Improving Waste Sorting Systems: Enhancing Sustainability and Resource Recovery

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Abstract

This research investigates through the design and implementation of the deep learning techniques for advanced waste classification system using hybrid transfer learning to enhance resource recovery and sustainability in environment. By using deep learning methods such as InceptionV3, MobileNetv2, ResNet50, VGG16 and EfficientB0, the study develops a multi-class classification model to categories the diverse waste categories. A dataset compromising real world data and augmented images for better training and evaluating the models, addressing challenges like class imbalances, diverse data types and low quality images. The models like InceptionV3 and VGG16 achieves high accuracy with high precision and recall on the pre trained models using weights. Results demonstrates InceptionV3 as champion model which gives us accuracy of 91%, precision and recall of 91% as well. This study highlights the advancement in pre processing, light weight model optimization and precise image detection. These findings and results gets us to sustainable practice by minimizing landfill dependency and promoting circular economy principles through effective waste sorting.

1 Introduction

1.1 Background and motivation

Waste is any object which is not being used and discarded or intend to be discarded. Waste is a natural outcome of any human activity. Waste management needs to be appropriate and systematic. There are multiple varieties of waste such as organic, non-organic, recyclable, non-recyclable, hazardous, bio-degradable and non-bio-degradable and so on. All the categories of waste need to be sorted appropriately and uniformly. Waste sorting is the process of categorizing waste into different categories so that it can be reused, recycled and dumped in an environmentally sustainable way. Hazardous waste can be harmful for humans and animals. Unsorted and poorly managed waste can lead to various challenges which can be air pollution, soil pollution and water pollution. There are some specific kinds of waste which falls under recyclable category but cannot be recycled due to its shape and structure which is different from the original object. There are seasonal waste as well which means in particular season the specific waste can be leading. There are some multi packaged products which can be more challenging to recycle. Moreover, the modern waste has become more challenging like electronic waste, e-cigarettes and so on. By separating waste into categories like recyclable, organic, and hazardous, we can limit landfill use, cut pollution, and recover materials for reuse.

However, current sorting practices often face challenges like contamination, inefficiency, and low public participation, which reduce their effectiveness. Previously, research has been done on waste sorting but on limited data and limited inputs for e.g. paper, plastic, cardboard and glass but not on different kinds of waste. Seasonal waste has not been noted and robust model has not been used for sorting. Waste sorting is essential for effective waste management, but gaps remain in addressing inefficiencies and handling complex materials like electronic waste, medical waste, and non-recyclable waste. This research builds on previous studies, focusing on overlooked areas and improving unclear findings related to sorting technologies. Key objectives include identifying limitations in current sorting practices, exploring behavioural and technological improvements, and assessing the benefits of optimized systems. The study combines data analysis, surveys, and testing of advanced sorting methods to achieve these goals. The research aims to enhance sorting efficiency, reduce landfill reliance, and promote sustainable practices, leading to environmental and economic benefits in waste management systems.

1.2 Research question

"How can improved waste sorting systems be designed and implemented to enhance environmental sustainability and optimize resource recovery?" The research question talks about upgrading waste sorting system to benefit the environment and reusability. It also aims to evaluate current practices, identify gaps in technology and behaviour, propose innovative solutions, and assess their environmental and economic benefits. To achieve this, we will collect data from research, surroundings, restaurant and explore various machine learning and deep learning technologies for sorting system. A solution model will be developed and tested to find the accuracy and performance of different models. By analyzing the results, this study hopes to offer practical recommendations for better waste sorting systems, paving the way for a more sustainable future. While efforts like public awareness campaigns and advanced technologies have been introduced, they face issues like high costs, low precision, and inconsistent participation.

1.3 Challenges and Assumptions

While the study aims to improve waste sorting systems and provide practical solutions, it is important to recognize certain limitations in the research. One major challenge can be the waste sorting system in various regions can be varied due to different cultures, economy, and infrastructure, which can be challenging for a universal solution. In addition, inconsistent and sometimes incomplete data from waste management systems can affect the precision of the analysis. Implementing advanced technologies, as proposed in this study, could also face practical challenges, such as high costs or user resistance. Moreover, the prototype system testing will take place in controlled environments, which may not capture the full range of real-world issues, such as user compliance or unexpected operational difficulties. Acknowledging these limitations ensures a clear and realistic perspective on the research outcomes.

This research is based on a few key assumptions. It assumes that waste generation patterns are similar in regions with comparable economic and social conditions, making comparisons possible. It also assumes that the data collected through surveys and case studies accurately reflect real waste management practices. Another assumption is that technological advancements, like ML-Dl based sorting systems, will become more affordable and efficient over time. Public participation in waste collection is also expected to improve with the help of awareness campaigns and user-friendly systems. It also assumes that the long-term benefits of better waste sorting will outweigh the initial costs, making the solutions practical and sustainable.

1.4 Structure of the report will be as follows

The research project will be consisting of various sections having important information of the research and methods used to answer the research question. Abstract: It will have overview of the research done, methods applied and results we got. Introduction: Current section will be of background and motivation, research question and challenges. Literature review: In this section, there will be overview of the existing research methods, gaps and how our research paper will be filling those gaps. Methodology: This section will give the information about the overall process of the model development from scratch. It contains all the necessary steps like data collection, preprocessing, model development, implementation and evaluation. Evaluation: This section will give the overall comparison of all the model performance with accuracy and precision. Conclusion and future work: Details about finding, application and room for further research and development. Bibliography: A compilation of all the research papers which are used for help. Figure 1 shows structure of report as shown below in a visual flowchart as follows:

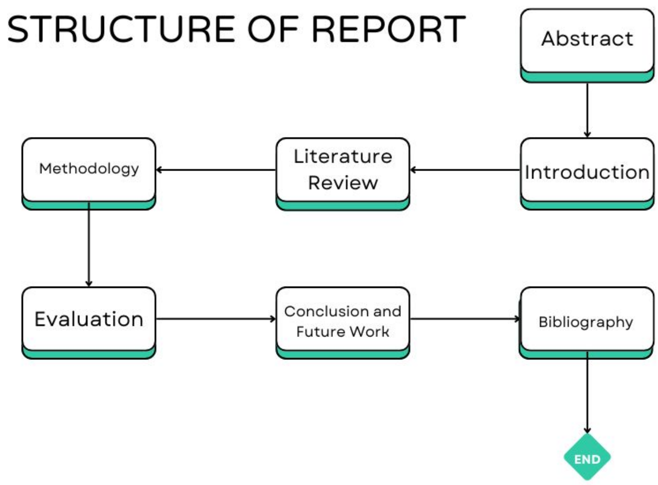

Figure 1: Structure of report

2 Literature Review

In this section, we will critically evaluate the existing research in the field which have been done previously. This section will highlight the major contributions, gaps and find solution for unresolved challenges in same.

