OPTIMIZING HOUSEHOLD WASTE SORTING THROUGH ITERATIVE LEARNING: YOLOv5 VS. YOLOv7

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FINAL YEAR DESIGN PROJECT REPORT

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

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APPROVAL

This Project titled "**Optimizing Household Waste detection and sorting Through Iterative Learning: YOLOv5 vs. YOLOv7**", submitted by **Jihad Khan Dipu** and **Mehedi Hasan Tusar** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **1st July 2024.**

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We hereby declare that this project has been done by us under the supervision of **Dr. Md. Taimur Ahad, Associate Professor and Associate Head of the Department of Computer Science and Engineering at Daffodil International University.** We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Efficient home trash management is crucial for sustainable urban living, particularly in densely populated areas like Dhaka City, Bangladesh. This thesis explores optimizing garbage sorting processes using iterative learning by comparing two advanced object detection models, YOLOv5 and YOLOv7. The primary objective is to develop a robust object identification system to recognize and categorize abandoned waste into seven categories: plastic, biological, cardboard, clothing, glass, metal, and paper. To achieve this, secondary data from Kaggle and primary data from the Dhaka waste plant were utilized. The models were trained and evaluated on these datasets, with performance metrics indicating YOLOv7 achieved a higher accuracy of 97.5% compared to YOLOv5's 96.2%. These results demonstrate YOLOv7's superior capability in accurately detecting and classifying waste materials, making it a promising tool for enhancing waste management systems. This research contributes to waste management by offering a comparative analysis of contemporary deep learning models and insights into their practical applications in urban environments. The findings underscore YOLOv7's potential to significantly improve the efficiency and accuracy of household waste sorting, thereby supporting more effective waste management strategies in Dhaka City.

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CHAPTER 1
INTRODUCTION

1.1 Overview

The World Bank study found that nearly 4 billion tonnes of solid waste are generated in the world every year, and only cities are the biggest contributors to this number, with waste expected to rise by 70 % by 2025 researched by Gupta et al(1998). Sharholy et al(2008) and her Researchers estimate that the accumulation of waste from the least developed countries will rise significantly over the next 25 years .The accelerated urbanization in Dhaka and other cities across Bangladesh has led to a noteworthy surge in waste generation, posing significant environmental and health hazards due to neglected waste. Putting appropriate waste management procedures in place is urgently needed in light of this critical challenge. Unsorted garbage not only clogs drainage systems, but also contributes to the spread of diseases such as dengue and malaria, which disproportionately impact vulnerable populations such as children, mothers, and the elderly. Waste Management in the present time is known to everyone but unfortunately, it is neglected by numerous people that are utilized to portray exercises for waste segregation to take care of issues brought about by wrong garbage disposal addressed by Singh et al(2017). Waste sorting arises as a fundamental solution, as it enables the separation of recyclables like plastic and paper, diverting them from landfills and facilitating their repurposing through recycling processes. This approach promises to yield multiple benefits, including the reduction of waste volume, improved water quality, and enhanced public health outcomes. Waste sorting arises as a fundamental solution, as it enables the separation of recyclables like plastic and paper, diverting them from landfills and facilitating their repurposing through recycling processes. This approach promises to yield multiple benefits, including the reduction of waste volume, improved water quality, and enhanced public health outcomes.

YOLO: The Fastest Object Detection Algorithm model, presents a promising avenue for automating waste sorting procedures. Utilizing machine learning capabilities, such technology can efficiently segregate waste, thereby facilitating streamlined recycling and composting procedures. This, in turn, contributes to minimizing greenhouse gas emissions, restoring valuable resources, and curbing landfill waste. Despite its potential, however, the adoption of deep learning-based waste sorting encounters challenges such as the availability of labeled waste image datasets and the substantial computational resources demanded by these models.

Regardless, the integration of machine learning-powered waste sorting automation marks a significant stride towards sustainability. By cultivating collaboration among governmental bodies, waste management entities, and technology developers, Bangladesh could open the way for a cleaner and more sustainable future. Using automated waste sorting systems has the ability to reduce waste amounts and their negative effects on the environment while also opening up job opportunities in the recycling sector. Ultimately, this technology emerges as a potent instrument in addressing the nation's escalating waste management challenges, steering Bangladesh towards a more sustainable trajectory.

1.2 Background and Present State

With the increasing concerns about environmental pollution and resource depletion, effective waste management has become a critical issue. An essential aspect of this is waste sorting, which involves separating different types of waste materials for appropriate treatment and recycling. Traditional waste sorting methods often depend on manual labor, which can be inefficient, time-consuming, and physically demanding.In recent years, advancements in computer vision and machine learning have introduced new possibilities for automated waste sorting systems. These systems employ object detection models, such as YOLOv7, to automatically identify and classify waste items in images or video streams. This technology enables faster, more accurate, and less labor-intensive waste sorting compared to conventional methods.
The YOLOv7 model is a cutting-edge object detection model renowned for its speed and accuracy. Researchers are leveraging its capabilities to explore its application in waste sorting systems, aiming to enhance efficiency and waste management practices.

1.3 Problem Statement

In many places, trash sorting is still done by hand, which is like picking through garbage! This isn't only dangerous for the people doing it, but it also means lots of good stuff gets thrown away that could be recycled. The world bank report showed that there are almost 4 billion tons of waste around the world every year and the urban alone contributes a lot to this number, the waste is predicted to increase by 70 percent in the year 2025 by Nnamoko et al(2022) Dhaka city produces approximately 646 tonnes of plastic waste every single day, which is 468 tonnes more than 15 years ago. In 2005, the daily plastic waste was 178 tonnes, but by 2020, it had increased to 646 tonnes per day from the information by Mitra et al(2020). With the rapid growth of population and unplanned urbanization, Dhaka faces enormous challenges of environmental degradation these days. Poor solid waste management further adds to the problem. With conventional waste management systems, the city authorities are not in a well-managed position to handle the total volume of wastes. The existing system for waste management has an average waste collection efficiency of 55% published by thedailystar (2022). Every year, Bangladesh faces substantial economic and environmental losses due to inadequate waste sorting and management across various regions. Moreover, an annual loss of approximately $6.5 billion, equivalent to about 3.4% of the country’s 2015 GDP estimeted by Kumar et al(2020). From the figure 1, studied by Roy, H. et al we can see an example of growing wastes of electronics mensoned by Huang et al (2021)

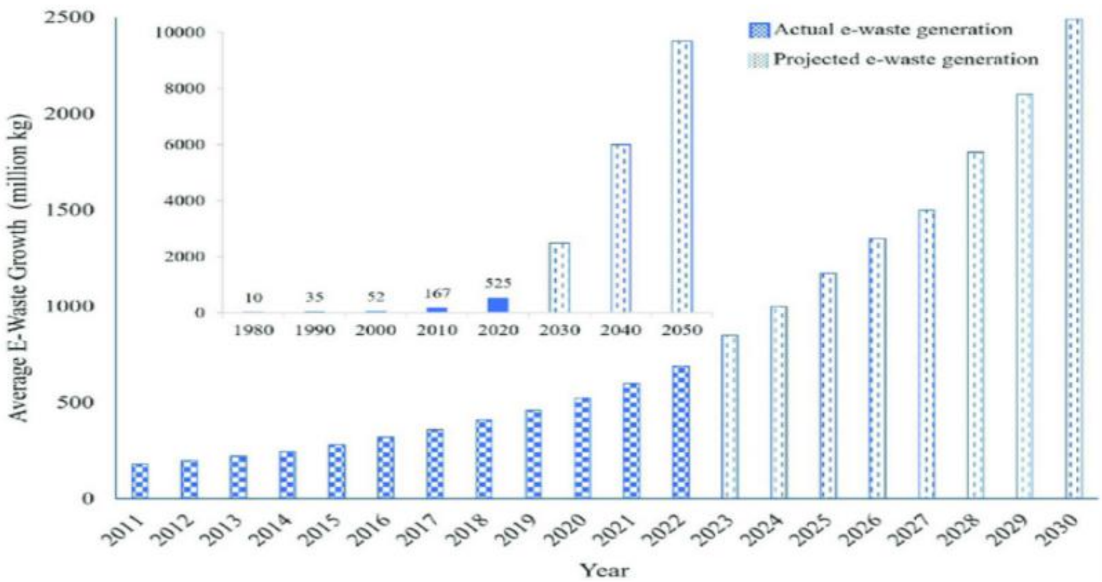


Figure 1.3.1: increase numbers wastes

1.4 Objectives

In Bangladesh, waste sorting is stuck in the past, relying on manual labor by "Tokais," who face risks to their health risks, inconvenience and well-being. Modern cities are buzzing with "Smart City" ideas, and one key component is Smart Waste Management Systems powered by the Internet of Things (IoT) and deep learning. Our research proposes a solution and that is by using computer vision to make a IoT-based real-time sorting to automatically separate different types of household waste. This innovative approach aims to make waste management in Bangladesh effective, efficient, and hygienic.As deep learning is a class of machine learning algorithm that uses multiple layer of data representation and feature extraction. Wu et al(2022) using convolution neural network, a class of deep feed-forward artificial neural network has been applied successively to analyze the image. Thus, in waste segregation using deep learning involves acquiring images from camera with detection by Morell et al (2022), object recognition, prediction and classification by Wu et al (2022) into various categories.

1.5 Scope and Limitations

This project proposes a smart waste sorting system using an deep learning model for classifying cardboard, biological waste, metal, plastic, glass, and general trash. Our - image dataset which contains more than 7000 images covers various waste types. By accurately sorting waste into groups with similar recycling processes, we aim to simplify and streamline recycling for almost everyone. This project has the potential to benefit governments, industries, and individuals economically by increasing recycling rates and reducing waste management costs. It can also effect in the waste recycling industries in Bangladesh

1.6 Report Organization

Chapter 1: Introduction

This chapter has introduced the concept of household waste sorting using deep learning. It has provided background on the current state of the art and defined the specific problem the project addresses. The objectives have been outlined, detailing what the project hopes to achieve. The scope and limitations of the project have also been established, acknowledging any constraints. Finally, a roadmap for the reader has been provided by outlining the structure of the report and summarizing the key points of the introduction.

Chapter 2: Literature Review

To gain a deeper understanding of existing solutions, Chapter 2 has delved into the literature related to deep learning and household waste sorting. This has involved discussing relevant research papers, articles, and projects. By comparing and contrasting these existing works, the chapter has highlighted their strengths and weaknesses, and how the project builds upon them. It has also identified any areas where current research may be lacking, pinpointing the specific open issues the project aims to address. Finally, the chapter has summarized the key takeaways from the literature review.

Chapter 3: Methodology/ Requirement Analysis & Design Specification

Chapter 3 has delved into the technical approach chosen for this project. It has described the specific deep learning model used (e.g., YOLOv5, YOLOv7) and how it has been implemented. This includes details on the training process, data preparation techniques, and the overall system design. Additionally, the chapter has listed the hardware and software resources required for the project, outlining any specific computing power or software libraries needed. An optional section might cover project management and financial analysis, outlining the project timeline, milestones, and any associated costs. Finally, the chapter has summarized the key aspects of the methodology and design.

Chapter 4: Implementation

Chapter 4 has explained the development process in detail. This has involved describing how the deep learning model has been trained, including details on data preparation, hyperparameter tuning, and the specific training procedures used. It has also explained how the functionality and performance of the model have been tested, outlining the chosen evaluation metrics and testing methodology. Finally, the chapter has been summarized, highlighting the key points of the implementation process.

Chapter 5: Result and Analysis

The findings of this project have been presented in Chapter 5. This has involved showcasing the results obtained from training and testing the model, focusing on metrics like accuracy, precision, and recall. Finally, the chapter has been summarized, highlighting the key findings and insights gleaned from the results analysis.

Chapter 6: Impact on Society, Environment and Sustainability

Chapter 6 has discussed the broader implications of this project. This has involved exploring how the project could improve people's lives, such as by increasing recycling rates or reducing waste management costs. The positive impact on society and the environment has also been explored, focusing on aspects like promoting sustainability and reducing pollution. Additionally, the chapter has addressed any ethical considerations related to the project, such as data privacy or potential biases. A sustainability plan outlining how the project ensures long-term viability (e.g., potential for future improvements, scalability) has also been included. Finally, the chapter has been summarized, highlighting the key points regarding the project's impact and sustainability.

Chapter 7: Conclusion and Future Work

The final chapter summarizes the project and looks ahead to future possibilities. Here, the chapter outlines the key conclusions drawn from the research and development process. Additionally, it discusses potential areas for further exploration and future work that could build upon this project. Finally, any limitations or potential conflicts of interest have been acknowledged.

