system's functionalities, such as "Preprocess Data," "Train Model," and "Make Prediction." The "Preprocess Data" use case involves preparing the input data for effective model training, while the "Train Model" details the process of training the deep learning model. The "Make Prediction" use case signifies the system's ability to utilize the trained model to classify waste based on the input received from the user.

Together, these use cases and actors in the diagram provide a comprehensive overview of the interactions between the user and the waste classification system, outlining the key functionalities and operations involved in the waste classification process.

3.7.4 Activity Diagram

An activity diagram in UML illustrates the dynamic aspects of a system by modeling the flow of activities and actions, demonstrating the sequential and parallel execution of processes. It provides a visual representation of the workflow within a system, showcasing the actions and decision points as nodes connected by transitions.

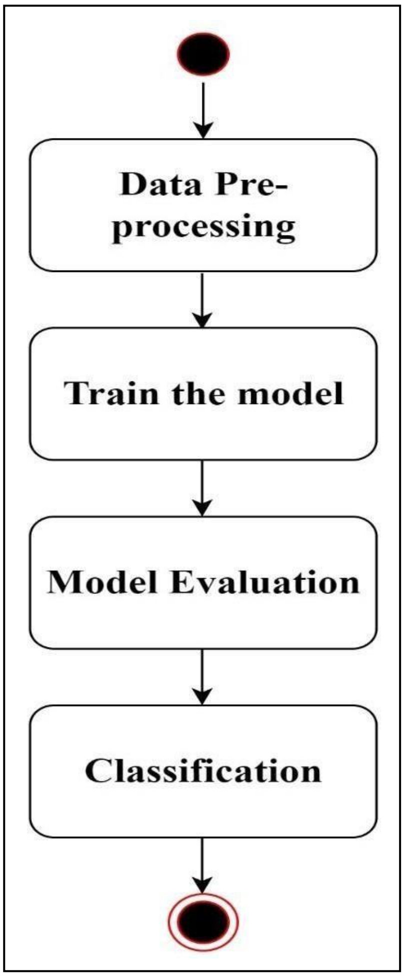

Figure 7. Activity Diagram

Figure 7 represents the activity diagram for the proposed method. In the activity diagram for the waste classification system, the intricate workflow involves several crucial activities: Data Pre-processing, Train the Model, Model Evaluation, and Classification.

The activity of Data Pre-processing encompasses a series of steps aimed at preparing the input data for effective model training. This involves tasks such as resizing images to a standardized format, normalizing pixel values to a common scale, and applying data augmentation techniques to diversify the dataset. These actions collectively enhance the quality of the data, enabling the subsequent training phase to be more robust and representative. The subsequent activity, Train the Model, provides a detailed depiction of the process where deep learning algorithms, such as CNN, VGG16, or ResNet50, are employed. Through multiple epochs of forward and backward passes, the model learns to recognize patterns and features in the waste images, adjusting its parameters to optimize classification accuracy. This activity involves parallel execution of tasks within each epoch, showcasing the iterative nature of the training process.

Following the training, the activity diagram introduces a branch for Model Evaluation. This activity involves assessing the performance of the trained model using various metrics such as accuracy, precision, and recall. The evaluation process provides valuable insights into the model's effectiveness and generalization capabilities, facilitating informed decisions about model deployment. The final activity, Classification, represents the fundamental functionality of the system. When a user submits an image for classification, the trained model is invoked to predict whether the waste in the image is biodegradable or non-biodegradable. This activity integrates the trained model's learned features to provide real-time classification results to the user.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Description about Dataset

The waste classification dataset consists of a total of 15,150 images, sourced from Kaggle [14]. These images are categorized into 12 distinct classes, each representing a different type of household garbage. The classes include Paper, Cardboard, Biological Waste (involving items like rotten vegetables and food remains), Metal, Plastic, Green Glass, Brown Glass, White Glass, Clothes, Shoes, Batteries, and Trash.