2.1 Garbage Detection and Classification Using a New Deep Learning-Based Machine Vision System

This approach improves MobileNetV2 using attention mechanisms, PCA, and transfer learning, enhancing classification accuracy and enabling real-time deployment on edge devices. Results show over 90% accuracy with efficient processing. While systems excel in lightweight design and single-object classification, they struggle with multi-object detection, cluttered images, and diverse environments. Our research tackles these gaps by integrating advanced detection models and multi-modal data to create scalable, sustainable waste sorting systems. These systems excel in real-time processing but struggle with multi-object detection, cluttered or low-quality images, and adapting to diverse waste types and environments.

2.2 An Efficient Multi-Label Classification-Based Municipal Waste Image Identification:

This study proposes the Query2Label (Q2L) framework with a Vision Transformer (ViT-B/16) backbone and an asymmetric loss function for multi-label classification of municipal waste. Tested on the "Garbage In, Garbage Out" dataset, it achieved a mean average precision (mAP) of 92.36%, outperforming ResNet-101 and YOLOv7. By leveraging self- and cross-attention mechanisms, the model demonstrates high accuracy and efficiency but struggles with rare or cluttered items, dataset diversity, and ViT's computational demands. This approach has been executed well but has some issues like the model is not compatible to low-power devices, it does not have any data diversity and not a multi label model. Our research fills these gaps by more diverse data, lightweight model and robust validation.

2.3 Waste Classification for Sustainable Development Using Image Recognition with Deep Learning Neural Network Model:

This study applies EfficientNet-B0 with transfer learning for municipal waste classification, achieving 81.2% accuracy on a Kaggle dataset of 34 categories. The model is cost-effective, resource-efficient, and adaptable to regional waste profiles, requiring 4.61 times fewer operations than EfficientNet-B3. However, it struggles with generalization and subclass classification. To address this, our research incorporates multi-modal data, diverse datasets, and improved subclass classification for a more robust, scalable waste management system.

2.4 Automated Waste Sorting Using Machine Vision and Robotics:

This study integrates machine vision and robotics for automated waste sorting, combining CNN-based image classification with a robotic arm for precise waste segregation. The system demonstrated high sorting accuracy and practical feasibility, reducing human intervention while improving efficiency and lowering labour costs. It adapts well to various waste types but faces challenges with poor lighting, cluttered environments, and scalability due to the robotic setup's cost. To address these gaps, our research explores advanced object detection models, multi-modal data integration for better performance in diverse conditions, and hardware optimization to enhance scalability for larger facilities.

2.5 Automated Waste Sorting: A Comprehensive Approach Using Deep Learning:

This study presents a comprehensive waste sorting approach for industrial plants, combining YOLOv8 for object detection and deep learning models like CNN, AlexNet, MobileNet-v2, and DenseNet for classification using the WaRP dataset with 28 waste categories. YOLOv8 achieved a precision of 74% for bottle detection and an mAP50 score of 76%, while DenseNet balanced precision and recall with an F1-score of 48%. Despite strong localization and classification capabilities, class imbalances and varying lighting conditions impacted the performance of less-represented categories. Additionally, training complexities and computational costs pose challenges for large-scale implementation. To address these issues, our research focuses on generating synthetic data to balance classes and integrating multi-modal data processing to improve accuracy in diverse conditions, creating a more robust and scalable waste sorting system.

2.6 Waste Material Classification Using Performance Evaluation of Deep Learning Models

This study compares deep learning models for waste classification to improve solid waste management. Models like ResNet50, GoogleNet, InceptionV3, and Xception were tested on a dataset of 1,451 images across four categories: cardboard, glass, metal, and trash. Xception performed best with 96.3% accuracy, followed by ResNet50 at 95%. While all models showed promise, misclassifications in tricky categories like glass and trash highlight challenges with overlapping features and uneven lighting. Our research aims to address these issues by using synthetic data, advanced augmentation, and multi-modal approaches to make waste classification more accurate and scalable.

2.7 Automated Waste Sorting using Convolutional Neural Network:

This paper explores combining machine learning and robotics to develop an automated waste sorting system, improving recycling efficiency and reducing manual labor. It uses computer vision with CNNs for waste detection and classification, paired with a robotic arm to sort waste based on model predictions. The system achieved high accuracy in controlled settings, significantly reducing human effort. While effective, its reliance on high-quality images and controlled lighting limits its adaptability to real-world conditions. To address these gaps, our research focuses on enhancing system robustness through advanced object detection, multi-modal data integration, and scalable robotic solutions for diverse waste environments.

2.8 Automatic Household Waste Sorting Using Machine Learning:

This study is all about creating a smart system to help people at home sort their waste automatically. It works by using a Raspberry Pi with sensors and motors to sort waste into biodegradable and non-biodegradable categories. The system uses a machine learning model called Random Forest, which was trained on 500 pictures of different types of waste. It's pretty accurate too—95% for things that break down naturally, 90% for metal, and

87% for plastic. It's a simple and cost-effective way to handle sorting, but there are some limitations. The system was trained on a small number of images, so it might not do well if the waste is mixed or something unusual. Plus, it's only trained for specific categories, which means anything different might confuse it. To make it better, our research will use more varied pictures, better detection methods, and more kinds of information so that the system can handle a wider range of waste and work well in real-life situations.

2.9 Automatic Waste Sorting Based on Image Processing Using ANN:

This study looks at a system that uses image processing and artificial neural networks (ANN) to sort different kinds of waste—like plastic, paper, and metal. The system takes pictures of waste using a high-speed camera and processes these images with a Raspberry Pi 3. Based on what it finds, the waste is sorted into the correct bins by a conveyor belt system. The accuracy was good, with 92% overall, and a little better for sorting paper and metal. While it's affordable and works well in controlled situations, it doesn't handle things like overlapping waste or poor lighting very well. Our research plans to use better detection models, larger datasets, and improve adaptability so the system works better in everyday messy situations.

2.10 YOLOv8-Based Waste Sorting and Collection System:

This study presents a real-time waste sorting system that uses YOLOv8 to classify waste into four main groups: biodegradable, recyclable, reusable, and general trash. The system was trained with over 10,000 images and achieved impressive results—96.1% overall accuracy, with good performance for each category (93% for recyclable and 96% for reusable items). To make it functional, hardware like Arduino UNO and ESP32 CAM is used, along with motors that move the waste into the correct bins. YOLOv8 showed improvements in both speed and accuracy compared to previous versions like YOLOv4. However, there are still challenges—it depends a lot on labelled images for training and struggles with mixed or cluttered waste. Our research focuses on addressing these gaps by expanding the dataset and making the model better at dealing with complex and messy waste types in real environments.

