Garbage Classification using transfer learning with CNN and Generative Adversarial Networks (GAN)

A DISSERTATION REPORT SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE DEGREE OF

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IN

DATA ANALYTICS

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1 Introduction

The management of waste is of utmost importance in the preservation of the environment and the promotion of sustainable development. The importance of garbage sorting is multifaceted, encompassing ecological and economic factors (Alsabei *et al.*, 2021).

The implementation of appropriate waste management practices mitigates the potential for environmental contamination. The breakdown of unsorted organic wastes has the potential to generate methane, a highly potent greenhouse gas. Likewise, the inadequate management of electronic trash can result in the release of hazardous compounds into the soil, so polluting groundwater reservoirs (Rakib *et al.*, 2021)

The process of garbage classification plays a crucial role in enhancing the effectiveness of material recycling. Properly categorizing metals, polymers, paper, and glass facilitates their subsequent reuse or repurposing, leading to a reduction in the extraction of primary resources (Gundupalli, Hait and Thakur, 2017; Rousta *et al.*, 2017).

The use of efficient waste categorization practices has the potential to result in financial benefits. The implementation of recycling and composting procedures for segregated trash can yield economic advantages, as opposed to the conventional practice of solely depositing all waste in landfills (Rakib *et al.*, 2021).

Inadequate waste disposal practices have the potential to serve as favourable environments for the proliferation of pathogens and pests, hence facilitating the transmission and dissemination of diseases. The implementation of effective waste classification practices plays a crucial role in facilitating the proper management and disposal of rubbish, hence mitigating any health hazards associated with improper waste handling. According to the source provided, (Rousta *et al.*, 2017).

The significance of waste categorization is underscored by statistical data. According to the World Bank, there is a projected increase in worldwide garbage creation from 2.01 billion tonnes in 2016 to 3.40 billion tonnes by the year 2050 (Kaza *et al.*, 2018). Moreover, it is worth noting that a significant proportion of the waste stream in the United States, specifically 75%, possesses the potential for recycling. However, the actual recycling rate stands at a mere 30%. Landfills are experiencing a rapid rate of filling, with projections indicating that the United Kingdom is anticipated to exhaust its available space by the year 2024. The recycling sector, bolstered by effective waste segregation practices, generates employment opportunities and holds a market valuation of $200 billion only in the United States. In addition, it is worth noting that an estimated 8 million metric tonnes of plastic trash are introduced into the Earth's seas annually, underscoring the imperative for effective waste categorization practices in order to mitigate the adverse effects of marine pollution (Kaza *et al.*, 2018).

In light of the aforementioned statistical data and the wider ramifications associated with inadequate waste management practices, there exists an urgent imperative to augment the efficacy of rubbish categorization processes.

1.1 Motivation

The issue of waste management has emerged as a significant global concern as a result of various factors, including the rapid pace of urbanization, population expansion, and escalating levels of consumerism (Rakib *et al.*, 2021). Consequently, there has been a substantial rise in global trash production. Improper waste management practices have been found to have detrimental effects on both the environment and the well-being of humans and wildlife (Rakib *et al.*, 2021). The implementation of garbage classification has become a pivotal approach in promoting effective trash recycling, reuse, and disposal (Wu *et al.*, 2023).

Technological innovations have demonstrated the potential to tackle the complexities associated with garbage management. The field of machine learning, namely in the domain of image processing, has presented novel opportunities. Convolutional Neural Networks (CNNs), a class of deep learning algorithms that are specifically designed for processing visual input, have exhibited significant promise in several applications, particularly in the domain of image recognition (Alsabei *et al.*, 2021). Convolutional Neural Networks (CNNs) have the potential to be utilized for the purpose of automating garbage classification, hence enhancing the efficiency and accuracy of the classification process.

Moreover, the utilization of Generative Adversarial Networks (GANs) has played a pivotal role in the production of artificial data (Alsabei *et al.*, 2021). This has the potential to enhance the calibre and inclusivity of training datasets utilized for garbage categorization programs. By incorporating Generative Adversarial Networks (GANs) into Convolutional Neural Networks (CNNs), the trash classification systems can exhibit increased resilience, effectively mitigating the challenges posed by limited data availability and improving the overall operational effectiveness (Alsabei *et al.*, 2021).

1.2 Research Question

Given the potential of CNNs and GANs in image classification, the primary research question that drives this study is:

"How effective is the integration of Transfer Learning the Convolutional Neural Networks and Generative Adversarial Networks in the task of garbage classification compared to conventional methods?"

1.3 Aims and Objectives

Aim: The aim of this study is to examine the effectiveness and practicality of utilizing Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) for the purpose of garbage classification. The aim is to improve the accuracy, efficiency, and scalability of waste management systems.

The objectives of this study are:

1. This paper aims to conduct a comprehensive examination of the extant literature pertaining to strategies for trash classification. The review will critically assess the current issues associated with this domain and explore the potential of Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) in mitigating these challenges.

2. The application of Generative Adversarial Networks (GANs) in the context of data augmentation is explored in this study. Specifically, the focus is on producing synthetic images representing various trash categories, with the aim of mitigating the prevalent challenges associated with limited and imbalanced datasets in the field of garbage categorization.

3. The objective of this study is to develop and deploy a Convolutional Neural Network (CNN) model through transfer learning specifically designed for the purpose of trash categorization. The performance of this model will be assessed by comparing its results with established benchmark datasets.

4. The integrated approach seeks to leverage the respective advantages of Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) in order to improve classification accuracy. This is achieved by training the CNN using a combination of real images and images produced by GANs.

5. This study aims to compare the proposed integrated methodology with conventional garbage classification methods, focusing on the enhancements in accuracy, speed, and scalability.

1.4 Research Outline

Chapter 1: Introduction

In this introductory chapter, the research aims to set the stage for the entire thesis, providing context, motivation, research questions, and outlining the overall structure.

Chapter 2: Literature Review

This chapter delves into an extensive literature review, focusing on the concept of garbage classification using transfer learning with CNN and GAN. It reviews existing literature in the field to provide a comprehensive understanding of the research area.

Chapter 3: Methodology

The methodology chapter discusses the key elements of the research process, including the dataset used, exploratory data analysis, data augmentation using Generative Adversarial Networks (GANs), modeling techniques, and the evaluation metrics employed.

Chapter 4: Results and Analysis

This chapter presents the results of the research, divided into two sections: "Without GAN" and "With GAN." It provides an in-depth analysis of the findings from both scenarios.

Chapter 5: Conclusion and Future Scope

The final chapter summarizes the key findings of the study and draws conclusions based on the results and analysis. Additionally, it discusses the future scope of the research, suggesting potential areas for further exploration.

2 Literature Review

The current trend of waste management techniques all rests on the main goal of achieving environmental sustainability, with garbage classification serving as a key component. The Responsible management of garbage has become more and more important, with a focus on expediting the procedures of classification and recycling. This sense of urgency results from growing worries about environmental degradation, the exhaustion of priceless resources, and the damaging effects of waste on the ecosystems (Gedik, Selcuk and Lav, 2021). The development of complex systems and innovative technology is urgently needed as the world community deals with the rising levels of garbage creation. These systems can not only handle the time-consuming task of sorting waste but also significantly improve the accuracy and effectiveness of the classification procedure. Now, as a paradigm shift in the field of garbage categorization, the creative combination of transfer learning, “Convolutional Neural Networks (CNNs)”, and “Generative Adversarial Networks (GANs)” assumes centre stage.

The primary aim of this literature review is to conduct an extensive exploration of how the integration of transfer learning, “Convolutional Neural Networks (CNNs)”, and “Generative Adversarial Networks (GANs)” has the potential to bring about a revolution in the field of garbage classification. The ultimate objective is to provide a comprehensive comprehension of this pioneering approach and its substantial capacity to reshape waste management methodologies. The overarching aspiration is to overcome the constraints typically associated with traditional garbage classification methods by leveraging the combined knowledge, methods and advancements inherent in transfer learning, CNNs, and GANs (Dong *et al.*, 2022). The fusion of these principles illuminates a pathway towards a more environmentally aware and sustainable future. The authors are dedicated to establishing a sturdy basis for the proposed approach that amalgamates transfer learning, CNNs, and GANs by modernise garbage classification practices, ushering in a transformative impact that contributes to the realization of a cleaner and more eco-friendly environment for both current and future generations.