The frequency counts for each class are as follows:

- Battery: 945 images
- Biological: 985 images
- Brown Glass: 607 images
- Cardboard: 891 images
- Clothes: 5325 images
- Green Glass: 629 images
- Metal: 769 images
- Paper: 1050 images
- Plastic: 865 images
- Shoes: 1977 images
- Trash: 697 images
- White Glass: 775 images

These numbers provide insights into the distribution of images across the various waste categories, indicating the frequency of occurrence for each class in the dataset. Understanding this distribution is crucial for researchers and developers working with the dataset, as it influences the training and evaluation of machine learning models. The dataset aims to cover a comprehensive range of waste materials commonly encountered in domestic environments. The images were collected using a combination of web scraping and targeted searches to ensure a diverse and representative set of garbage items. This inclusivity sets the dataset apart, offering a more extensive set of waste classes compared to traditional waste classification datasets.

4.2 Detailed Explanation about the Experimental Results

In the waste classification project, the goal was to categorize images into two main classes: biodegradable and non-biodegradable waste. Various deep-learning models, including CNN, VGG-16, and ResNet50, were employed for this classification task. The detailed explanation of the experimental results of the modules are as follows:

a. Module 1: Data Pre- processing

The initial step involves segregating the dataset into training, validation, and test sets. For each waste class, images are split into these sets using the train_test_split function from the sklearn.model_selection module. The resulting sets are organized into respective directories, facilitating seamless integration with deep learning models.

The available dataset is divided into three sets: training, validation, and test sets.

- **Training Set:** The training set consists of 10,854 images belonging to 12 different waste classes.
- **Validation Set:** The validation set comprises 2,333 images, distributed across the same 12 waste classes.
- **Test Set:** The test set contains 2,328 images, also categorized into the 12 waste classes.

Subsequently, image data generators are employed to augment and preprocess the images before feeding them into the neural network. The training set undergoes augmentation processes like shearing, zooming, and horizontal flipping through the train_datagen. Meanwhile, the validation and test sets are rescaled using val_datagen and test_datagen, respectively, to maintain consistency in preprocessing without introducing additional variations.

b. Module 2: Train the Model

In the project, the training phase is pivotal as it enables the model, built using CNN, ResNet50, and VGG16 architectures, to learn and adapt to patterns in the input data. Through optimization of parameters and hyperparameter tuning, the models extract features from images, generalize well to unseen data, and avoid overfitting. The training process involves iterative improvement, with model evaluation using performance metrics to ensure effectiveness in classifying waste items into specific categories. CNN , VGG-16 and Resnet50 algorithms are used to train the model . The algorithm that gave better training, test and validation accuracy was considered to make predictions.

- **CNN Model**

The training accuracy of the CNN model reached 91.37%, indicating that the model performed well on the training dataset. For the validation set, the accuracy was 75.87%, suggesting that the model generalized reasonably well to unseen data but might have encountered some challenges in classifying certain instances.

- **VGG-16 Model**

The training accuracy of the VGG16 model reached approximately 93.85%, demonstrating effective learning on the training dataset. The validation accuracy was 88.98%, indicating good generalization to unseen data. These results suggest that the VGG16 architecture performed well in both training and validation, with a relatively small performance gap, indicating successful training and potential effectiveness in classifying new, unseen instances.

- **Resnet50 Model**

The ResNet50 model achieved a training accuracy of 99.58%, demonstrating excellent learning on the training dataset. The validation accuracy was 97.47%, indicating strong generalization to unseen data. These results highlight the robustness and effectiveness of the ResNet50 architecture in capturing intricate features of the waste classification dataset, leading to high accuracy on both the training and validation sets. The minimal performance gap between training and validation accuracies suggests successful training and good generalization capabilities.

c. Module 3: Model Evaluation and Visualization

In the evaluation phase, the performance of the trained models was assessed using a dedicated test dataset. The CNN model achieved a test accuracy of approximately 76.07%. The VGG16 model exhibited improved performance, attaining a test accuracy of around 88.83%. Notably, the ResNet50 model outperformed the others, demonstrating a remarkable test accuracy of approximately 97.47%. These accuracy values signify the models' ability to make correct predictions on previously unseen data, highlighting the efficacy of ResNet50 in this waste classification task.

