WASTE CLASSIFICATION USING TRANSFER LEARNING AND DENSENET

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering.

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APPROVAL

This Project titled **"Waste Classification Using Transfer Learning and DenseNet",** submitted by **Sabrina Islam** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **14/07/2024**.

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I hereby declare that this project has been done by me under the supervision of **Ms. Most. Hasna Hena, Assistant Professor, Department of Computer Science and Engineering, Daffodil International University.** I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Efficient waste management is an essential component of sustainable development, because using traditional methods can be time-consuming and hazardous to the environment. Automating trash categorization procedures through the incorporation of deep learning algorithms is a possible solution to these problems. This article suggests a garbage detection system that successfully classifies different waste kinds by using deep learning algorithms. Through the application of machine learning and deep learning, the system can discern between various waste categories, making appropriate sorting and disposal easier. The waste categorization efficacy of DenseNet architecture and transfer learning. The study uses pre-trained algorithms to improve sorting accuracy and refine them using a dedicated waste dataset. We investigate the possibility of DenseNet's dense connection patterns to extract complex characteristics and relevant patterns from waste photos. Significant accuracy gains are shown by the experimental findings, demonstrating the effectiveness of this strategy in waste classification system optimization. The experimental findings show significant accuracy gains, demonstrating this strategy's effectiveness in optimizing waste classification systems procedures. Through the creation of more precise and automated waste categorization systems, this research helps to promote environmental sustainability through the advancement of robust waste sorting technology. ResNet152, Inceptionv3, DenseNet were used in this work. The best accuracy comes from ResNet152, which is 98%.

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ML	Machine Learning
DL	Deep Learning
CNN	Convolutional Neural Network

CHAPTER 1
Introduction

1.1 Overview

Waste classification is a crucial step in contemporary waste management, entailing the division of waste materials into discrete groups to optimize recycling, treatment, and disposal processes. By guaranteeing that every kind of trash is managed correctly, this procedure reduces its negative effects on the environment, preserves resources, and safeguards public health. Effective trash classification systems are essential to sustainable waste management practices because they precisely identify and classify various waste kinds.

1.2 Background and Present State

Waste management has a direct impact on the environment's health and sustainability. Due to the rising amount of waste produced each year in today's society, the issue only seems to become worse. [1] The identification and classification of various waste materials in order to ensure efficient and effective trash disposal is one of the main issues in this business. Since manual garbage sorting is time-consuming, expensive, and prone to mistakes, automated waste identification systems using machine learning and deep learning approaches have been developed. Using machine learning and deep learning algorithms, a variety of waste products can be automatically identified and categorized based on their properties, such as colour, texture, and shape. By examining enormous volumes of data from images or sensors, these algorithms may classify different waste types into groups that are suitable for composting, recycling, or disposal. These automated solutions could increase efficiency while lowering costs and the environmental impact of waste disposal. [1,2] Complex computer algorithms must be used in order to identify and categorize various waste types, including plastic, metal, paper, and organic trash. Technology can assist decrease human error while improving the precision and effectiveness of waste management systems by automating the garbage identification process. This technique has been applied in the past in a variety of waste management settings, including landfills, recycling plants, and waste collection centres, and it has generated encouraging results. We will investigate the different uses of trash detection utilizing machine learning and deep learning on a bigger scale; as well as how this technology might assist create a cleaner and healthier future for future generations. A potent technique for addressing waste management issues and advancing sustainable practices is waste detection utilizing machine learning and deep learning. I will examine the importance of waste classification, the major variables that affect waste classification, and its contribution to a future that is more ecologically conscious and sustainable. As we go more into this topic, we will learn the intricate details of managing waste efficiently, reducing its impact on the environment, and fostering a circular economy where resources are stored and reused, ultimately leading to a cleaner, healthier, and more sustainable world.

Waste is currently roughly divided into a number of categories, such as biological waste, hazardous waste, electronic trash, and municipal solid garbage. Efficient waste classification contributes to resource recovery, enhanced public health, and less environmental impact. Efficient waste classification contributes to resource recovery, enhanced public health, and less environmental impact. It makes it possible to recycle specific items, handle hazardous materials safely, and use landfill space more effectively.

1.3 Problem Statement

Incorrect waste classification is still a major problem in waste management, even with advances in technologies and procedures. Waste that is incorrectly classified can cause health risks, environmental pollution, and ineffective recycling operations. For example, recyclable products in landfills represent a missed chance for resource recovery, while hazardous materials combined with regular garbage might result in harmful leaks. Some things make the issue worse:

Insufficient Public Awareness: Many people dispose of garbage incorrectly because they don't know enough about appropriate waste segregation techniques.

Poor Infrastructure: Inadequate facilities and resources for recycling and garbage segregation obstruct efficient waste management initiatives.

Resolving these issues is essential to attaining environmental sustainability and strengthening waste management systems.

1.4 Objectives

The following are the waste categorization project's main goals:

Examine the garbage classification systems and techniques in use today. Create a deep learning model that can correctly categorize various trash kinds. Gather and organize a collection of discarded photos for assessment and training. Use the dataset to train and adjust the deep learning model. Implement and assess the model's effectiveness in trash sorting situations. Record the project's findings and make suggestions for additional enhancements.

1.5 Scope and Limitations

It is essential to recognize the scope and limitations of this research.

This report's scope is limited to the evaluation of particular waste categorization models. It excludes additional components including deployment considerations, interpretability of models, and also data augmentation strategies. Therefore, the analysis of the models and their waste classification accuracy should be the only conclusions taken from this study.

Some significant limitations are as follows:

Concentration on Specific Models: The research does not examine other classification approaches or techniques; instead, it is limited to evaluating specific trash categorization models.

Exclusion of Data Augmentation Techniques: Although data augmentation techniques may improve model performance, they are not included in this research.

Absence of Interpretability Analysis: This study does not analyse the models' interpretability, or how they choose which categories to classify.

Concerns about Deployment: This work does not address issues with the actual deployment of the models in real-world scenarios.

Regional Focus: Although trash classification methods may differ internationally, the study is restricted to analysing existing practices within a certain region.

1.6 Report Organizations

Chapter 2: In this chapter, I review important vocabulary and relevant literature related to my research topic. I next go over a few pertinent novels that touch on the topic of my investigation. Furthermore, I highlight the benefits and drawbacks of the several sentiment analysis methods now in use by contrasting and comparing them. Next, I outline the open issue and the summary that I want to address in this research.

Chapter 3: I go into my research approach for this study in this chapter. I gave an explanation of the study topic and the tools I utilized to gather and process data. I next go into the performance evaluation indicators I used to assess the model's design and my suggested methodology's efficacy and also project management and financial analysis for this project. Lastly, I describe the summary of this chapter.

Chapter 4: In this chapter, I describe the implementation for this project. Then I go over the model or design for my project which I used. After that, I explain evolution of model and summary.

Chapter 5: I detail my study's findings and the experimental outcomes in this chapter. I go over how I set up the experiment and how I went about gathering data. After that, I compile and evaluate the outcomes of using several categorization algorithms on my dataset. I also weigh the pros and cons of my suggested approach against the current ones. I then go into the limits and ramifications of my research.

Chapter 6: I go over how my research has affected sustainability, the environment, and society in this chapter. I look at how my research may help society by revealing attitudes and opinions of the general people on a range of subjects and problems. I also think about how my research might benefit the environment by lowering the demand for manual analysis and human involvement. After that, I discuss the study's ethical considerations and how I protected the confidentiality and privacy of my data. Lastly, I suggest a sustainable strategy for upkeep and system updates.

Chapter 7: We provide an overview of the key findings and contributions of my work in this chapter. The questions, research aims, and hypotheses that shaped my investigation are outlined below. Next, I emphasize the main conclusions and results of my research. I also talk about the implications for future study and offer ideas for expanding and enhancing my work.