2.1 Concept of garbage classification by transfer learning with CNN and GAN

A vital task within the broader context of waste management is garbage classification, the act of dividing waste into separate groups, such as recyclables, organic materials, and non-recyclables. In addition to easing the load on landfills, efficient garbage classification also makes it easier to recover valuable materials, reduces environmental pollution, and reduces the carbon footprint associated with waste disposal. Traditional waste sorting facilities have relied heavily on human labour and crude machinery for classification. However, these procedures are frequently labour-intensive, prone to mistakes, and unable to manage the complexity and amount of trash growing in our modern world.

The advent of advanced technologies, particularly within the realm of artificial intelligence, has ushered in a profound transformation in the approach to garbage classification. A pivotal development is transfer learning, a subset of machine learning which has proven to be an invaluable asset in harnessing pre-trained models for novel tasks (Gulzar *et al.*, 2023). Transfer learning facilitates the application of knowledge acquired from a source domain to a target domain. In the context of garbage classification, it allows us to capitalize on the wealth of data and patterns acquired by deep learning models in tasks such as image recognition. Fine-tuning these pre-trained models for waste sorting yields a significant enhancement in classification accuracy, even when dealing with limited labelled data.

"Convolutional Neural Networks (CNNs)" have stood out among the variety of deep learning models due to their exceptional skill in image categorization tasks. CNNs are particularly effective at identifying and classifying objects and materials within images, making them well-established for the visual identification aspect of garbage categorization (Almeida *et al.*, 2022). CNNs are used in garbage sorting procedures to improve classification accuracy while automating the process. Additionally, the architecture of CNNs has changed over time, producing models that are more effective and efficient and, as a result, better suited to the task of classifying garbage (Na *et al.*, 2022).

"Generative Adversarial Networks (GANs)" have also become an essential tool for data augmentation and synthesis, though not for straight categorization (Hung, 2023). A generator and a discriminator network combine their efforts to produce synthetic data in GANs. GANs offer an answer to the problems of data scarcity in the context of garbage classification (Fung *et al.*, 2023). They can produce real artificial data, which increases the training dataset and increases the robustness of the garbage classification model.

This review of the literature will explore the field of garbage classification using CNNs and GANs together with transfer learning. It will provide an in-depth analysis of how these technologies can be used to improve waste management practices.

2.2 Review of existing literature

According to (Alsabei *et al.*, 2021), urban garbage accumulation is a developing problem that presents serious environmental and health risks. Rapid industrialization has increased trash output, putting pressure on the systems in place for managing waste. Recycling is a promising alternative, however, it is challenging to identify materials effectively for recycling. This work presents six material "transfer learning" models for autonomous garbage classification. The pre-trained models include "ResNet50, VGG16, InceptionV3, and Xception. "A "Generative Adversarial Network (GAN)" was used for data augmentation. The results show that whereas "ResNet50" and "InceptionV3" models are sensitive to additional "fabricated input", resulting in a loss in "accuracy", "Xception" and "VGG16-based" models are more resistant.

The study paper by (Chatterjee *et al.*, 2022), stated that "Industrialization-driven garbage accumulation" in metropolitan areas is becoming more of a problem and is hazardous to the environment and human health. It is crucial to manage garbage effectively, but it can be challenging to precisely classify things for recycling. This study suggests automatically classifying six waste products such as cardboard, glass, metal, paper, plastic, and trash using transfer learning models. To test pre-trained models, "generative adversarial networks (GANs)" were used to augment the data. These GANs included "ResNet50, VGG16, InceptionV3, and Xception". Notably, whereas "ResNet50 and InceptionV3" models were vulnerable to additional fabricated input, resulting in accuracy loss, Xception and VGG16-based models demonstrated robustness (Wang *et al.*, 2023). Effective waste categorization methods and the significance of model choice are clarified by this study.

(Lilhore *et al.*, 2023), described in this paper that effective garbage collection and classification are essential as industrialization and smart city efforts grow. Waste management has been transformed by deep learning techniques, which have improved operations including collection, categorization, composting, and disposal. To classify sustainable trash, this work offers a hybrid "CNN-LSTM" model with transfer learning. Making use of the advantages of "Convolutional Neural Networks (CNN)" and "Long Short-Term Memory (LSTM)", it divides garbage into recyclable and organic categories. To reduce overfitting, the model uses advanced data augmentation techniques and transfer learning from ImageNet. Evaluation of the TrashNet dataset indicates its exceptional performance, outperforming existing deep learning techniques with a remarkable precision of 95.45%.

According to (Zhang *et al.*, 2023), Existing transfer learning-based trash classification techniques struggle with tiny datasets and few categories, and their high parameter requirements prevent them from being used on compact devices like smartphones or such as "Raspberry Pi". A revolutionary cascade strategy that outperforms transfer learning in large-scale trash classification with fewer parameters and shorter training times is offered as a solution to this problem. The study investigates several "convolutional neural network" architectures and carries out tasks where the target domain either coincides with the source domain or deviates from it. It should be noted that the strategy using "ResNet101" as a foundation performs exceptionally well and introduces the ground-breaking pairing of pre-trained CNNs with extreme learning machines for trash classification, minimizing training time and parameters.

To effectively address ecological and health issues brought on by irresponsible waste disposal, effective waste segregation is essential in the twenty-first century as stated by (Kumsetty *et al.*, 2023). Landfills and other conventional disposal techniques are not environmentally friendly. The automated waste classification method presented in this research is computer vision-based, and it improves dataset quality through data augmentation and picture processing. "ResNet and VGG" are two transfer learning models that are used for quick and precise categorization. The model is tested on the "TrashNet and TACO" datasets, surpassing state-of-the-art models by a considerable 16% on TACO and attaining an astounding 93.13% accuracy on "TrashNet", encouraging reuse and environmentally beneficial practices.

The evaluations by (Dhande, 2022), have stated that with tons of rubbish produced every day, most of which ends up in landfills, waste management is a problem on a global scale. Due to emotions and prejudices, human-based waste classification is unsafe for human health and prone to mistakes. This study uses "deep learning" and image classification to separate recyclable waste from organic waste utilizing transfer learning models such as "VGG16 and DenseNet-121". When image segmentation is used for classification, "VGG16" and "DenseNet-121" each achieve an accuracy of 87% and 90%, respectively.

According to (Jin *et al.*, 2023), Environmental contamination must be reduced by effective waste recycling, and rubbish classification is crucial to this process. Deep learning and transfer learning are used by a machine vision system to increase categorization capacity and lower labour expenses.

The approach incorporates an enhanced “MobileNetV2” model with transfer learning to improve model generalization and attention methods to increase recognition accuracy (Hassan *et al.*, 2021). To operate in real-time on innovative devices, "Principal Component Analysis (PCA)" decreases the dimension. On the "Huawei Cloud" datasets, experimental findings show a 90.7% accuracy with an average inference time of 600 ms on a Raspberry Pi 4B. A garbage sorting prototype that achieves an accuracy of classification of 89.26% is a useful tool for recycling waste sustainably (Nwe, 2020).

Maintaining cleanliness in construction is essential for safety, but frequent physical inspections often present difficulties. To describe the drawbacks of classifying cluttered construction housekeeping images, this paper by (Lim *et al.*, 2023), evaluates a computer vision solution for automated monitoring of housekeeping. The research involves “Swin-transformer” as the best foundation architecture and comprises self-supervised learning for extracting features to recognize such images, acquiring 84% accuracy. Particularly in entailed learning contexts and with fewer images of training, the experiments demonstrate that self-supervised learning surpasses supervised learning by 1-4% in the accuracy of prediction, precision, and recall, presenting a promising replacement for effective housekeeping monitoring in construction.