Table 2. Comparison of CNN, VGG-16 and Resnet50

Sno.	Model	Training Accuracy	Validation Accuracy	Test Accuracy
1.	CNN	91.37%	75.87%	76.07%
2.	VGG-16	93.85%	88.98%	88.83%
3.	Resnet50	99.58%	97.47%	97.47%

Table 2 presents a detailed comparison of the performance metrics for three distinct models employed in waste classification: CNN, VGG-16, and ResNet50. These models have been assessed based on their training accuracy, validation accuracy, and test accuracy. The CNN model exhibits a training accuracy of 91.37%, a validation accuracy of 75.87%, and a test accuracy of 76.07%. Moving on to the VGG-16 model, it demonstrates higher accuracy across all metrics, with a training accuracy of 93.85%, a validation accuracy of 88.98%, and a test accuracy of 88.83%. Notably, the ResNet50 model outshines the others, achieving a remarkable training accuracy of 99.58%, a validation accuracy of 97.47%, and maintaining the same high accuracy of 97.47% on the test set. These results underline the superior performance of ResNet50 in waste classification, emphasizing its potential for accurate and reliable predictions compared to the other models.

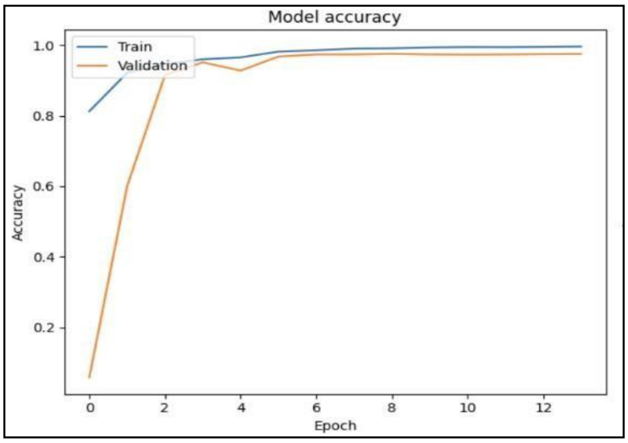

Figure 8. Graph plotted between Epochs and accuracy for the Resnet50 model

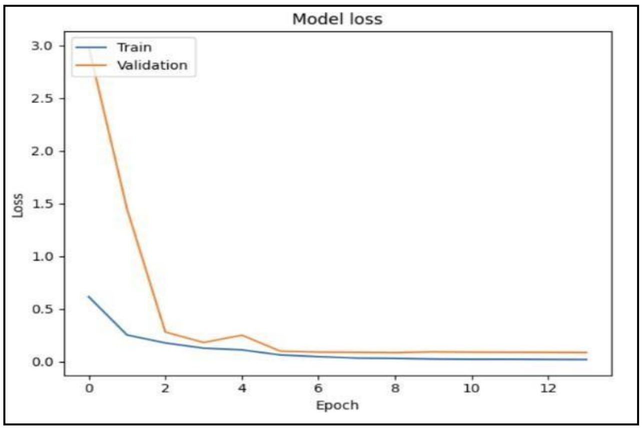

Figure 9. Graph plotted between Epochs and loss for the Resnet50 model

Figure 8 shows the graphical representation illustrating the relationship between the number of training epochs and the accuracy achieved by the Resnet50 model. The graph provides a visual understanding of how the accuracy of the model evolves as the training process progresses through different epochs.