1.7 Summary

In summary of this chapter, trash categorization is essential to controlling the many and expanding waste streams that contemporary civilization produces. Waste may be categorized systematically to increase recycling rates, lower contamination, and enhance disposal techniques. Nonetheless, issues including erratic categorization guidelines, low public knowledge, and poor infrastructure continue to exist. To ensure efficient and sustainable waste management practices, addressing these concerns calls for comprehensive initiatives that include public education, standardized norms, and enhanced waste management systems.

CHAPTER 2

Background

2.1 Overview

This chapter offers an extensive analysis of the body of research on trash categorization that has been done. It seeks to compare current approaches, contextualize the present level of research, highlight noteworthy achievements, and pinpoint unresolved problems in the area. This review lays the groundwork for comprehending the difficulties and possibilities in enhancing trash categorization systems by looking at comparable studies.

2.2 Related Works

Rushnan Faria et al, [15] In this work, it use five convolutional neural networks model like-3-layer CNN, VGG-16, VGG-19, Inception V3 and ResNet50 models to classify images. It also works with the OrgalidWaste dataset, which has 4 classes, 5600 images, and a highest accuracy of 88.42%. It can be easily work with real-time dataset in future and then the accuracy maybe changed.

Sylwia Majchrowska et al, [16] in particular, this study used DL and CNN based model and worked on mixed dataset for classify. It contains 7 classes. The proposed method achieved up to 70% average precision and around 75% of classification accuracy on test dataset by using EfficientNet-B2 CNN based model. This proposed work can be baseline in waste detection and classification for further research.

Victoria Ruiz et al, [19] In this work, the TrashNet dataset of garbage photos with six classes and 2,527 images was utilized to categorize images using multiple CNNs, including, VGG, Inception, and ResNet. With a combined Inception-ResNet model, they achieved the highest accuracy of 88.6%. By adding more photographs to the collection, the system's accuracy can be raised. In order to train the model on genuine images with various forms of rubbish before testing it on actual photographs with various types of waste, future work will concentrate on producing realistic composite photographs including various types of waste.

Md. Wahidur Rahman et al, [17] convolutional neural network model was used for this classification such as- ResNet34, VGG16, AlexNet, ResNet50 and also this study worked on real time dataset. Its accuracy is 95% by ResNet-34 and it works with divided into 6 categories. In this study there are three limitations, like- they used only six categories, using only two sensors and other is limitation on model experiences. In future this research will fix these three limitations to ensure best result.

Xiangru Chen, in this study, [18] suggests the ML and IOT related model automatic machine learning-based waste recycling framework (AMLWRF) for classify the materials and boasts an accuracy of 96.1%.

Grourou Aya Aridj et al, [20] Convolutional Neural Network (R-CNN) model was used for classification in this article and work on the large amount of plastic waste dataset with 97% accuracy. In the future, it will be added multiple classes of materials such as- paper, glass, metal etc. and then this accuracy can be changed.

Md. Shahariar Nafiz et al, [21] In this study, the accuracy of classification using a deep convolutional neural network-based ComboWaste model as Inception-ResNet-V2 model, working with 12000 images and 6 classes, is 98%.

Shuang Liang et al, [22] the accuracy of classification using convolutional neural network-based on Multi Task Learning Architecture (MTLA) and WasteRL dataset which has 4 categories and 56,964 images are respectively 97% in this paper.

Qiang Zhang et al, [23] In this study, deep learning network DenseNet169, AlexNet, GooleNet V2, VGG16 and combined of DenseNet169 and transfer learning image classification model was used for this classification. It processes NWNU-TRASH datasets and has 5 classes of images of 2528 with accuracies of 82% respectively by DenseNet169 model based on transfer learning.

Mohammad Kamrul Hasan et al, [24] this classification uses DenseNet121, DenseNet169, InceptionV3 and MobileNet models. It uses the real-time data set, which has 4 classes with accuracy of 97% by DenseNet169. The dataset can be easily extended in the future, so the same model can be maintained.

Meena Malik et al, [25] In this study, used the CNN model EfficientNetB0 and EfficientNetB3 model and uses ImageNet dataset with 23628 images and 10 classes with 80% and 85% accuracy. Used. The proposed model can be extended for subclass or other related class and expect further development in this field in the future.

Mohammed Imran Basheer Ahmed et all, [26] for this classification, models CNN and three pre-trained model such as- DenseNet169, MobileNetV2, ResNet50V2 were used in this study. It also used the dataset from Kaggle which is “Garbage Classification” with 5 classes and 5000 images. CNN model has 88.52% accuracy and pre-trained model are 94.40%, 97.60% and 98.95% accuracy. For further work, we suggested that expanding the dataset in the future.

Haruna Abdu et al, [29] this paper used AlexNet, VGG16, Inception-ResNet (InceptionResNetV2), MobileNet, Deep Residual Network, Densely Connected Convolutional Networks, R-CNN, YOLO, EfficientDet, ExtremeNet, Mask-RCNN models. It used different types of dataset from different source, such as-TACO, Water trash, Roadside, TrashNet, Self-collected etc. It also identify 6 types of waste known as metal, paper, glass, plastic, trash and cardboard to classification and object detection. The highest accuracy is 96.7% from YOLOV5 and MobileNet V3.

Arghadeep Mitra, [28] the accuracy of classification using convolutional neural network-based on Faster R-CNN model and uses dataset from GitHub Repository. There were around 2527 images with 6 classes of waste like- paper, plastic, glass, trash, metal and cardboard and the accuracy was near 91%. In this paper there are some limitation- model works with multiple objects in a single image that’s why sometimes model predict wrongly. In future, this paper improve its dataset and can analysis various models like- SSD-MobileNet, YOLO etc.

David Rutqvist et al, [27] This study's primary objective is to investigate empty bins and containers. Sensor technology more especially, intelligent sensors make it feasible. Find garbage in photos by applying the simplest categorization of photographs technique.

2.3 Comparison between existing works

The approaches, conclusions, and ramifications of several research on waste categorization are contrasted in this section. It starts by contrasting the many technical approaches—such as image processing, sensor-based systems, and machine learning—and highlighting the distinctive techniques of each. It examines the efficacy and precision of several categorization schemes and models, including information on their dependability and performance measures. A comparison of different systems' real-world implementations is also made, focusing on how these technologies might be incorporated into the infrastructures already in place for waste management. Finally, the assessment of the efficiency and cost-effectiveness of various waste categorization technologies and procedures is covered, with a focus on the operational and financial advantages of each strategy. This thorough comparison highlights the many approaches used in trash sorting as well as their advantages and disadvantages.

Table 2.3: Comparison between some works

Authors	Used Algorithms	Accuracy With Algorithm
Rushnan Faria et al [15]	3-layer CNN, VGG16, VGG19, InceptionV3 and ResNet50	88.42%
Sylwia Majchrowska et al [16]	DL and CNN	75% (EfficientNet-B2 CNN)
Victoria Ruiz et al [19]	VGG, Inception, ResNet, Inception-ResNet	Inception-ResNet 88.6%
Md. Wahidur Rahman et al [17]	ResNet34, VGG16, AlexNet, ResNet50	ResNet34 95%
Shahriar Nafiz et al [21]	Convolutional Neural Network	Inception-ResNet-V2 97%
Qiang et al [23]	DenseNet169, AlexNet, GooleNetV2, VGG16	DenseNet169 82%

2.4 Open Issues

In spite of great progress, there are still a number of unresolved problems in the waste categorization field:

Inconsistency in Standards: The absence of uniform classification schemes in various locales and situations.

Technological Restrictions: Difficulties with modern categorization technologies' scalability, dependability, and interpretability.

Public Participation and Understanding: There is a need for more public participation and understanding of appropriate waste segregation procedures.

Resources and Infrastructure: Not enough resources and infrastructure to enable efficient trash management and categorization.

