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RECYCLABLE AND NON-RECYCLABLE SOLID WASTE DETECTION USING EFFICIENTDET

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SUPERVISOR APPROVAL

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This thesis was prepared under the supervision of the project supervisor. It was submitted to the College of Computing, Informatics and Mathematics, and was accepted in partial fulfillment of the requirements for the degree of the Bachelor of Information Systems (Hons.) Intelligent Systems Engineering.

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JANUARY 23, 2024

STUDENT DECLARATION

I certify that this proposal and the project to which it refers is the product of my own work and that any idea or quotation from the work of other people, published or otherwise, are fully acknowledged in accordance with the standard referring practices of the discipline.

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ABSTRACT

The issue of waste management has become a significant global challenge, leading to the development of innovative solutions aimed at improving efficiency and sustainability. In response to this pressing need, the present study introduced "RecycleSight," a web-based system specifically designed to detect recyclable and non-recyclable solid waste. The research identified a crucial flaw in waste management efforts, characterized by a lack of effective differentiation between valuable waste and trash, as well as limited community involvement in recycling initiatives. The rapid growth of the population and socioeconomic development has resulted in a substantial increase in municipal solid waste generation. Consequently, there is a need to adopt more precise and automated waste management approaches. To address these challenges, this research aimed to identify the distinguishing characteristics of recyclable and non-recyclable solid waste, utilize object detection algorithms to differentiate between different types of waste, and develop a prototype of a web-based system that integrates the EfficientDet model. To achieve these objectives, data from the TRASHNET and Kaggle datasets, consisting of images of solid waste, were collected and preprocessed using Roboflow. The EfficientDet-D1 method was then employed for object detection. The experimental results demonstrated the effectiveness of the system, achieving a maximum average precision (mAP) of 72% with model 6. However, it should be noted that the system had limitations in detecting objects that were too distant, indicating the necessity for future expansion of the dataset. This research has made a significant contribution to the advancement of waste management practices by providing a practical tool to facilitate waste sorting and recycling efforts. By harnessing advanced technology and expanding datasets, RecycleSight offers a promising solution to promote sustainability and mitigate the environmental impacts associated with waste mismanagement.

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LIST OF ABBREVIATIONS

NGO	Non-Governmental Organization
DoSM	Department of Statistics Malaysia
MSW	Municipal Solid Waste
CNN	Convolutional Neural Network
R-CNN	The Region-based Convolutional Neural Network
SVM	Support Vector Machines
SPP	Spatial Pyramid Pooling
RoI	Regions of Interest
RPN	Region proposal Network
YOLO	You Only Look Once
SSD	Single Shot Multibox Detector
FPN	Feature Pyramid Network
GPU	Graphics Processing Unit
BN	Batch Normalization
CSPNet	Cross Stage Partial Networks
SPPF	Spatial Pyramid Pooling-Fast
KSA	Kestrel-based Search Algorithm
CPU	Central Processing Unit
mAP	Mean Average Precision
HTML	Hypertext Markup Language
CSS	Cascading Style Sheets

CHAPTER 1

INTRODUCTION

This chapter provides the background and rationale for the study. It also gives details of the significance of recyclable solid waste using object detection, the issues and problems that led to this research, the objectives of this research, and the scope of this research.

1.1 Background of Study

The proper management of waste became increasingly important as the amount of waste generated continued to rise. Recycling waste had become a popular way to reduce the amount of waste sent to landfills, but it was a challenge to correctly identify which materials could be recycled and which could not.

In recent years, solid waste management had been a vast issue that was being observed vigilantly by the public, the Local Council, the Government, politicians, the Non-Governmental Organization (NGO), environmentalists, and the media. Solid waste management was one of the most challenging issues faced by the Local Authorities in Malaysia. It was supported by the previous study conducted by Burntley (Malik et al., 2015). By 2025, Malaysia had wanted to recycle 40% of all solid waste, but the country's current recycling rate was only 31.5%. Malaysia's recycling rate was less than half as high as that of other developed nations, which was more than 60% (Syifaa et al., 2023).

The amount of waste produced was increasing day by day. In September 2018, the World Bank had predicted that if no urgent action was taken for waste management soon, global waste production would rise by 70% within 2050 (Faria et al., 2021). Trash was an inevitable consequence of human life and production. On average, a person generated 0.74 kg of trash every day. This amount of daily household trash included leftovers, paper, old clothes, damaged electronics, etc. The benefit of trash classification at the place of residence helped to save resources and was a great economic source (Tran & Nguyen, 2022).

1.2 Problem Statement

A fundamental deficiency in understanding how to effectively differentiate valuable waste from trash significantly impeded waste management efforts. The proper methodologies and guidelines for segregating recyclable and non-recyclable materials were not widely disseminated. Community involvement in solid waste segregation and recycling initiatives remained minimal due to limited exposure to the long-term benefits of recycling, as indicated by Timlett and Williams (Malik et al., 2015).

Rapid population expansion and socioeconomic development contributed to a swift escalation in municipal solid waste generation. Conventional waste management methodologies proved to be inefficient and imprecise. Consequently, there arose a necessity for automated detection of various waste materials, as emphasized by Ahmed Chowdhury et al. (2022). Moreover, failure to categorize waste renders its recycling profoundly challenging. Thus, waste classification prior to recycling is imperative, albeit manual classification is laborious, time-consuming, and demands substantial human and financial resources (Faria et al., 2021).

Furthermore, insufficient awareness resulted in low engagement in waste reduction, reuse, and composting endeavors. Active involvement from the public was deemed indispensable for achieving sustainable waste management in Malaysia, as underscored by Malik et al. (2015).

1.3 Research Questions

The research questions formed for this research are as follows:

i. What are the characteristics that differentiate recyclable and non-recyclable waste?
ii. How can object detection be applied to various types of waste?
iii. How to develop a waste recognition prototype system?

1.4 Research Objectives

The research objectives of this research consist of:

i. To identify the characteristics of recyclable and non-recyclable solid waste.
ii. To apply object detection algorithm to identify types of solid waste.
iii. To develop a prototype of a web-based system with implementation of the EfficientDet model.

1.5 Research Scope

There are four scopes for this research as follows:

i. Classify the solid waste into 2 different types of waste which is recyclable waste and non-recyclable waste.
ii. Develop an image recognition system that distinguishes between recyclable and non-recyclable waste.

iii. The images for testing will be sourced from the TrashNet dataset combined with the Kaggle dataset. The image size will be resized to a minimum of 640 pixels and a maximum of 640 pixels, based on the requirements of EfficientDet-D1.

iv. The programming languages for developing the web-based systems will include PHP, JavaScript, Python, HTML, and Cascading Style Sheets.

1.6 Research Significance

This research was deemed necessary to promote recycling through the proper identification and separation of recyclable materials, holding significant importance in achieving key environmental and sustainability goals. Ensuring that recyclables were accurately identified and separated at the source resulted in diverting a significant amount of waste from landfills, thus alleviating associated environmental risks. This practice also prevented contamination of soil and water sources, thus safeguarding the quality of natural resources.

Furthermore, efficient recycling reduced greenhouse gas emissions by minimizing the need for energy-intensive waste management processes like incineration. It also preserved valuable natural resources by promoting the reuse of materials instead of extracting new resources. Improving waste management practices was crucial for achieving these environmental and sustainability benefits, leading to a cleaner environment, reduced pollution, and long-term resource preservation.