On the other hand, Figure 9 depicts a graph showing the correlation between the number of training epochs and the loss incurred by the Resnet50 model. This graph is informative in revealing how the loss, a measure of the model's deviation from the actual values, changes over the course of training epochs. Analyzing both figures can offer valuable insights into the performance and convergence of the Resnet50 model during the training phase.

```
73/73 [==============================] - 5s 58ms/step
Classification Report for ResNet50:
              precision    recall  f1-score   support

           0       0.08      0.08      0.08       142
           1       0.08      0.08      0.08       148
           2       0.04      0.04      0.04        91
           3       0.07      0.07      0.07       134
           4       0.35      0.35      0.35       799
           5       0.04      0.04      0.04        94
           6       0.03      0.03      0.03       115
           7       0.07      0.07      0.07       157
           8       0.03      0.03      0.03       130
           9       0.11      0.11      0.11       297
          10       0.05      0.05      0.05       105
          11       0.08      0.08      0.08       116

    accuracy                           0.17      2328
   macro avg       0.09      0.09      0.09      2328
weighted avg       0.17      0.17      0.17      2328
```

Figure 10. Classification Report for Resnet50 Model

Figure 10 provides a detailed breakdown of performance metrics for each class in the classification task. The report includes precision, recall, and F1-score for all twelve classes (0 to 11) along with the support, which represents the number of instances of each class in the test set. This detailed breakdown is valuable for understanding the strengths and weaknesses of the ResNet50 model across different waste classes in the dataset.

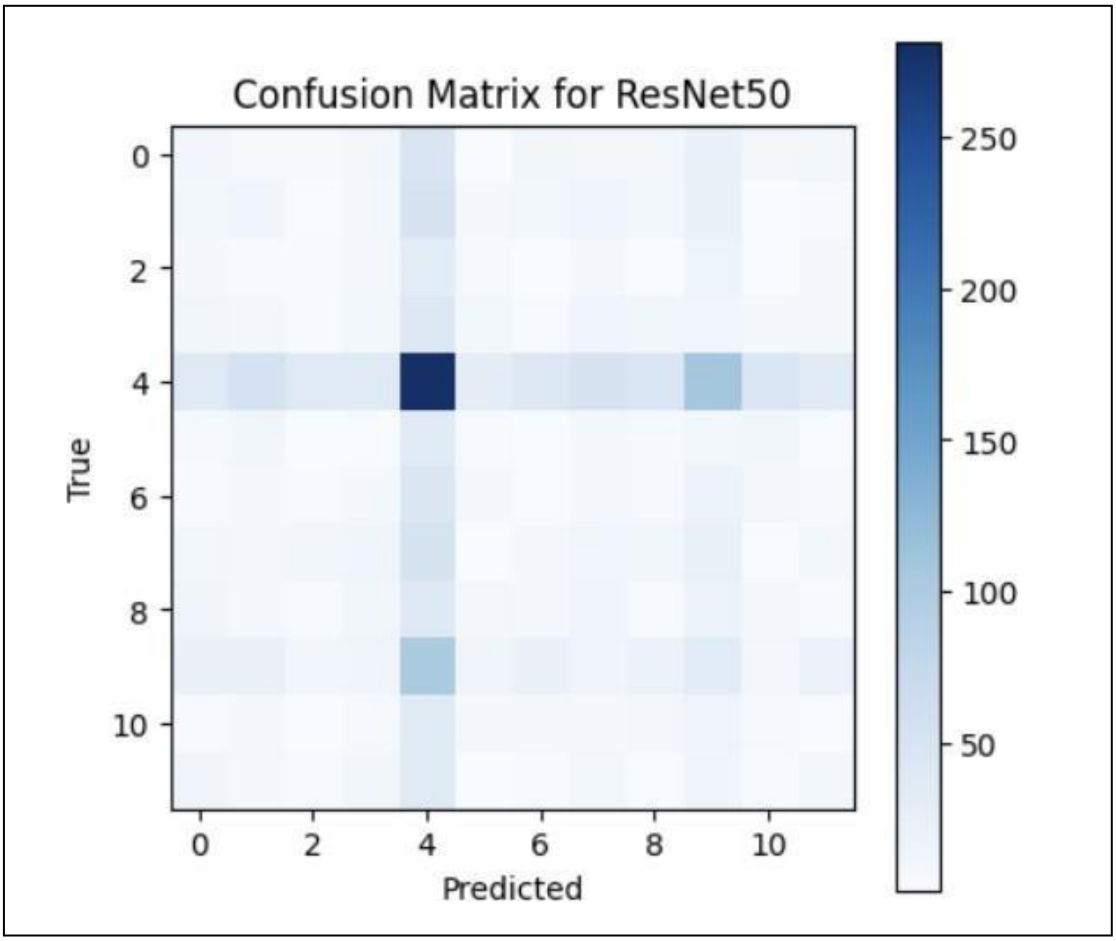

Figure 11. Confusion matrix for Resnet50

Figure 11 presents the confusion matrix for the ResNet50 model in the waste classification task. This visualization is valuable for understanding where the model excels and where it might struggle, providing insights into potential areas for improvement in the classification performance.