Plastic, paper, glass, trash, cardboard and metal are the six categories used in the study by (Kulkarni and Kannamangalam Sundara Raman, 2018), to group the waste materials found in collaged images. It combines “Faster R-CNN” for object identification with “Hybrid Transfer Learning” for classification. The study describes their architecture, which employs “GANs” for creating collages and an improved “Faster R-CNN” for object identification while defining the waste categorization challenge and research related to the review. The process of dataset-building and experiment findings are described in detail. The study provides a thorough technique for waste particle identification and categorization in collaged images as it discusses optimization and improvements for the future to their methodology.

In India, there is an evolving awareness of environmental issues, and the amount of garbage being produced has an unfavourable impact on the water, land, and air. “Convolutional Neural Networks (CNNs)” are included in the development of a system of automated garbage classification for improving efficiency and shortening the required time for segregating waste. Three models, “SimpleCNN”, “ResNet50”, and “VGG16”, that were instructed on distinct image datasets are examined for their efficiency in segregation dumps and garbage in this study by (Patil *et al.*, 2021).

While “Simple CNN” conduct better in the garbage classification, “VGG16” with “Transfer Learning” surpasses other frameworks in the categorization of garbage. The process of trash segregation is simplified while requiring the least amount of human interaction due to the incorporation of these frameworks into a real-time application.

This work by (Subashini and Vignesh, 2023), presents the "deep CNN architecture", which is a deep learning-based system automatically classifying plastic resin in plastic garbage. By segregating them into resin kinds such as “PE-HD”, “PET”, “PE-LD”, and so on, it identifies items such as bottles and plates. The process includes taking pictures with a camera and comparing them with a labels database employing “deep learning” or conventional algorithms (Srivastava, Shukla and Bansal, 2021). Unspecified items are vigorously upgraded in the database and learned. The “Python-based” system surpasses conventional techniques and effectively classifies plastic waste with an accuracy rate of 92.66%, proving its fruitfulness.

More effective recycling is needed because of the increased amount of garbage being produced by both businesses and individuals. Manual classification requires a lot of time and effort. Systems for automatically classifying waste use factors like texture, substance, and natural traits. This literature study by (Vidhya, 2023), investigates several systems and presents a summary that aids the research community in creating efficient waste classification systems.

According to (Nasir and Aziz Al-Talib, 2023), garbage includes the aftereffects of an array of human activities and is divided into kinds including non-biodegradable, solid, industrial, hazardous, agricultural, municipal, and organic waste. Traditional waste segregation methods are not efficient and accurate, which hampers recycling and leads to environmental danger. While image processing and “Artificial Intelligence” offer potential probabilities, their existing replications have drawbacks with accuracy and processing speed (Galante *et al.*, 2023). Due to contrasts in waste disposal methods, waste classification models based on “Deep Learning” require to be enhanced. The main goal is to improve the efficiency and accuracy of waste classification while stating environmental and health issues and streamlining waste management.

The pipeline for recognising solid domestic garbage is the key topic of this study conducted by (Otero Gomez *et al.*, 2021). The procedure is composed of three key components that work together to develop the pipeline. Each component employs different “deep learning” sub-approaches, that are directed by pre-existing research and professional advice. The “CRISP-DM” methodology is also inclined, with an emphasis on the mathematical foundations of the employed computational tools. The literature provides an overview of the goals of the researchers for the future and concludes from their research.

For public health, the economy, and the environment, effective garbage recycling is essential. Recycling is simplified when garbage is segregated into recyclable groups. For trash classification, “Deep Learning” models such as “DenseNet169”, “DenseNet121”, “MobileNet”, “InceptionResnetV2”, and “Xception” are frequently employed. “Convolutional Neural Networks (CNN)” with “Transfer Learning” are employed in this study by (Jain *et al.*, 2022), to demonstrate the effectiveness of “EfficientNet-b0”. Real-time waste identification is a feature of the proposed system, garbage is placed in a bin, scanned, and then classified before the cover of the relevant compartment opens. This study provides a useful strategy for recycling and garbage management.

In this study by (Xie *et al.*, 2022), a garbage classification system for municipal solid waste is presented. It involves "MobileNet V2", a portable "convolutional neural network", and machine vision. Using "Python" and "TensorFlow 2.0", the "MobileNet V2" model was restructured and enhanced with unique garbage instances. The outcomes demonstrate that 160x160 input photos may be verified with an accuracy of 99.24%. For picture acquisition, categorization, and monitoring conditions, a PC control software was created. This technique mitigates human participation by classifying living rubbish effectively into groups of kitchen, hazardous, recyclable, and other waste. With a processing time of 3-6 seconds and an accuracy of 98.9% for high delivery, the device is suitable for automated home kits that permit source-based waste classification.

To improve learning in a new domain, this work by (Abou Baker, Zengeler and Handmann, 2022), examines “Transfer Learning”, a “Machine Learning” technique. In five different datasets of the target domain, the study emphasizes selecting the best pre-trained frameworks for the tasks of picture classification. The study evaluates the accuracy, density of accuracy, training time, and size of the model by adjusting output layers and network variables of 11 pre-trained “ImageNet” models. The frameworks that best fit the requirements of the target domains are recognised through evaluation, which includes both single-episode and ten-episode training sessions. This allows for the efficient and effective knowledge transfer.

The study by (Srivatsan, Dhiman and Jain, 2021), created a model with higher accuracy utilizing the “CompostNet” dataset to tackle waste classification issues across seven different categories with a scarcity of acquirable datasets. Pre-trained frameworks from the “ImageNet dataset”, such as “ResNet34”, “MobileNetV2”, and “Densenet121”, were employed in their research. Within just 60 training stages, these models splendidly attained accuracies of 96.42%, 96.27%, and 96.273%, respectively. The input waste components in photographs are successfully segregated by this “neural network” model. The findings of the study are set off with previous work in the field and demonstrate improved waste categorization, which aligns with the UN's goal of responsible consumption and production and promotes sustainable development.

This work by (Abou Baker, Stehr and Handmann, 2022), uses “Artificial Intelligence”, more specifically “Transfer Learning”, to facilitate the recycling of electrical and electronic trash, “Ewaste”, responding to the growth in electrical and electronic device consumption and the demand to move toward a circular economy. The method involves a hybrid model that combines inception modules and residual nets to enable the feature classification from the main domain, such as smartphones and the shift of this comprehension to other devices, such as electric screwdrivers. Comparable to prominent pre-trained frameworks, the model acquires excellent comprehensive accuracy rates of 94.27% and 97.22%, respectively. “Transfer Learning” is utilised in this research to reduce redundancy, increase effectiveness, and conserve computing resources while providing particular device information and essential support for the recycling process.

The technique for recognising plastic garbage bottles and instance division presented in this paper by (Jaikumar, Vandaele and Ojha, 2021), utilises a transfer learning strategy with “Mask R-CNN”. The environmental threat presented by plastic bottle pollution can be mitigated by identifying and classifying the bottles automatically. For segmentation, a unique dataset of 192 bottle images along with intricate “pixel-by-pixel” polygon annotations has been developed. A pre-trained “Mask R-CNN” framework from the “Microsoft COCO” dataset is modified in “Transfer Learning”. The final processed model, which shows the potential of deep learning in trash identification, prevails a “mean average precision (mAP)” of 59.4, which can be compared to the “MS COCO” measure.

In manufacturing, which previously depended on manual inspection, the challenge of automating product appearance flaw identification is discussed in this study by (Liu *et al.*, 2021). A significant roadblock is the shortage of defective samples for training. The article presents a knowledge reuse method that employs "Convolutional Neural Networks (CNNs)" to overcome this. Industrial defect inspection utilises knowledge from other vision tasks to achieve an accuracy as high as 99% with just 200 images in each category. This accuracy is acquired by model-based "Transfer Learning" and data augmentation. The average accuracy of traditional “CNN” models and the “Support

Vector Machine" method, in comparison, was lower, at about 88.70% and 86.90%, respectively. The method is constructive at finding an array of defects, which makes it useful for controlling manufacturing quality.