2.11 Comparing Deep Learning and Support Vector Machines for Autonomous Waste Sorting:

This study compares CNN and SVM models for waste sorting using a dataset of 2,000 images. CNN was built using AlexNet, while SVM used a bag-of-features approach. SVM achieved higher accuracy at 94.8%, compared to CNN's 83%, and was implemented on a Raspberry Pi 3 for real-time sorting with a processing speed of 0.1 seconds per image. While SVM proved more efficient and accurate, both models struggled with more complex waste due to the small dataset. CNN also faced overfitting due to hardware constraints. Our research addresses these challenges by expanding datasets, using advanced deep learning methods, and optimizing CNN models through transfer learning and data augmentation.

2.12 Deep Learning-Based Waste Classification for Enhancing Recycling Efficiency and Sustainability:

This study combines CNN and ANN to improve waste classification and recycling efficiency. Using 1,201 images across five categories (cloth, bottle, metal, paper, and plastic), data augmentation techniques like flipping and rotation helped improve model performance. The hybrid ANN-CNN model achieved a 97% accuracy, outperforming Random Forest, SVM, and AlexNet models. However, the limited dataset and controlled conditions restrict its real-world application. Our research expands on this by using larger datasets, incorporating diverse data sources, and optimizing the model for use in resource-constrained environments, aiming for scalability and practicality.

2.13 A Novel YOLOv3 Algorithm-Based Deep Learning Approach for Waste Segregation:

This study uses the YOLOv3 algorithm for sorting biodegradable and non-biodegradable waste. With a dataset of 6,437 images across six categories (cardboard, glass, metal, paper, plastic, and organic waste), YOLOv3 achieved a high mean average precision (mAP) of 94.99%, well above YOLOv3-tiny's 51.95%. Its high accuracy and real-time capabilities make it ideal for automated waste management systems, but reliance on a controlled dataset and its computational needs pose challenges for scalability. Our research addresses these by optimizing YOLOv3 for lightweight hardware, diversifying datasets, and incorporating multi-modal data to improve performance in complex scenarios.

2.14 Automatic Waste Sorting in Industrial Environments via Machine Learning Approaches:

This thesis assesses the use of CNN and SVM for classifying industrial waste into paper, plastic, and metal. Image datasets of 200, 400, and 600 images per category were used, with feature extraction through bag-of-features for SVM and deep features for CNN. CNN achieved 82.2% accuracy, slightly better than SVM's 79.4%, demonstrating superior handling of complex data, though SVM was more computationally efficient. Limitations include the small dataset size and challenges with mixed-material classification. Our research aims to overcome these by adding diverse real-world waste data and optimizing CNNs for resource-constrained environments.

2.15 Deep Learning Networks for Real-Time Regional Domestic Waste Detection:

This study uses the YOLOv3 model for real-time waste detection with region-specific datasets. YOLOv3 was trained on TrashNet, which features single-object images, and the Taiwan Recycling Waste Dataset (TRWD), which includes multiple objects per image. Data augmentation was used for generalization, and the TRWD-trained model achieved a mean Average Precision (mAP) of 92.12%, outperforming TrashNet's model (84.1%) and effectively detecting multiple objects at 80 FPS. Despite its high accuracy, the model is limited to six categories and struggles in cluttered environments. Our research expands on this by increasing the number of categories and optimizing YOLOv3 for diverse environments.

2.16 Intelligent Waste Classification Model Using Multi-Objective Beluga Whale Optimization:

This study introduces a smart waste classification model that combines the InceptionV3 deep learning architecture with a new optimization method called multi-objective beluga whale optimization (MBWO) to improve performance. Using the TrashNet dataset, the model classifies six types of waste—cardboard, glass, metal, paper, plastic, and general trash. Techniques like data augmentation and random oversampling were used to address imbalanced classes, while MBWO optimized important hyperparameters. The model achieved impressive results with 97.75% accuracy, outperforming other well-known models like MobileNetV2 and VGG16. Despite its success, limited dataset diversity and computational complexity may pose challenges in real-world applications. Our research builds on this by using more diverse datasets and exploring simpler optimization techniques to make waste sorting more adaptable and suitable for practical use.

2.17 Enhancing Trash Classification in Smart Cities Using Federated Deep Learning:

This study explores using federated deep learning for trash classification to support waste management in smart cities. Using the TrashBox dataset with seven trash categories, it evaluated ten deep learning models, like ResNeXt-101 and ShuffleNetV2. ResNeXt-101 achieved the best accuracy (89.62%) and F1-score (89.66%). Federated learning, which aggregates model parameters across sites, showed strong potential for improving trash classification through collaborative training. While effective, high computational needs and performance issues with less-represented categories remain challenges. Our research aims to optimize these frameworks for resource efficiency, expand dataset diversity, and develop scalable, real-world waste sorting solutions.

2.18 Smart Waste Management and Classification System for Smart Cities Using Deep Learning:

This study proposes a smart waste management system combining IoT and deep learning to improve real-time waste monitoring and classification in urban areas. IoT-enabled bins use sensors to measure waste level, humidity, and weight, while a CNN model sorts waste into plastic, metal, paper, and glass categories. The system includes a centralized database and optimizes waste collection routes, achieving efficient monitoring and accurate classification. However, limited sensor types, reduced accuracy for mixed waste, and reliance on network connectivity pose challenges. Our research aims to address these by integrating advanced sensors, enhancing classification with new models, and exploring decentralized architectures for better scalability and reliability.

2.19 Waste Sorting Using InceptionV3:

This study uses the InceptionV3 model to automate waste sorting, achieving 94.5% accuracy with five waste categories (paper, plastic, metal, glass, and organic). Data augmentation helped improve performance, particularly for less common types. Despite its high accuracy, the model struggles with low-quality images and lacks real-world data diversity. Our research aims to address these issues by adding more diverse waste images and integrating additional data types to enhance performance in complex environments.

2.20 Waste Classification System using a Hybrid Deep Transfer Learning Model:

The paper follows the methods of transfer learning models such as MobileNetV2, Xception, DenseNet201, ResNet152V2, and EfficientNetB7. This model classifies the waste into five categories: paper, plastic, metal, glass, and organic while achieving 97% of accuracy which is pretty good. MobilNetV2 outperforms every other model with its great performance due to its smaller size and faster inference times. But the limitations of this paper is less waste categories, although it has 16250 images but only in five categories. Higher misclassification rates for certain classes, such as glass and plastic, indicate the need for improved feature extraction methods or larger datasets. Our research tackles these scenarios by having 20+ categories more diverse dataset and more efficient and light weight models. The research will follow multi-modal data processing.

2.21 Conclusion:

Based on the paper we are referring, we have a simple conclusion to make a lightweight deep learning model which is simple to implement, detect all the categories we have, scalable and has good ability to extract features. We have some of them in mind like YOLO, CNN, InceptionV3, MobileNet, Vision Transformers, ResNet50 and VGG-16. These are some of the techniques we will use to get the results and solve the research question.