1.7 Summary

In conclusion, effective waste management and recycling practices were deemed crucial as waste generation continued to rise. This chapter outlined the background of the study, emphasizing the importance of solid waste management and the challenges associated with recyclable material identification. The research aimed to apply object detection algorithms for waste classification, thereby contributing to environmental goals by enhancing waste management practices. Overall, this chapter established the foundation for the study, emphasizing the significance of accurate waste identification and separation to promote recycling and sustainability.

CHAPTER 2

LITERATURE REVIEW

This chapter furnished a literature review for the study, encompassing a review of various articles sourced from the internet that were pertinent to the research. The review encompassed topics such as Solid Waste, Waste Management, Image Recognition methods, comparisons of these techniques, and related previous works. An overview of the literature's mind map is available in Appendix A.

2.1 Solid Waste

Solid waste refers to any discarded material that is not liquid or gas. Solid waste management is a critical issue that affects the environment and human health. The increasing generation of solid waste has become a burden on municipal budgets, especially in developing countries. Municipal solid waste (MSW) collection and disposal is one of the major problems of urban environment in most countries worldwide today. Poor waste management practices can lead to air, water, and soil pollution, which can have negative impacts on human health. The collection, storage, transportation, and final disposal of solid waste are major challenges faced by urban cities and areas, particularly in developing countries. Conventional landfills, incineration, composting, and ways of handling solid waste are common as mature technologies for waste disposal (Abdel-Shafy & Mansour, 2018).

2.1.1 Type of waste

This research will focus on Recyclable and Non-Recyclable solid waste. Solid waste that can be recycled has qualities that allow it to be used in recycling procedures to create new goods or resources. It can be reused, is separated at the source, has material value, and profits from market demand and existing recycling infrastructure. Recycling such garbage helps the environment by preserving natural resources, cutting back on energy use, greenhouse gas emissions, and the effects of resource extraction on the environment. In contrast, non-recyclable solid waste cannot be reused and frequently needs to be disposed of by landfilling or cremation.

The improper handling of non-recyclable garbage, which may include hazardous waste that requires specialized processing, can have a negative influence on the environment. While waste reduction techniques are essential for reducing non-recyclable waste, continual improvements in infrastructure and technology for recycling could widen the spectrum of materials that are recyclable. Overall, for efficient waste management, resource conservation, and environmental sustainability, it is essential to understand the characteristics of recyclable and non-recyclable solid waste (Abdel-Shafy & Mansour, 2018).

2.1.2 Waste Impact on Environment

Waste has a significant impact on the environment, including air, water, and soil pollution, as well as greenhouse gas emissions, and other environmental impacts. Landfills, for example, can release methane gas, a potent greenhouse gas, into the atmosphere if not properly managed. Solid waste affects the environment through emissions to the air, land, and water resulting from its production and management. The technologies designed to minimize the environmental impact of waste also impact the environment (Vergara & Tchobanoglous, 2012).

The collection, management, and disposal of MSW in urban areas is one of the main environmental issues. Significant environmental issues are being caused by improper management and disposal of MSW. This covers pollution of the land, air, water, and aesthetics. Due to the rise in greenhouse gas emissions, such environmental issues are connected to health issues in humans (Abdel-Shafy & Mansour, 2018).

2.1.3 Source of waste

The sources of solid waste include agricultural waste, household food waste, human and animal waste, plastics, and municipal solid waste (MSW). MSW is a major problem in both urban and rural areas in many developed and developing countries (Abdel-Shafy & Mansour, 2018). Municipal solid waste (MSW) reflects the culture that produces it. People are discarding growing quantities of waste, and its composition is more complex than ever before, as plastic and electronic consumer products diffuse. The source of waste is mainly from households, commercial establishments, and institutions (Vergara & Tchobanoglous, 2012).

It includes non-hazardous waste such as food waste, paper, plastics, yard waste, and other materials. Residential waste is a type of MSW that is generated by households (Hoornweg, 2012). Understanding the sources of waste is crucial for effective waste management strategies. It helps in developing targeted approaches for waste reduction, recycling, and proper disposal, thereby minimizing the environmental impact, and promoting sustainable waste management practices.

2.2 Waste Management

Waste management is a widespread issue that raises several environmental issues. Waste items must be collected, moved, disposed of, and treated in order to reduce their detrimental effects on the environment and human health. Various waste management techniques have been developed worldwide to address the increasing global waste generation. Common methods include composting, recycling, incineration, and landfilling. However, landfilling and incineration have negative environmental effects such as air and groundwater pollution, as well as greenhouse gas emissions. Recycling and composting offer numerous benefits, including reduced greenhouse gas emissions, energy savings, and resource preservation (Abdel-Shafy & Mansour, 2018). Implementation of waste reduction strategies like source reduction and material substitution, waste generation can be minimized. Reuse involves using waste materials for their original or alternative purposes, while recycling involves collecting and processing waste materials to create new products. In conclusion, waste management is a critical concern impacting the environment, public health, and economy. Effective waste management requires a comprehensive plan that integrates waste reduction, reuse, and recycling to promote sustainability and mitigate environmental impacts (Abdel-Shafy & Mansour, 2018).

2.2.1 Waste Collection and Transportation

Waste collection and transportation are critical components of solid waste management systems. Municipal solid waste collection rates vary widely across global cities, with industrialized cities investing more money in solid waste and achieving higher collection rates compared to less-industrialized cities. Waste transfer and transport involve two steps: the transfer of wastes from smaller collection vehicles to larger transport vehicles and the transport of wastes to a processing or disposal site. Waste collection is generally the most expensive component of waste management, with middle-income cities spending 50-60% of their waste management budgets on collection and low-income cities spending about 80% (Vergara & Tchobanoglous, 2012).

Waste collection and transportation are also crucial for proper waste management. Efficient systems are necessary to maintain cleanliness and protect the environment. Smart technologies like sensors and GPS tracking can optimize waste collection routes, reduce fuel consumption, and reduce emissions. Alternative fuel vehicles, such as electric and hybrid vehicles, can also improve efficiency and reduce pollution. Effective planning and management, including scheduling and proper disposal, are essential. Overall, improving waste collection and transportation requires a combination of technology, planning, and management to create sustainable systems. Further research is needed to develop solutions that meet community needs and environmental goals (Lahcen et al., 2022).

2.2.2 Waste Treatment and Disposal

Different waste management treatments and disposal methods have been developed because of the rising worldwide trash generation. The most popular waste management techniques are composting, recycling, incineration, and landfilling(Vergara & Tchobanoglous, 2012). Landfill is the primary method of disposing of waste in Europe and the USA, with more than 71% of MSW being disposed of in landfills globally. However, landfill disposal is considered unsustainable from an environmental point of view, and landfill sites and their capacity are decreasing rapidly (Abdel-Shafy & Mansour, 2018).

Incineration is another method of waste disposal, particularly for plastics, which possess a calorific value that can be burned or incinerated in municipal or other dedicated wastes with power and heat generation (Abdel-Shafy &

Mansour, 2018). Composting and anaerobic digestion (AD) are the most commonly used technologies for the treatment and valorization of the organic fraction of MSW (Vergara & Tchobanoglous, 2012). The collection, processing, and reuse of waste materials all fall under the category of recycling as a waste management technique. Reuse involves the use of waste materials for their original purpose or for a different purpose. Recycling involves the collection, processing, and reuse of waste materials to produce new products(Vergara & Tchobanoglous, 2012). In conclusion, the most effective waste management technique is recycling.