d. Module 4: Generate Predictions

In the module for generating predictions, the experiment involved loading the saved ResNet50 model previously trained on waste classification data. The code demonstrates the process of predicting the class of a given test image using the loaded model. The model predicts the waste class based on the features extracted from the test image. The predict_class function preprocesses the input image and uses the ResNet50 model to predict the class probabilities. The predicted class is then mapped to a waste category (e.g., cardboard, plastic) based on the highest probability. Additionally, the code classifies the waste item as either 'Biodegradable' or 'Non-Biodegradable,' depending on the predicted class. This classification is determined by checking if the predicted class falls into certain waste categories associated with biodegradable or non-biodegradable materials.

```
1/1 [==============================] - 1s 1s/step
Predicted Class: cardboard
Classified as: Biodegradable
```

Figure 12. Predicting Unseen Data for Class: Cardboard

Figure 12 depicts the process of predicting unseen data using the trained ResNet50 model. In Figure 12, the test image is predicted to belong to the class "cardboard." The classification label associated with this prediction is "Biodegradable," indicating that the waste item in the image is likely composed of biodegradable materials.

```
1/1 [==============================] - 0s 24ms/step
Predicted Class: plastic
Classified as: Non-Biodegradable
```

Figure 13. Predicting Unseen Data for Class: Plastic

Figure 13 illustrates the prediction process for unseen data using the ResNet50 model. In this particular case, the model predicts that the test image belongs to the class "plastic." The corresponding classification label is "Non-Biodegradable".

Figure 14. Predicting Unseen Data for Class: Battery

Figure 14 depicts the prediction results for another unseen data instance using the ResNet50 model. In this instance, the model predicts that the test image corresponds to the class "battery." The associated classification label is "Non-Biodegradable," indicating that the waste item in the image is likely composed of non-biodegradable materials.

Figure 15. Predicting Unseen Data for Class: Clothes

Figure 15 showcases the prediction outcome for unseen data instance using the ResNet50 model. In this case, the model predicts that the given test image belongs to the class "clothes." The corresponding classification label is "Biodegradable".

4.3 Significance of the Proposed Method with its Advantages

The proposed method represents a significant advancement in the field of waste classification and management, introducing a novel and impactful approach. One key strength lies in the exceptional accuracy rates achieved across multiple waste classes, a testament to the efficacy of the implemented CNN and ResNet50 models. The ResNet50 model, in particular, exhibited a remarkable 97.47% accuracy in the test set, underscoring the proficiency of your chosen models in accurately categorizing waste items into distinct classes.

This high level of accuracy is crucial for effective waste management, as misclassifying waste can have serious environmental and operational implications. The robust performance of your models reflects a meticulous approach to model selection, training, and evaluation, contributing to the project's credibility and reliability. The utilization of deep learning techniques, such as CNN and ResNet50, showcases a commitment to employing cutting-edge technologies in solving real-world challenges. These models, known for their ability to extract intricate features from images, are well-suited for the complex task of waste classification.

Furthermore, achieving such high accuracy rates is a notable achievement in the context of waste management, where diverse and often visually similar materials must be accurately distinguished. This accuracy is not only a testament to the effectiveness of your models but also positions your project as a potential benchmark for future research in the field. The meticulous attention to detail in model training, validation, and testing phases contributes to the robustness of your results and strengthens the overall impact of your work.