Data Restrictions: Insufficient high-quality data are available for classification model validation and training.

2.5 Summary

The literature analysis concludes by highlighting the variety of strategies and noteworthy advancements in the waste categorization sector. The efficient categorization of trash is contingent upon societal issues, technological advancements, and resource management tactics. Nonetheless, issues including erratic standards, technical constraints, low public awareness, and inadequate infrastructure still exist. In order to advance trash categorization systems and achieve sustainable waste management practices, it is imperative that these open challenges be addressed via ongoing study and collaboration.

CHAPTER 3

Methodology/ Requirement Analysis & Design Specification

3.1 Overview

This chapter delves deeply into the methodologies and design requirements that are critical to the project's success. The system design, which includes data flow diagrams, development methodologies, and system architecture, is first described in depth. After that, it lists the hardware and software requirements needed to implement the project, providing a summary of its crucial technical elements. The chapter also explores risk management, resource allocation, and planning as aspects of project management methodologies. A comprehensive financial analysis is also provided, including financing alternatives, cost-benefit analysis, and budget estimates. A strong and organized project foundation is ensured by this all-encompassing method.

3.2 Proposed Methodology/System Design

For analyzing data sets, machine learning algorithms have grown to be crucial tools. Deep learning, machine learning is applied.

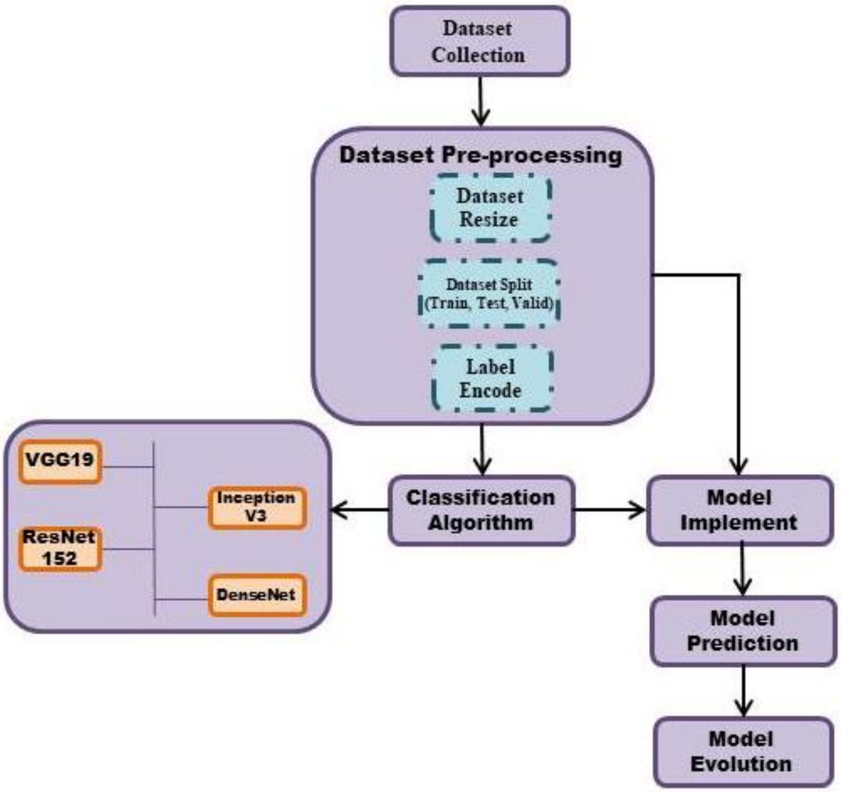

Figure 3.2 The Process of Experiments

Gathering trash photos and data for the dataset is the first step in the machine learning trash categorization process. Preprocessing of this dataset include scaling the photos, dividing it into training, testing, and validation sets, and encoding the labels for classification. Classification techniques include a variety of pre-trained deep learning models including DenseNet, ResNet152, and InceptionV3. After implementing these methods, the trash is classified using model prediction. The models are then assessed and improved upon in accordance with their performance, guaranteeing a constant rise in classification accuracy.

3.2.1 Data Description:

I gathered two distinct kinds of garbage data from my home, the side of the road and also some Kaggle. Take pictures of different waste products in a variety of settings, making sure that the lighting and background are varied, in order to collect raw data. Clearly identify each image with the type of garbage (e.g., plastic, metal). Use a relevant Kaggle dataset to augment this raw data, like "(Garbage Classification)". In order to construct a comprehensive and diversified dataset for training an efficient waste picture classification model, to follow standard preprocessing methods like scaling, normalization, and augmentation.

There are actually seven categories in the volume of input data. Yet, I use two separate datasets for classify the waste. There are around 2663 of image data, 1083 of metal and 1580 of plastic data

Table 3.2.1: Dataset Description

	Metal	**Plastic**
Raw Dataset	1083	1580

Figure 3.2.1 Waste dataset (real-time) with two classes

3.3 Hardware/ Software Requirement:

The project's hardware and software requirements are listed in this section.

Hardware requirements: Details on the GPU, CPU, RAM, and storage capacity of the employed hardware.

Software Requirements: The tools and software used, including operating systems, libraries, frameworks, and programming languages.

Python Libraries: The creation and execution of machine learning projects are made considerably easier by the extensive library that Python offers. The Python libraries used in this project are listed below.

NumPy**:** NumPy, commonly referred to as Numerical Python, is a potent open-source Python toolkit for mathematical and numerical computations. It can perform a number of complex mathematical operations on big, multi-dimensional arrays and matrices. This makes computations quick and effective. Academics, engineers, and data scientists working on projects like data manipulation, statistical analysis, and machine learning will find it indispensable due to its skills in random number generation, linear algebra, Fourier analysis, and integration with other scientific libraries.

Pandas: A panda is a robust Python data manipulation and analysis package that is available as free software. Effectively cleaning, converting, and analyzing structured data is also provided, along with user-friendly data structures like DataFrame and Series. Users may manage a variety of data formats and carry out operations like grouping, filtering, and indexing with Pandas.

Scikit-learn: This well-known machine-learning package contains a wide range of tools and algorithms. For data preparation, model training, model assessment, and feature selection, it offers a wide variety of functions.

Split-folders: A Python module named split-folders was developed to facilitate the preprocessing of image datasets for machine learning techniques. It makes it easier to separate the test, validation, and training sets from a single photo directory. Split folders provide an easy-to-use method for this segmentation, making it easier to organize data for machine learning model training and assessment. This toolkit is very helpful for academics and practitioners dealing with huge picture datasets since it allows creation of the data splits required for model development, testing, and validation quick and simply. This contributes to the seamless creation of trustworthy machine-learning systems.

Keras: Keras is an open-source, high-level neural network application programming interface written in Python. For deep learning models, it serves as an easy-to-use, modular building and training interface. Keras, practitioners may quickly develop, test, and deploy neural network designs since it was designed with ease of use in mind. Both inexperienced and experienced researchers may use it because of its design philosophy, which emphasizes simplicity and adaptability. The default backend engine that Keras supports is TensorFlow.

Matplotlib: It’s a robust Python visualization library for data. It provides an abundance of capabilities and functions for creating static, dynamic, and interactive visualizations. Matplotlib may be used to construct a wide variety of graphs, plots, and charts.

3.4 Project Management and Financial Analysis

The waste classification project aims to develop an automated waste classification system using deep learning techniques. The project seeks to address the challenges associated with manual waste sorting and promote efficient waste management practices. This report provides an overview of the project management approach undertaken to accomplish the project objectives. The researchers raised all of the project's funding on their own. There was no need for outside financing or sponsorship for this initiative. However, extra financing would be required to cover the expenditures if the project were scaled up to handle higher data quantities or more difficult tasks. The following are the main goals of the trash sorting project:

Create a deep learning model that can correctly classify various trash kinds. Gather a sizable collection of image for assessment and training. Use the dataset and adjust the deep learning model. Implement the model's effectiveness in actual trash sorting.