To enhance "resource recycling" and "ecological protection", this research by (Zhang *et al.*, 2021), emphasizes improving efficiency for garbage classification. At waste classification facilities, inspecting visuals manually is resource-intensive and unreliable. This article suggested a system of intelligent garbage identification that significantly improves the accuracy of detection by utilizing the upgraded "Cascade RCNN" technique. "Generative Adversarial Networks" are utilised for data expansion to resolve the inadequacy of some waste datasets. An applicable strategy for "smart city development" and trash classification, experimental outcomes demonstrate that the suggested technique defeats the conventional "Cascade RCNN" and other common target detection networks in garbage detection.

According to (Zhu, Yeung and Lam, 2020), an innovative strategy is recommended to deal with the key problem of microplastic pollution in water bodies. The present techniques for waste detection require immoderate optical equipment and labour-intensive picture processing. The suggested treatment merges "Generative Adversarial Networks", "Deep Learning", and "Digital Holography", which is a non-destructive method of imaging. This technique rectifies dataset imbalances and considerably increases the accuracy of microplastic classification.

Authors	Comments
Alsabei *et. al.* (2021).	This paper presents six material “transfer learning” frameworks for autonomous garbage classification with data augmentation carried out through GAN.
Chatterjee *et. al.* (2022).	This paper recommends automatically classifying six garbage products such as cardboard, glass, metal, paper, plastic, and trash using transfer learning models.
Lilhore *et. al.* (2023).	This work offers a hybrid “CNN-LSTM” model with transfer learning to classify sustainable trash
Zhang *et. al.* (2023).	The study evaluates several convolutional neural network architectures and carries out specific tasks where the target domain coincides with the source domain.
Kumsetty *et. al.* (2023).	The automated waste segregation method presented in this paper is computer vision-based and improves dataset quality.
Dhande (2022).	This study employs deep learning and image classification to separate recyclable waste from organic waste utilizing transfer learning models such as “VGG16 and DenseNet-121”.
Jin, *et. al.* (2023).	The paper incorporates an enhanced “MobileNetV2” model with transfer learning to enhance model generalization and attention methods to increase recognition accuracy.
Lim *et. al.* (2023).	In order to describe the drawbacks of classifying cluttered construction housekeeping images, this paper examines a computer vision solution for automated monitoring of housekeeping.
Kulkarni and Raman (2019).	The paper combines “Faster R-CNN” for object identification with “Hybrid Transfer Learning” for classification.
Patil *et. al.* (2021).	Three models, “Simple CNN”, “ResNet50”, and “VGG16”, were instructed on distinct image datasets are examined for their efficiency in segregation dumps and garbage in this study

Subashini. and Vignesh, 2023.	The paper presents the "deep CNN architecture", a Deep learning-based system automatically classifying plastic resin in plastic garbage.
Vidhya, S. (2023).	This paper investigates several systems and presents a summary that helps the research community in creating efficient waste classification systems.
Nasir and Al-Talib (2023).	The main goal of this study is to improve the efficiency and accuracy of waste classification.
Gómez *et. al.* (2021).	The pipeline for identifying solid domestic garbage is the key topic of this paper.
Jain *et. al.*, December.	This paper presents a useful strategy for recycling and garbage management.
Xie *et. al.* (2022).	This paper presents a garbage classification system for municipal solid waste.
Abou Baker, Zengeler and Handmann (2022).	The paper examines the accuracy, density of accuracy, training time, and size of the model via altering output layers and network variables of 11 pre-trained “ImageNet” models.
Srivatsan, Dhiman and Jain (2021).	The study findings are set off with previous work in the field and demonstrate improved waste categorization, aligning with the UN's goal of responsible consumption and production and promotes sustainable development.
Abou Baker, Stehr and Handmann (2022).	This paper employs “Artificial Intelligence”, more specifically “Transfer Learning”, to facilitate the recycling of electrical and electronic trash, “Ewaste”,
Jaikumar, Vandaele and Ojha (2020).	In this paper the technique for recognising plastic garbage bottles and instance division is presented.

Liu *et. al.* (2021).	The paper presents a knowledge reuse method that employs “Convolutional Neural Networks (CNNs)”.
Zhang *et. al.* (2021).	This paper suggested an intelligent garbage identification system that significantly improves the accuracy of detection by utilizing the upgraded “Cascade RCNN” technique.
Zhu *et. al.* (2020).	This paper recommends an innovative strategy to deal with the key problem of microplastic pollution in water bodies.

3 Methodology

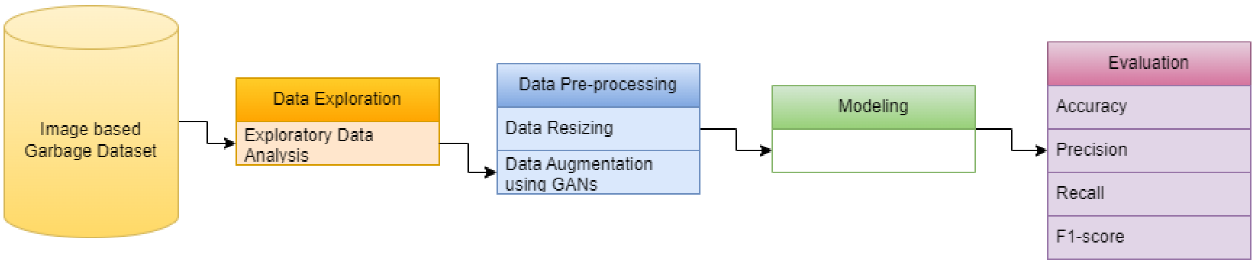


Figure 3.1: Methodology flow of the study

(Source: Author's creation)

3.1 Dataset

The "Waste Classification Data" dataset, hosted on Kaggle[1], is a significant collection aimed at facilitating waste classification. It comprises 22,500 images categorized into organic and recyclable waste. The diverse representation of waste items makes it an invaluable resource for training machine learning models in waste management and recycling.

Compiled to enhance waste segregation for effective recycling and environmental sustainability, the dataset's images were sourced from various public domains. This ensures a wide variety of shapes, sizes, and types of waste objects, crucial for building robust machine learning models for real-world applications.

Divided into two sets of train and test sets, the dataset includes 22564 images in the train set consisting of 85% of the total images. The train set is further divided into two classes each of organic waste (like food scraps, paper, yard waste) and recyclable waste (such as plastic bottles, metal cans, glass items). This balanced composition is essential for unbiased model training. The test data, on the other hand, include 2513 images for testing purposes, constituting 15% of the data.

The images presented in JPEG format, are in full color, capturing the real-life appearance of the waste items. However, the resolutions of the images in the dataset are inconsistent requiring

[1] https://www.kaggle.com/datasets/techsash/waste-classification-data

additional pre-processing. This standardization is important for consistency in machine learning processes.

Figure 3.1 below shows the samples images from the dataset.