CHAPTER 5
CONCLUSION AND FUTURE ENHANCEMENTS

5.1 Summary of the Project

The objective is to design a system that utilizes deep learning for automated waste classification, distinguishing between biodegradable and non-biodegradable categories. This addresses challenges in manual waste sorting which is labor-intensive, slow, and error-prone. An accurate automated solution can enhance recycling and sustainability. The dataset consistsof 15,000 images across 12 waste categories sourced from Kaggle. The classes cover commonhousehold waste materials. The images are split into training (70%), validation (15%) and test(15%) sets for model development and evaluation.

Three deep learning models are implemented - CNN, VGG16, and ResNet50. These are trained on augmented training data. ResNet50 achieved the best performance with 99.58% training accuracy and 97.47% validationand test accuracy, demonstrating effective learning and generalization. The optimized ResNet50 model is used for prediction by classifying new waste images as biodegradable or non-biodegradable based on visual features. The high accuracy of ResNet50 highlights the significance of deep learning for automated waste classification. This technique can enhance waste segregation, recycling, and sustainability by enabling large-scale automated categorization of waste with high accuracy.

The system has immense real-world potential to transform waste management practices through large-scale, reliable categorization of waste into biodegradable and non-biodegradable streams. This can crucially augment recycling efforts and sustainability initiatives. The project sets a strong foundation for continued research into optimized implementation of such deep learning solutions to create smarter, more efficient waste management systems and processes for a greener future.

5.2 Future Enhancements

While the current project demonstrates remarkable accuracy in categorizing waste, there remain ample opportunities to extend its capabilities and practical applications in the future. One important enhancement would be expanding the dataset to incorporate more waste types and images, which can improve model generalization. Additionally, exploring more advanced deep learning architectures like DenseNets and implementing model ensembles could further optimize accuracy. To handle real-world complexity, adding modules for detecting regions of interest in images prior to classification would be beneficial. Implementing edge computing capabilities to process data closer to the source (garbage bins) rather than relying solely on centralized cloud servers. This reduces latency and enhances real-time processing efficiency. Integration of advanced sensors, such as multispectral cameras and chemical sensors, to improve the accuracy of waste classification. This can enable the system to identify the composition and nature of the waste more precisely. Develop energy-efficient hardware components to ensure sustainable and long-lasting operation of IoT devices, especially in remote or off-grid locations where traditional power sources may be limited. Enhancement of communication protocols to ensure reliable and secure data transmission between the IoT devices and the central server. This is crucial for maintaining the integrity of the data and the proper functioning of the garbage segregation system. Integrate swarm robotics for automated waste collection.

CHAPTER 6

APPENDICES

6.1 Sample Code

1. Splitting the Data into train, test, and validation sets

```
import shutil
from sklearn.model_selection import train_test_split
for class_dir in class_directories:
    class_path = os.path.join(main_data_dir, class_dir)
    all_images = [img for img in os.listdir(class_path) if img.endswith('.jpg')]
    train_images, test_val_images = train_test_split(all_images, test_size=0.3,
random_state=42)
    test_images, val_images = train_test_split(test_val_images, test_size=0.5,
random_state=42)
    for img in train_images:
        src = os.path.join(class_path, img)
        dest = os.path.join(train_dir, class_dir, img)
        os.makedirs(os.path.dirname(dest), exist_ok=True)
        shutil.copy(src, dest)
    for img in test_images:
        src = os.path.join(class_path, img)
        dest = os.path.join(test_dir, class_dir, img)
        os.makedirs(os.path.dirname(dest), exist_ok=True)
        shutil.copy(src, dest)
    for img in val_images:
        src = os.path.join(class_path, img)
        dest = os.path.join(val_dir, class_dir, img)
        os.makedirs(os.path.dirname(dest), exist_ok=True)
        shutil.copy(src, dest)
```