3.5 Summary:

Summarize the chapter's important topics, emphasizing the relevance of methodology, design specifications, and careful consideration of hardware/software needs as well as budgetary factors. Describe how each of these elements works together to ensure that the project is carried out successfully.

CHAPTER 4
Implementation

4.1 Overview:

The use of strong data preparation methods relevant to waste characterization, this step includes the implementation of machine learning models designed for waste categorization. The chapter focuses on how parameters may be optimized to improve classification efficiency and accuracy through an iterative process of model training and prototyping. Model performance is validated by systematic testing procedures, which use measures such as accuracy and recall to provide a thorough analysis.

4.2 Train Model/ Prototype Design:

The following details are covered in detail in the "Train Model/Prototype Design" portion of the trash classification implementation chapter:

4.2.1 InceptionV3:

A convolutional neural network with 48 layers deep is called Inception-v3. The ImageNet database contains a pre-trained version of the network that has been trained on more than a million images. The pre-trained network can categorize photos into 1000 different object categories, including several animals, a keyboard, a mouse, and a pencil. An Inceptionv3 network's architecture is developed gradually and methodically, as follows: Factorized Convolutions, Smaller convolutions, Asymmetric convolutions, Auxiliary classifier, Grid size reduction

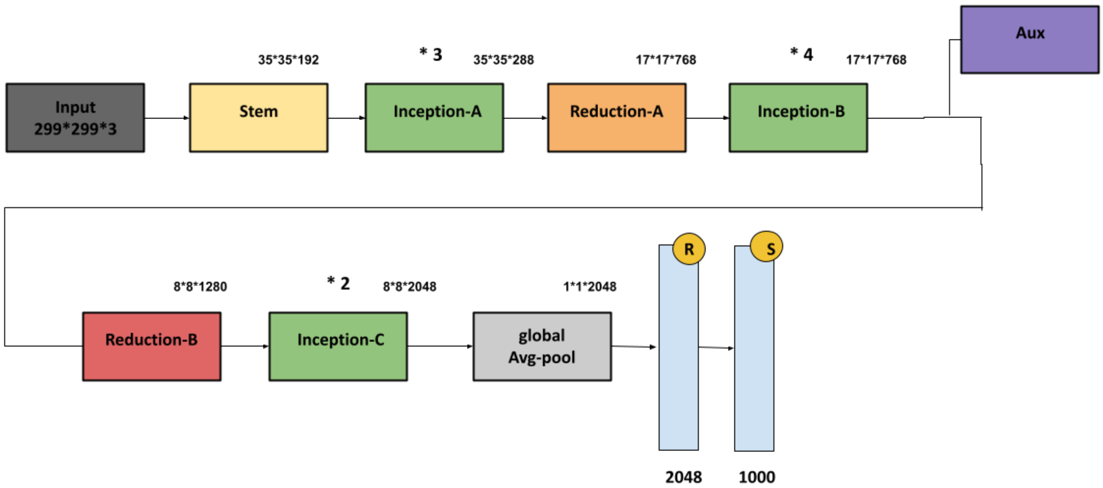

Fig.4.2.1: Inception V3 Model Architecture

4.2.2 ResNet152:

An artificial neural network (ANN) known as a residual neural network (ResNet) is based on architectures derived from pyramidal cells in the cerebral cortex. This comes from Image Recognition Using Deep Residual Learning. In order to accomplish this, residual neural networks use skip connections, or short cuts, to bypass certain layers. The way that the remaining brain systems accomplish this is by using skip associations, or short cuts to move across a few levels. ResNet-152 introduced the idea of residual learning, which uses shortcut connections to learn the removal of a feature from that layer's input.

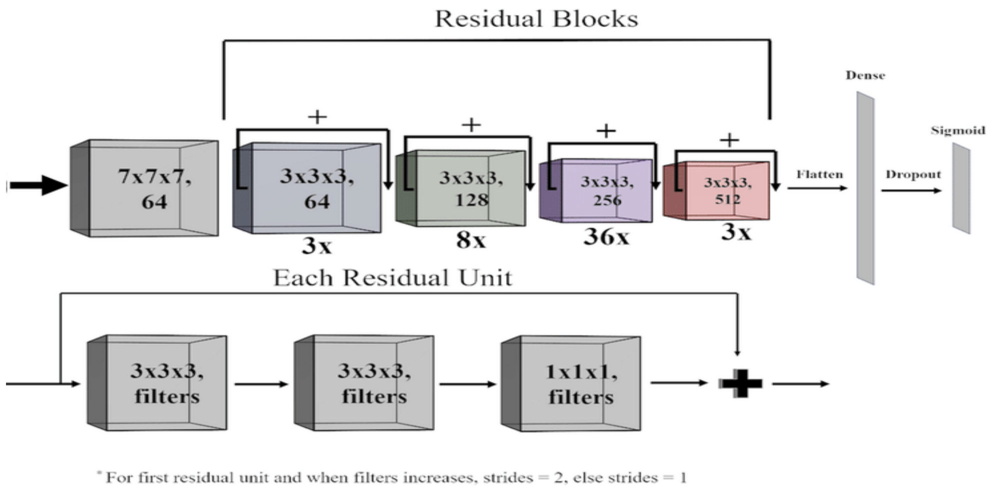

Fig.4.2.2: ResNet152 Architecture

4.2.3 DenseNet

The novel deep-learning architecture known as DenseNet—short for Densely Connected Convolutional Networks—is used for picture categorization applications. Each layer in a dense block gets direct input from all layers that came before it. Robust blocks, global average pooling layer, and transition layers make up the architecture. Dense blocks have closely spaced layers that facilitate effective information transfer and improve the expressiveness of the model. A few of the transition layers that regulate the quantity of feature maps are batch normalization and 1x1 convolutional layers. For a variety of computer vision applications, DenseNet is a popular option due to its exceptional performance on picture classification tasks.

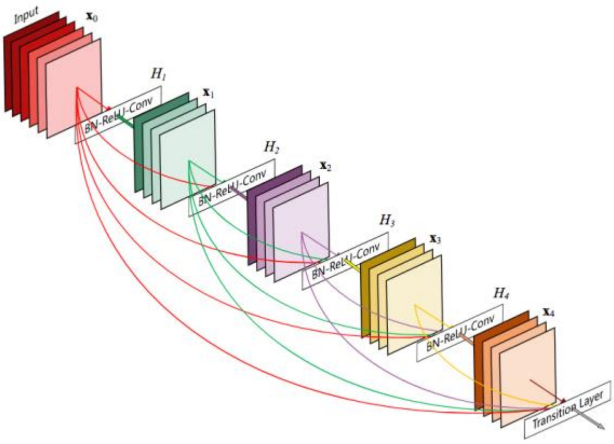

Fig.4.2.3: DenseNet Architecture

Training:

In this stage, a CNN learner model is produced. A model was trained on the dataset and its classification accuracy was tested using ResNet152, InceptionV3, DenseNet, and Vgg19. During 30 epochs (10 iterations), all representations were trained using Early Stopping call-backs. The amount of epochs without development before training is completed is known as patience. 22 = 0.999, 11 = 0.9, learning rate = 0.0001, and = 1107. The three representations were saved as.h5 files and subjected to a comparable optimizer. Every epoch, DenseNet takes 40 seconds, while InceptionV3 takes 35 seconds.

Since there were no significant imbalances in the dataset, the standard deviation was used as a model performance indicator in this analysis. Given that this work involves multi- class sorting, categorical cross-entropy was chosen as the loss objective for all CNN designs, 36 epochs, 17 batches, 0.3 dropouts, and 0.0001 learning were recorded. Model weights were optimized by Adam. Before resizing, every photo was scaled down to the architecture's standard picture size.