3 Methodology

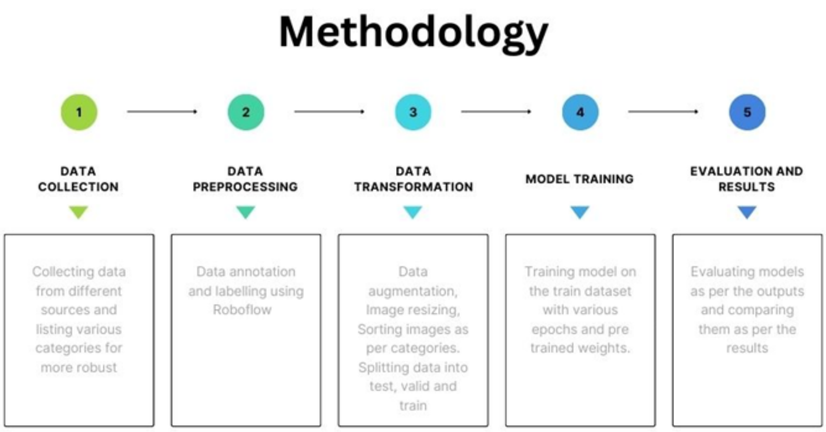

Figure 2: Methodology

The methodology used for this study has different phases to work on such as Data collection, Data Preprocessing, Data Transformation, Model Training, Evaluation and Results. Every phase is important to work on because it is crucial in the process of making multi-class classification.

3.1 Data Collection

To carry out our research, the first step was to find out the types of wastes and which categories falls under which type. We used bio-degradable, non-bio degradable, hazardous and organic types with their categories and making a single dataset. We began by gathering a diverse image dataset from various sources. We utilized publicly available platforms like Data.gov and Kaggle, conducted online searches through Google, and collected images from our immediate surroundings to get wide range of images. These included scenes from restaurants, households, and litter bins, giving us a wide range of visual data. Additionally, we also performed more online research on google to collect the relevant images needed for the data. To make data practical and real, we started clicking images from the phone of the surroundings These smartphone images helped us in enriching the dataset with real world images by adding depth and variability.

Figure 3: Kaggles samples

Figure 3 shows the image collected from Kaggle from three different categories like medical waste, greased pizza boxes and crushed boxes.

Figure 4: Google samples

Fig 4 shows some samples from google which we collected from research for categories like paint cans which is hazardous waste, cigarette butts and battery image samples.

Initially, the dataset featured 33 categories, representing various objects and scenarios. However, to streamline the classification process and improve the accuracy of our model, we decided to reduce the number of classes to 25. We carefully looked into each category and checked if the classes make the dataset weak. For instance, like milk box, dirty paper plates, foil, and sauce lids had less images as compared to others and performing weak in training the models. Chopsticks and chopsticks cover has been found irrelevant as compared to the requirements. We also merged band aid class with medical waste class because it falls in the same category. The removed categories that were either redundant or less relevant, ensuring a more focused dataset having balance.

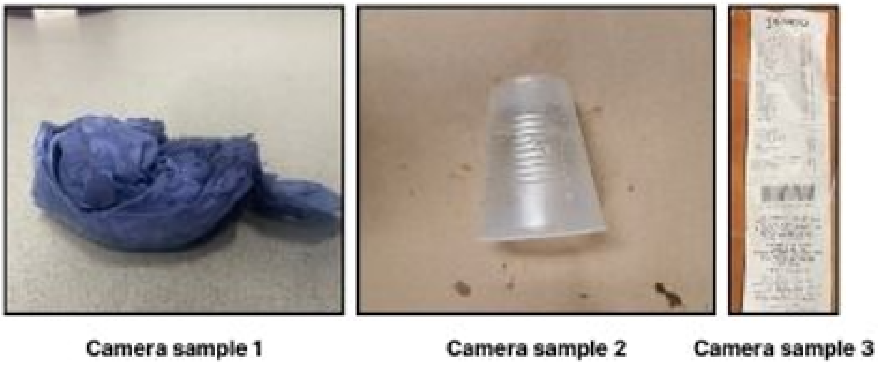

Figure 5: Camera samples

Figure 5 shows same camera samples from three different categories which are used napkins, plastic cup and paper. These images are collected from surroundings using smartphone camera which is placed in the respective class.

3.2 Data preprocessing:

Data has been also prepared for the yolo models for getting trained. In this preparation, we have to make data annotations, labels in coco format. We started with annotations of data; annotation is nothing but labelling the images as per the images. The images are loaded first and at each image we had to create a bounding box and label it with the object we can see in the image. There are tools like LabelImg and RoboFlow which we can use to make data annotations. We tried with LabelImg first but due to the computational power or some error, we were unable to make bounding boxes around the images. Later, we used roboflow to make annotations of the images. We had 5213 images in total and to label each image properly would consume lot of time and energy. So, we decided to annotate 1000 images, we annotated 1000 images with help of some friends and got the labels in YOLO format and COCO format as well. There were images which had more than 3 objects in a single frame, it was challenging to annotate 1000 images with accuracy and as per the particular categories. The annotations have been saved and ready for modelling of yolo model.

3.3 Data transformation:

Once we gathered all the images, the next step was to prepare the data for training the model. We carefully organized and labelled them to get everything ready for training the model. We meticulously organized the images by sorting them into category-specific folders and personally labelled each one to ensure precision and order. This detailed labelling process allowed us to create a well-structured and organized dataset, minimizing errors during model training. After completing this process, we split the dataset into three portions: 70% for training to help the model learn effectively, 20% for validation to fine-tune its accuracy, and the final 10% for testing to assess its real-world performance. All the splitting part was done using python script to get each category in all the split folders, to get data in proper proportion and to get it done quickly as this had around 6300 images at the initial stages but after removing classes and merging, we got around 5213 images in 25 classes. We still felt the data was not enough and need more images but due the similar images on internet and same datasets all over the websites having only 4-5 classes. So, to make the dataset even more effective instead of using more similar images, we added some variety by using data augmentation. This meant rotations, zooming, flipping, and slight shifts in angles. By creating 2-3 augmented versions of every image, we introduced greater variability into the dataset. These extra versions helped the model learn to recognize objects from different perspectives, making it more adaptable to real-world situations. This technique implementation was important for addressing the challenge of limited dataset. This process allowed us to build a solid foundation for training and testing, ensuring reliable and accurate results. By implementing these steps careful data collection, meticulous preparation, and strategic augmentation we established a solid foundation for training and testing our model. This comprehensive approach ensured that the dataset was both diverse and well-prepared, paving the way for reliable and accurate results in our research.