1.7 Summary

The rapid urbanization in Dhaka and other cities in Bangladesh has led to increased waste generation, posing significant environmental and health hazards. Effective waste management, particularly waste sorting, is crucial for mitigating these issues. Traditional manual waste sorting methods are inefficient and labor-intensive, contributing to poor waste management and associated health risks. Advancements in computer vision and deep learning, such as the YOLOv7 object detection model and , offers promising solutions for automating waste sorting. These technologies enable faster, more accurate, and less labor-intensive sorting processes. Despite challenges like the need for labeled datasets and high computational resources, automated waste sorting can significantly improve sustainability. In Bangladesh, adopting automated waste sorting systems can reduce waste volumes, mitigate environmental impacts, and create job opportunities in the recycling sector. Collaboration among government bodies, waste management entities, and technology developers is essential to address the country's escalating waste management challenges and move towards a more sustainable future.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

Automatic waste classification has become increasingly pivotal in addressing the challenges of efficient and sustainable waste management. Recent advancements in deep learning have significantly enhanced the accuracy and effectiveness of waste classification systems. Studies highlight notable achievements, such as Mookkaiah et al. (2022) achieving 94.44% accuracy with Inception ResNet V2 in distinguishing biodegradable and non-biodegradable waste, and Rahman et al. (2022) attaining 95.3125% accuracy using ResNet34 for categorizing waste into six types. However, varying accuracies across different models and datasets underscore the importance of careful model selection and dataset preparation. Hewagamage et al. (2021) and Lahoti et al. (2024) demonstrate this variability, achieving accuracies ranging from 80% to 90% with models like VGG16 and YOLOv5, respectively. Despite these challenges, deep learning models excel in learning intricate patterns from image data, facilitating precise waste segregation even amidst subtle variations.

Deep learning models offer distinct advantages for waste classification due to their ability to handle diverse datasets and real-time processing capabilities. Kumar et al. (2020) showcase the capability of YOLOv3 in accurately identifying various waste categories, while Desta et al. (2023) demonstrate the generalizability of YOLOv4 across different geographical contexts. Moreover, the real-time processing capabilities of some models, as exemplified by Hua et al. (2020), enable immediate waste classification at collection points, thereby streamlining operations and potentially reducing errors in waste management processes. However, challenges such as dataset quality, computational resource requirements, and sensitivity to image variations remain significant hurdles that necessitate ongoing research and innovation in the field of deep learning for waste classification. Addressing these challenges is crucial for realizing the full potential of automated waste management systems in both developed and developing regions alike.

2.2 Related Works

The ever-growing challenge of waste management necessitates innovative solutions to promote efficiency and sustainability. Automatic waste classification, a crucial step in this process, has seen significant advancements with the adoption of deep learning techniques. This review delves into the effectiveness of deep learning models for waste classification, exploring their accuracy, strengths, limitations, and promising future directions.

Studies reveal a diverse range of accuracies achieved by deep learning models in waste classification tasks. Highlighting the potential for exceptional precision, Mookkaiah et al. (2022) employed the Inception ResNet V2 model to achieve an impressive 94.44% accuracy in distinguishing biodegradable and non-biodegradable waste. Similarly, Rahman et al. (2022) leveraged the ResNet34 model to attain a remarkable 95.3125% accuracy for classifying waste into six distinct categories: cardboard, glass, metal, plastic, paper, and trash. These findings demonstrate the capability of deep learning models to achieve highly accurate waste classification.

However, accuracy can vary depending on the specific model, dataset, and classification task. Studies by Hewagamage et al. (2021) and Lahoti et al. (2024) illustrate this point. While Hewagamage et al. (2021) achieved a validation accuracy between 88-90% using the VGG16 model for waste identification, Lahoti et al. (2024) reported an accuracy of 80% with their YOLOv5 model for classifying various waste categories. Malik et al. (2022) further solidify this notion by achieving an accuracy of 85% with the EfficientNet-B0 model for classifying a wider range of 34 solid waste categories. These findings suggest that while deep learning can be highly effective, achieving peak accuracy requires careful consideration of model selection, dataset composition, and the complexity of the classification task.

Deep learning models offer distinct advantages for waste classification tasks. Their ability to learn intricate patterns and features from image data is a key strength. As demonstrated by Kumar et al. (2020), the YOLOv3 algorithm achieved high accuracy in classifying various waste categories like cardboard, glass, plastic, and organic waste. This capability allows deep learning models to differentiate between waste types with subtle variations, a crucial aspect for effective waste segregation.

Another significant strength lies in the ability of deep learning models to be trained on large and diverse datasets. This enhances their generalizability, enabling them to perform well in real-world scenarios with potential variations in waste composition and image quality. Desta et al. (2023) exemplify this concept with the YOLOv4 model demonstrating good performance for waste detection in Ethiopia, showcasing its applicability across different geographical contexts.

Furthermore, some deep learning models boast real-time processing capabilities. Hua et al. (2020) developed a CNN model for real-time video processing to identify hazardous waste among recyclable materials. This real-time functionality allows for immediate waste classification at collection points or sorting facilities, streamlining the waste management process and potentially reducing human error.

Despite their strengths, deep learning models face certain roadblocks that need to be addressed. A significant challenge lies in the quality and size of training datasets. Deep learning models rely heavily on large datasets with accurate labeling for optimal performance. However, creating such datasets can be a time-consuming and expensive endeavor. Annotating images requires human expertise to accurately identify and categorize waste types within the image. The sheer volume of data needed for training deep learning models can be immense, further adding to the cost and time required for dataset creation. Additionally, class imbalances within datasets, where certain waste categories are underrepresented, can hinder model performance for those specific classes. Majchrowska et al. (2022) highlight this concern, emphasizing the need for techniques to address imbalanced datasets and improve model generalizability across diverse waste compositions.

Another hurdle is the computational resource requirement. Training complex deep learning models often demands significant processing power and memory. This can be a barrier for implementation in resource-constrained settings, particularly in developing regions with limited access to high-end computing infrastructure. The computational resources required for training deep learning models can be substantial, often necessitating powerful graphics processing units (GPUs) or specialized hardware like tensor processing units (TPUs). Dubey et al. (2020) proposed a waste management system using a KNN algorithm, which requires less computational power compared to deep learning models. This alternative approach offers a viable solution for scenarios where computational resources are limited.

Furthermore, deep learning models can be susceptible to variations in image quality, lighting conditions, and object orientation within waste images. Nnamoko et al. (2022) observed decreased model accuracy for waste classification tasks when using images captured from mobile cameras or downloaded from the web. This is because the data distribution in these images might differ significantly from the training dataset. Training data typically consists of high-quality, controlled images captured under specific lighting conditions. Images from mobile cameras or the web can be blurry, have variations in lighting and background clutter, and may not be captured from the same angles as the training data. These discrepancies can lead to the model performing poorly on real-world data that deviates from its training experience.

2.3 Comparison between existing works

Deep learning has emerged as a game-changer in automatic waste classification, offering a powerful tool for more efficient and sustainable waste management (Mookkaiah et al., 2022; Rahman et al., 2022). Studies report impressive accuracy levels, with some models exceeding 94% in distinguishing waste types (Mookkaiah et al., 2022). However, accuracy can vary depending on the model, dataset, and complexity of the task (Hewagamage et al., 2021; Lahoti et al., 2024; Malik et al., 2022).

One of the key strengths of deep learning lies in its ability to learn intricate patterns from image data, allowing it to differentiate between waste types with subtle variations (Kumar et al., 2020). Additionally, training on large and diverse datasets enhances the generalizability of these models, enabling them to perform well even with variations in real-world waste composition and image quality (Desta et al., 2023). Some models even boast real-time processing capabilities, facilitating immediate waste classification at collection points (Hua et al., 2020).

Despite these advantages, deep learning models face challenges. Creating high-quality, labeled datasets can be expensive and time-consuming, and class imbalances within datasets can hinder performance for underrepresented waste categories (Majchrowska et al., 2022). Furthermore, training complex models often requires significant computational resources, limiting their implementation in resource-constrained settings (Dubey et al., 2020). Additionally, variations in image quality, lighting, and object orientation can impact model accuracy (Nnamoko et al., 2022). Future research efforts are crucial to address these limitations and unlock the full potential of deep learning for a more sustainable future in waste management.

TABLE 2.3.1: Comparative Analysis Table

Study	**Image type**	**CNN Model**	**Accuracy**
Mookkaiah et al. (2022)	Biodegradable, Non-biodegradable	Inception ResNet V2	94.44%
Hewagamage et al. (2021)	Standard Waste, 'Other', Specific Groups (e.g., wires, metal objects)	VGG16	88-90%

Teh (2020)	Unspecified Household Waste	VGG-19 (highest), CNN-SVM	91%, 94%
Lahoti et al. (2024)	Biodegradable, Glass, Metal, Plastic, Cardboard	YOLOv5	80%
Malik et al. (2022)	34 FMCG categories (Broad)	EfficientNet-B0 (Transfer Learning)	85%
Kandel (2020)	Plastic, Glass, Metal, Garbage	ResNet101V2 (Transfer Learning)	82%
Hua et al. (2020)	Hazardous Waste, Recyclable Materials (e.g., batteries, syringes)	CNN	90%
Rahman et al. (2022)	Cardboard, Glass, Metal, Plastic, Paper, Trash	ResNet34	95.31%
Dubey et al. (2020)	Biodegradable, Non-biodegradable	KNN	93.30%
Azis et al. (2020)	Glass, Metal, Paper, Plastic, Cardboard, Others	Inception-v3	92.50%
Wang et al. (2021)	Plastic, Glass, Paper/Cardboard, Metal, Fabric, Other Recyclable Waste	MobileNetV3 (highest)	94.26%
Shukhratov et al. (2024)	PET, PP Plastic Waste	Faster R-CNN, RetinaNet, YOLOv8	95.67%
Kunwar (2023)	Trash, Plastic, Paper, Metal, Glass, Cardboard	Unspecified Neural Network	92%

Majchrowska et al. (2022)	Background, Bio, Glass, Metals & Plastic, Non-recyclable, Other, Paper	EfficientDet-D2, EfficientNet-B2	73%
Kumar et al. (2020)	Cardboard, Glass, Plastic, Paper, Metal, Organic Waste	YOLOv3	94%
Wu et al. (2022)	Various Household Waste Items	YOLOv4 (highest), EfficientDet	79.12%, 93.2%
Morell et al. (2022)	Clean Water, Polluted Water	Image Classification Algorithm	91%
Nnamoko et al. (2022)	Unspecified Waste Categories	CNN	79.21%
Mitra (2020)	Unspecified Waste Materials	Unspecified CNN Model	91%
Desta et al. (2023)	Cardboard, Glass, Metal, Organic, Paper, Plastic, Trash	YOLOv4	91.25%
Cheema et al. (2022)	Unspecified Waste Categories	VGG16	96%
Gupta et al. (2022)	Biodegradable, Non-biodegradable	InceptionNet	98.15%
Verma et al. (2022)	Solid Waste	CNN1	94%

Huang et al. (2021)	Plastic Bottles, Cardboard	Vision Transformer	99.29%
Zhou et al.(2022)	Construction waste	Yolov5	0.9480
Jabed et al(2022)	chips packet, plastic bottle, polythene	Yolov5, Yolov7	95.1,95.9

2.4 Open Issues

Despite the advancements in deep learning for waste classification, several critical issues persist that hinder widespread adoption and optimal performance of these systems. One of the foremost challenges is the quality and size of training datasets. Deep learning models heavily rely on large, accurately labeled datasets to generalize well across different waste compositions and environmental conditions. However, creating such datasets is costly, time-consuming, and requires substantial human expertise. Moreover, ensuring these datasets are representative of real-world scenarios—capturing variations in lighting, object orientation, and image quality—remains a significant challenge.

Another pressing issue is the computational resources required for training and deploying deep learning models. Training complex models often demands high processing power and memory, which can be prohibitive in resource-constrained settings, particularly in developing regions. The dependency on specialized hardware like GPUs or TPUs further complicates deployment feasibility, limiting accessibility in areas lacking robust computing infrastructure.

Class imbalance within datasets poses yet another hurdle. Certain waste categories may be underrepresented compared to others, leading to biased model performance where less frequent categories are inaccurately classified. Techniques to mitigate class imbalance, such as data augmentation and sampling strategies, are crucial but require careful implementation to maintain model accuracy and fairness across all waste types.