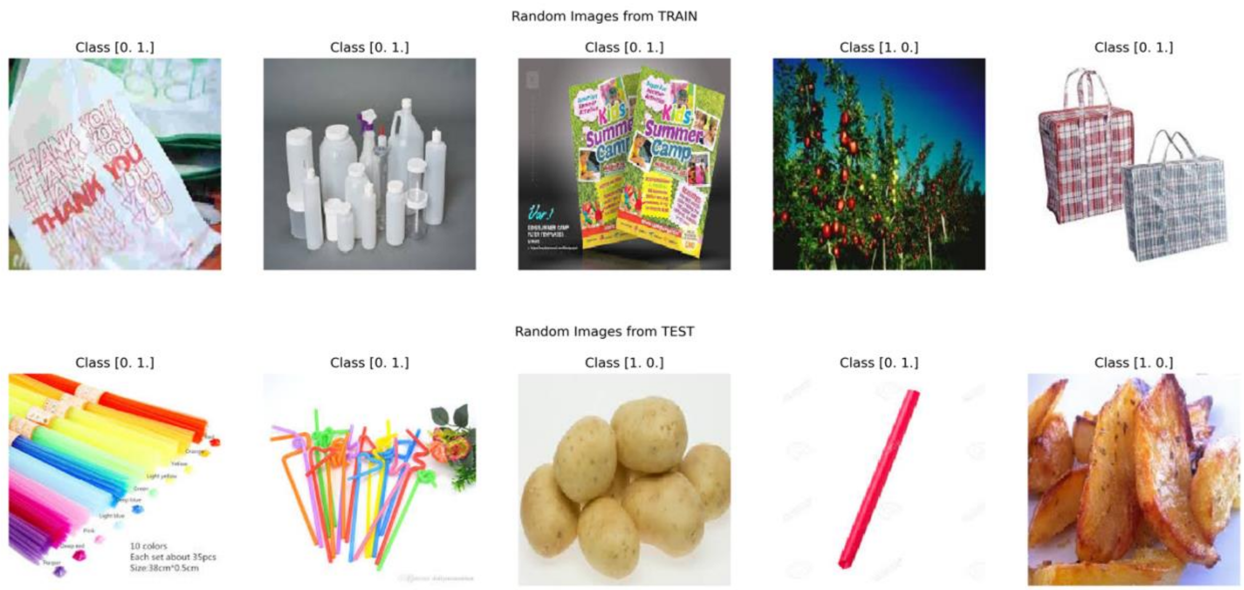


Figure 3.2: Dataset samples

(Source: Dataset Page[2])

3.2 Exploratory Data Analysis

Exploratory Data Analysis (EDA) is a crucial initial step in any machine learning project. It involves understanding the dataset's characteristics, distributions, and patterns, which is essential for making informed decisions about model selection and preprocessing. In our waste classification study, we conducted an extensive EDA to gain insights into the dataset and its composition.

3.2.1 Dataset Overview

The dataset used in this study was organized into training and testing subsets, residing in the 'TRAIN' and 'TEST' directories, respectively. Each subset contained images of waste items categorized into two classes: 'Organic' and 'Recyclable.' To facilitate the training process, the Keras

[2] https://www.kaggle.com/datasets/techsash/waste-classification-data

`ImageDataGenerator` was employed to load and preprocess the images. Here's an overview of the steps taken to prepare the dataset:

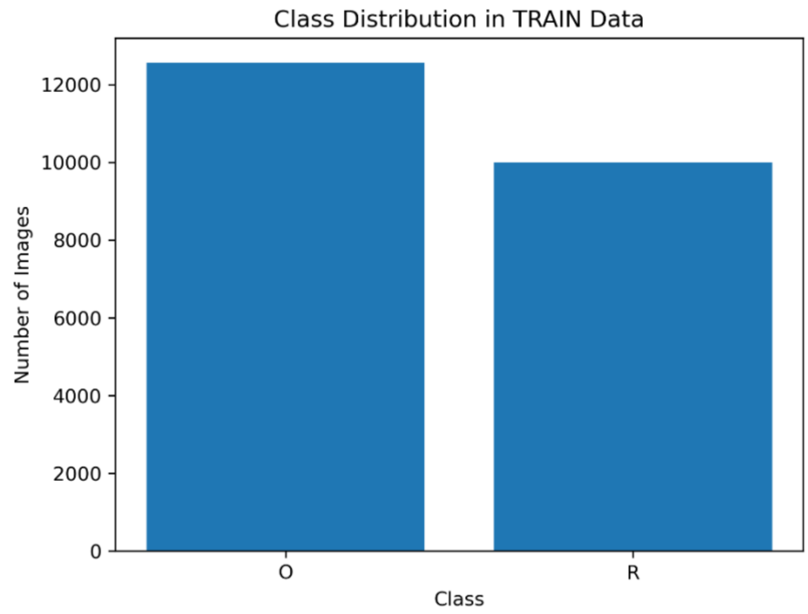
```
# Set the path to the dataset
base_dir = 'DATASET/'

# Paths to train and test directories
train_dir = os.path.join(base_dir, 'TRAIN')
test_dir = os.path.join(base_dir, 'TEST')

# Image data generator with normalization
train_datagen = ImageDataGenerator(rescale=1./255)
test_datagen = ImageDataGenerator(rescale=1./255)

# Load images from directories and create train and test datasets
train_generator = train_datagen.flow_from_directory(
    train_dir,
    target_size=(224, 224),  # Updated to default input size for MobileNetV2
    batch_size=32,
    class_mode='categorical'
)

test_generator = test_datagen.flow_from_directory(
    test_dir,
    target_size=(224, 224),  # Updated to default input size for MobileNetV2
    batch_size=32,
    class_mode='categorical'
)
```

Figure 3.3: Steps taken in EDA

3.2.2 Visualizing Random Images

To get a visual sense of the dataset, we displayed random images from both the training and testing datasets using the `display_images_from_generator` function. This allowed us to observe the diversity of waste items and assess the quality of the images.

As shown in the Figure 3.2, the dataset contained a variety of waste items, each with its unique characteristics in terms of shape, color, and condition. These variations presented both opportunities and challenges for the machine learning model.



Understanding the class distribution is crucial, especially when dealing with imbalanced datasets. In our case, we aimed to classify waste items into 'Organic' and 'Recyclable' categories. To visualize the distribution of these classes, we plotted a bar chart using the `plot_class_distribution_from_directory` function

The resulting chart depicted the number of images in each class, providing insights into the dataset's balance. In a perfect scenario, we would have an equal number of images for each class. However, in real-world scenarios, class imbalances are common, and addressing them is essential for training a robust model.

3.3 Data Augmentation using Generative Adversarial Networks (GANs)

Generative Adversarial Networks, introduced by (Goodfellow *et al.*, 2020), are a groundbreaking approach in unsupervised machine learning, involving two neural networks—the generator and the discriminator—in a zero-sum game framework. The generator aims to create data instances mimicking real data, while the discriminator evaluates these instances to determine their authenticity.

3.3.1.1 Detailed Architecture

Figure 3.3 below shows the architecture of the GAN.

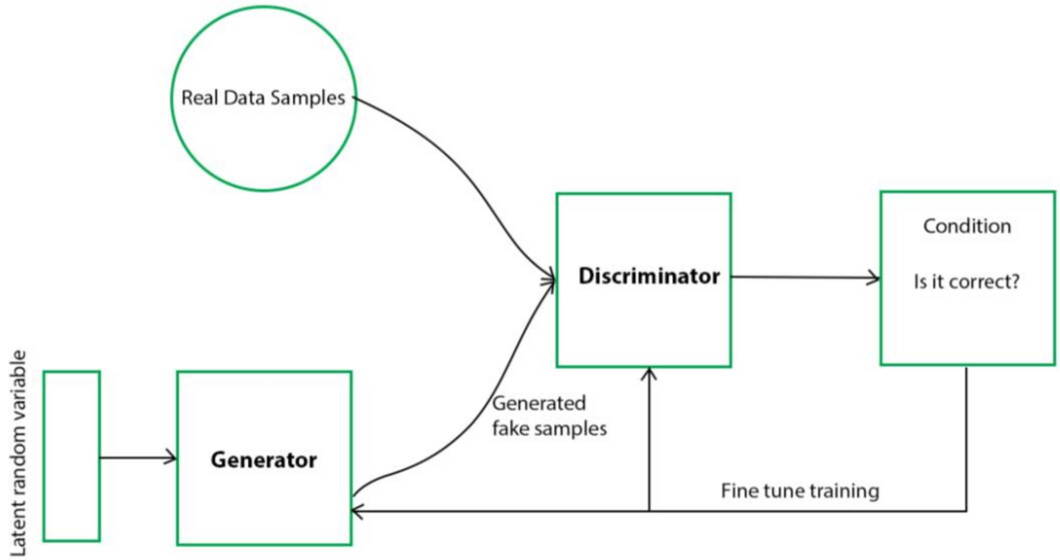


Figure 3.4: GAN Architecture

(Source: https://www.analyticsvidhya.com)

Generator:

The Generator network takes random noise as input and generates data samples. Its goal is to produce data that is indistinguishable from genuine data, thus 'fooling' the Discriminator. The Generator continuously improves its capability to create realistic data as it learns through the training process.