2.2.3 Public Awareness of Waste Management

Public awareness of waste management has become increasingly important in recent years due to growing concern over environmental issues and the impact of waste on the planet. Several studies have been conducted to investigate the attitudes and behaviours of the public towards waste management, as well as the effectiveness of various awareness campaigns and programs. One study conducted in Malaysia found that there was a weak but positive correlation between community participation in recycling programs and their attitudes and knowledge on solid waste segregation (Malik et al., 2015).

Table 2.1 Knowledge on solid waste segregation (Malik et al., 2015)

Knowledge on Solid Waste Segregation	Number of respondents	Percentage (%)
Yes	194	50.8
No	188	49.2

Based on Table 2.1, (50.8%) of the respondents stated that they have read and gained knowledge on solid waste segregation from various types of information sources. Unfortunately, (49.2%) of the respondents have stated “No” which indicate that they do not know about solid waste segregation.

Table 2.2 Community attitude on solid waste segregation (Malik et al., 2015)

Do you segregate the solid waste?	Number of respondents	Percentage (%)
Yes	180	47.1
No	202	52.9

Based on Table 2.2, The community attitude on solid waste segregation has been recorded systematically. Based on the question ‘Do you segregate the solid waste?’, (52.9%) of the respondent’s state “No” and (47.1%) of respondent’s state “Yes”.

2.3 Object Detection

Object detection methods fall into two categories: traditional and deep learning-based approaches. Traditional methods rely on handcrafted features and machine learning algorithms to detect objects in images. On the other hand, deep learning-based methods use convolutional neural networks (CNNs) to learn features and spatial relationships directly from the data (Bhagya C & Shyna A, 2019).

Traditional object detection methods, like Haar-like features and Histogram of Oriented Gradients (HOG), combined image features with machine learning algorithms such as Support Vector Machines (SVMs) and AdaBoost. However, they faced challenges with variations in objects and occlusions. Deep learning-based methods, categorized into two-stage (R-CNN, Fast R-CNN, Faster R-CNN) and one-stage detectors (YOLO, SSD), significantly outperform other approaches. In two-stage detectors, region proposals are generated and then classified, while in one-stage detectors, detection involves directly predicting object classes and bounding boxes in a single forward pass. Despite their superior accuracy and speed, deep learning methods demand substantial annotated data and computational resources for effective training and inference (Bhagya C et al., 2019).

2.3.1 Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) have emerged as a powerful deep learning technique for various computer vision tasks. CNNs are specifically designed to process and analyses visual data, such as images and videos, by leveraging the concept of convolution.

As shown in Figure 2.1, CNN computes the feature map corresponding to the kernel by convoluting the kernel (weight filter) on the input image. Feature maps corresponding to the kernel types can be computed as there are multiple kernels. The pooling feature map then reduces the size of the feature map. As a result, geometrical alterations, such as a little translation or rotation of the input image, can be absorbed.

To extract the feature map, the convolution and pooling processes are regularly used. The fully connected layers get the extracted feature map as an input, and the probability for each class is then output. In this instance, the network topology between the input and output layers comprises units for the picture and the number of classes.

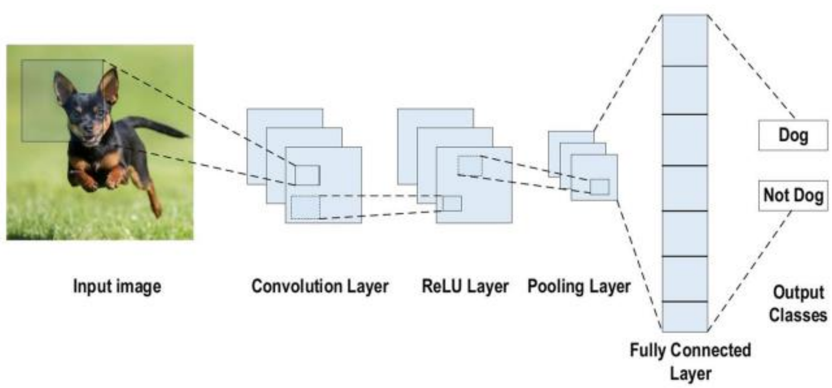
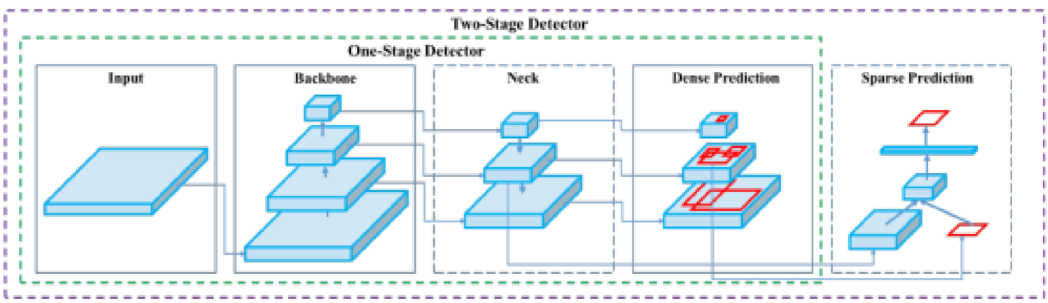


Figure 2.1 Example of CNN architecture for image classification (Alzubaidi et al., 2021)

2.3.2 Deep Learning-Based Object Detector

Deep learning-based object detectors fall into two categories: two-stage and one-stage. A two-stage model has separate modules to generate region proposals (object candidates) where the model try to find some number of object candidates within the input image in the first stage, 25 before classifying (regression on class) and localizing (regression on bounding box) them in the second stage. One-stage detector models on the other hand use semantic understanding of objects to densely predict a lot of examples and keep the ones with an object (positive examples) while ignoring the background (negative examples). The object 16 detection algorithms based on deep learning are largely composed of three parts, i.e., backbone, head, and neck.



Input: {Image,Patches, Image Pyramid, etc.}

Backbone: {VGG, ResNet-50, ResNeXt-101, Darknet53, etc.}

Neck: {FPN, PANet, Bi-FPN,etc.}

Head:
Dense Prediction(one-stage): {RPN, YOLO, SSD, etc.}
Sparse Prediction(two-stage): {R-CNN, Faster R-CNN, etc.}

Figure 2.2 Architecture of object detectors (Bochkovskiy et al., 2020)

I. **Two-stage models**

The Region-based Convolutional Neural Network is an early two-stage object detector that revolutionized object detection by introducing deep learning methods at an industrial level R-CNN (Gupta et al., 2014). It consists of three steps: region proposal extraction using the selective search algorithm, feature extraction using a CNN model trained on ImageNet, and prediction using a linear SVM classifier for object location and class identification. However, R-CNN suffers from slow processing speeds due to the large number of regions of interest and subsequent forward calculations for each image.

SPP-Net is a two-stage model that solves a problem from previous detectors where the loss of accuracy could be caused by using fixed-size CNN (224x224) on arbitrary-sized input images SPP-Net (He et al., 2014). In previous methods, proposed images with different sizes are either cropped or warped to fit the input image to the fixed size of convolution layers, which could result in removing parts of the object from the image or distorting its geometry. SPP-Net uses Spatial Pyramid Pooling (SPP) layer, as seen in Figure 2.3, as its pooling strategy to combat the issue. After the last convolutional layer, an SPP layer is added before outputting a fixed-length feature vector. The SPP layer does multiple pooling processes with different dimensions (256-d, 4x256-d and 16x256-d for filter size of 256) on the feature windows, depending on the size of the last convolutional layer, which is known as the filter size. This results in an ability to map the region proposals directly onto the feature maps from the convolutional layer, instead of feeding each proposed region into the convolutional layer (which needs warping of the proposed region).