3.4 Model Development and training:

ViT Model: Initially, we started by experimenting while making a vision transformers model from scratch to check how it goes and what will be results. Constructing it from scratch made us get a deeper understanding of the architecture and functionality. The vision transformers work by dividing images into smaller patches which are then processed as sequences. These sequences are analysed using self-attention mechanisms, allowing the model to capture intricate relationships and dependencies between different regions of an image. However, this approach came with lot of challenges while moving forward. It was resource heavy and it requires lot of memory to process and more computational power. Additionally, the absence of pre-trained weights become a big obstacle because it required lot of time to process because of no pre-trained weights, heavy computational requirements and insane amount of time. This became difficult to move forward because of the more time and large dataset. Recognizing these limitations, we decided to pivot away from building ViT models from the ground up.

InceptionV3 model: Inception-V3 is widely used for its high accuracy, efficiency, and versatility in image recognition tasks. It combines multi-scale feature extraction with computational optimizations like factorized convolutions and pre-trained weights, making it both powerful and resource-efficient. Additionally, it excels in transfer learning, enabling quick adaptation to specialized tasks. This involves fine tuning the pre trained model of Inception V3 for image classification. The inception V3 model is pre-trained on

ImageNet and used as a base with the base model frozen to retain the learned features. Custom layers are added, including a global average pooling layer for feature extraction, a dense layer with 1024 units and ReLU activation for learning new patterns, a dropout layer to prevent overfitting, and a final softmax layer for classification. The model is compiled with the Adam optimizer, categorical crossentropy loss, and accuracy as the metric. Training is conducted for 20 epochs with a batch size of 32 and 64 while experimenting with the size of image as well, and performance is monitored using validation data. After training, the model is saved for future use, and training and validation performance is visualized with accuracy and loss plots to evaluate and refine the model's effectiveness.

Convolutional Neural Network: CNN are used because of its ability to extract the features from images like edges and patterns. This makes CNN better for identifying and categorizing the images. The process starts with data preparation for training set. The training data has been augmented with techniques such as rotation, zoom, shifting and flipping. The image data which we will use to train is already an augmented data and we are again performing more in the training set preparation. So, it will be more robust and better training of model. Validation data has been rescaled to normalize the pixel values of the images. The image size has been set to 224*224. It is not been augmented again to keep it consistent for testing. The model has three convolutional layers to extract the features from the images. After each convolutional layer there is a max pooling layer which will help in reducing the size of data while extracting important features. It will not only make the model faster but efficient as well. A dense layer of 128 neurons after this layering help the model learn complex relationship in data. A dropout layer of 0.5 is used to avoid any overfitting of model and perform well on unseen data. The final layer is of 'softmax' activation function to predict the probability of the classes. The model is then compiled with the Adam optimizer and categorical crossentropy loss which is used in multi-class classification. The model is done with all the layers and compilation. Now, we trained the model on 20 epochs at first to check the time the model takes for training and accuracy. Then, we tried with 40 epochs and 50 epoch for better training and accuracy. Training set has been used to train the model and validation set is used for monitoring the performance. After the training the model has been saved as .h5 file to increase the reusability.

MobileNetV2: MobilNetV2 is a lightweight and efficient CNN technique which is used to classify waste images into categories. MobilNetV2 is a technique which we used due to its high accuracy and low computational cost. The model is used with its pre-trained weights from ImageNet and is used for transfer learning by freezing its base layer to extract the learned features. The training dataset has been augmented and used the same way like CNN. A custom classifier layer of global average pooling layer is added at the top of the base model. We also added dense layer, dropout layer and softmax layer for multi-class classification has been added. Then the model is compiled same way as before with Adam optimizer, categorical crossentropy and accuracy as the metric. Training was performed using 20 epoch at start then moved to 30 and 40. We also tried MobileNet due to MobileNetV2 has an inverted residual structure and linear bottlenecks add architectural complexity, which may complicate implementation and tuning compared to simpler models. Both the models used pre-trained weights but MobileNet was trained using dense layer of 1024 units for feature extraction. Initially, the base layer of the model was frozen and fine tuning was done later with lower learning rate. MobileNetV2, on the other hand, added more advanced architectural elements for improved accuracy, making it slightly more computationally intensive but better suited for complex tasks requiring fine-grained feature extraction.

ResNet50: ResNet50 is another image classification model. It is also called as residual network with 50 layers; it is a deep convolutional neural network architecture known for its ability to train the deep models. So, we used this model with transfer learning and data augmentation for better performance. The training data has been augmented with techniques such as rotation, zoom, shifting and flipping. The validation data is rescaled for better consistency. The model has been trained on the pre-trained weights of ImageNet with its top layers and the base layer has been frozen. We did batch normalization for stable training, a fully dense layer with regularization, dropout layer for overfitting and softmax layer for multi-class classification. The model is compiled using Adam optimizer, categorical crossentropy loss and accuracy. It is only started with 10 epochs to test then we used 20 and 30 for better understanding of overfitting and the results. We tried this on the original dataset which is not been augmented to know how it performs and then used the augmented data for better understanding. The model was then saved as .h5 file for future use.

VGG-16: VGG-16 is a popular Convolutional Neural Network architecture because is simple, effective and sustainable for transfer learning. Here's why VGG16 is a great choice. It's architecture which has 16 layers, including convolutional layers with 3 by 3 filters. We used VGG-16 because of its simplicity, consistency and feature extraction ability. We have done same thing in this model as well using transfer learning. The training set has been augmented, validation set has been kept as it is, the model is loaded with its pre-trained weights and has been customised. The base layer has been frozen to use the model for new task and custom layers are added like global average pooling layer. A dense layer with 512 units for better learning, dropout layer to avoid overfitting and at last softmax layer for multi class classification has been added. The model is compiled using Adam optimizer, categorical crossentropy loss and accuracy. It is trained using 10 epochs at start then we moved to 20 and 40 for better training results. Then the model is saved as .h5 file for future use and detection of waste.

EfficientNetB0: EfficientNetB0 is a highly efficient convolutional neural network that balances accuracy, cost-efficient and resolution systematically. This model is scalable which can be scaled between EfficientNetB0 to B7 depending on the computational resources available. It's a lightweight model which can be used on mobile and IoT devices as well. The model we are using is a TCNN based EfficientB0 model as pre-trained base for image classification. The model uses the pre-trained weights for processing and further learning. Pre-trained weights have been used using ImageNet and the base layer has been frozen to learn new features and work more on the features it has already learned. A pooling layer, dense layer having 128 units of neurons to learn specific tasks, dropout layer and softmax for multi-class classification. The model complied with Adam optimizer and has been trained using 20 epochs at first and 30 epochs later. Finally, the training and validation loss has been plotted and classification report is plotted as well to visualise the results we get out of it.