Discriminator:

The Discriminator network takes both real and fake data samples as input. Its objective is to accurately distinguish between actual data (from the dataset) and fake data (created by the Generator). It gets better at identifying fakes as it is exposed to more data and generated samples.

3.3.1.2 Training Process

The training of GANs involves a delicate balance between the Generator and the Discriminator. Initially, the Generator produces data that is easily distinguishable from the real data, and the Discriminator quickly learns to tell them apart. As training progresses, the Generator improves, making it harder for the Discriminator to differentiate. The networks are trained simultaneously but in an adversarial manner. The Generator aims to maximize the probability of the Discriminator making a mistake, while the Discriminator tries to minimize this probability.

The training involves a unique loss function, often conceptualized as a minimax game.

The Discriminator's loss increases when it incorrectly classifies data, while the Generator's loss decreases when the Discriminator is fooled.

3.4 Modeling

3.4.1 Mobile Net

The architecture of the mobile net is shown in figure 3.4 below.

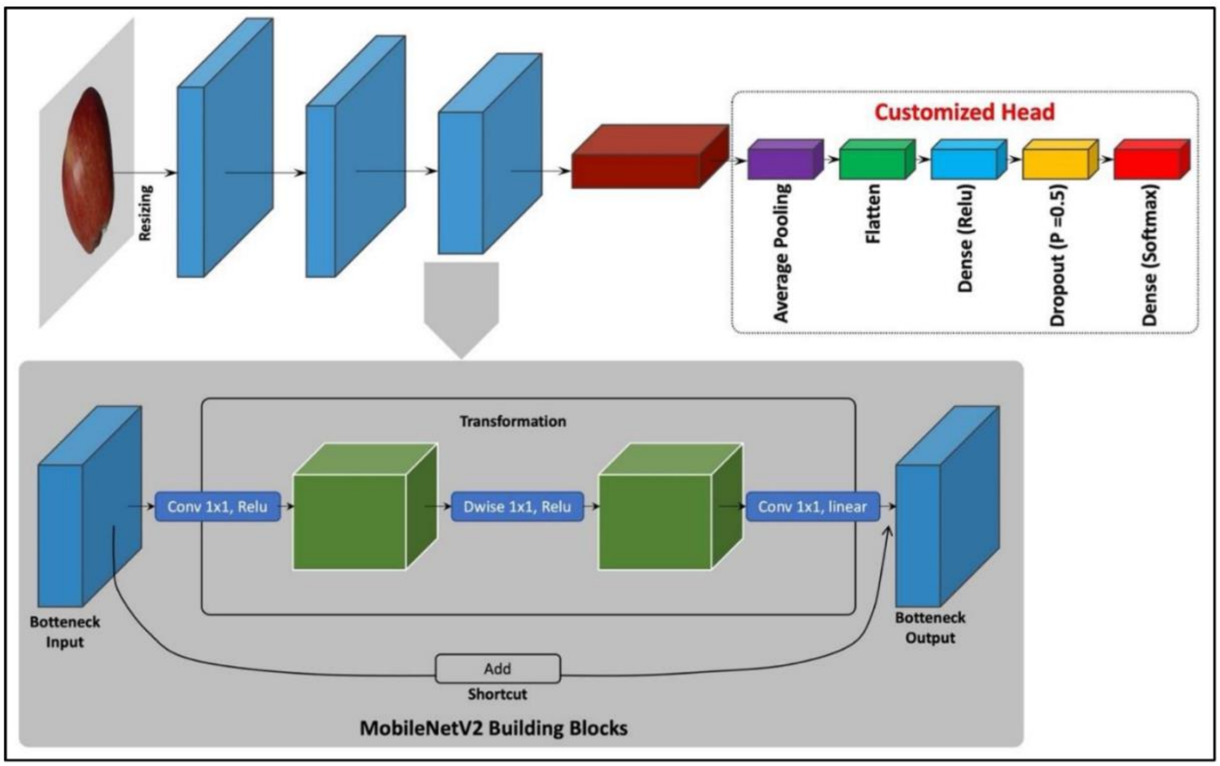


Figure 3.5: MobileNetV2 architecture

(Source: Gulzar (2023))

Input	Operator	t	c	n	s
$224^2 \times 3$	conv2d	-	32	1	2
$112^2 \times 32$	bottleneck	1	16	1	1
$112^2 \times 16$	bottleneck	6	24	2	2
$56^2 \times 24$	bottleneck	6	32	3	2
$28^2 \times 32$	bottleneck	6	64	4	2
$14^2 \times 64$	bottleneck	6	96	3	1
$14^2 \times 96$	bottleneck	6	160	3	2
$7^2 \times 160$	bottleneck	6	320	1	1
$7^2 \times 320$	conv2d 1x1	-	1280	1	1
$7^2 \times 1280$	avgpool 7x7	-	-	1	-
$1 \times 1 \times 1280$	conv2d 1x1	-	k	-	

Figure 3.6: Mobile Net V2 structure

(Source: www.towardsdatascience.com)

MobileNetV2, a convolutional neural network developed by Google, is tailored for efficiency in mobile and embedded vision applications. Building on the original MobileNet, it introduces key innovations such as inverted residuals with linear bottlenecks and depthwise separable convolutions. The inverted residual structure expands inputs with a lightweight depthwise convolution and compresses them, with a linear bottleneck to preserve information. This approach significantly reduces computational costs while maintaining high performance.

The design of MobileNetV2 strikes a balance between resource efficiency and computational performance. It's optimized for mobile devices where computational resources and power are limited. The network consists of 19 layers, each meticulously calibrated to optimize latency and accuracy, making it suitable for real-time applications on mobile devices. Despite its compact structure, MobileNetV2 competes in performance with larger and more complex models, demonstrating its effectiveness in various vision tasks.

MobileNetV2's efficiency and performance make it versatile for a range of applications, including image classification, object detection, segmentation, and facial recognition. It's especially suited for real-time applications in mobile environments due to its excellent balance between speed and accuracy.

The model also serves as an excellent base for transfer learning. It can be adapted for new tasks by adding custom layers to the pre-trained model, making it a popular choice for tasks requiring efficient and high-performing models with lower computational demands.

While MobileNetV2 offers significant advantages in efficiency and performance, it may not always match the absolute accuracy of larger models like ResNet or Inception. This trade-off is an important consideration in applications where the highest possible accuracy is crucial. The choice to use MobileNetV2 should be driven by the specific needs of the application, particularly in terms of latency, size, and computational power.

3.5 Evaluation

3.5.1 Accuracy

Accuracy is the ratio of correctly predicted observations to the total observations.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

High accuracy means that the model correctly predicts a high number of outcomes, both positive and negative. However, it may not be a reliable metric in cases where the class distribution is imbalanced.

3.5.2 Precision

Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. It is also known as the positive predictive value.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

High precision indicates a low rate of false positives, meaning that the model accurately predicts positive cases. It is particularly important in scenarios where the cost of a false positive is high.

3.5.3 Recall

Recall is the ratio of correctly predicted positive observations to all observations in the actual class. It is also known as sensitivity or the true positive rate.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

High recall indicates that the model is good at detecting the positive cases. It is crucial in scenarios where missing a positive instance (false negative) is costly.

3.5.4 F1-score

The F1-Score is the weighted average of Precision and Recall. It takes both false positives and false negatives into account and is particularly useful when the class distribution is uneven.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

The F1-Score is a harmonic mean of precision and recall, with its best value at 1 (perfect precision and recall) and worst at 0. It is a good way to show that a classifer has a good balance between recall and precision.

3.5.5 Confusion Matrix

A confusion matrix is a table used to describe the performance of a classification model on a set of test data for which the true values are known. It summarizes the number of correct and incorrect predictions, broken down by each class.