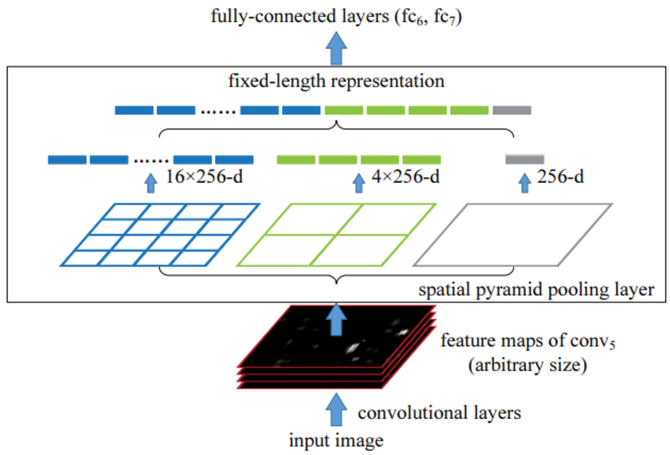
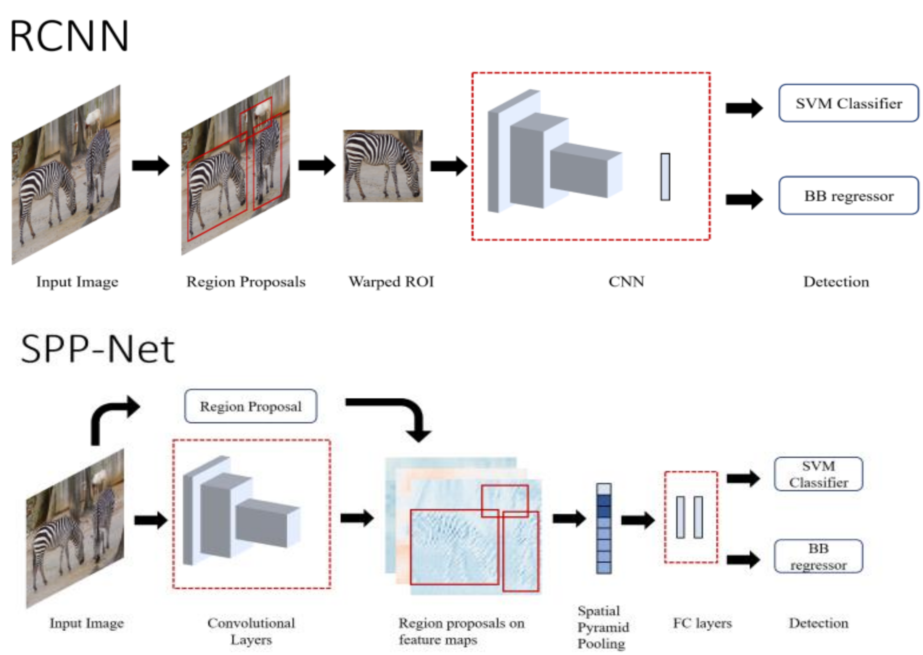


Figure 2.3 Spatial Pymarid Pooling (SPP) layer (He et al., 2014)

Fast R-CNN (Girshick, 2015) was proposed to overcome the speed issue. This model absorbs the features of SPP-Net (Spatial Pyramid Pooling) as shown in Figure 2.3, significantly improving processing speed. Fast R-CNN takes both the entire image and candidate region proposals as input. It generates a convolutional feature map by pooling the image and identifies regions of interest. The pooling layer employs SPP to extract constant feature vectors. The fully connected layer branches into two output layers for object classification and bounding box regression.



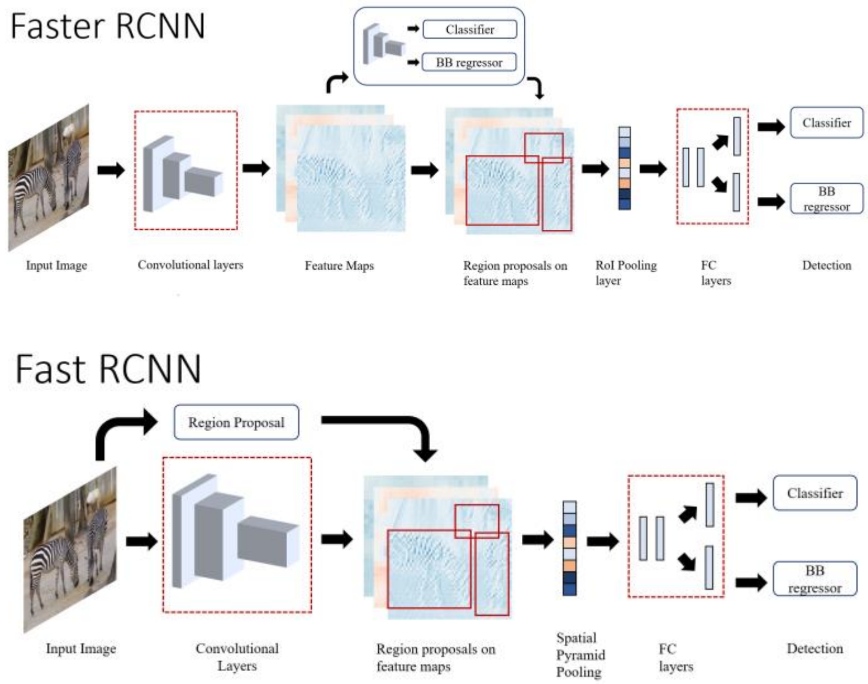


Figure 2.4 Illustration the architecture of different two-stage object detectors (Zaidi et al., 2021)

Building upon Fast R-CNN, Faster R-CNN (Ren et al., 2017) replaces the selective search with a region proposal network (RPN) for candidate region generation. RPN uses anchor points of fixed size and scale and employs softmax and region regression to determine foreground or background status and refine candidate regions. This approach enhances both speed and accuracy compared to its predecessors. Figure 2.4 above shows the architecture of two-stage object detectors.

II. **One-stage models**

YOLO-You Only Look Once (Redmon et al., 2015) . YOLO reframed object detection as a regression problem, directly predicting object pixels and bounding box attributes. It divided the input image into a grid and each cell was responsible for detecting objects. YOLO achieved high accuracy and speed but had limitations in localizing small or clustered objects and the number of objects per cell.