YOLO-v4: YOLO (You Only Look Once) is a powerful and efficient model which can be used to detect objects in image, it balances high accuracy with real time performance. It detects images by predicting bounding boxes around the objects and class probabilities in a single look which makes it faster to than other regional approaches. The pre-trained model of yolov4 is loaded and required config as well as weights files has been downloaded to move with the process. Annotations containing class ID and bounding box are extracted from file for evaluation. The model detects objects by generating predictions with class IDs, confidence scores, and bounding box coordinates, filtering low-confidence detections, and applying Non-Maximum Suppression (NMS) to remove overlapping boxes. When all the information, annotations, weights of pre trained model is combined and processed further the resulting image pops up to provide feedback on model performance. All the annotations and pre-processing has been noted in the data preparation.

YOLO-v3: YOLOv3 is a third version of yolo model which we tried on the features and capabilities are almost similar in both versions of the YOLO. We tried yolov3 because of its requirement and low computational capacity than v4. We worked on this model the same way we used v4. We also tried YOLOv8 but it did not work on our CPU and GPU. Later, it has been used on google colab to test if it works or not. This version has worked with less efforts, the version used a dataset.yaml file for processing which consists of the paths of the images folder and classes listed.

Ensemble Modelling: Due to the other model's performance and the results seen, we tried ensemble modelling with the advice of the supervisor to make an ensemble model. Generally, the idea of the ensemble model was of binary classification like crushed and not crushed bottles, carboards or not carboard boxes, medical waste or not medical waste and so on. The idea was to make 24 binary classification model and ensemble it for better accuracy and detection which was a great but due to less time and more categories we only succeeded with crushed bottle or not crushed bottles. We implemented basic CNN model for binary classification while applying transformations with data augmentation technique. Validation data is only normalized for normal pixel values. The model has three convolutional layers with increase in filter after each layer like 32, 64 and 128 followed by max pooling layer, final pooling layer, dense layer with 128 neurons, dropout layer and sigmoid activation function which is use for binary classification has been added. The model is compiled using the Adam optimizer, binary cross-entropy loss function, and accuracy as the evaluation metric. It is trained for 30 epochs, with performance monitored using the validation dataset. The model was saved as .h5 file for future use. Now instead of making more binary model we will try to combine this binary model with ResNet50 model for experimentation. So, we will use our two pre-trained model's binary.h5 and ResNet50.h5 for an ensemble learning approach. Both models are loaded and the base layer is frozen to get pre-trained weights instead of retraining. An input shape of 150 by 150 has been provided to both models for generating individual predictions. The outputs are then combined using averaging layer, which computes the mean of the predictions to leverage the strengths of both models while mitigating individual biases. The resulting ensemble model is compiled with the Adam optimizer and binary cross-entropy loss, optimized for binary classification tasks. The approach has been unique from other models and techniques. The model is later saved in a .h5 file for future use.

3.5 Implementation:

This section explains how we worked on the project from beginning to end. It covers how we designed the model, tested it, checked its accuracy, and made plans to improve it in the future. The main aim of this project was to create a system that makes sorting waste easier and more efficient to support recycling. We built a reliable model that can recognize different types of waste, like plastic bags, bottles, paper, and other materials, to help with proper waste management. For this purpose, some models have been developed to make the predictions and check outcomes. To implement this process, we used some python and its libraries such as NumPy, TensorFlow, Keras, OpenCV. The augmented data has been prepared using python script to flip images, resize, zoom in and zoom out. The data has been split into valid, train and test using python script where the images has been selected using python and divided into three categories 70%, 20% and 10%. Various model has been trained and tested on the CPU and GPU. The CPU has around 16GB of RAM, processor of intel i7 and graphic card of Nvidia GeForce RTX4050 GPU.

4 Evaluation:

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

In terms of the confusion matrix (for binary or multi-class classification):

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

In this section, we will be looking at the performance of the models we have implemented and their results. It involves analyzing the metrics, accuracy, precision, recall and f-1 scores to understand how well the model performs on the data. Confusion matrix and classification reports will give us the deeper understanding of class specific performance of the model. This will make us identify the strength, weakness and area of improvements of the model.

Experiment 1 with ViT: We made a ViT model from scratch making all the layers and ready for training model. But the model didn't have any learning or has been previously trained it took lot of time around 8 hrs for single epoch due to compatibility and image size. We dropped this model and moved forward with other one.

Experiment 2 with InceptionV3:

This model performed with 26 classes and around 20000 images. The confusion matrix and classification report demonstrate the model performance with 91% accuracy with precision and recall and f1 score about 93%, 90% and 92% respectively. While most of the classes showed high precision and recall, classes like 'plastic bag' and 'napkin' tends be on lower and weaker side of the model. The model's strength includes ability to classify images as per the categories, like 'dirty paper plates' and 'sauce cup' with nearly perfect precision and recall. But still there are some occasional misclassifications between categories like 'medical waste' and 'paper' which suggest for fine tuning and further improvements. Overall, the results indicate this as a well performing strong model with real time object detection application with areas of targeted improvements. We also tried this model training on the first-hand dataset which has 25 classes and 5213 images. It gave accuracy around 76% with precision, recall and f-1score 83%, 71% and 74% respectively, which made us move with augmented dataset.

Experiment 3 with CNN: This model was trained on the same dataset. The model's overall accuracy is 7% with lower precision, recall and f-1 score which indicate

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

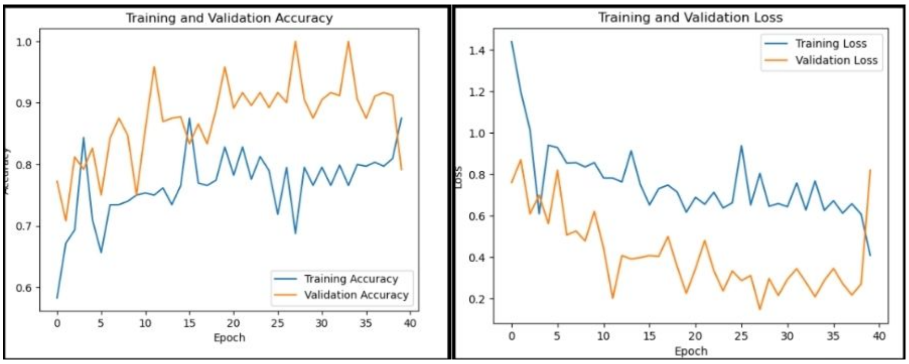

Figure 6: Training and validation accuracy

Classification Report:

	precision	recall	f1-score	support
Crushed bottles	0.98	0.81	0.89	72
Dirty paper plates	1.00	0.96	0.98	25
Entangled plastic bags	0.89	0.96	0.93	53
Greased pizza boxes	1.00	0.90	0.95	58
Medical waste	0.84	0.91	0.87	681
Paint cans	1.00	0.78	0.88	55
Paper Bowl	0.99	0.98	0.99	107
Plastic Cup	0.96	0.92	0.94	72
Sauce Cup	0.98	1.00	0.99	62
bandaid	0.95	0.93	0.94	290
battery	0.90	0.97	0.93	450
bulb	0.94	0.94	0.94	450
cans	0.90	0.95	0.93	456
cardboard	0.93	0.95	0.94	998
cigarettebutt	1.00	0.86	0.92	49
diapers	0.94	0.95	0.95	251
glass	0.92	0.89	0.90	717
leftovers	0.98	0.93	0.95	258
metal	0.90	0.90	0.90	449
nailpolishbottle	0.92	0.87	0.90	360
napkin	0.96	0.69	0.80	155
newspaper	0.93	0.93	0.93	219
paper	0.86	0.91	0.88	625
pesticidebottle	0.88	0.83	0.86	227
plasticbag	0.92	0.79	0.85	240
plasticbottle	0.82	0.94	0.88	133
accuracy			0.91	7512
macro avg	0.93	0.90	0.92	7512
weighted avg	0.91	0.91	0.91	7512