Moreover, the sensitivity of deep learning models to variations in image quality and environmental conditions remains a significant concern. Models trained on high-quality, controlled images may struggle with real-world data captured under diverse conditions, such as images from mobile cameras or differing lighting environments. This discrepancy can lead to reduced accuracy and reliability in waste classification systems when deployed outside controlled laboratory settings.

Addressing these open issues requires interdisciplinary collaboration involving waste management experts, computer scientists, and policymakers. Improving dataset quality through standardized annotation protocols, developing robust transfer learning techniques to adapt models to diverse environmental conditions, and exploring alternative machine learning approaches that require fewer computational resources are essential steps toward enhancing the reliability and scalability of deep learning-based waste classification systems. By overcoming these challenges, automated waste management solutions can better contribute to environmental sustainability and efficiency globally.

2.5 Summary

Deep learning is a promising technique for automatic waste classification, achieving high accuracy rates in some cases. Studies report accuracy exceeding 94% for differentiating waste types. However, there are limitations. The accuracy can vary depending on the model, dataset, and complexity of the task. Deep learning models excel at recognizing intricate patterns in image data, enabling them to distinguish between waste types with subtle variations. Another advantage is the ability to be trained on large and diverse datasets, making them generalizable to real-world scenarios with variations in waste composition and image quality. Real-time processing capabilities of some models allow for immediate waste classification at collection points. However, challenges remain. Creating high-quality, labeled datasets is expensive and time-consuming, and class imbalances within datasets can affect performance for underrepresented waste categories. Additionally, training complex models often requires significant computational resources, limiting their implementation in resource-constrained settings. Furthermore, variations in image quality, lighting, and object orientation can impact model accuracy. Future research efforts are needed to address these limitations to unlock the full potential of deep learning for sustainable waste management.

CHAPTER 3

METHODOLOGY/ REQUIREMENT ANALYSIS & DESIGN SPECIFICATION

3.1 Overview

This research, as detailed in the thesis "Leveraging Advanced AI Frameworks for Automated Household Waste Sorting," proposes a novel methodology for developing a robust and accurate model for automated household waste sorting. The core principle lies in the iterative refinement of a YOLO models object detection framework through a meticulously designed training and validation loop.

The process commences with the initial training of the YOLOv7 and YOLOv5 model on a curated dataset of labeled household waste images. This dataset serves as the foundation for the model's learning process, allowing it to identify and categorize various waste items. The YOLO framework is specifically chosen due to its real-time object detection capabilities and its proven effectiveness in handling complex and diverse datasets.

Following this initial training phase, the model is trained by set of images with manual annotations. Then the trained model is used to make automate annotation.This

automated annotation involves the model predicting bounding boxes and assigning class labels to objects present within each image. The resulting output is a collection of annotation files corresponding to the new images, detailing the detected objects and their designated labels. To guarantee the accuracy of these predictions, a validation script is implemented. This script meticulously compares the predicted labels in the annotation files against the actual image file names, which act as ground truth references. Through this comparison, the script categorizes the images into two distinct groups: those with matching labels and those with discrepancies. Images with mismatched labels undergo a crucial manual review process. During this phase, We have meticulously correct the annotations to ensure they accurately reflect the actual contents of the images. This manual intervention is for maintaining the integrity of the dataset and guaranteeing that the model is retrained on reliable and accurate data.

This methodology thrives on an iterative approach. The model is continuously improved through a cycle of training, validation, correction, and retraining. Each cycle progressively enhances the model's ability to accurately detect and classify household waste items, ultimately leading to a more reliable and robust system for automated waste sorting. By emphasizing a systematic and meticulous approach, incorporating validation and correction steps, and adopting an iterative nature, this research methodology paves the way for the development of advanced AI frameworks that can revolutionize household waste sorting practices.

3.2 Proposed Methodology/ System Design

This methodology outlines a step-by-step process for automating image annotation and achieving incremental learning using a deep learning model, specifically YOLOv7 and YOLOV5.

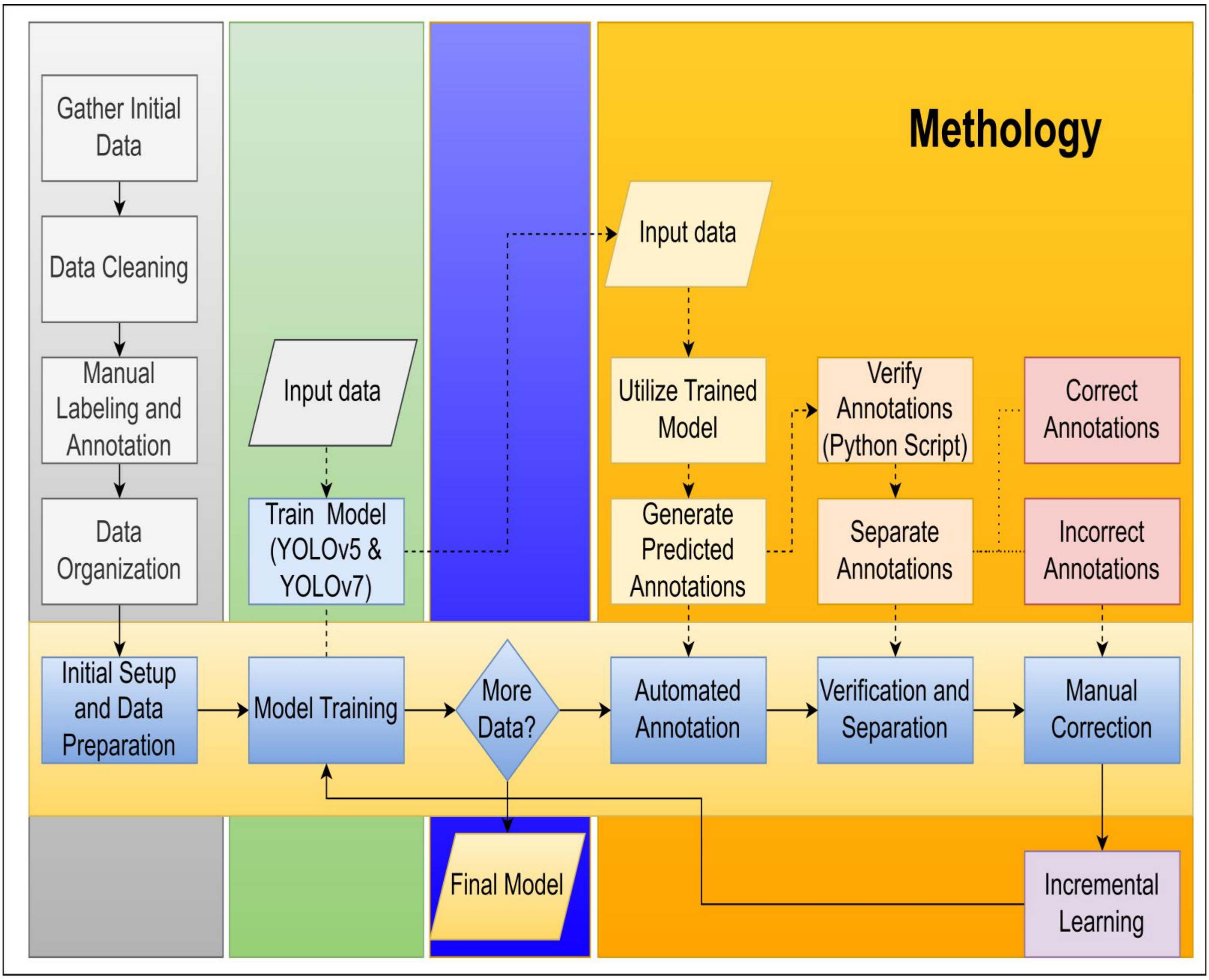


Figure 3.2.1:Proposed Methodology

3.2.1. Initial Setup and Data Preparation

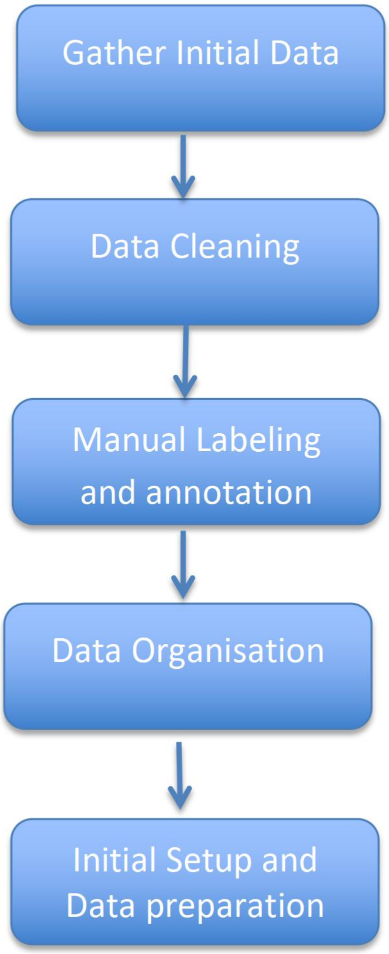


Figure 3.2.2: Initial Setup and Data Preparation

Gather Initial Data: This involves collecting a representative subset of images (1200 images) for the initial training of our model for each class. The type of images is in Jpg format. The class are biological, cardboard, clothes, glass, metal, paper and plastic.

Data Cleaning: Clean all the data, resize the image in 544x544.

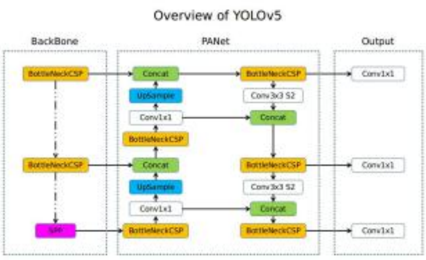
Manual Labeling and Annotation: Each image needs to be meticulously labeled and annotated with bounding boxes and corresponding class labels (biological, cardboard, clothes, glass, metal, paper and plastic). This creates a "ground truth" dataset that the model will learn from.

Data Split: The data gets split into training and validation sets (80% training, 20% validation).

Data Organization: Organize the images and annotation files into separate folders. Ensure the folder structure adheres to the YOLOv5 and YOLOv7 model's format. This typically involves splitting datastet into "images" and "labels" folders, with corresponding subfolders for training ("train") and validation ("val") sets.

3.2.2. Model Training

Training the Initial Model: We utilize the YOLOv5 and YOLOv7 framework to train the model on our manually annotated dataset.



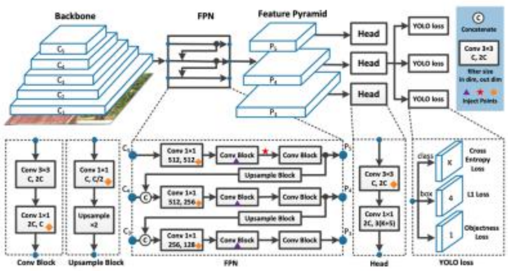


Figure 3.2.3: yolov5 model architecture Figure 3.2.4: yolov7 model architecture

Training: The training process continues until the model achieves satisfactory performance metrics, like: precision (correctly identified objects), recall (identifying all relevant objects), and mAP (mean Average Precision across all classes). In tranning there are 50 epochs.

Evaluating the Model: The validation set helps assess the model's ability to generalize to unseen data. Performance metrics on the validation set indicate how well the model performs on real-world scenarios.

3.2.3. Automated Annotation

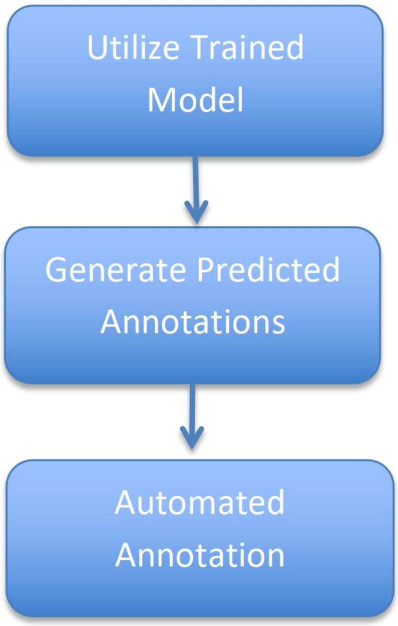


Figure 3.2.5: Automated Annotation

Utilizing the Trained Model: Once we have a well-trained model, we checked its capabilities for automated annotation. We feed the 2000 unlabeled images.

Predicted Annotations: The model analyzes these images and generates predicted annotations for each. These annotations include bounding boxes images and predicted class labeled annotation files.