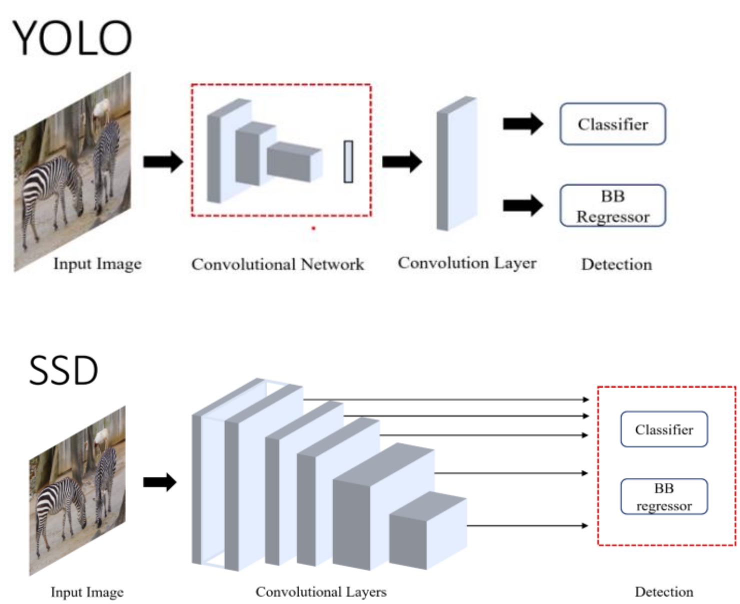
Single Shot MultiBox Detector (SDD) (Liu et al., 2015) was the first single-stage detector to match the accuracy of contemporary two-stage detectors while maintaining real-time speed. It incorporated additional auxiliary structures to improve performance and utilized VGG-16 as the backbone architecture. SSD detected smaller objects earlier in the network and used deeper layers for adjusting default boxes and aspect ratios. Although SSD was faster and more accurate than previous models, it faced challenges in detecting small objects, which were later mitigated through the use of better backbone architectures.

YOLOv2 (Redmon & Farhadi, 2016). YOLOv2 provided an improved trade-off between speed and accuracy by replacing the GoogleNet backbone with DarkNet-19. It introduced techniques such as batch normalization and joint training of classification and detection systems. These versions of YOLO offered increased flexibility, improved convergence, and better priors for detection.

RetinaNet (T.-Y. Lin et al., 2017) . RetinaNet addressed the extreme foreground background class imbalance that hindered single-stage detectors. It introduced the Focal loss, a reshaped cross-entropy loss, which reduced the loss contribution from easy examples. RetinaNet employed ResNet augmented with Feature Pyramid Network (FPN) as the backbone and utilized a class-agnostic bounding box regressor. It achieved better accuracy and runtime performance compared to two-stage detectors and introduced a new loss function that advanced object detector optimization.

YOLOv3 (Redmon & Farhadi, 2018). YOLOv3 featured incremental improvements over previous versions, such as replacing the feature extractor network with a larger Darknet-53 network and incorporating various techniques like data augmentation, multi-scale training, and batch normalization. Despite being faster than YOLOv2, YOLOv3 lacked groundbreaking changes and exhibited lower accuracy than some state-of-the-art detectors.

YOLOv4 (Bochkovskiy et al., 2020). YOLOv4 incorporated numerous techniques and ideas to design a fast and easy-to-train object detector. It utilized both "bag of freebies" and "bag of specials" methods, focusing on improving training efficiency and inference time, respectively. YOLOv4 achieved comparable performance to EfficientDet while being twice as fast and easily trainable on a single GPU.



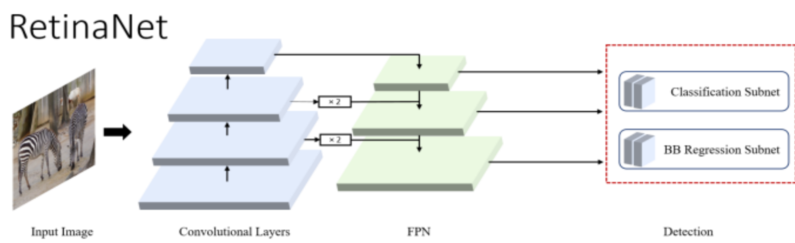


Figure 2.5 Illustration the architecture of different one-stage object detectors (Zaidi et al., 2021)

2.3.3 EfficientDet: Scalable and Efficient Object Detection

EfficientDet, adopts a deep convolutional neural network (CNN) architecture consisting of a backbone network, a neck network, and a head network. The backbone network, usually a variation of the EfficientNet architecture, is responsible for extracting high-level features from the input image. Neck networks improve feature representation by combining multi-scale features. Then, the main network performs object detection through predicting bounding boxes, class probabilities, and confidence scores.

EfficientDet is designed to be scalable and adaptive, using a hybrid scaling approach to uniformly scale the resolution, depth, and width of all network elements (Tan et al., 2019). This approach ensures efficiency and accuracy despite many resource constraints. The introduction of bidirectional feature pyramid networks (BiFPN) contributes to improving model efficiency by facilitating fast and efficient multi-scale feature fusion (Tan et al., 2019). Additionally, the use of EffielNet's backbone, known for its scalability and efficiency, will establish a solid foundation for the overall architecture (Tan et al., 2019). The collective application of these methods leads to the development of EfficientDet, a family of object detectors known for achieving superior accuracy with considerably fewer parameters and FLOPs compared to previous object detectors.

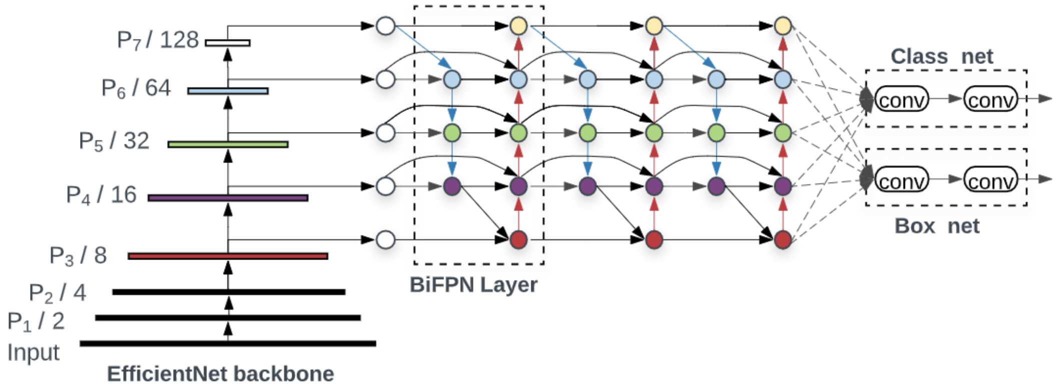


Figure 2.6 EfficientDet architecture(Tan et al., 2019).

Backbone: The architecture above employs the EfficientNet as the backbone network. EfficientNet is a scalable and efficient convolutional neural network architecture that provides a good balance between accuracy and efficiency.

BiFPN (Bi-directional Feature Pyramid Network): The BiFPN serves as the feature network in the architecture. It takes level 3-7 features from the backbone network and repeatedly applies top-down and bottom-up bidirectional feature fusion. This allows for easy and fast multi-scale feature fusion, contributing to improved efficiency in object detection.

Class and Box Prediction Networks: The combined features from the BiFPN are inputted into common class and box prediction networks, generating predictions for object class and bounding boxes, respectively. The weights of the class and box networks are uniform across all feature levels, enhancing the overall efficiency of the architecture.

Compound Scaling Method: The architecture additionally integrates a compound scaling approach, which uniformly scales the resolution, depth, and width for the entire backbone, feature network, and box/class prediction networks simultaneously. This approach aims to harmonize various dimensions of the architecture, enhancing overall efficiency.

2.4 Related Work

Several research studies have been conducted on the detection of solid waste objects employing diverse methodologies. These investigations delve into various techniques for identifying and categorizing solid waste in different environments.

2.4.1 Solid Waste Detection

Research by W. Lin (2021) implement the YOLO-Green for real time waste classification. The author used two combined datasets which are Trash X and TrashNet. The result from this technique is 78.04% of mean average precision (mAP).

Another research by Agbehadji et al., (2022) uses a combination of YOLO and Kestrel-based Search Algorithm (KSA), the methodology involved collecting data on waste images that were labeled with ground truth boxes for training the custom YOLO model. The results of the experiment indicate that Yolov3 model produces the best performance results (80%) (mAP).