Dataset Preprocessing:

The dataset is organized by me such that the image sizes are similar. This preprocessing step is essential since most machine learning models require input data with uniform dimensions. Every trash item has to have a corresponding picture in order to train the model. I organize the photos based on their subjects' identities or classifications. Augmentation, normalization, and scaling are popular picture preprocessing techniques used in deep learning to enhance model performance. Data should be resized to a standard size of 224 by 224 pixels. The following step, normalization, involves scaling pixel values to a common range, often [0, 1], in order to facilitate faster training. The training dataset is diversified, and the model's resistance to size, orientation, and augmentation changes—such as shifting, rotation, and zooming—is improved.

Dataset Resize:

After loading the photos, read and process those using Python libraries. To improve the training performance, normalize the pixel values to the interval [0, 1]. Use tools like cv2 to resize each image to a standard size, usually 64x64 or 128x128 pixels. Use image.resize() or resize(). For effective processing, save these scaled photos in numpy arrays. Use a data generator to add data on-the-fly when training so that your model gets a variety of input variants.

Dataset Split:

The images need to be adjusted in size. Then their pixel values should be adjusted to range between 0 and 1. Next split the combined dataset into training, validation and testing subsets using the train test split function from sklearn. Usually this is done with 80% training, 10% validation and 10% testing split. To enhance and prepare the data during training utilize Keras ImageDataGenerator.

4.3 System Testing/ Model Evaluation:

Performance metrics play an important role in classification algorithms as they allow evaluation of the models' effectiveness and accuracy. These measurements give more detailed information about the classification outcomes and the accuracy with which the algorithm is able to distinguish between positive and negative attitudes. Now let's take a closer look at these performance metrics:

True Positive (TP):

True Positive refers to the situations in which the feeling is accurately categorized as completely positive. It indicates that the system can correctly detect the cases when there is, in fact, a favorable sentiment. TP is a metric for the number of positive examples that the algorithm successfully identified.

True Negative (TN):

True Negative denotes the situations in which the sentiment is accurately categorized as somewhat positive. It indicates that the computer can correctly detect cases with a little favorable attitude. The number of accurately detected somewhat positive situations is reflected in TN.

False Positive (FP):

False Positive refers to the situations in which the attitude is mistakenly labeled as somewhat negative. These are mistakenly classified as negative cases, even though they have a little positive attitude. FP stands for the number of cases that are mistakenly classified as negative.

False Negative (FN):

False Negative is the term used to describe situations in which a feeling is mistakenly categorized as entirely negative. These are the cases that are mistakenly classified as negative, even if they are entirely positive. FN denotes the number of cases that were mistakenly classified as negative.

All of these measures add together to help analyze and judge the sentiment categorization system. Through the examination of the TP, TN, FP, and FN distributions, we are able to have a thorough grasp of how well the algorithm performs in properly recognizing attitudes. To give a comprehensive assessment of the sentiment classification algorithm, additional performance measurements are used in addition to the metrics mentioned above:

Precession:

The percentage of pertinent occurrences among the retrieved examples is expressed as precision. It shows the proportion of really positive events among those anticipated to be positive. To compute precision, divide the total number of TP by the sum of TP and FP.

$$\text{Precision} = TP / (TP + FP) \quad \text{---------(1)}$$

Recall:

The percentage of pertinent examples that have been successfully recovered from the entire number of relevant instances is known as recall. It illustrates the efficiency with which the system detects positive examples. The calculation of recall involves dividing the total number of TP by the sum of TP and FN.

$$\text{Recall} = TP / (TP + FN) \quad \text{----------(2)}$$

F1-Score:

The F-measure takes both precision and recall into account to give a fair evaluation of an algorithm's accuracy. It emphasizes a balance between accuracy and recall, and its harmonic mean is what it is. The following formula is used to determine the F-measure:

F-measure = 2 * (Precision * Recall) / (Precision + Recall) ----------(3)

Accuracy:

Accuracy indicates how accurate the classification method is overall by comparing the anticipated and actual numbers. It is computed by dividing the total number of occurrences by the sum of TP and TN:

Accuracy = (TP + TN) / (TP + TN + FP + FN) ------------(4)

We may obtain a thorough knowledge of the efficacy of the classification algorithm by carefully examining these performance measures. We can assess the model's accuracy, precision, recall, and harmony among these metrics thanks to these measurements. We can improve the classification system and make sure it generates accurate and dependable predictions and good accuracy by using the results of this evaluation.

4.4 Summary

A summary of the implementation phase, highlighting key activities, outcomes, and lessons learned. This section concludes the chapter on implementation, providing a comprehensive view of the progress and achievements in waste classification.

CHAPTER 5
Result And Analysis

5.1 Overview:

This chapter presents the results of the evaluation of the classification model and explores the specifics of the experimental results. It describes how well the model classifies different kinds of garbage, with quantitative measures like accuracy, precision, recall, and F1-score providing evidence. Furthermore, qualitative analysis offers better understanding of the model's performance by illuminating instances of waste items that have been categorized properly and wrongly. The chapter highlights the importance of the findings for waste management methods by discussing the effects of preprocessing procedures on model outcomes and offering a critical assessment of the findings.

5.2 Experimental/ Simulation Result:

In this section, we present the implementation results of our study. Using a dataset of 2080 picture data, we deployed five different machine learning and deep learning algorithms and evaluated how well they performed in terms of accuracy, F1 score, precision, and recall. In order to obtain insight into the most common and distinguishing terms used by each class as well as the causes of misclassification, we also carried out exploratory data analysis and displayed the word clouds and confusion matrices for each method.

We employed the following machine learning algorithms:

ResNet152

InceptionV3

DenseNet.

Our random seed of 42 helped us divide the dataset into three categories: 80% training, 10% validation, and 10% testing. For all algorithms aside from CNN we employed their default settings.

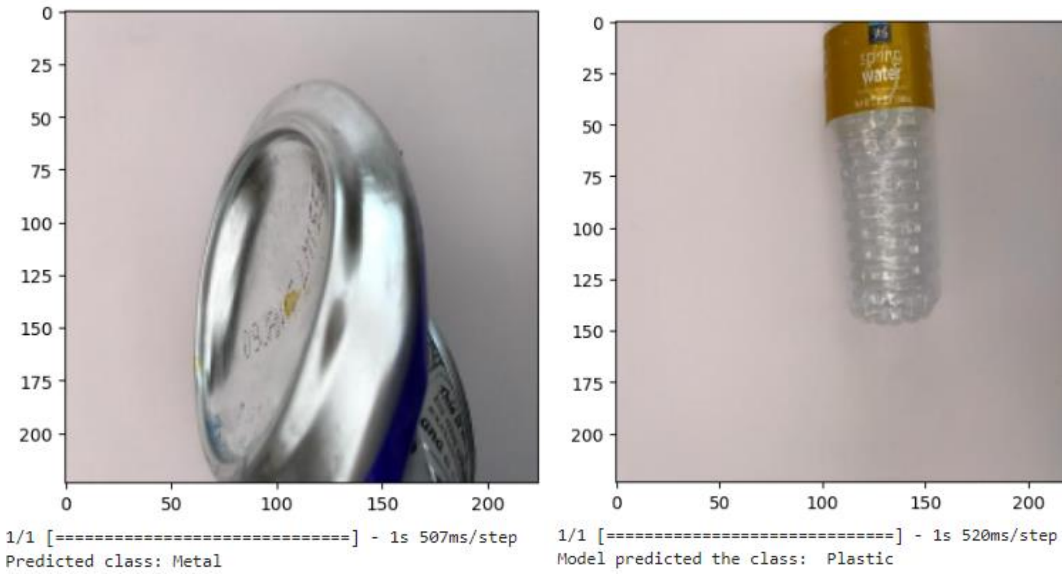

Fig.5.2.1 Output of different classes

In the first image, a close-up of a metal can's top is shown and the model accurately predicted that the image would be classified as "Metal." In image number two, there is a yellow label on a plastic water bottle, and the model correctly identified the class as "Plastic." In order to show how well the model is in recognizing and classifying materials according to their visual attributes, the bottom of each photo displays the model's prediction time and step count.