3.2.4. Verification and Separation

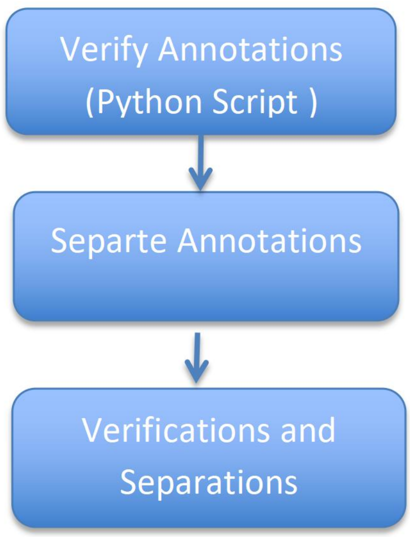


Figure 3.2.6: Verification and Separation

Verification Process: The automatically generated annotations need verification to ensure their accuracy. The annotated file's detected object mostly corrosponding to its file name. so using python we seperate the annotation files thats object and file name don't matches.

Separation of Annotations: Based on the verification process, the images are separated into two categories:

Correct Annotations: These images have high-confidence predictions deemed accurate by same object detecton by python as the file name.

Incorrect Annotations: These images contain annotations identified as incorrect during verification.

3.2.5. Manual Correction

Correcting Annotations: The images with incorrect annotations were manually corrected. This involves using annotation tools MakeSense re write the annotations

3.2.6. Incremental Learning

Preparing Incremental Data: The next step involves combining the following data for further training:

Correctly annotated images from the initial setup (after manual correction)

Correctly annotated images identified during verification

This combined dataset ensures the model learns from both the initial manual annotations and the verified automated annotations.

3.2.7. Iterative Refinement

Iterative Process: This methodology emphasizes an iterative approach. Steps 2 through 6 (automated annotation, verification, correction, and incremental training) are repeated in a loop.

Performance Improvement: Each iteration aims to improve the model's ability to perform accurate automated annotations. The cycle continues until the model was trained with all the dataset

3.2.8. Final Model Deployment

Model Evaluation: Once the iterative process is complete, the final model undergoes a thorough evaluation using a separate test set. not used in the training or validation process. This ensures the model generalizes well to unseen data and performs accurately in real-world deployment scenarios.

Deployment: The final trained model is then deployed for real-world image annotation tasks. This involves giving it some realworld images to see the performance

Feedback Loop: A crucial aspect for long-term success is a feedback loop. As new data becomes available, we can incorporate it into the process. This involves re-annotating some incorrectly classified images by the deployed model and feeding them back into the training process. This continuous learning loop helps the model improve and maintain its accuracy over time.

3.3 Hardware/ Software Requirement

3.3.1. High-Performance Computing System

Central Processing Unit (CPU): A multi-core processor, such as an Intel i9 or AMD Ryzen 9, is prefarable.

Rationale: The CPU underpins efficient data preprocessing, data pipeline management, and script execution during training and validation phases.

Graphics Processing Unit (GPU): An NVIDIA GPU with CUDA support, like NVIDIA RTX 3080/3090 or Tesla V100/A100, is indispensable.

Rationale: Training deep learning models, such as YOLOv7 and YOLOv5, demands substantial computational power, effectively delivered by high-end GPUs. CUDA support facilitates parallel processing, significantly accelerating model training and inference.

Memory (RAM): A minimum of 16 GB RAM, with 32 GB or more preferred, is crucial.

Rationale: Ample RAM is required to handle large datasets during training and validation, guaranteeing seamless processing.

Storage: A Solid-State Drive (SSD) with at least 1 TB of storage capacity, preferably an NVMe SSD for faster read/write speeds, is essential.

Rationale: High-speed storage expedites data access and ensures smooth handling of voluminous image data and annotation files.

3.3.2. Data Storage and Backup

External Hard Drive or NAS: An external HDD/SSD or Network Attached Storage (NAS) with a capacity of 1-2 TB is recommended.

Rationale: This provides supplementary storage for data backups, safeguarding raw images, annotated datasets, and trained models for future reference and accessibility.

3.3.3. Annotation Tools and Interface

Monitor: A high-resolution monitor, such as one with 4K resolution, is optimal. **Rationale:** A high-resolution display facilitates precise manual annotation and correction of image labels by offering clear and detailed views of the images.

Input Devices: A standard keyboard and mouse are essential for interacting with annotation tools and performing manual corrections.

3.3.4. Power Supply and Cooling

Power Supply Unit (PSU): A high-wattage PSU, with a capacity of 750W or higher depending on GPU requirements, is necessary.

Rationale: This ensures a stable and reliable power supply for the CPU, GPU, and other system components, particularly during resource-intensive training sessions.

Cooling System: Adequate cooling solutions, such as liquid cooling or high-performance air cooling, are required.

Rationale: Maintaining optimal operating temperatures for the CPU and GPU is crucial to prevent overheating during extended training periods.

3.3.5. Network Infrastructure

Internet Connection: A high-speed internet connection, preferably fiber optic, is recommended.

Rationale: This facilitates the download of pre-trained models, datasets, and software updates, as well as collaboration and data sharing through cloud services.

3.3.6. Software for annotation:

Use MakeSence: use MakeSence for annotation

Rationale: This web software allows as to annotation images by class and then download the annotation files for YOLO model.

3.4 Project Management and Financial Analysis

The proposed automated waste sorting system using deep learning and robotics stands on two crucial pillars: effective project management and responsible financial oversight. These pillers are essential for ensuring the project's success and long-term sustainability.

Table 3.4.1: Project Management

Tasks	**Time**							
	Oct-23	Nov-23	Dec-23	Jan-24	Feb-24	Mar-24	Apr-24	May-24
Theoretical Research & Writing Introduction								
Literature Review								
Model Selection								
Writing the methodology								
Data Collection								
Training the Model & accurecy								
Configaration robotic arm								
Implimentation & Documantation								

Table 3.4.2:Project Management color indicator

Estimated Work Period	
Actual Work Period	

This research management plan outlines a structured approach we've taken to develop the automated waste sorting system. We divided the project into seven key phases, each with defined deliverables and timelines.The initial phase focused on theoretical research and writing. This resulted in a comprehensive literature review and a well-defined project introduction. We also carefully selected the most suitable deep learning model for real-time waste object detection.The next steps involved crafting a detailed methodology document and embarking on data collection. We've created a robust dataset of labeled waste images. This data will now be used to train the chosen model, aiming for high accuracy in real-time object detection. With a well-trained model in hand, we'll move on to configuring a robotic arm and integrating it with the deep learning system for automated sorting based on detected objects. Finally, the complete system will be implemented and rigorously tested in a controlled environment, followed by comprehensive documentation of the entire development process. By following this well-defined plan, the research team is well-positioned to successfully develop and deploy this innovative automated waste sorting system.

Table 3.4.3: Financial Analysis

Components	Estimated Cost (BDT)
Hardware/Infrastructure	66,550 - 73,400
Visiting Stakeholders	1,500 - 2,000
Software and Tools	3,000 - 4,000
Data Collection and Processing	4,000 - 5,000
Documentation and Report Writing	500 - 1,000
Miscellaneous (e.g., licenses, tools)	500 - 1,000
Power Supplies	28,000 - 32,000
Contingency (10% of total)	10,400 - 11,800
TotalEstimated Cost	1,04,050 - 1,18,400

We've developed a detailed cost breakdown to ensure responsible financial management of the automated waste sorting system project. This breakdown will be our guide for effective cost control. We'll be meticulously tracking expenses against each category, like hardware, software, and data collection. Whenever a significant cost arises, we'll justify it by considering project needs and exploring more affordable options. The allocated contingency fund provides a safety net for unforeseen challenges. We'll strategically utilize it to address unexpected situations without derailing the project budget. Based on this breakdown, we can prioritize our funding requests. Hardware, power supplies, and data collection might require larger allocations compared to documentation or miscellaneous items. We can maintain transparency throughout the project by regularly communicating financial progress to stakeholders. These updates will include detailed reports outlining actual spending compared to the budgeted amount for each category. Beyond initial development, we'll also consider the long-term operational costs of the system. This includes energy consumption for power supplies, potential maintenance needs, and future upgrades. By implementing these financial management strategies, we can ensure responsible use of allocated funds and navigate the project towards successful completion within budget constraints.

The successful implementation of an automated household waste sorting system, as outlined in the research methodology, necessitates a robust hardware foundation. This section details the essential hardware components and their functionalities to ensure efficient system operation.

3.5 Summary

This research proposes a novel methodology to develop a robust system for automated household waste sorting using deep learning. The core idea is to iteratively refine a YOLO object detection model. The process involves training the model on a curated dataset of labeled household waste images, followed by automated annotation on unseen images. A validation script checks the accuracy of these annotations, separating images with discrepancies for manual correction. This cycle of training, validation, correction, and retraining progressively improves the model's ability to accurately detect and classify waste items. To achieve this, the research suggests using high-performance computing systems with powerful CPUs, GPUs, ample RAM, and SSD storage. The project management plan outlines a structured approach with well-defined phases and timelines. The financial analysis provides a detailed cost breakdown for hardware, software, data collection, and other expenses. Finally, the hardware requirements section details essential components for efficient system operation.

CHAPTER 4

IMPLEMENTATION

4.1 Overview

the implementation process for an automated household waste sorting system utilizing the YOLOv7 and YOLOv5 object detection framework. The methodology emphasizes a structured and iterative approach to guarantee accurate and efficient waste classification.

The process commences with the meticulous collection of a diverse set of household waste images encompassing various categories (biological, cardboard, clothes, glass, metal, paper and plastic). Each image is meticulously labeled with the corresponding waste category to facilitate model learning. Subsequently, the images undergo rigorous preprocessing, including resizing, normalization. Resizing ensures uniformity, while normalization enhances training. This meticulous preparation results in a comprehensive training dataset for successful model training.

The preprocessed dataset serves as the training ground for the YOLOv7 YOLOv5 model. Hyperparameters are meticulously optimized to achieve optimal learning. The model is then trained on the prepared dataset, with checkpoints saved periodically for progress preservation. Upon completion, the model is evaluated on a new set of images, predicting bounding boxes and assigning class labels documented in annotation files. A validation script meticulously compares these predicted labels with actual image file names (ground truth) to categorize images with discrepancies for further refinement.

Images with mismatched labels undergo a crucial manual review process. We meticulously examine and correct annotations to ensure they precisely reflect the image content. This step maintains the integrity of the training dataset, guaranteeing the model is retrained on accurate data for improved classification. The corrected dataset is then strategically merged with the original one, creating an enriched training set. This enriched dataset incorporates valuable insights from the initial training and validation phases. The model undergoes retraining on this comprehensive dataset, potentially employing data augmentation techniques for further robustness enhancement. Following successful retraining, the model is meticulously integrated into the existing hardware and software infrastructure for real-world waste classification tasks.

The implementation adopts an iterative approach. New images and annotations are periodically collected to augment the training dataset, incorporating variations in waste items. The model is then retrained with these updated datasets, enabling it to adapt to new waste patterns and maintain exceptional accuracy and efficiency over time. This structured and iterative methodology paves the way for a dependable and efficient automated household waste sorting system, leveraging advanced AI technologies to significantly improve waste management processes.

4.2 Train Model/ Prototype Design

4.2.1. Environment Setup:

Dependency Installation: The process commences by establishing a compatible Python environment. Essential deep learning libraries are meticulously installed to facilitate the execution of the YOLOv7 and YOLOv5 model and efficient image data management. PyTorch and torchvision form the core foundation, providing the necessary functionalities for deep learning tasks. Additional dependencies, such as OpenCV and NumPy, are strategically incorporated to bolster the overall functionality and streamline various operations.

Repository Acquisition: The next crucial step involves retrieving the YOLOv7 and YOLOv5 repository from GitHub. This repository houses the core implementation of the YOLOv7 model, along with essential scripts for training, evaluation, and inference. Following acquisition, navigation to the repository's directory is necessary to proceed with subsequent steps.

Install necessary modules: the requirements of the repository is installed.

4.2.2. Dataset Preparation:

Data Collection: A comprehensive dataset, encompassing more than 7,500 household waste images, is meticulously constructed. This dataset is strategically sourced from three distinct datasets readily available on Kaggle. To further enrich the dataset and capture a wider range of variations, an additional 900 raw images are meticulously collected. These images comprehensively cover various waste categories, including plastics, metals, paper, glass, cardboard, biological waste.