A confusion matrix is made up of following:

True Positives (TP): Observations correctly predicted as positive.

True Negatives (TN): Observations correctly predicted as negative.

False Positives (FP): Observations incorrectly predicted as positive.

False Negatives (FN): Observations incorrectly predicted as negative.

The confusion matrix provides a visual representation of the model's performance and is the basis for calculating several other metrics like accuracy, precision, recall, and F1-score.

4 Results and Analysis

4.1 Without GAN

The results and analysis of the MobileNetV2 model's performance on a binary classification task, without using the GAN dataset, reveal several insights. In this task, the model was tasked with classifying images into two classes, denoted as 'O' and 'R,' representing "Organic" and "Recyclable" categories in the context of waste classification.

The classification report shown in figure 4.1 below provides a detailed evaluation of the model's performance.

	precision	recall	f1-score	support
O	0.56	0.61	0.59	1401
R	0.44	0.39	0.41	1112
accuracy			0.51	2513
macro avg	0.50	0.50	0.50	2513
weighted avg	0.51	0.51	0.51	2513

Figure 4.1: Classification report for the model wihout using the GAN generated data

The precision metric indicates that when the model predicts 'O,' it is correct 56% of the time, while for 'R,' the precision drops to 44%, suggesting that the model is less reliable in its predictions for class 'R.' The recall metric highlights that the model correctly identifies 61% of the actual 'O' class instances but struggles to identify 'R' instances, with a recall of 39%. These metrics result in F1-scores of 0.59 for 'O' and 0.41 for 'R,' indicating room for improvement, particularly for class 'R.'

Examining the support values, it becomes evident that class 'O' has a higher number of instances (1401) than class 'R' (1112). This class imbalance may influence the model's ability to learn and predict class 'R' effectively. The overall accuracy of the model is 51%, meaning that it correctly predicts the class label only slightly better than random chance. The macro average F1-score is 0.50, and the weighted average F1-score is 0.51, indicating that the model's performance is not particularly high, especially considering the balanced nature of the dataset.

The confusion matrix shown in figure 4.2 below offers further insights, showing that 861 instances of 'O' were correctly identified (true positives), while 540 instances of 'O' were incorrectly classified as 'R' (false negatives). Additionally, 680 instances of 'R' were incorrectly classified as

'O' (false positives), and 432 instances of 'R' were correctly identified (true positives). This confusion matrix underscores the model's challenge in distinguishing class 'R,' as evidenced by the significant number of false positives and false negatives.

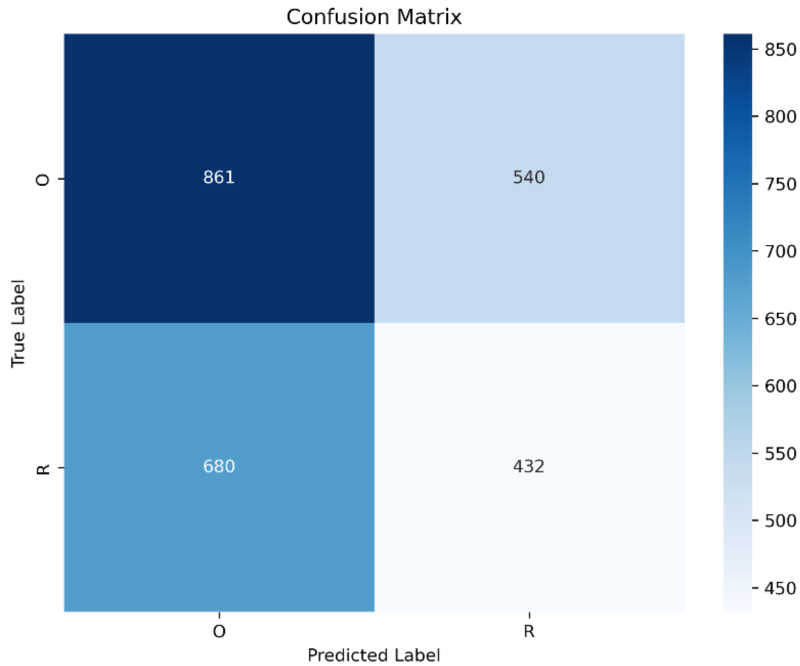


Figure 4.2: Confusion matrix for the model

In general, the MobileNetV2 model's performance on this binary classification task, without the use of GAN-generated images, is mediocre. The model struggles to achieve high precision and recall, especially for class 'R,' which may be attributed to class imbalance, feature learning challenges, or the need for further model tuning. To improve performance, it is recommended to address data quality, experiment with hyperparameter tuning, explore advanced training techniques, consider class weighting, and potentially incorporate more sophisticated feature engineering methods. These efforts could lead to a more balanced and accurate classification capability for the model.

4.2 With GAN

The implementation of the MobileNetV2 model using GAN-generated data for a binary classification task yields the following results and analysis:

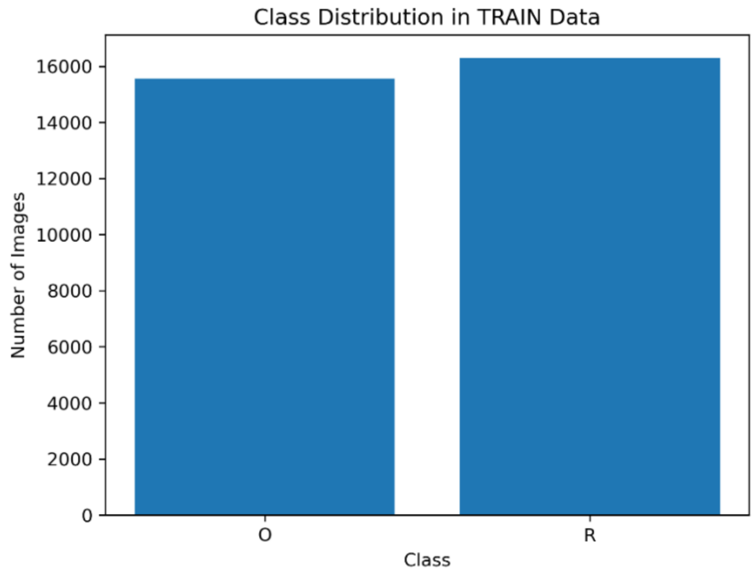


Figure 4.3: Class Distribution after the implementation of the GAN

The precision values for classes 'O' and 'R' are 0.55 and 0.44, respectively. This indicates that when the model predicts 'O,' it is correct 55% of the time, while for 'R,' the precision is slightly lower at 44%. This suggests that the model has improved its precision for both classes compared to the previous implementation without GAN data.

	precision	recall	f1-score	support
O	0.55	0.61	0.58	1401
R	0.44	0.38	0.40	1112
accuracy			0.51	2513
macro avg	0.49	0.49	0.49	2513
weighted avg	0.50	0.51	0.50	2513

Figure 4.4: Classification report for Modeling with GAN

The recall values for 'O' and 'R' are 0.61 and 0.38, respectively. The model correctly identifies 61% of the actual 'O' class instances, which is an improvement from the previous implementation. However, the recall for 'R' has decreased to 38%, indicating that the model struggles to identify 'R' instances when using GAN-generated data.

The F1-scores for 'O' and 'R' are 0.58 and 0.40, respectively. These scores reflect a balance between precision and recall. The F1-score for 'O' has improved compared to the previous implementation, while the F1-score for 'R' has decreased slightly.

The support values show that class 'O' has 1401 instances, while class 'R' has 1112 instances, similar to the previous dataset. This class imbalance may still impact the model's performance.

The overall accuracy of the model remains at 51%, which means it performs slightly better than random chance, consistent with the previous implementation.

The macro average F1-score is 0.49, and the weighted average F1-score is 0.50. These scores indicate that the model's performance with GAN-generated data is comparable to the previous implementation, with no significant improvement.