5.3 Performance/ Comparative Analysis:

The following table summarizes the performance metrics of each algorithm on the test-set.

Table 5.3.1: Performance metrics of different methods

Algorithms	Accuracy	F1 Score	Precision	Recall
ResNet152	*98.00%*	98%	96%	90%
InceptionV3	*88.00%*	*87%*	*88%*	*87%*
DenseNet	*90.00%*	*89%*	*90%*	*88%*

In the process of classifying garbage using several deep learning algorithms. The ResNet152, InceptionV3, and DenseNet designs are the performance measures used in the experiment. With an F1 Score of 98%, precision of 96%, and recall of 90%, ResNet152 attained the greatest accuracy of 98.00%. With 88.00% accuracy, 87% F1

Score, 88% precision, and 87% recall, InceptionV3 is performing well. DenseNet achieved competitive performance with 90.00% accuracy, 89% F1 Score, 90% precision, and 88% recall. These results highlight the higher performance of ResNet152 in waste material classification, with InceptionV3 and DenseNet both demonstrating efficacy, but with somewhat lower total metrics. These metrics, which were calculated in the context of trash categorization using conventional assessment techniques, confirm that these deep learning models are appropriate for use in environmental applications of this kind.

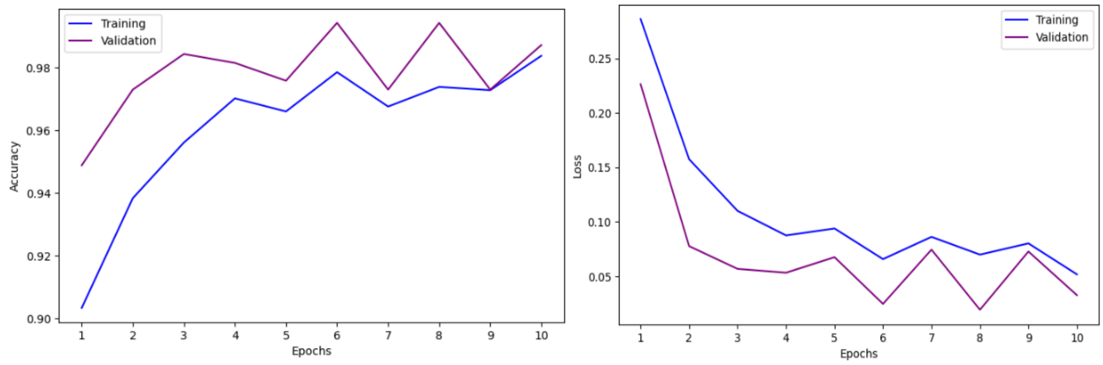

Fig.5.3.1: Accuracy and Loss of ResNet152

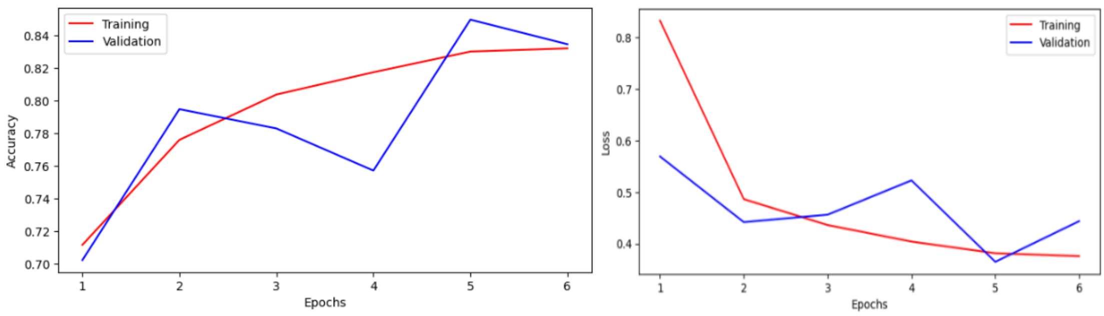

Fig.5.3.2: Accuracy and Loss of InceptionV3

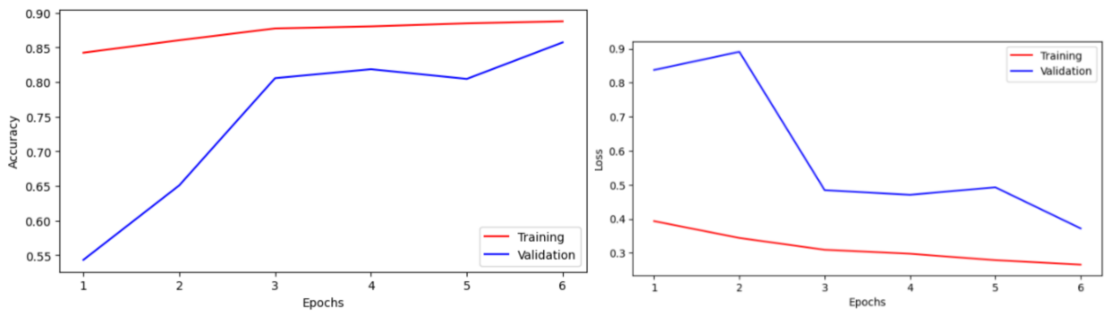

Fig.5.3.3: Accuracy and Loss DenseNet

Fig.5.3.4: Confusion Matrix of ResNet152

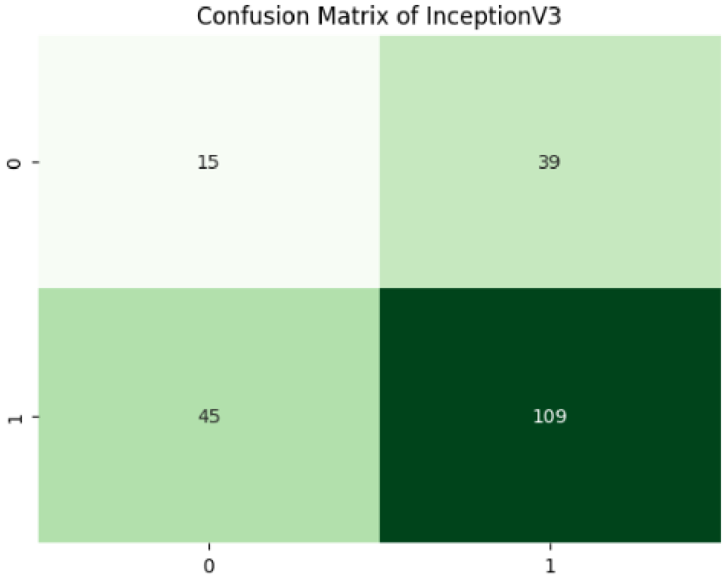

Fig.5.3.5: Confusion Matrix of InceptionV3

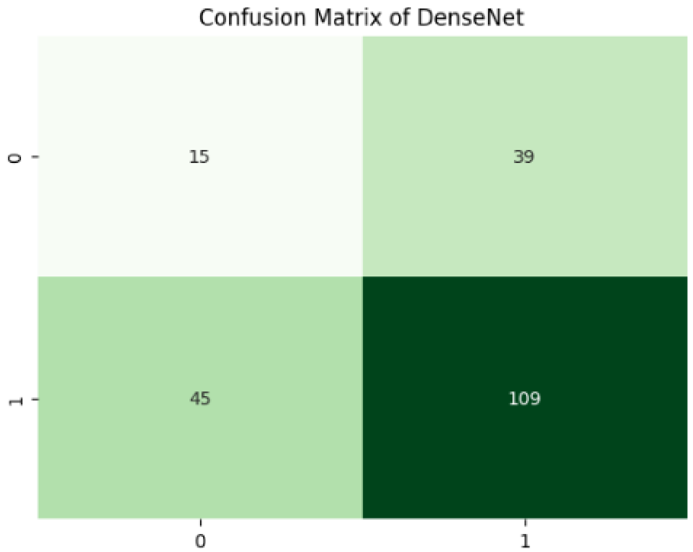

Fig.5.3.6: Confusion Matrix of DenseNet

From table 4.2.1 see that ResNet152 has the highest accuracy from others. After that added accuracy and loss plots for different models. From those plots, we can easily understand them. And then, added confusion matrix of models.