Data Labeling:

Each image undergoes a meticulous labeling by renaming them. Then using tools like MakeSence annotate the initial data. This crucial step involves drawing bounding boxes around objects of interest within the image. Annotators meticulously assign the corresponding waste category label to each bounding box, ensuring accurate representation of the waste item. Consistency is paramount, and the annotations are saved in a standardized format, such as TXT for YOLO, for seamless integration with the training process.

Dataset Organization:

The meticulously collected and labeled dataset is then meticulously organized into a structured directory structure. This structure separates training and validation images within the "images" directory, with corresponding directories within "labels" housing their respective annotations. This meticulous organization streamlines data management and is essential for the proper functioning of the training scripts.

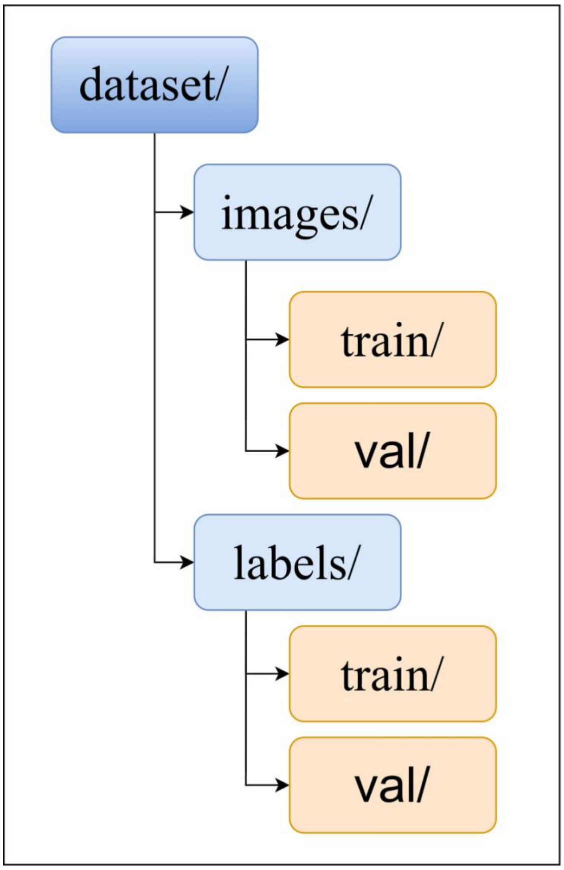


Figure 4.2.1: Data organaization folder

4.2.3. Data Preprocessing:

Image Resizing and Normalization: Ensuring Compatibility and Enhanced Learning: A crucial preprocessing step involves resizing all images to a uniform size of 544x544 pixels. This ensures compatibility with the YOLOv7 and YOLOv5 model's input requirements. Additionally, pixel values are meticulously normalized to a specific range. This standardization of the input data enhances the model's learning process and overall performance.

Data Augmentation: To bolster the diversity of the training dataset and prevent overfitting, data augmentation techniques are strategically employed. These techniques involve random rotations, flips, scaling adjustments, and color modifications applied to the images. This process effectively expands the training dataset and enhances the model's ability to generalize effectively to unseen variations in waste items, leading to robustness in real-world scenarios.

4.2.4. Model Training:

Hyperparameter Configuration: The YOLOv7 model is meticulously configured with a set of optimal hyperparameters. These parameters encompass the learning rate, batch size, number of training epochs, and other model-specific settings. The selection of these parameters is based on a thorough consideration of the dataset's complexity and size. A well-tuned hyperparameter configuration guides the model's learning process towards achieving peak performance in waste classification tasks.

Initial Training: The initial training phase commences with a subset of 1,200 images, strategically split into an 80:20 ratio for training and validation sets (960 training images and 240 validation images). The model undergoes training for 50 epochs. During this process, key metrics such as loss and accuracy are meticulously monitored to assess the model's performance and identify areas for potential improvement. GPUis used for accelerating significantly expedite this process.

Checkpointing: To safeguard progress and enable the resumption of training if necessary, regular checkpoints of the model state are meticulously saved throughout the training process. These checkpoints act as snapshots

4.3 System Testing/ Model Evaluation

4.3.1. Validation Set Evaluation:

Performance Metrics:

Description: A comprehensive suite of metrics is employed to quantify the model's effectiveness. These metrics provide numerical scores that indicate how well the model performs in various aspects of waste classification.

Precision: This metric focuses on the positives predicted by the model. It measures the proportion of correctly classified waste items out of all the items the model identified as belonging to a particular category.

Precision = TP / (TP + FP)

TP (True Positives): Number of correctly classified waste items for a specific category.

FP (False Positives): Number of items the model incorrectly classified as belonging to that category.

In simpler terms, precision tells us how accurate the model is when it predicts a specific waste category. A high precision value (closer to 1) indicates the model rarely makes mistakes when assigning a class label.

Recall: This metric focuses on the ground truth (actual labels) in our dataset. It measures the proportion of correctly classified waste items for a specific category out of all the actual items belonging to that category in the dataset.

Recall = TP / (TP + FN)

FN (False Negatives): Number of actual waste items from a category that the model missed (failed to detect).

Recall tells we how good the model is at identifying all the actual waste items of a particular category. A high recall value (closer to 1) indicates the model misses very few items belonging to that class.

Mean Average Precision (mAP): This metric provides a single score that summarizes the average precision across all waste categories in our dataset. It's calculated by taking the average of the precision values obtained for each individual category.

mAP = (Sum of Average Precision (AP) across all categories) / Number of categories

Average Precision (AP) for each category is often calculated using a Precision-Recall (PR) curve. This curve summarizes the trade-off between precision and recall for various detection thresholds.

mAP offers a comprehensive overview of the model's performance on all waste classes. A high mAP value (closer to 1) indicates the model performs well in identifying and classifying waste items across various categories.

Intersection over Union (IoU): IoU is a metric used in object detection to measure the overlap between the bounding box predicted by the model and the ground truth bounding box for an object. It's calculated as the area of intersection divided by the area of union between the two boxes. A higher IoU value indicates a more accurate bounding box prediction.

mAP@0.5: This refers to the mAP calculated using an IoU threshold of 0.5. In simpler terms, for an object to be considered correctly detected, the overlap between the predicted bounding box and the ground truth box must be at least 50%. This is a more relaxed threshold and reflects the model's ability to identify objects with a de

mAP@0.95: This refers to the mAP calculated using a much stricter IoU threshold of 0.95. Here, for an object to be considered correctly detected, the overlap between the predicted bounding box and the ground truth box must be at least 95%. This is a very high threshold and reflects the model's ability to pinpoint objects with very precise bounding boxes.

Confusion Matrix

A confusion matrix is a visualization tool that helps understand the performance of our YOLO model on a classification task. It's a table with rows representing the actual waste categories (ground truth) and columns representing the predicted categories by the model. Here's how it works in the context of household waste sorting:

Rows: Each row represents an actual waste category (biological, cardboard, clothes, etc.).

Columns: Each column represents a category the model predicted for the waste items.

Diagonal Elements: Ideally, the highest values should be present along the diagonal elements of the matrix. These represent the number of correctly classified waste items for each category (true positives).

Off-Diagonal Elements: These elements represent the model's mistakes. A high value in a cell (i, j) where $i \neq j$ indicates the model incorrectly classified waste items belonging to category 'i' as category 'j' (false positives and false negatives).

By analyzing the confusion matrix, we can identify specific waste categories where the model struggles and requires further training or data augmentation.

Error Analysis:

Description: This analysis involves a deep dive into the validation set results to pinpoint specific areas where the model performs poorly.

Process: By examining the misclassified images and the assigned labels, we can identify recurring patterns of errors.

4.3.2. Real-World Testing:

Test Dataset Construction:

Description: A new dataset specifically designed to mimic real-world waste scenarios is meticulously constructed. This dataset goes beyond the training and validation sets by incorporating additional complexities.

Examples:

Challenging lighting conditions (harsh shadows, low light)

Cluttered backgrounds (multiple objects close together)

Occluded objects (partially hidden by other waste items)

4.3.3. Iterative Improvement:

The insights gleaned from the system testing and model evaluation phases are instrumental in refining the model and enhancing its overall performance. Based on the identified errors and limitations, the following iterative improvement strategies can be implemented:

Data Augmentation and Recollection:

The training dataset can be strategically expanded to address the model's weaknesses. This involves incorporating:

Images with variations of waste items that caused misclassifications.

Images representing specific object types the model struggled with.

Recollection: we have added new data with a more diverse range of waste items

Hyperparameter Tuning:

Description: Re-evaluating and potentially fine-tuning the model's hyperparameters can lead to performance improvements. These parameters control the model's learning process.

Learning rate: This parameter affects how quickly the model adjusts its internal weights during training. Adjusting it can influence the model's ability to learn complex patterns.

Batch size: This parameter determines the number of images processed by the model at a time during training. Adjusting it can impact the model's convergence speed and generalization ability.

Model Retraining:

Once the training dataset is augmented or hyperparameters are adjusted, the model can be retrained to incorporate these refinements.

Process: The system testing and evaluation process is then repeated to assess the effectiveness of the implemented improvements. This iterative cycle ensures continuous improvement and refinement of the model's performance.

4.4 Summary

This document outlines a structured and iterative approach for building an automated household waste sorting system using YOLOv7 and YOLOv5. High accuracy and efficiency in waste classification are achieved through meticulous data collection and preparation.

A diverse dataset of 8,420 labeled images is meticulously assembled, encompassing various waste categories. Preprocessing involves resizing and normalizing images to prepare them for the YOLOv7 and YOLOv5 model. Data augmentation techniques further enhance the model's ability to generalize to unseen waste variations.

The YOLOv7 and YOLOv5 model undergoes iterative training, starting with a 2,000-image subset. Hyperparameter optimization and checkpointing ensure efficient learning and progress preservation. Evaluation metrics (precision, recall, mAP) guide model improvement.

Real-world simulations and human evaluation assess the model's robustness and accuracy, informing further refinements. Iterative data augmentation, hyperparameter tuning, and retraining continuously enhance waste classification capabilities.

This meticulous approach, leveraging YOLOv7 and YOLOv5 , ensures a dependable and efficient waste sorting system, effectively addressing real-world waste management challenges.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

We conducted a comprehensive study on waste detection and sorting in Dhaka City, Bangladesh, utilizing a total of 8,420 images. The dataset comprised 7,500 pictures sourced from the Kaggle website, supplemented by 920 primary data images captured using our phones. For training purposes, we employed 7,180 images to instruct the machine learning models, while an additional 1,240 images were allocated for validation to assess model performance. Our methodology incorporated the YOLOv5 and YOLOv7 models, recognized for their proficiency in object detection tasks. Through these models, we aimed to enhance the accuracy and efficiency of waste detection and categorization, addressing a critical environmental issue in urban waste management. The use of advanced deep learning techniques in this context demonstrates significant potential for improving waste sorting processes, contributing to more effective waste management strategies and sustainability efforts in densely populated urban areas like Dhaka. This study underscores the importance of integrating technology with environmental initiatives to achieve substantial ecological benefits.

5.2 Experimental/ Simulation Result

Simulation result for YOLOv5 in last iterative:

Table 5.2.1: Validation result for YOLOv5

Class	Precision	Recall	mAP@0.5	mAP@0.5:0.95
all	0.925	0.924	0.962	0.827
biological	0.789	0.83	0.869	0.671
cardboard	0.915	0.935	0.964	0.835
clothes	0.991	0.983	0.995	0.881

glass	0.951	0.917	0.972	0.785
metal	0.955	0.908	0.981	0.898
paper	0.947	0.966	0.983	0.89
plastic	0.925	0.926	0.967	0.829

Precision:

Overall: The model has a high overall precision of 0.925, indicating it rarely makes mistakes when classifying waste items.

Individual Categories: Precision is generally high for most categories (biological being the lowest at 0.789) suggesting the model accurately assigns class labels to most waste items.

Recall:

Overall: The overall recall is 0.924, implying the model successfully detects a high proportion of actual waste items in the dataset.

Individual Categories: Recall varies across categories. Cardboard (0.935) and paper (0.966) have the highest recall, indicating the model misses very few items in these classes. Biological waste (0.83) has the lowest recall, suggesting the model might struggle to identify some biological waste items.

mAP@0.5:

Overall: The mAP@0.5 is 0.962, which is a very good score. This indicates the model performs well in identifying waste items with a moderate level of overlap between predicted and ground truth bounding boxes (at least 50% overlap).

mAP@0.5:0.95:

Overall: The mAP@0.95 is 0.827, which is a lower score compared to mAP@0.5. This suggests the model's performance drops significantly when requiring highly precise bounding boxes (at least 95% overlap).