Figure 7: Classification report for InceptionV3

that the model struggles to perform well with this dataset and fails. The majority of classes shows misclassification and unable to detect between categories or is affected by imbalance. The classification report shows that the model has almost all the classes with precision and recall close to zero which is very poor. The model needs significant optimization and fine tuning which should be starting from data preprocessing for this model and all the steps needs to be reviewed. Present your findings.

Experiment 4 with VGG-16: We performed same training process in this model as well with same set of images and classes. This model showed overall solid performance with accuracy of 76% on the validation dataset. The model achieved macro-average precision of 80%, recall of 73% and f-1 score of around 76% which indicate overall better and balanced performance across all the categories. There are some class imbalances and misclassifications. In the confusion matrix, we can see strong performance in categories like 'bulb' with 88% precision and 96% recall. The model shows better diagonal dominance due to dataset issues and less finetuning. While some classes such as 'cigarettebutt' and

Classification Report:

	precision	recall	f1-score	support
Crushed bottles	0.00	0.00	0.00	72
Dirty paper plates	0.00	0.00	0.00	25
Entangled plastic bags	0.00	0.00	0.00	53
Greased pizza boxes	0.00	0.00	0.00	58
Medical waste	0.10	0.14	0.12	681
Paint cans	0.00	0.00	0.00	55
Paper Bowl	0.02	0.03	0.02	107
Plastic Cup	0.00	0.00	0.00	72
Sauce Cup	0.00	0.00	0.00	62
bandaid	0.03	0.03	0.03	290
battery	0.06	0.08	0.07	450
bulb	0.07	0.06	0.06	450
cans	0.05	0.08	0.06	456
cardboard	0.11	0.12	0.12	998
cigarettebutt	0.00	0.00	0.00	49
diapers	0.05	0.05	0.05	251
glass	0.07	0.08	0.08	717
leftovers	0.02	0.03	0.03	258
metal	0.06	0.05	0.05	449
nailpolishbottle	0.05	0.03	0.04	360
napkin	0.00	0.00	0.00	155
newspaper	0.02	0.02	0.02	219
paper	0.09	0.08	0.08	625
pesticidebottle	0.00	0.00	0.00	227
plasticbag	0.06	0.04	0.05	240
plasticbottle	0.01	0.02	0.01	133
accuracy			0.07	7512
macro avg	0.03	0.04	0.03	7512
weighted avg	0.06	0.07	0.06	7512

Figure 8: CNN classification report

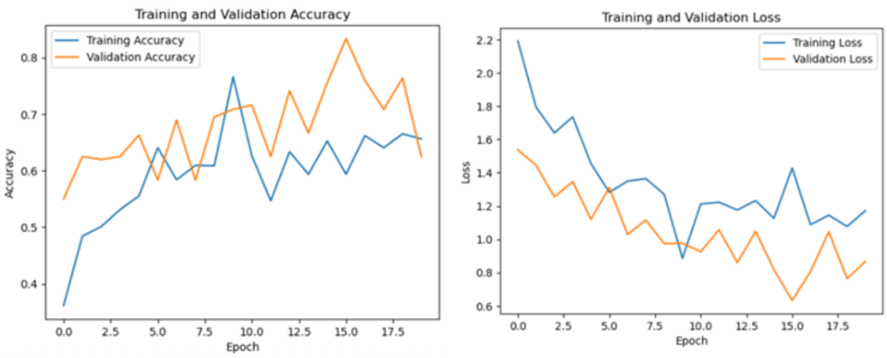

Figure 9: VGG-16 Classification report

'medical waste' has lower values such as 62% and 60% respectively. Overall, this model performs with good predictability but struggles with certain challenges in similar classes. The model can be made better by fine tuning, making class boundaries to enhance the recall and f-1 scores.

Experiment 5 with ResNet50: This model has been trained using the augmented data with overall accuracy of just 7% and macro average precision, recall and f-1 score of 4% indicating poor performance of classes across all 26 classes. The classification report shows that most classes have precision, recall and f-1 score close to zero with minimum of true positive identification. Cardboard class has 18% of recall and bulb has 7% though this is not the ideal output needed but still better than other categories. The performance is poor due to dataset issue, model limitations in learning or suboptimal training process, maybe this can be reasons for poor performance. To address these challenges data preprocessing, balancing, model optimization and fine tuning can be done for better performance.