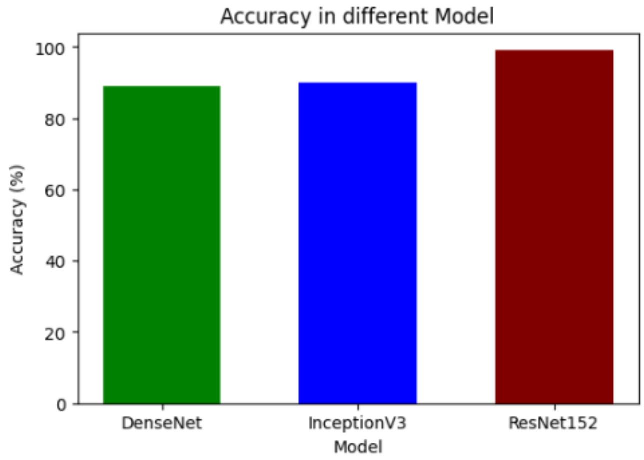

Fig.5.3.7: Accuracy in different model

ResNet152 was the algorithm that performed the best in terms of accuracy and F1 score, as shown by the table and fig4.2.6. InceptionV3, was the method with the lowest accuracy than ResNet152 and F1 score performance. Waste pictures most often utilized the phrases "metal" and "plastic."

We may use other classification research tools to investigate these data and uncover the factors influencing each algorithm's performance. We can consider the following factors: The dataset's features, which include the quantity, quality, balance, and representativeness of the waste materials; algorithms' feature labels, which include the models' interpretability, scalability, robustness, and complexity; and classification process features, which include the methods for data collection, preprocessing, feature engineering, model selection, training, testing, and evaluation. By examining these factors, we may learn about the advantages and downsides of each method, as well as how to tweak or improve them for application in various circumstances. For example, we might look at how to optimize each algorithm's settings to get better results, how to manage unequal data, and how to extract additional information from the data using various feature extraction methodologies.

5.4 Summary:

In this chapter's summary, the trash classification project's outcomes demonstrated that ResNet152 was the best algorithm, with the maximum accuracy of 98.00% and reliable metrics for F1 Score, precision, and recall. DenseNet and InceptionV3 both performed admirably, with accuracy rates of 90.00% and 88.00%, respectively. These results highlight how well deep learning models recognize waste products, which has ramifications for improving waste management procedures by using automated sorting and recycling systems. In order to achieve environmental conservation goals, further research might concentrate on integrating real-time classification systems in waste facilities, investigating model optimization strategies, and growing the dataset to better generalization across a variety of waste kinds and situations.

CHAPTER 6

Impact on Society, Environment and Sustainability

6.1 Impact on Life

Lack of waste management has a tremendous effect on life since it poses serious risks to biodiversity and human health. Inadequate disposal techniques cause dangerous materials and organisms to contaminate the air, water, and soil, raising the risk of infections, respiratory illnesses, and other health problems in populations exposed to contaminated surroundings. Waste pollutants also cause habitat disruption, pollute food chains, and lead to biodiversity reductions, which negatively impacts wildlife and ecosystems. Furthermore, the cumulative consequences of pollution linked to waste worsen climate change, endangering the resilience and stability of ecosystems that are necessary to support life on Earth. In order to preserve biodiversity, protect human health, and guarantee a sustainable future for all species, it is imperative that these issues be addressed through sustainable waste management techniques.

6.2 Impact on Society & Environment

The environment and society are greatly impacted by improper waste management, making the adoption of sustainable waste management strategies imperative. Inadequate waste management practices have a social cost that increases pollution of the air, water, and land. Through greenhouse gas emissions from decomposing trash, this pollution worsens global warming by endangering ecosystems, biodiversity, and natural resources. When poorly disposed of garbage attracts pests that spread illness and exposes populations to potentially harmful chemicals, the hazards to public health increase. In addition, the overuse of resources in the manufacturing and disposal of products further depletes priceless natural resources, hence efforts to reduce waste, recycle, and adopt a circular economy are required in order to preserve resources for future generations.

Improper garbage management has significant negative effects on the environment. The main disposal locations, landfills, damage soil and water with hazardous liquid that is created during the breakdown of trash. Waste, especially plastics, that is burned for energy releases greenhouse gases and toxic chemicals into the atmosphere, endangering human health and aggravating climate change. Waste that is thrown into water bodies damages aquatic ecosystems, causing ecosystems to be upset, water quality to be compromised, and marine life to be endangered. The repercussions of climate change are exacerbated by methane emissions from the decomposition of landfill trash, which emphasizes the urgent need for sustainable waste management techniques to reduce environmental degradation and foster ecological resilience.

6.3 Ethical Aspects

At several phases of its lifespan, including extraction, manufacture, use and disposal, waste can have irreversible consequences on the ecosystem. Along with garbage, the following are some of the major environmental effects:

Inadequate waste management has an impact on many different environmental areas. In addition to depleting valuable resources, the extraction and fabrication of materials for products—such as metal extraction, oil drilling, and deforestation for paper production also contribute to the disturbing loss of biodiversity and habitats. Contamination has far-reaching effects, including soil, water, and air pollution. Air quality problems are made worse by improper waste disposal techniques, most notably incineration, which emits hazardous chemicals and greenhouse gases into the environment. Similarly, typical disposal sites like landfills have the potential to pollute water bodies through leachate, endangering the delicate balance of aquatic ecosystems. Organic waste is often disposed of in landfills, which exacerbates environmental problems by producing methane, a powerful greenhouse gas that intensifies the effects of climate change. The widespread problem of inappropriate plastic waste disposal results in marine pollution, which poses a threat to marine life by causing ingestion, entanglement, and habitat loss. The consequences encompass soil deterioration resulting from hazardous waste disposal and landfills, making the soil unusable for farming and perhaps endangering human health due to the build-up of harmful materials. Furthermore, waste management activities—which include collection, transportation, recycling, and treatment—constitute a significant amount of energy and add to carbon emissions, escalating climate change concerns and depleting already limited fossil fuel supplies. People who live close to garbage disposal plants run the danger of developing respiratory ailments and other illnesses as a result of being exposed to pollutants and harmful chemicals. A thorough strategy is required to mitigate these complex environmental problems. It is imperative to put into practice appropriate waste management techniques, which include recycling, trash reduction, and the creation of a circular economy. Simultaneously, raising public awareness and promoting responsible consumption are essential elements of a comprehensive plan to reduce waste's total environmental impact and clear the path for a more resilient and sustainable future.