Key Observations:

The model performs well in terms of overall precision and recall, indicating good accuracy in classifying and detecting most waste items. There's a trade-off between precision and recall for individual categories. High precision in clothes (0.991) suggests the model rarely misclassifies them, but the lower recall (0.983) might indicate some missed detections.

The significant difference between mAP@0.5 and mAP@0.95 highlights the model's struggle with precise bounding box placement.

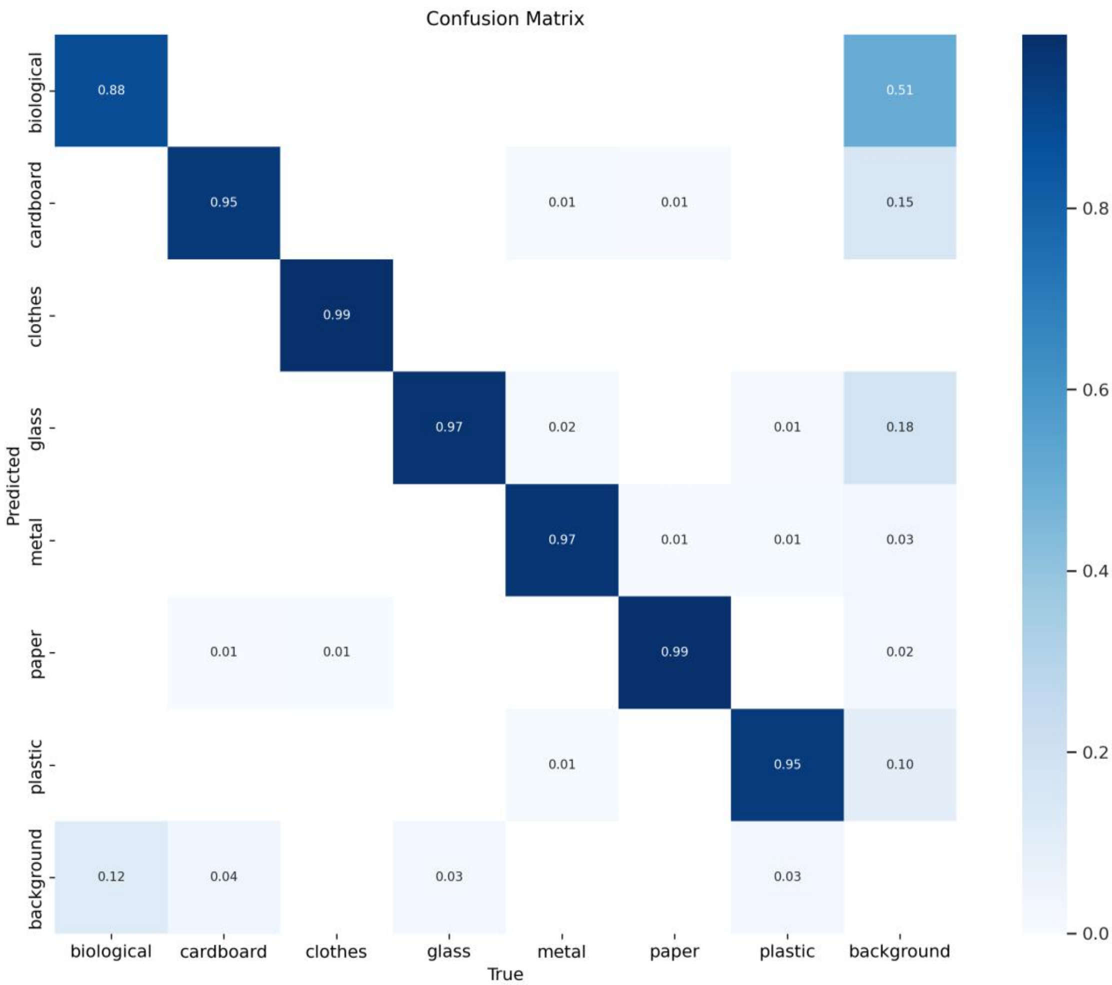


Figure 5.2.1: confusion matrix for YOLOv5

Observations from the Confusion Matrix:

Biological Waste: The model seems to perform well with biological waste, with a high value on the diagonal (likely true positives). However, there might be some confusion with plastic (off-diagonal element in the biological waste row).

Cardboard: Similar to biological waste, cardboard also has a high diagonal value, indicating good classification. There might be some misclassification with metal (off-diagonal element in the cardboard row).

Clothes: The model appears to classify clothes accurately (high diagonal value).

Glass: Glass also has a high diagonal value, suggesting good performance in classifying glass items.

Metal: There might be some confusion between metal and cardboard (off-diagonal element in the metal row).

Paper: The model seems to perform well with paper waste (high diagonal value).

Plastic: Similar to biological waste, there might be some confusion between plastic and biological waste (off-diagonal element in the plastic row).

Background: The background class seems to have a high value on the diagonal, indicating the model effectively avoids classifying actual waste items as background.

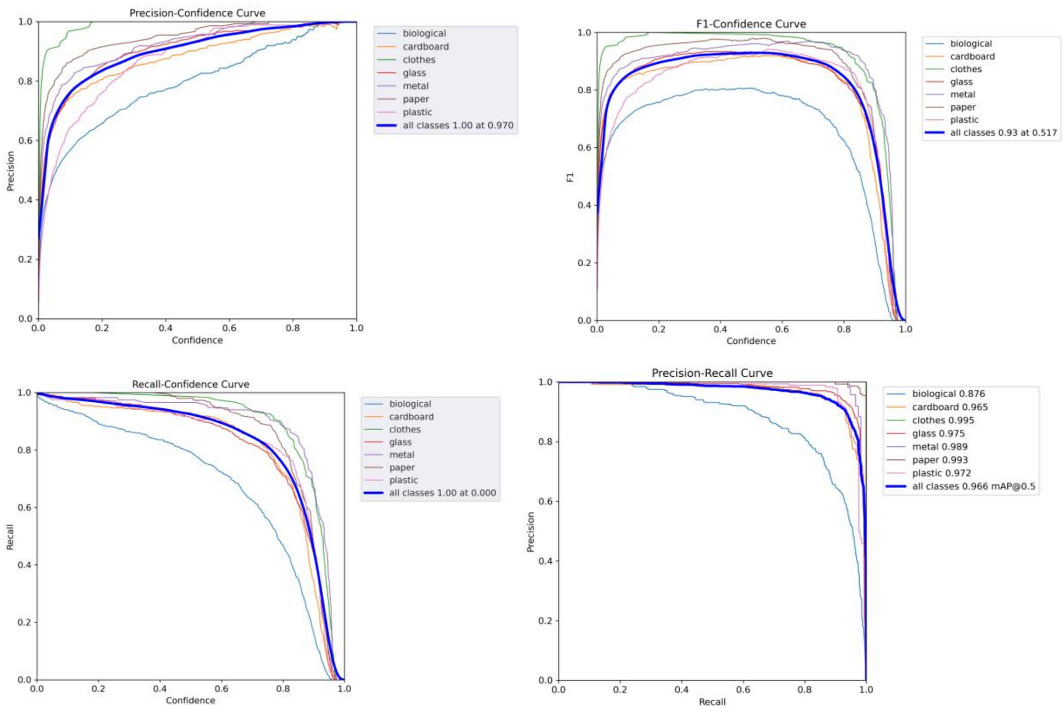


Figure 5.2.2: P, F1, R, PR graph for YOLOv5

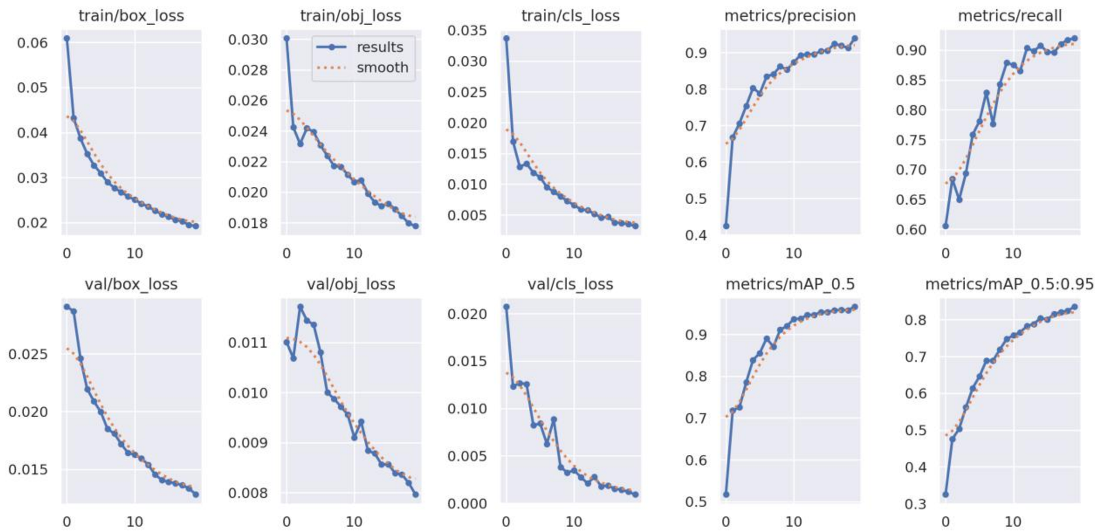


Figure 5.2.3: Result graph for YOLOv5

Simulated output

Figure 5.2.4: Output for YOLOv5

Simulation result for YOLOv7 in last itaretive:

Table 5.2.2: Validation result for YOLOv7

Class	**Precision**	**Recall**	**mAP@0.5**	**mAP@0.5:0.95**
all	0.942	0.938	0.975	0.871
biological	0.836	0.839	0.906	0.716
cardboard	0.896	0.927	0.973	0.882
clothes	1	0.979	0.996	0.933
glass	0.961	0.92	0.986	0.821
metal	0.984	0.966	0.993	0.942
paper	0.964	0.993	0.991	0.938
plastic	0.951	0.946	0.978	0.867

Precision:

Overall: The model has a high overall precision of 0.942, indicating it rarely makes mistakes when classifying waste items. This means that out of all the items the model assigns a specific category label to, a high percentage (94.2%) are actually that category.

Individual Categories: Precision is generally high for most categories, with clothes (1.0) being perfect. This suggests the model accurately assigns class labels to most waste items. However, biological waste (0.836) has a lower precision, indicating the model might sometimes misclassify other items as biological waste.

Recall:

Overall: The overall recall is 0.938, implying the model successfully detects a high proportion (93.8%) of actual waste items in the dataset.

Individual Categories: Recall varies across categories. Paper (0.993) and metal (0.966) have the highest recall, indicating the model misses very few items in these classes.

Biological waste (0.839) has a lower recall, suggesting the model might struggle to identify some biological waste items.

mAP@0.5:

Overall: The mAP@0.5 is 0.975, which is a very good score. This indicates the model performs well in identifying waste items with a moderate level of overlap between predicted and ground truth bounding boxes (at least 50% overlap).

mAP@0.5:0.95:

Overall: The mAP@0.95 is 0.871, which is a lower score compared to mAP@0.5. This suggests the model's performance drops significantly when requiring highly precise bounding boxes (at least 95% overlap).

Key Observations:

The model performs well in terms of overall precision and recall, indicating good accuracy in classifying and detecting most waste items.

There's a trade-off between precision and recall for individual categories. High precision in clothes (1.0) suggests the model rarely misclassifies them, but the lower recall (0.979) might indicate some missed detections.

The significant difference between mAP@0.5 and mAP@0.95 highlights the model's struggle with precise bounding box placement.