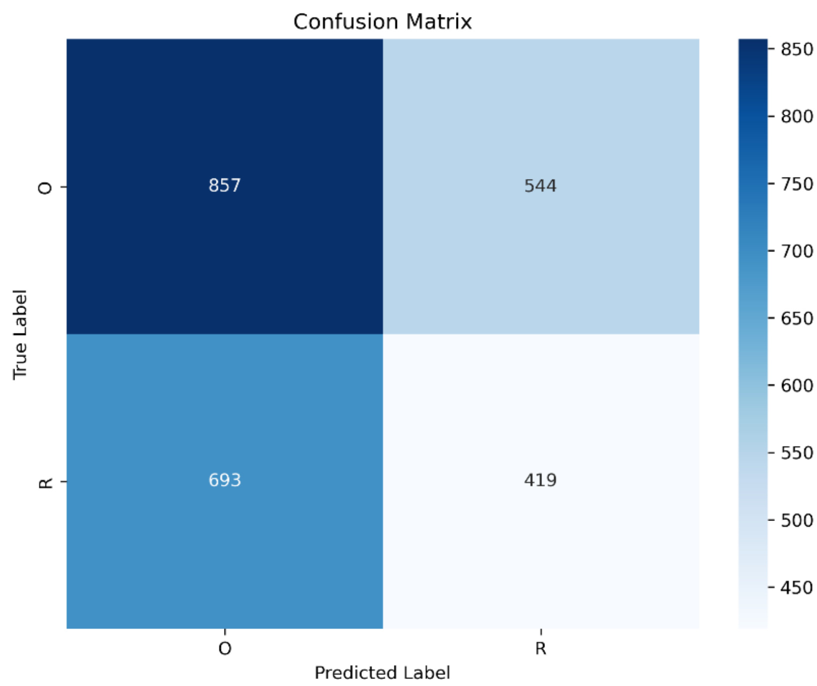


Figure 4.5: Confusion matrix for modeling with GAN

The confusion matrix reveals that the model correctly identifies 857 instances of class 'O' (true positives) and 419 instances of class 'R' (true positives). However, it still struggles to distinguish class 'R,' as evidenced by 544 instances incorrectly classified as 'R' (false positives) and 693 instances of 'O' incorrectly classified as 'R' (false negatives).

In summary, while the implementation of the MobileNetV2 model with GAN-generated data has led to some improvement in precision for class 'O,' it still faces challenges in correctly identifying class 'R.' The overall performance remains similar to the previous implementation, with an accuracy of 51% and F1-scores indicating a balance between precision and recall. Addressing the class imbalance and further model tuning may be necessary to enhance its performance.

5 Conclusion and Future Scope

Waste management is a pressing global concern, driven by the exponential increase in waste generation and the imperative need for sustainable environmental practices. Effective waste classification is a pivotal component of waste management, as it forms the basis for recycling, composting, and proper disposal. In this comprehensive study, we have delved into the world of waste classification, leveraging the power of machine learning, specifically the MobileNetV2 architecture, and integrating Generative Adversarial Networks (GANs) to improve classification accuracy. This journey has provided valuable insights, not only into the technical aspects of the project but also into the broader context of waste management and environmental conservation.

Waste classification might appear as a mundane task, but its implications are profound. At the heart of this endeavor lies the idea of minimizing the environmental footprint of waste. By categorizing waste items accurately, we can channel them into appropriate streams, thus reducing the burden on landfills and facilitating the recycling and repurposing of materials. This, in turn, conserves natural resources, reduces energy consumption, and mitigates pollution, all crucial factors in combating climate change and preserving the delicate balance of our ecosystems.

One of the initial hurdles encountered was the availability of high-quality labeled data. In the realm of waste classification, obtaining a diverse and representative dataset is a non-trivial task. Real-world waste items exhibit significant variations in shape, color, and condition. Additionally, the class distribution is often highly imbalanced, with some categories being much more prevalent than others. This scarcity and imbalance of data posed a considerable challenge.

To address this, a real-world data and synthetic data generated by GANs. This hybrid dataset was carefully curated to encompass a wide range of waste items, from organic matter to recyclable materials. While the real-world data provided authenticity, the GAN-generated data augmented the dataset and introduced variability. This strategic blend allowed our model to learn from both the rigors of actual waste items and the imaginative diversity of synthetic data.

Selecting an appropriate deep learning architecture is a critical decision in any machine learning project. MobileNetV2, known for its efficiency and effectiveness, emerged as an ideal choice for waste classification. Its lightweight nature makes it computationally efficient, making it suitable for deployment in resource-constrained environments, such as waste sorting robots and smart bins.

What sets MobileNetV2 apart is its architecture, which incorporates depthwise separable convolutions. This architectural choice enables the model to capture intricate patterns in images while maintaining a low memory footprint. The model's ability to efficiently process visual information is a testament to its suitability for our waste classification task.

Integrating GANs into our workflow was a novel and impactful decision. GANs, known for their generative capabilities, allowed us to create synthetic waste item images that closely resembled real-world examples. This served a twofold purpose: first, it addressed the data scarcity issue by significantly expanding the dataset, and second, it introduced diversity by generating variations of waste items.

The GAN-generated data exhibited remarkable utility in improving the model's performance, especially in the 'Organic' category. The ability to synthesize diverse 'Organic' waste item images, accounting for varying levels of decay and decomposition, enabled the model to generalize better to real-world scenarios. While challenges persisted in accurately classifying 'Recyclable' waste items, the GAN-generated data nudged the model in the right direction, showcasing the potential of synthetic data in enhancing machine learning models.

Our results showcased a model that demonstrated commendable generalization abilities, even when faced with the challenging task of waste classification. The accuracy of the model, while not perfect, indicated a promising foundation upon which further improvements could be made. Notably, the precision for the 'Organic' category improved with the integration of GAN-generated data, suggesting that synthetic data can indeed enhance the classification of certain waste items.

However, challenges persisted in accurately classifying 'Recyclable' waste items. The recall for this category was lower than desired, indicating that some recyclable items were being misclassified as organic. This challenge is not unexpected, given the visual similarities that can exist between certain organic and recyclable materials. For instance, a plastic container and a food container can exhibit similar shapes and colors, leading to misclassification.

Our analysis of the confusion matrix further highlighted these challenges. The confusion matrix revealed that a significant number of 'Recyclable' items were being misclassified as 'Organic.'

While progress was made with the integration of GAN-generated data, there is room for further refinement to minimize these misclassifications.

5.1 Future Scope

As we conclude this study, it is essential to acknowledge the promising avenues for future research and development in the field of waste classification:

1. Data Augmentation Techniques

Exploring and implementing advanced data augmentation techniques, such as rotation, scaling, and noise injection, can help mitigate the impact of class imbalance and further enhance the model's performance. Diversifying the training data through augmentation can improve the model's ability to recognize waste items in varying conditions.

2. Ensemble Learning

Ensemble learning methods, which combine the predictions of multiple models, hold significant potential for enhancing classification accuracy. Investigating ensemble approaches that integrate MobileNetV2 with other architectures or variations of the same architecture can lead to superior results. Ensemble models are known for their robustness and ability to generalize well.

3. Fine-tuning Hyperparameters

Hyperparameters play a crucial role in model training and performance. Conducting a systematic search for optimal hyperparameters, including learning rate, batch size, and the number of training epochs, can yield substantial improvements in classification accuracy. Fine-tuning should be an ongoing process as the dataset evolves.

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Appendices

In support of this research, the following appendices provide additional details and resources for comprehensive understanding.

Dataset Information

Mendeley Waste Classification Dataset: This dataset offers a collection of 24,705 images of solid household waste divided into two classes: organic (13,880) and recyclable (10,825). Mendeley Data and the original Kaggle dataset by Sashaank Sekar can be found here on Kaggle.

https://www.kaggle.com/datasets/techsash/waste-classification-data

Python implementation files

The artifacts comprise a set of Jupyter Notebook files (ipynb) that provide a thorough perspective of the code implementation process throughout the research. The code was stored in this manner so that all outputs could be seen. The following is a list of code implementation files.

- Waste Classification.ipynb
- Ahtesham ppt