In a study conducted by Majchrowska et al., (2022), an efficient and precise solution was developed for waste detection and classification in both natural and urban environments, employing deep learning methodologies. The dataset utilized in the study was obtained by amalgamating and refining existing open-source datasets depicting waste observed across various environments. Test results pertaining to detection revealed that the mean average precision (mAP) attained a level of 77% with the utilization of the EfficientDet-D2 model. Appendix A provides a comprehensive overview of the literature review table.

2.4.2 Application for Classifying Solid Waste

Research by Adedeji & Wang, (2019) proposed an intelligent waste material classification system using a 50-layer residual net pre-train (ResNet-50) convolutional neural network model and Support Vector Machine (SVM) to classify waste into different group. The dataset is acquired from TrashNet. The proposed system achieves an accuracy of 87% on the dataset.

Finally, research by Thumiki & Khandelwal, (2022) proposed Real-time mobile application for classification of solid waste material. The author utilizes Convolutional Neural Networks (CNNs) combined with image recognition concepts. The dataset is acquired from TrashNet. The proposed application was able to classify solid waste materials into six labels with an accuracy of about 80%.

2.5 Summary

In conclusion, this chapter provides a comprehensive literature review on research on waste disposal and image recognition methods. It covers various aspects such as types and sources of waste, environmental impact, waste management technology, and the role of image recognition technology. This review highlights the importance of effective waste management strategies to reduce waste-related environmental and health risks. This chapter highlights the benefits of recycling and composting while discussing the challenges associated with landfilling and incineration. This chapter also discussed the development of image recognition technology, its application in various fields, and potential further advances. The review concludes with an overview of the main findings and contributions of the research to date, laying the groundwork for future research.

CHAPTER 3

RESEARCH METHODOLOGY

This chapter explains the methodology that has been selected to execute the studies. There are five phases that have been planned in this research methodology and the seven phases are preliminary study, data collection and preparation, model development, prototype development and documentation.

3.1 Research Framework

In this phase, it summarizes the overall research framework for this research. There are three main objectives that need to be achieved. All objectives have some activities that have been done to achieve all the deliverables in every objective. Table 3.1 shows how it was done.

Table 3.1 Research framework for the first objective

Objective	Phase	Activities	Deliverables
To Identify the characteristics of recycle waste and non-recycle waste.	Preliminary Study	• Identify problems. • Background study of waste management. • Review articles and case study of the domain, techniques and related works used for this study.	CHAPTER 1 1. Background Study 2. Problem Statement 3. Research Questions 4. Research Objectives 5. Scope 6. Significant CHAPTER 2 Literature Review

To apply EfficientDet for the detection of solid waste.	Data Collection and Preparation	● Dataset collected from TrashNet and Kaggle ● Data labelling, preprocessing and Augmentations using Roboflow.	Selected from combine image: Recyclable waste -239 Non-Recyclable waste – 175 Image After Preparation: Train Set - 1056 Images Test Set - 62 Images
	Model Development	● Develop the EfficientDet-D1 algorithm model. ● Train the dataset with developed model. ● Evaluate the trained algorithm's performance on the validation set or a separate test set.	EfficientDet model Evaluated model: - mAP - Recall Model evaluation comparison and select the best model for deployment.
To develop a prototype of a web-based system using the EfficientDet-D1 model.	Prototype Development	● Create a web-based application design using HTML, Java, and CSS style programming language. ● Develop a user interface that allows users to upload waste images for classification. ● Implement the trained model within a web-based prototype.	A web-based prototype is designed to recognize solid waste in real-time, distinguishing between different types of waste with recyclable and non-recyclable classes.
	Documentation	Writing a full report.	Final Year Project report.

3.2 Phase 1: Preliminary Study

The preliminary study stage in this research is crucial. This step's major components include learning about the waste related problem, the industry and waste identification techniques. The goal of the preparatory study phase was to compile and comprehend the body of research related material that was already in existence.

One of the activities at this stage is the identification of waste issues. This includes recognizing the difficulties and problems associated with waste management and the need for effective waste identification systems. In addition, it requires research and evaluation of various research papers. As a result, it has become easier to understand the situation on the ground, recognize the techniques and methods previously employed, and gain a new perspective on the strengths and weaknesses of current approaches. The final activity is to identify waste detection characteristics. Waste characteristics such as color, shape and size should be considered.

The deliverable of this phase is the entire first chapter of the proposal, consisting of the research background, problem statement, research question, research objectives, research scope, and importance. The results present statistics, data and trends related to waste generation, environmental impact, and current waste management practices. It provides a comprehensive overview of the waste management sector. A whole second chapter is one of the results of this stage. The results obtained from the survey and analysis of previous studies and publications are summarized in a literature review where all fields, techniques and related studies are discussed here. Finally, the waste detection properties are presented, giving a detailed analysis of the identified properties that can be used for waste recognition. It discusses the importance and effectiveness of each feature in identifying different types of waste such as recyclable waste and non-recyclable waste.

3.3 Phase 2: Data Collection and Preparation

The goal of this phase is to collect the data required for the investigation and to prepare the waste picture dataset from the TrashNet and Kaggle dataset for further analysis and model training. The goal is to analyse a good dataset that can be used to fit the research goal which is for image recognition of recyclable and non-recyclable solid waste. The activity involved in this phase is to find the dataset that is suitable for this research. The dataset of the waste derived from the examined research publications is the main output of this phase. The dataset that has been found and suitable for the research is TrashNet and Kaggle waste image. The TrashNet dataset was created by Mindy Yang and Gary Thung from Stanford University. However, the dataset lacks non-recyclable images. Consequently, the TrashNet dataset was combined with Kaggle's images to include a variety of recyclable and non-recyclable solid waste selections. For this research, the images that will be used have been selected to get the balance class for recyclable and non-recyclable for detection. Figures 3.1 show the TrashNet and Kaggle dataset examples.

Light Bulb Plastic Bottle Letter Paper

Glass Diapers

Figures 3.1 Image example from TrashNet and Kaggle dataset

The total data collected was 414 images. Table 3.2 below shows the total number of images in each class. After the dataset was acquired, the preparation phase involved performing three activities: Data annotation, data pre-processing and data augmentation. In the data annotation activities, it involves labelling the images from the collected dataset in specific class based on the research that has been done which are recyclable and non-recyclable types of waste.

Table 3.2 Total amount of images for every class

No.	Class	Number of Images
1	Recyclable	239
2	Non-Recyclable	175

Next, the dataset underwent data pre-processing. The steps in the data pre-processing that was done in this research were the auto-orient, resizing the data, and auto-adjusted contrast. For the auto-orient data, the image was automatically adjusted to the orientation based on its embedded orientation metadata. This metadata is often included by using cameras or devices when capturing an image. Auto oriented ensures that the image from Kaggle and TrashNet dataset were processed in the correct orientation to avoid any unintended rotations.

Another major data pre-processing process that was done for this research was resizing the images. Since the pre-trained EfficientDet-D1 model can read a specific size of images, resizing process becomes an essential process in this research. The images were resized to 640 x 640 pixels images since EfficientDet-D1 models require an image in 640 x 640 pixels.

Other than resizing, this dataset also has done auto-adjusted contrast using contrast stretching, this process is an image enhancement technique that adjusts the contrast of an image to improve its visual quality. Auto adjustment is done to waste images to ensure the specific characteristics of each image.