2. Data Pre- processing

```
import os
from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

```
from tensorflow.keras.applications import ResNet50, VGG16, InceptionV3
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D
img_width, img_height = 224,224
input_shape = (img_width, img_height, 3)
train_datagen = ImageDataGenerator(rescale=1./255, shear_range=0.2, zoom_range=0.2,
horizontal_flip=True)
val_datagen = ImageDataGenerator(rescale=1./255)
test_datagen = ImageDataGenerator(rescale=1./255)
train_generator = train_datagen.flow_from_directory(train_dir, target_size=(img_width,
img_height), batch_size=32, class_mode='categorical')
val_generator = val_datagen.flow_from_directory(val_dir, target_size=(img_width,
img_height), batch_size=32, class_mode= 'categorical')
test_generator = test_datagen.flow_from_directory(test_dir, target_size=(img_width,
img_height), batch_size=32, class_mode='categorical')
```

3. Train the Model

- **Using CNN**

```
cnn_model = Sequential()
cnn_model.add(Conv2D(32, (3, 3), activation='relu', input_shape=input_shape))
cnn_model.add(MaxPooling2D(pool_size=(2, 2)))
cnn_model.add(Conv2D(64, (3, 3), activation='relu'))
cnn_model.add(MaxPooling2D(pool_size=(2, 2)))
cnn_model.add(Flatten())
cnn_model.add(Dense(128, activation='relu'))
cnn_model.add(Dense(12, activation='softmax'))
cnn_model.compile(optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])
cnn_model.fit(train_generator, epochs=20, validation_data=val_generator)
```

- **Using VGG-16**

```
vgg16_model = Sequential()
vgg16_model.add(VGG16(weights='imagenet', include_top=False,
input_shape=input_shape))
```

```
vgg16_model.add(BatchNormalization())
vgg16_model.add(Flatten())
vgg16_model.add(Dense(512, activation=’relu’))
vgg16_model.add(BatchNormalization())
vgg16_model.add(Dropout(0.5))
vgg16_model.add(Dense(256, activation=’relu’))
vgg16_model.add(Dense(12, activation=’softmax’))
for layer in vgg16_model.layers[:-6]:
    layer.trainable = False
vgg16_model.compile(optimizer=’adam’, loss=’categorical_crossentropy’,
metrics=[‘accuracy’])
history_vgg16 = vgg16_model.fit(train_generator, epochs=30,
                                validation_data=val_generator,
                                callbacks=[lr_scheduler, early_stopping, checkpoint])
```

- **Using Resnet50**

```
resnet_model = Sequential()
resnet_model.add(ResNet50(weights='imagenet', include_top=False,
input_shape=input_shape))
resnet_model.add(GlobalAveragePooling2D())
resnet_model.add(BatchNormalization())
resnet_model.add(Dense(512, activation=’relu’))
resnet_model.add(BatchNormalization())
resnet_model.add(Dropout(0.5))
resnet_model.add(Dense(256, activation=’relu’))
resnet_model.add(Dense(12, activation=’softmax’))
for layer in resnet_model.layers[:-12]:
    layer.trainable = False
resnet_model.compile(optimizer=’adam’, loss=’categorical_crossentropy’,
metrics=[‘accuracy’])
history_resnet = resnet_model.fit(train_generator, epochs=30,
                                  validation_data=val_generator,
                                  callbacks=[lr_scheduler, early_stopping, checkpoint])
```

4. Generate Predictions