6.4 Sustainability Plan

Creating a circular economy and efficient waste management need creating a sustainability strategy for trash classification. You may maximize recovered resources, lessen environmental effects, and encourage sustainable production and consumption by putting into practice appropriate waste categorization procedures. Obviously, here some further instructions for developing a trash sorting sustainability plan: Waste evaluation: To identify particular difficulties and possibilities for waste management, do a detailed evaluation of the types and amounts of trash generated in your community or company. Categorization System: Sort garbage into four categories, like- organic, recyclable, hazardous, and non-recyclable. Create a method that is both understandable and useful. Make ensure the appropriate disposal procedures for each category are outlined explicitly. Community-Based Learning: Conduct seminars, educational campaigns, and community outreach activities to increase awareness of the importance of disposing of garbage properly. Encourage community involvement by highlighting the advantages sustainable waste management procedures have for the environment and human health. Segregation Techniques: Provide distinct containers for every type of garbage and instruct people on proper waste sorting techniques to establish efficient waste segregation techniques. Community Education: Highlight the advantages of sustainable waste management for the environment and human health by putting a focus on community outreach programs, seminars, and educational campaigns that emphasize the significance of proper trash disposal. Rules and Guidelines Compliance: Verify that the sustainability strategy abides with the rules and procedures currently in place for waste management. Keep abreast of any modifications to waste management-related laws, and adjust the strategy as necessary. Innovation and Improvement: Foster a culture of innovation in waste management technology and investigate novel approaches to reduce trash generation, optimize recycling procedures, and advance the circular economy. Encourage ongoing participation and engagement from companies, stakeholders, and the community to maintain a shared commitment to ethical waste categorization and management.

These steps might help you create a solid waste categorization sustainability strategy that promotes a more sustainable future and a healthier environment.

6.5 Summary

This chapter describes our investigation into the complex effects of waste categorization. We started by looking at how it directly affects ecosystems and human health, emphasizing how important it is to accurately categorize in order to reduce hazards. The environmental and social aspects emphasized how mismanagement has significant negative economic effects and how urgent it is to implement sustainable practices to stop social injustice and environmental deterioration. The moral requirements for managing garbage were made clear by ethical considerations. A sustainable plan offered creative approaches that used technology and law to effectively control waste and save resources. In conclusion, it is clear that correctly classifying trash is essential to the health of society, the environment, and the economy. As such, it is necessary to conduct continuing study and work together to develop classification methods and techniques in order to ensure a sustainable future.

CHAPTER 7

Summary, Conclusion, Recommendation And Implication For Future Research

7.1 Conclusions

To sum up, the combination of transfer learning with DenseNet architecture in the context of trash categorization signifies a notable advancement in the precision and effectiveness of waste management systems. The study's examination of pre-trained models and optimization on a particular trash dataset highlights how useful and efficient it is to use current knowledge for targeted applications. Improved classification results are achieved by catching subtle characteristics in garbage photos thanks to DenseNet's flexible dense connection patterns. The experimental findings, which show significant accuracy increases, amply illustrate the approach's real benefits. Combining DenseNet with transfer learning not only expedites training but also gives waste classification models the ability to identify complex patterns with greater accuracy. The combination of transfer learning and DenseNet provides a workable answer to the problems arising from garbage sorting, opening the door to more ecologically friendly and sustainable waste management techniques.

Moreover, the accomplishment of this research has greater significance for practical waste management implementations. One way that cutting-edge machine learning algorithms help with the continuous attempts to minimize environmental effect is by optimizing categorization systems. The development of precise and automated garbage sorting technology becomes essential as waste creation rises internationally. This study highlights the potential of cutting-edge technology to generate positive change in environmental sustainability by utilizing DenseNet and transfer learning to stimulate the growth of intelligent waste management systems.

7.2 Further Suggested Works

In general, using transfer learning to identify garbage is a promising approach to resolving waste management issues. As these technologies develop, they have the potential to revolutionize recycling and waste management and contribute to the creation of a cleaner, healthier, and more sustainable future. We plan to add even more variability to our dataset in our next study so that we may test it with other CNN architectures and cross-sensor validation methods. Another line of investigation is the application of our proposed method to video using a robotic garbage sorting system.

7.3 Limitations/ Conflict of Interests

In this paper or project, I use small size of dataset for trash classification. The reduced dataset size may make it difficult to capture the entire diversity and unpredictability of waste materials seen in real-world circumstances, thereby restricting the algorithm's performance in detecting less frequent or variable trash items. A further danger is over fitting to the unique features of the small dataset, which might impair model's performance on bigger datasets. To improve the model's applicability and dependability in real-world waste management settings, these constraints would need to be addressed by enlarging the dataset to include a wider variety of trash kinds and circumstances.

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APPENDIX A

COURSE OUTCOMES, COMPLEX ENGINEERING PROBLEMS (EP) AND COMPLEX ENGINEERING ACTIVITIES (EA) ADDRESSING

Title:

WASTE CLASSIFICATION USING TRANSFER LEARNING AND DENSENET

Student ID: 193-15-2941

CO Description for FYDP

CO	CO Descriptions	PO
Phase - I		
CO1	Integrate recently gained and previously acquired knowledge to identify a pneumonia detection problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO3**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO4**
Phase - II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO5**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO6**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO7**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO8**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO9**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO10**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO11**

CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering
Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project demonstrates **fundamental engineering (K3)** principles by employing ML and DL, data resize, dataset preprocessing techniques and diverse CNN architectures for image processing and classification tasks. The project demonstrates **specialist knowledge (K4)** by conducting transfer learning with advanced CNN architectures like-ResNet152, VGG19 and DenseNet, enhancing waste detection accuracy in metal and plastic images, crucial for computer-aided diagnosis.	**Page no:** [11-12] **Section:** [3.2] **Page no:** [1] **Section:** [1.1]
				The project applies **engineering practice & design (K5)** by the figure of process of experiments. The project addresses **engineering practice & technology (K6)** by employing CNN model.	**Page no:** [11-12] **Section:** [3.2] **Page no:** [14] **Section:** [3.4]
				This project ensures to **K8 (Research Literature)** by synthesizing insights from recent studies, to advance waste detection	**Page no:** [6-9] **Section:**

				using deep learning, showcasing a comprehensive understanding of current methodologies.	[2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2 and CO7	This project addresses **EP-2** by recognizing the hurdles in waste detection, including limitations of traditional methods and the complexities of integrating transfer learning and deep CNNs. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining diagnostic methodologies.	**Page no:** [9-10] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis requirements**	Yes	CO2 and CO6	This project addresses **EP-3** by meticulously comparing experimental outcomes, highlighting Transfer Learning as the chosen significant solution for enhancing waste detection amidst multiple potential approaches.	**Page no:** [15-17, 18] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach extends beyond computer science and engineering, impacting environmental impact of waste disposal like waste, contributing to reduce waste from our environments which indicate **EP-4**.	**Page no:** [6-9] **Section:** [2.2, 2.4]
5.	**EP5: Extends of Application codes**	No	CO5	N/A	N/A
6.	**EP6: Extent of stakeholder**	No	CO5	N/A	N/A

7.	**Interdependence**	Yes	CO5	This project's comprehensive approach addresses high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology, ensuring a holistic solution to complex challenges in waste detection which ensures **EP-7**.	**Page no:** [11-14] **Section:** [3.2,3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EP Definition	Attainment	CO	Justification	References
1.	**EA1: Range of Resource**	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in waste detection through transfer learning and deep CNNs.	**Page no:** [14] **Section:** [3.5]
2.	**EA2: Level of interaction**			NO	
3.	**EA3: Innovation**			NO	
4.	**EA4: Consequences for society and the environment**	Yes		This project contributes to society by improving human welfare and environmental sustainability through advanced waste detection methods, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines for our waste data privacy.	**Page no:** [21,22,26] **Section:** [5.1, 5.2, 5.4]
5.	**EA5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach in trash detection	**Page no:**

				through transfer learning and deep CNNs, demonstrated through preliminary terminologies and a Comprehensive comparative analysis, offering new insights into the field.	[6,8,9] **Section:** [2.1, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	EP Definition	Attainment	Justification	References
1.	**CO4**	**Yes**	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [4] **Section:** [1.6]
2.	**CO9**	**Yes**	The project demonstrates adherence to ethical principles by prioritizing environmental protection, obtaining community consent, and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of advanced robotic systems which comply with **CO9**.	**Page no:** [22-25] **Section:** [5.3]
3.	**CO10**		NO	
4.	**CO12**	**Yes**	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [22-25] **Section:** [5.3]

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