Next, the combined dataset, containing labelled waste images, was gathered, and split into training and test sets as shown in Figure 3.2. The dataset is then converted into the TensorFlow format, which includes annotation files specifying bounding boxes and class labels for each image in csv file.

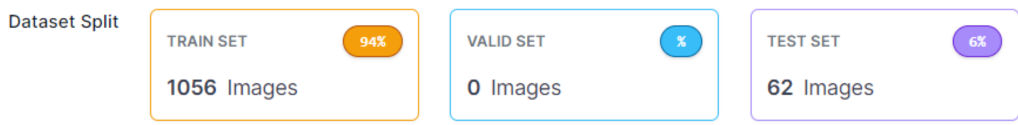


Figure 3.2 Splitting percentage of the dataset

All of these activities have been done using Roboflow as tool for efficient and accurate data annotation, data pre-processing, and data augmentation. The major output of this phase was a prepared waste picture dataset that had undergone all the steps above. The dataset was then ready for further analysis and model training.

3.4 Phase 3: Model Development

In this phase of the research, the focus was on developing, training, and evaluating the EfficientDet-D1 model for the recognition of solid waste. The model development process involved a series of meticulously planned steps to ensure optimal performance solid waste detection model.

This phase initiated the development of the EfficientDet-D1 model, the TensorFlow Model was utilized. The library package, available on GitHub, provides various implementations of state-of-the-art (SOTA) models and modeling solutions as shown in Figure 3.3.

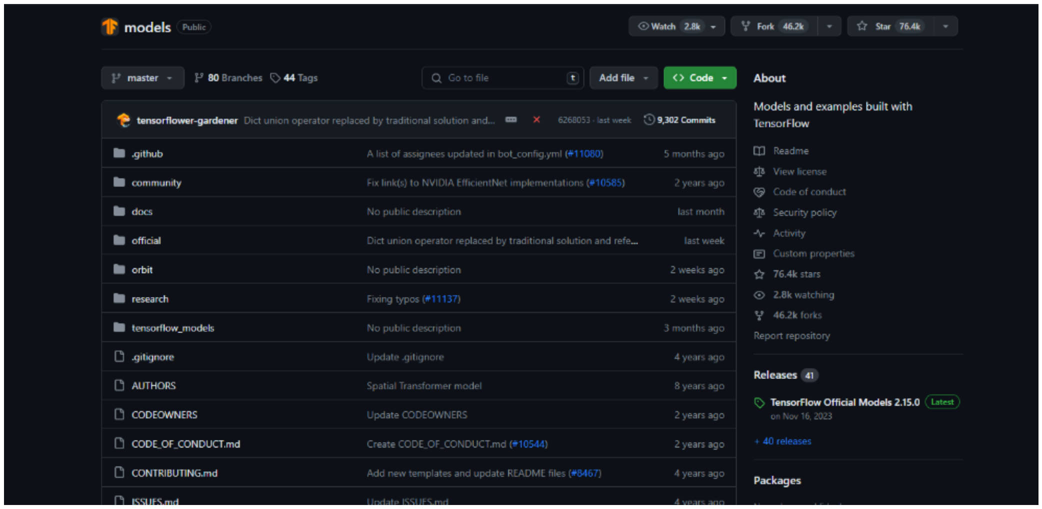


Figure 3.3 TensorFlow Model repository website

Initially, we obtained the EfficientDet-D1 model by downloading it from TensorFlow 2 Detection Model Zoo on GitHub repository. The model was pre-trained on COCO 2017 dataset and came with weights that we used to initialize the network. This methodology of transfer learning was undertaken to expedite the learning process. Subsequently, we fine-tuned the model by using a combined Kaggle and Trashnet dataset to recognize two different classes. During the process of training, we carefully monitored metrics of loss convergence by running the training script that was provided in the TensorFlow model Garden.

The EfficientDet-D1 model configuration employs a Single Shot Multibox Detector (SSD) with an EfficientNet-b1 + BiFPN feature extractor, shared box predictor, and focal loss. This architecture, introduced in (Tan et al., 2019), demonstrates the effectiveness of combining efficient backbone networks with efficient object detection strategies.

In Figure 3.4, the architecture of recyclable and non-recyclable solid waste detection is depicted. The model employed the EfficientDet architecture with an EfficientNet-B1 backbone, known for its well-balanced performance and efficiency in feature extraction. The BiFPN layer integrated features from levels 3 to 7 of the backbone, amalgamating higher-resolution and more abstract features. With 4 iterations and 88 filters per node, the BiFPN enhanced feature exchange and refinement across different levels. The model consisted of separate heads for class and box prediction. The Class Prediction Head utilized convolutional layers for object categorization (recyclable or non-recyclable), while the Box Prediction Head predicted precise bounding boxes for localized waste objects. This architecture ensured a robust detection process, leveraging the strengths of EfficientNet-B1 for feature extraction and BiFPN for effective multi-scale feature fusion, ultimately providing clear outputs for both categorization and localization of waste objects.

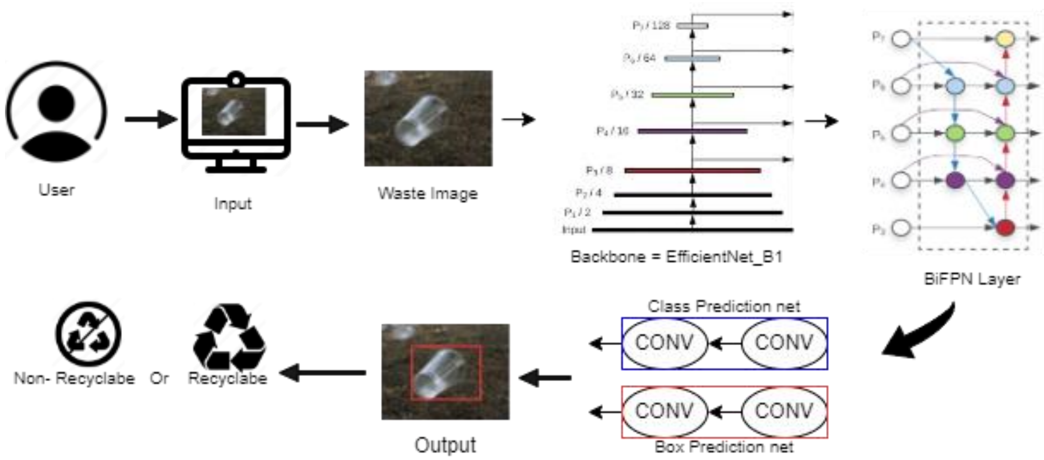


Figure 3.4 Recyclable and Non-Recyclable solid waste detection Architecture

After training, the model is evaluated using the test dataset to assess its performance. Evaluation metrics such as mean average precision (mAP), precision, Loss values and recall are measured to gauge the model's accuracy and detection capabilities, specifically in waste classification. The Recall measures how good the model is at hitting the positive class. The formula for recall is shown in equation 3.1 below, where (TP) is stance for true positive and (FN) is stance for false negative and (FP) is stance for false positive.

$$\text{Equation 3.1: } R = \frac{TP}{TP + FN}$$

Next metric that will be evaluated is mean average precision (mAP). (mAP) is a commonly used metric in object detections evaluated, providing a comprehensive measure of a model's precision across different categories. The formula for calculating the mean average precision is shown in equation 3.2 below, where C is the total number of classes and APi is the average precision for class *i*. Mean average precision (mAP) is defined as the mean of AP across all C classes.

$$\text{Equation 3.2: } mAP = \frac{1}{C} \sum_{i=1}^{C} APi$$

Precision and recall are computed using Intersection over Union (IoU) thresholds. IoU is a metric defined as the ratio of the area of the intersection to the area of the union between a predicted bounding box (B_p) and a ground-truth box (B_t). The formula is depicted in equation 3.3 below.

$$\text{Equation 3.3: } IoU = \frac{area\ (B_p \cap B_t}{area(B_p \cup B_t)}$$

Following the evaluation results, the subsequent step involves fine-tuning hyperparameters to compare and determine the best optimal outcome, considering factors such as the number of steps, learning rate, and batch size, all geared towards optimizing the model's performance. After the training, the models were evaluated based on the Evaluation metrics to determine which models produced better results. The models were evaluated, and the best model was used for the system development.