```
import numpy as np
from tensorflow.keras.preprocessing import image
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
loaded_resnet_model = load_model('/kaggle/input/savedmodel/best_resnet_model.h5')
def preprocess_image(image_path):
    img = image.load_img(image_path, target_size=(224, 224))
    img_array = image.img_to_array(img)
    img_array = np.expand_dims(img_array, axis=0)
    img_array /= 255.0  # Rescale to [0, 1]
    return img_array
def predict_class(image_path, model):
    classes=['battery', 'biological', 'brown-glass', 'cardboard', 'clothes', 'green-glass',
'metal', 'paper', 'plastic', 'shoes', 'trash', 'white-glass']
    img_array = preprocess_image(image_path)
    predictions = model.predict(img_array)
    predicted_class = classes[np.argmax(predictions)]
    if predicted_class in {'biological', 'cardboard', 'clothes', 'paper', 'shoes', 'trash'}:
        res='Biodegradable'
    else:
        res='Non-Biodegradable'
    return predicted_class, res
```

REFERENCES

[1] “ How can we #managewaste"? “ [Online], Available: https://twitter.com/simmifoundation/status/1407673904831746059

[2] Gupta, T., Joshi, R., Mukhopadhyay, D. *et al.* A deep learning approach based hardware solution to categorise garbage in environment. *Complex Intell. Syst.* **8**, 1129–1152 (2022). https://doi.org/10.1007/s40747-021-00529-0

[3] Iyyanar, P., Balaji, V., Ravikiran, K., Sagar, K.D., Cholla, R.R. and Banerjee, K., 2022. Efficient and Smart Waste Categorization System using Deep Learning.IJCSNS International Journal of Computer Science and Network Security, VOL.22 No.6, June 2022 ,https://doi.org/10.22937/IJCSNS.2022.22.6.60

[4] Gunaseelan, J.; Sundaram, S.; Mariyappan, B. A Design and Implementation Using an Innovative Deep-Learning Algorithm for Garbage Segregation. Sensors 2023, 23, 7963. https://doi.org/10.3390/ s23187963

[5] M. S. Nafiz, S. S. Das, M. K. Morol, A. Al Juabir and D. Nandi, "ConvoWaste: An Automatic Waste Segregation Machine Using Deep Learning," *2023 3rd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST),* Dhaka, Bangladesh, 2023, pp. 181-186, doi: 10.1109/ICREST57604.2023.10070078.

[6] M. W. Rahman, R. Islam, A. Hasan et al., Intelligent waste management system using deep learning with IoT, Journal of King Saud University – Computer and Information Sciences, https://doi.org/10.1016/j.jksuci.2020.08.016

[7] Akanksha S, Bindushree K, Rachana R, Sharadhi MK, Saravana MK. “Efficient Garbage Management System Using Machine Learning”. *Perspectives in Communication, Embedded-Systems and Signal-Processing - PiCES*, vol. 5, no. 10, Feb. 2022, pp. 97-101, doi:10.5281/zenodo.6026635.

[8] Wei Liu, Hengjie Ouyang, Qu Liu, Sihan Cai, Chun Wang, Junjie Xie, Wei Hu, "Image Recognition for Garbage Classification Based on Transfer Learning and Model Fusion", *Mathematical Problems in Engineering*, vol. 2022, Article ID 4793555, 12 pages, 2022. https://doi.org/10.1155/2022/4793555

[9] Nnamoko, N.; Barrowclough, J.; Procter, J. Solid Waste Image Classification Using Deep Convolutional Neural Network. Infrastructures 2022, 7, 47. https:// doi.org/10.3390/infrastructures 7040047

[10] Jianchun Qi, Minh Nguyen, Wei Qi Yan, Waste Classification from Digital Images Using ConvNeXt. In: Wang, H., *et al.* Image and Video Technology. PSIVT 2022. Lecture Notes

in Computer Science, vol 13763. Springer, Cham. https://doi.org/10.1007/978-3-031-26431-3_1

[11] Yang, Z.; Xia, Z.; Yang, G.; Lv, Y. A Garbage Classification Method Based on a Small Convolution Neural Network. Sustainability 2022, 14, 14735. https://doi.org/10.3390/su142214735

[12] Thien Khai Tran, Kha Tu Huynh, Dac-Nhuong Le, Muhammad Arif, Hoa Minh Dinh, *Intelligent Automation & Soft Computing* **2023**, *35*(2), 2479-2491. https://doi.org/10.32604/iasc.2023.029078

[13] S. Nisar, Y. Jhaveri, T. Gandhi, T. Naik, S. Shah and P. Kanani, "Waste Segregation into Biodegradable & Non-Biodegradable using Transfer Learning," *2022 IEEE International Conference on Data Science and Information System (ICDSIS)*, Hassan, India, 2022, pp. 1-6, doi: 10.1109/ICDSIS55133.2022.9915984.

[14] "Garbage Classification (12 classes)" [Online] , Available: https://www.kaggle.com/datasets/mostafaabla/garbage-classification