Experiment 6 (Failed models): Apart from the listed models is evaluation there

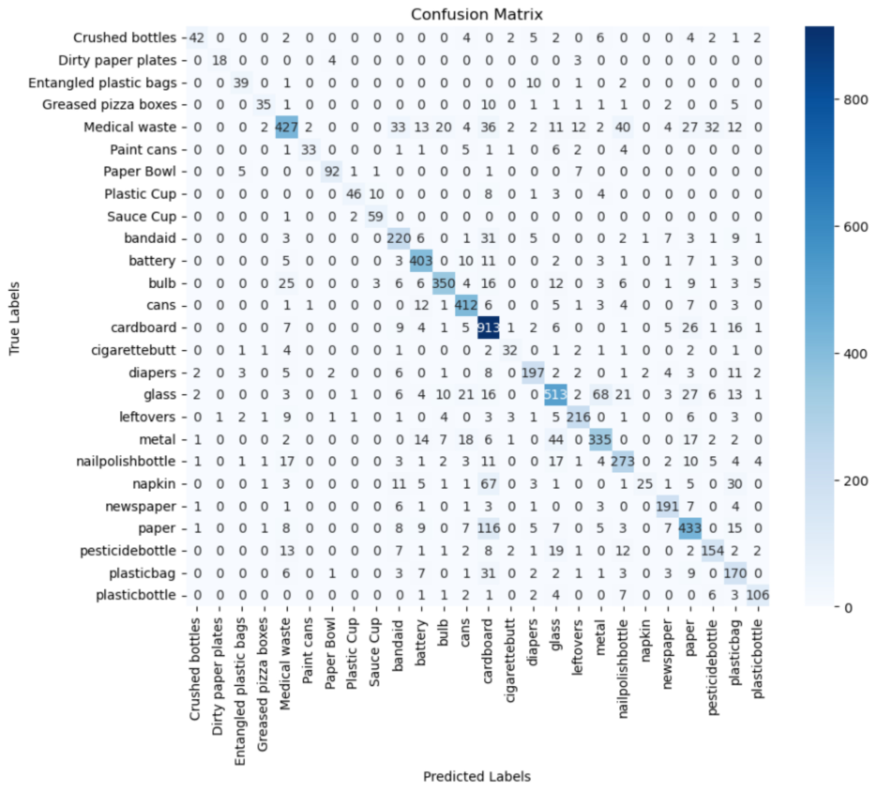

Figure 10: Confusion Matrix of VGG16

are some other models as well which failed to train and move forward. There is MobileNet mode which performed same way like ResNet50 and CNN. There is Yolov3, v4 and v8 failed to perform due to the annotation error which was time consuming process. As listed above, LabelImag failed to work and the annotations which were made using roboflow was not in the format needed to run the model. The format was like

```
metal-395-_jpg.rf.e81f757791bd4a4bf8d465c5af3c7f04.jpg 94,1,449,398,14
```

but this format is not acceptable. We also tried with removing the image name but it still failed and we moved forward with other models. There is not a strong reason to drop this model apart from annotation because YOLO is one the most successful object detection technique which can be useful in this topic. Other models have performed poorly because of the improper learning of models, dataset issue and less finetuning.

4.1 Discussions:

The evaluation of the models which we have experimented with, was trained to asses the classification accuracy and adaptability around different scenarios. The summary of all the models which have been trained in the experiments has been displayed in the below table for better understanding. Figure 11 Model Comparison Notably, InceptionV3 and VGG-16 has performed well, particularly when applied to augmented dataset. These models have shown their ability to extract the features from the images to classify them as per the complex categories, with some classes with strong precision and recall. These models can also be successful in real world implementation for detecting objects and finding which category they fall in and will it be recyclable or on-recyclable.

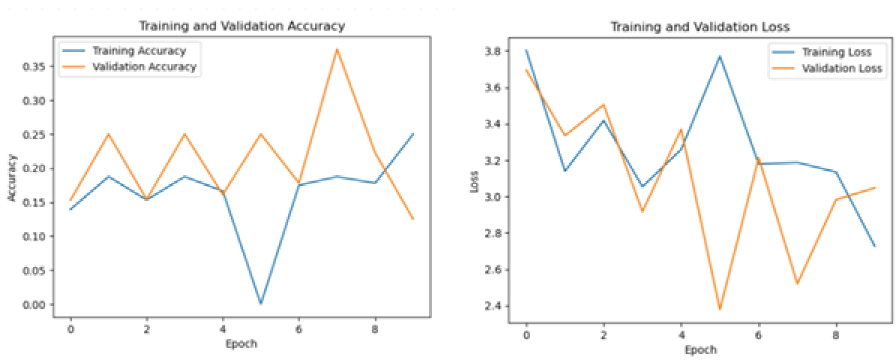

Figure 11: Training and validation accuracy/loss for ResNet50

Model	Accuracy	Precision	Recall
CNN	7%	6%	7%
VGG16	76%	77%	76%
InceptionV3	91%	91%	91%
ResNet50	7%	7%	7%

Figure 12: Comparison of models

The results here highlights some of the challenges and opportunities for improvement in the models. Some issues appear to be data augmentation and preprocessing. Other works can be done on the dataset imbalance which likely can be issue like we have some classes where images are not much for better training on the class. Balancing the dataset, either through oversampling underrepresented classes or using techniques like SMOTE, can also reduce biases and improve model learning. Annotation quality and compatibility were significant bottlenecks in certain models, such as YOLO variants, where format mismatches and errors hindered training. Ensuring high-quality, properly formatted annotations through tools like LabelImg or automated pipelines is critical for effective model training.

There are some class-specific weaknesses which will not only hinder the model accuracy but also be difficult for the classes which is strong with high precision. There are some classes in our dataset which has been moderately week, very weak and moderately strong which is not good for overall model performance. So, to avoid these challenges, we can use class specific training which can refine the boundary between classes.

5 Conclusion and Future work:

5.1 Conclusion:

In this paper, we started the research for the main research question **"How can improved waste sorting systems be designed and implemented to enhance environmental sustainability and optimize resource recovery?"** The research question tends to improve the waste sorting system by using various experiments and working on varied challenges. Effective design and implementation of the system needs many-sided approach in which the system can detect multiple objects accurately using advanced technology. By using automated methods and technique like deep learning and machine learning we can improve the system overall.

The evaluation of various deep learning methods for waste classification provides insights into making a better waste sorting system. Our models like InceptionV3 and VGG16 showed strong potential with high accuracy and precision. Required prediction were done with high accuracy and been able to detect the categories. Their ability to predict between nuance categories shows the importance of advanced technology and deep learning architecture in waste sorting. However, there are still gaps which can be filled using fine tuning and make more refined dataset and model. The design has been light weight model specific which is required to make the model scalable.

To answer the question, better waste sorting systems can be made using machine learning and deep learning techniques like InceptionV3 and other models which are available. Using more categories and more data can be helpful as well as important to get best results. Adding real time object detection tool with good balance will make the sorting system much better and faster. This will not only give us chances to recover the reusable materials but also reduce waste contamination and landfills. These improvements can be important to protect the environment and manage resources which are limited for future. These kinds of advanced technologies can make the waste sorting system precise and protect environment.

5.2 Future work:

Future work in waste sorting systems should focus on enhancing datasets and optimizing models. Developing larger, high-quality, and well-annotated datasets with diverse waste categories will improve classification accuracy and address class imbalances. Leveraging advanced annotation tools and transfer learning with pre-trained models can enhance model performance and reduce training time. Fine-tuning advanced models like InceptionV3 and VGG-16 will help improve their ability to distinguish between overlapping categories, ensuring more reliable results.

Additionally, integrating real-time object detection technologies, such as optimized YOLO models, can make sorting systems faster and more practical for deployment. Exploring hybrid approaches, like combining binary classification model on each category can help in making more better models. Sustainability should also be prioritized by adopting energy-efficient training and deployment methods. Pilot testing these systems in real-world scenarios will provide critical insights for refinement, enabling accurate, efficient, and environmentally sustainable waste sorting systems. Future advancements should also explore the use of lightweight models for on-device processing, enabling cost-effective and scalable solutions for waste management. Collaboration with industry and municipalities can help align these systems with practical needs and regulations. By iteratively improving performance through real-world feedback, these systems can significantly enhance waste recovery and reduce environmental impact.

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