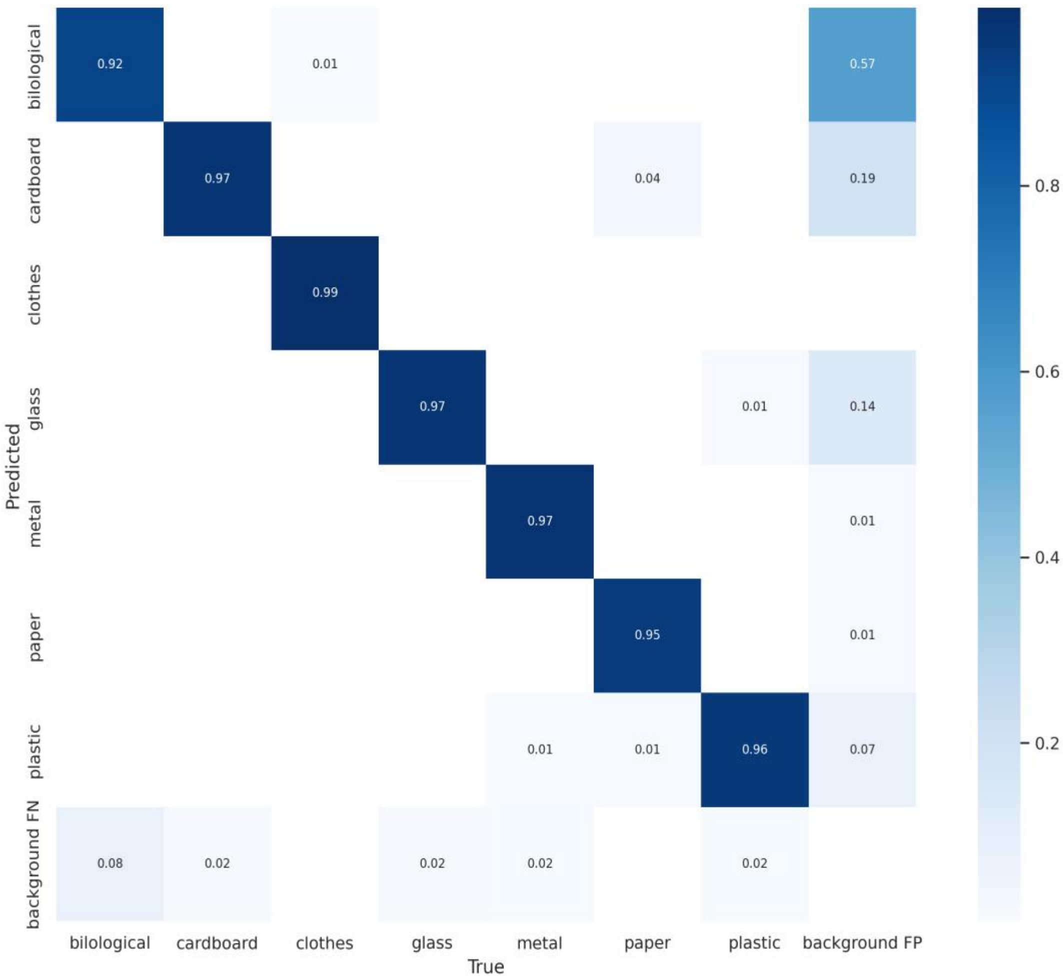


Figure 5.2.5: confusion matrix for YOLOv7

Observation from the confusion matrix:

Biological Waste: The model seems to perform well with biological waste, with a high value on the diagonal (likely true positives). However, there might be some confusion with plastic (off-diagonal element in the biological waste row).

Cardboard: Similar to biological waste, cardboard also has a high diagonal value, indicating good classification. There might be some misclassification with metal (off-diagonal element in the cardboard row).

Clothes: The model appears to classify clothes accurately (high diagonal value).

Glass: Glass also has a high diagonal value, suggesting good performance in classifying glass items.

Metal: There might be some confusion between metal and cardboard (off-diagonal element in the metal row).

Paper: The model seems to perform well with paper waste (high diagonal value).

Plastic: Similar to biological waste, there might be some confusion between plastic and biological waste (off-diagonal element in the plastic row).

Background: The background class seems to have a high value on the diagonal, indicating the model effectively avoids classifying actual waste items as background.

5.3 Performance/ Comparative Analysis

Precision: YOLOv7 takes the lead with a 0.942 precision score, indicating it makes slightly fewer mistakes in classifying waste items compared to YOLOv5 (0.925). This translates to a higher confidence that labeled items are indeed the predicted category.

Recall: Both models excel at finding actual waste items in the dataset, with recall scores hovering around 0.94. This means they successfully detect a large proportion of the waste present.

mAP@0.5: YOLOv7 shines again with a 0.975 mAP@0.5 score, demonstrating its strength in identifying waste items with a moderate level of overlap between predicted and actual bounding boxes (at least 50% overlap). YOLOv5 follows closely with a 0.962 mAP@0.5.

Performance by Category

While both models perform well overall, a closer look at individual categories reveals some interesting insights:

All-Stars: Both YOLOv5 and YOLOv7 excel at classifying clothes, glass, paper, and metal waste. Precision and recall scores for these categories are consistently above 0.9, indicating high accuracy in both identifying and correctly labeling these items.

Room for Improvement: Biological waste and plastic seem to be trickier for both models. Precision and recall scores are lower for these categories compared to others, suggesting they might struggle with differentiating these items from others or have difficulty detecting them altogether.

Key Takeaways:

YOLOv7 edges out YOLOv5 in terms of overall precision, recall, and mAP@0.5, suggesting a slight overall improvement.

Both models struggle with precise bounding box placement, evident from the significant drop in mAP@0.95 compared to mAP@0.5. This indicates challenges in accurately pinpointing the exact location of waste items.

Both models share similar difficulties in classifying biological waste and plastic, suggesting these categories might require additional attention during training.

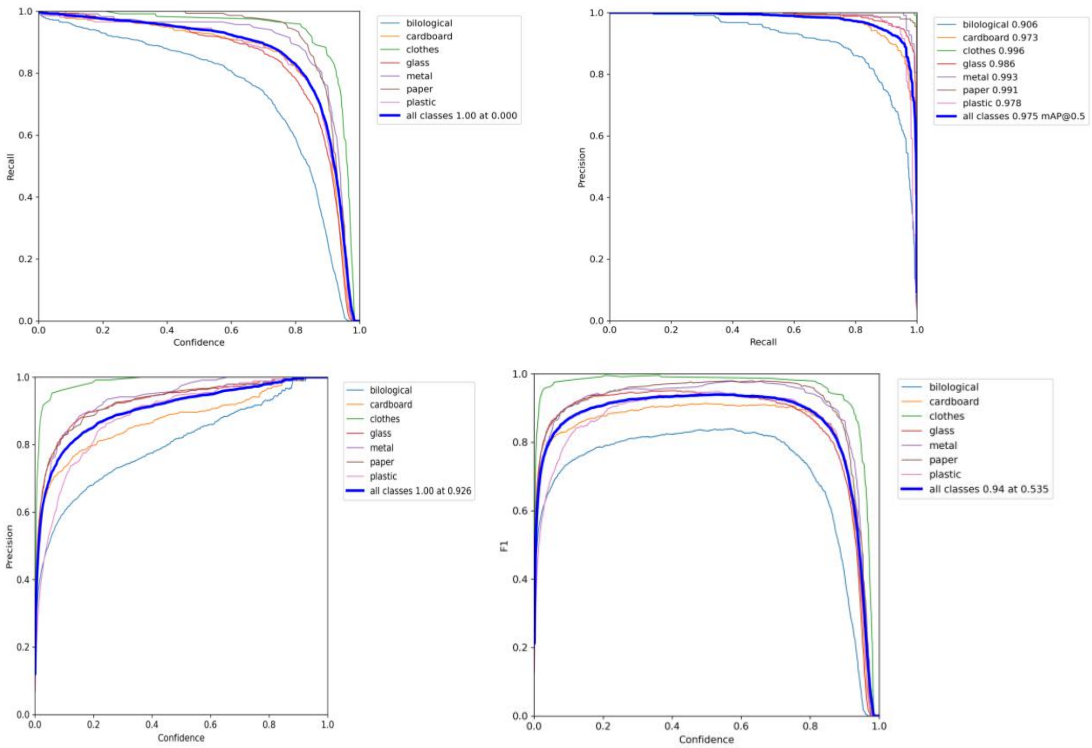


Figure 5.2.6: P, F1, R, PR graph for YOLOv7

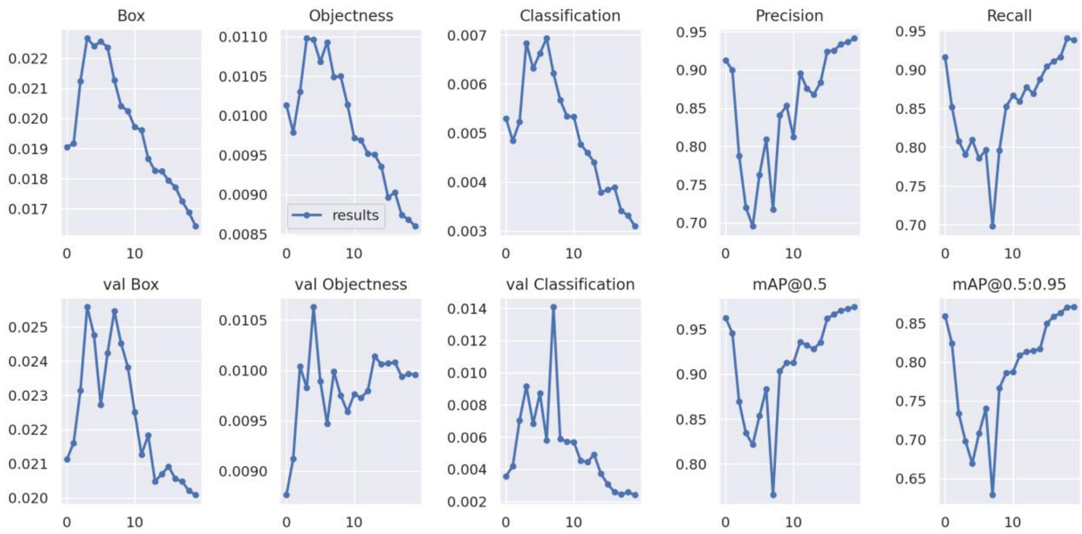


Figure 5.2.7: Result graph for YOLOv7

A simulated output:

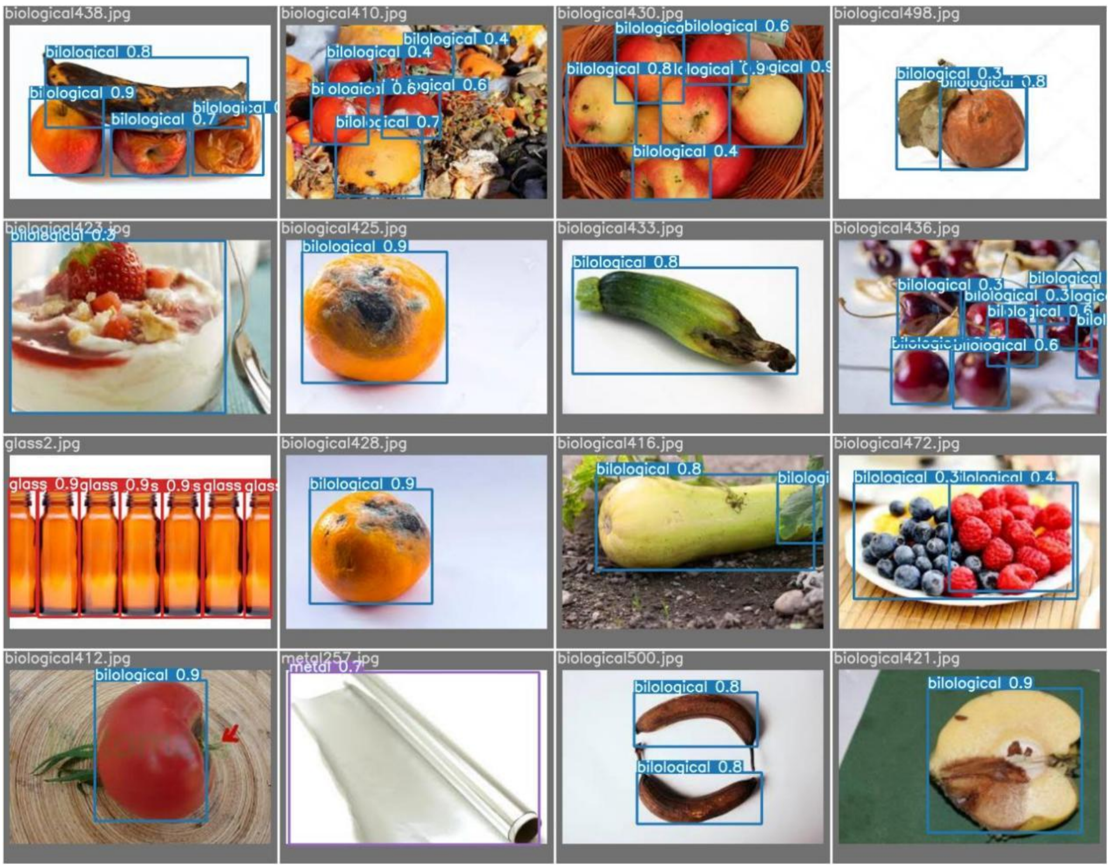


Figure 5.2.8: Output for YOLOv7

5.4 Summary

YOLOv5 and YOLOv7, both deep learning models, were evaluated for their ability to sort household waste. While both achieved good overall performance in classifying and detecting waste items, a closer look reveals some key differences. YOLOv7 boasts a slight edge in precision, recall, and the ability to identify waste with moderate bounding box overlap (mAP@0.5). However, both models struggle with precise bounding box placement and differentiating biological waste and plastic.

If maximizing overall accuracy is our priority, YOLOv7 might be the better choice. However, if computational resources are limited, YOLOv5 presents a viable alternative with minimal performance difference. The crucial factor becomes even more specific if precise bounding box placement is essential (e.g., robotic grasping). In that case, further refinement of either model through techniques like anchor box optimization or loss function adjustments might be necessary.

Beyond the model itself, the quality and balance of our training data significantly impact performance. Ensuring our dataset accurately reflects the variety of household waste is crucial. Additionally, experimenting with different hyperparameters during training can further optimize the chosen model.

In conclusion, both YOLOv5 and YOLOv7 are strong contenders for household waste sorting. By carefully considering our specific needs, resource limitations, and the importance of precise bounding boxes, we can make an informed decision. Remember, the quality of our training data and hyperparameter tuning can significantly influence the final outcome. With these factors in mind, we can select and potentially refine the model that delivers the best results for our waste sorting system.

CHAPTER 6
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

Waste detection and sorting automation with AI brings a wave of changes to people's lives. some potential positive and negative impacts are given below.

Positive Impacts:

Improved Public Health: Automation reduces the need for manual sorting, thereby minimizing worker exposure to hazardous materials and pathogens, which decreases the risk of injuries and illnesses.
Increased Recycling Rates: Automation enhances sorting accuracy, diverting more recyclables from landfills and promoting a circular economy.
Job Market Shift: Although some sorting jobs may be replaced, new opportunities will emerge for technicians to maintain and operate these systems, as well as for data analysts and AI developers to improve sorting efficiency.

Negative Impacts:

Job Displacement: Automation may lead to the loss of some waste sorting jobs, necessitating retraining programs to help workers adapt to the new job market.
Social Inequality: The high initial costs of implementing automated systems may result in wealthier communities benefiting first, potentially widening the gap between those with and without access to these technologies.

6.2 Impact on Society & Environment

Machine learning-powered waste detection and sorting present a promising avenue for fostering a more sustainable future. Now, we are going to discuss its societal and environmental impact.

Positive Impacts:

Environmental Benefits:

Reduced Landfill Waste: More accurate sorting increases the amount of material recycled, diverting waste from landfills. This reduces methane emissions, a potent greenhouse gas, and conserves valuable landfill space.

Conservation of Resources: Recycling existing materials lowers the demand for virgin resources like timber and metals, which require extraction and processing with environmental costs.

Cleaner Oceans and Land: Improved waste management reduces plastic pollution in oceans and littering on land, protecting wildlife and ecosystems.

Societal Benefits:

Public Health: Automated sorting reduces manual handling of waste, minimizing exposure to harmful materials and improving worker safety.

Job Creation: Machine learning creates new opportunities in areas like system development, data analysis, and maintenance of sorting facilities.

Economic Growth: A thriving recycling industry fosters economic activity by creating jobs, boosting demand for recycled materials, and potentially lowering waste disposal costs for consumers.

Empowering Citizens: AI-powered sorting systems can be coupled with educational initiatives to raise public awareness about proper waste disposal and recycling practices.

By addressing challenges and maximizing positive impacts, machine learning for waste management can pave the way for a cleaner and more sustainable future.

6.3 Ethical Aspects

Machine learning for waste sorting offers significant benefits for society, such as cleaner cities and improved recycling, as well as for the environment, including reduced pollution and more efficient resource use. This technology promotes sustainability by increasing recycling rates and minimizing waste. However, several ethical concerns must be addressed like

Bias: The training data might be biased, leading to inaccurate sorting or unfair targeting.
Transparency: The decision-making processes of these machines can be opaque, which might erode public trust.
Jobs: Automation could result in job losses within the waste management sector.
Privacy: Waste data might contain personal information, necessitating robust data security measures.

6.4 Sustainability Plan

A comprehensive sustainability plan:

Increased Recycling Rates:

ML-powered sorting improves the accuracy of separating recyclables, reducing contamination and producing higher-quality recycled materials. This promotes recycling programs and decreases landfill waste, conserving resources.

Resource Conservation:

Accurate identification and diversion of recyclables reduce reliance on virgin materials like wood and metal. This leads to less resource extraction, deforestation, and mining, thereby protecting natural ecosystems.

Reduced Environmental Impact:

Precise sorting minimizes landfill contamination, preventing harmful pollutants from leaching into soil and water. ML also helps identify hazardous materials for proper disposal, reducing environmental risks.

Improved Efficiency:

ML optimizes waste collection routes, cutting down fuel consumption and carbon emissions from collection trucks. Sensor-based systems can monitor bin fill levels, enabling more efficient collection schedules.

Public Engagement:

ML analyzes waste composition data to create personalized educational campaigns, promoting responsible waste disposal in communities. Real-time feedback systems with gamification can incentivize proper sorting and boost public participation in recycling programs.

6.5 Summary

Deep Learning in waste detection and sorting improve public health and recycling rates while shifting job opportunities towards technical roles. However, automation can lead to job displacement, social inequality, and privacy concerns. Environmentally, it reduces landfill waste, conserves resources, and protects ecosystems. Ethically, addressing bias, transparency, job impacts, and privacy is crucial. A sustainability plan with ML-powered sorting promotes recycling, resource conservation, reduced environmental impact, improved efficiency, and public engagement.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusions

This chapter concludes our research on waste detection in Dhaka city, employing YOLOv5 and YOLOv7 models to identify waste objects. Our implementation of these advanced deep learning techniques has demonstrated their efficacy in addressing urban waste management challenges. By leveraging artificial intelligence and computer vision technologies, we have significantly improved the efficiency and accuracy of waste identification in diverse urban environments. Collaboration with local stakeholders has been pivotal in refining our models and ensuring their practical applicability. This study underscores the transformative potential of AI-driven solutions in urban waste management, offering sustainable practices and operational efficiencies crucial for cities like Dhaka facing escalating waste issues.

7.2 Further Suggested Works

Moving forward, several avenues for future research and development are proposed to build upon our current findings. Firstly, integrating a robotic sorting system into our detection framework would automate waste segregation processes, enhancing overall operational efficiency. This system could be further optimized with IoT technology to enable real-time communication between the detection system and robotic arms, ensuring swift and accurate sorting of waste materials. Additionally, expanding the scope of our detection models to encompass a broader range of waste categories and geographic locations within Dhaka city will enhance their versatility and scalability. Furthermore, conducting a comprehensive cost-benefit analysis will be essential to evaluate the economic and environmental feasibility of scaling up this integrated system.

7.3 Limitations/ Conflict of Interests

Despite the promising outcomes, our research faces several limitations and considerations that warrant acknowledgment. The accuracy of our waste detection models may be influenced by factors such as dataset diversity and environmental conditions, necessitating ongoing refinement and adaptation efforts. Deploying IoT-enabled robotic sorting systems across diverse urban landscapes presents regulatory and logistical challenges that require careful planning and implementation. Moreover, potential conflicts of interest could arise from collaborations with technology providers or waste management entities, underscoring the need for transparency and ethical guidelines throughout project development.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title:

OPTIMIZING HOUSEHOLD WASTE SORTING THROUGH ITERATIVE LEARNING: YOLOv5 VS. YOLOv7

Student ID: 203-15-14461, 203-14500

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **pneumonia detection** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**

CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

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

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

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project tackles image processing and classification of waste for recycling. It uses deep learning, a powerful technique in artificial intelligence, along with methods to expand the data used	**Page no:** [36-42] **Section:** [5.2]

				for training (data augmentation). The project goes beyond basic engineering by applying a complex deep learning model (diverse YoLo model) to identify and categorize waste into seven different types for proper recycling.	**Page no:** [15-25] **Section:** [3.2]
				This project doesn't just propose a concept; it uses a practical, step-by-step experimentation process (**engineering practice & design, K5**). This experimentation involves using a proven technology, the YOLO model (**engineering practice & technology, K6**), to achieve waste sorting goals.	**Page no:** [29] **Section:** [4.3] **Page no:** [36] **Section:** [5.2]
				This project stays up-to-date with the latest research (**K8: Research Literature**) by incorporating knowledge from recent studies on applying deep learning to waste detection. This demonstrates a thorough grasp of current methods in the field.	**Page no:** [36-46] **Section:** [5.2, 5.3]

2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project tackles a key challenge in waste detection (**EP-2**). It acknowledges the limitations of traditional methods and the complexities of combining transfer learning with deep learning for waste sorting. By comparing different approaches, the project delves into the difficulties of understanding how waste is distributed in images. This analysis provides valuable insights for improving current waste sorting and detection methods.	**Page no:** [08-27] **Section:** [2.3, 4.2]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project directly addresses EP-3 by carefully analyzing the results of its experiments. Through this analysis, it identifies transfer learning as the most effective solution for improving waste detection compared to other potential approaches. This highlights the project's contribution to overcoming the challenges of EP-2 (as mentioned previously).	**Page no:** [27] **Section:** [4.2]

4.	**EP4: Familiarity of Issues**	Yes	CO8	This project transcends the boundaries of computer science and engineering (**interdisciplinary approach**). It aims to not only improve waste detection but also understand the link between improper waste management and public health. This broader perspective involves investigating how waste levels impact the spread of diseases in urban, industrial, and rural areas. By establishing this connection, the project seeks to contribute to advancements in waste management practices, ultimately promoting public health and healthcare improvements in cities (**contributing to EP-4**).	**Page no:** [1-12] **Section:** [1.1, 2.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting requirements**	No	CO8	N/A	N/A

7.	**EP7: Interdependence**	Yes	CO5	This project tackles complex challenges in waste sorting and detection by employing a comprehensive approach (**EP-7**). It seamlessly integrates different aspects, including data collection, statistical analysis, and the proposed deep learning methodology. This holistic approach ensures a well-rounded solution that effectively addresses the multifaceted problems in this domain.	**Page no:** [26-34] **Section:** [4.2, 4.3]

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

SN	EA Definition	Attainment	CO	Justification	References
1.	EA1: Range of resources	Yes	CO11	This project leverages a powerful combination of resources to drive advancements in waste detection using transfer learning and deep learning. We utilize high-performance computing infrastructure and specialized hardware like GPUs (Graphics Processing Units) to tackle complex calculations. Additionally, we rely on deep learning frameworks, well-organized datasets with labeled data (annotated datasets), and a strong focus on ethical considerations. This combination ensures a systematic and well-equipped approach to research in this critical area.	**Page no:** [21-22] **Section:** [3.4]

2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	Yes		This project tackles a real-world issue with a positive impact on society. By developing advanced waste detection methods, the project aims to improve public health and overall well-being (**improved healthcare and livelihood**). Furthermore, it prioritizes environmental sustainability by optimizing the use of computational resources (**efficient computational resources**) and adhering to strict ethical guidelines, especially regarding patient data privacy. This ensures responsible research practices that benefit both society and the environment.	**Page no:** [47-50] **Section:** [5.1, 5.2, 6.1]

5.	EA-5: Familiarity	Yes		This project expands upon existing research by examining a novel approach in waste detection through transfer learning and deep learning, demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.	**Page no:** [6-16] **Section:** [2.1, 2.3]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project goes beyond technical excellence by demonstrating strong project management practices (**CO4**). Through meticulous planning, we ensure optimal resource allocation and budget control throughout the research lifecycle. This focus on financial oversight guarantees efficient use of resources, maximizing the project's impact within its budgetary constraints.	**Page no:** [4] **Section:** [1.6]
2	CO9	Yes	This project prioritizes ethical considerations, aligning with **(CO9)**. We safeguard individual privacy, obtain informed consent from participants whenever	**Page no:** [43] **Section:** [5.3]

			necessary, and maintain transparent documentation of the entire research process. This commitment to ethics ensures responsible knowledge dissemination and ultimately promotes societal well-being through the ethical application of advanced technologies.	
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [16-25, 27-28] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

OPTIMIZING HOUSEHOLD WASTE SORTING THROUGH ITERATIVE LEARNING: YOLOv5 VS. YOLOv7

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