3.5 Phase 4: Prototype Development

This phase will focus on developing the prototype that implements the optimized EfficientDet-D1 model for waste recognition in web-based applications involving several key steps. First, the application needs to determine the specific which is real-time solid waste recognition. Next, create a design for the user interface, including elements for video capture box and displaying the found waste and its classification.

The development process then moves to the backend, where the infrastructure is set up to handle image processing and EfficientDet-D1 model inference. A suitable web framework which is Flask, and the server environment is configured. The EfficienDet-D1 model is integrated into the backend system by loading the trained model weights and defining functions for image preprocessing, model inference, and postprocessing of detection results.

At the same time, the front-end components of the web application are developed, using the programming languages PHP, HTML, CSS and JavaScript. The framework chosen for this research is Laravel as shown in Figure 3.5. This framework provides a structured and efficient environment for developing robust and scalable web applications. Laravel's flexibility and ease of use make it an ideal choice for creating the user interface and interactivity of a waste identification application. The integration of these programming languages and the Laravel framework ensures a seamless and user-friendly experience in the final prototype.

Figure 3.5 Laravel: web application framework

This includes implementing features for real time waste detection, displaying detection results, and enabling user interactions. Comprehensive testing is conducted to ensure the application functions correctly, handles different types of solid waste images, and provides accurate detection and classification results. Any issues or bugs encountered during testing are addressed and fixed in the feedback section.

3.6 Phase 5: Documentation

The preparation of a thorough and well-organized final year report that summarizes the recyclable and non-recyclable solid waste using image recognition research, development method, and conclusions is the primary goal of documentation phase. The material obtained during the research must be arranged and presented in a clear and straightforward manner during this phase.

The final year project report is the deliverable of this documentation phase. A trough summary of this research paper consists of three chapters which is, chapters 1,2 and 3. Chapter 1 is documentation about background study of the purposed title, problem statement, research question, research objective, scope of study, research significance, summary of chapter 1. Chapter 2 is about the literature review that has been studied and acquired from past related paper/works. Chapter 3 is about the Methodology that is being used in this research. All these chapters have been documented thoroughly with the given format. The font that will be used in this report is Times New Roman and the

Line and paragraph spacing will be 1.5. Lastly the documented uses justify alignment for clean, crisp edges so it looks more polished. It should demonstrate a thorough understanding of solid waste detection research and detail the findings and lessons learned from the investigation.

3.7 Summary

This chapter focuses on the methodology employed throughout the research. It begins with the importance of preliminary study, which involves understanding waste related issues, reviewing existing literature, and identifying waste detection methods. The data collection phase involves acquiring the TrashNet and Kaggle images dataset, consisting of categorized waste images, for analysis. Data preparation involves resizing images and applying data augmentation techniques to enhance dataset diversity. The model development phase utilizes the EfficientDet-D1 model, trained and fine-tuned using the prepared dataset, and evaluated for accuracy. Prototype development includes designing the user interface, integrating the model into a web-based application, and conducting comprehensive testing. Lastly, the documentation phase emphasizes the creation of a well-organized final report summarizing the research background, objectives, methodology, and conclusions. The chapter serves as a guide for understanding the research 's methodology and sets the stage for subsequent chapters in the report.

CHAPTER 4

RESULT AND FINDINGS

This chapter summarized the research's results and findings after the techniques were implemented. All the dataset preparation, model training, model evaluation results, and a summary of the overall findings.

4.1 Dataset Preparation Result

As mentioned in the previous chapter, the dataset used for this research is acquired from TrashNet and Kaggle. After data was selected, All the images have been labelled based on their specific classification which has been done using the Roboflow annotation tools as shown in Figure 4.1 below.

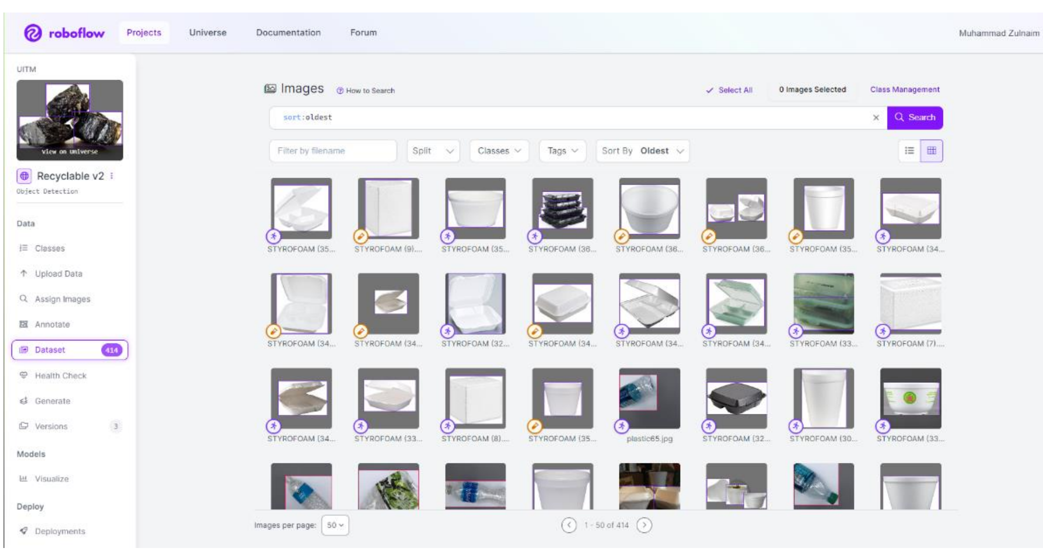


Figure 4.1 Sample of annotation result using Roboflow

4.1.1 Data Pre-processing Result

The most essential process of the research was the data pre-processing. Before the data went through pre-processing, the original dataset was split into 94% training and 6% testing. After being split, only the training dataset underwent pre-processing and augmentation. Table 4.1 below shows the sample of data before pre-processing and the result after pre-processing.

Table 4.1 Data Pre-Processing Result

Image Pre-processing	Image Result
Image Before Pre-processing: Image Size: 2448 X 3264 pixels Auto Orient: Not Applied Auto Adjusted Contrast: Not Applied	
Image After Pre-processing: Image Size: 640 X 640 pixels Auto Orient: Applied Auto Adjusted Contrast: Contrast Stretching	

4.1.2 Data Augmentation Result

After the data has been processed, the next one is data augmentation. Data augmentation is a technique used to artificially increase the diversity of the dataset by applying various transformations to the original images. For this research, the augmentation that has been applied to original images are flip horizontal and vertical, rotation between -15° and +15°, and Noise up to 6% of pixels to expose the model to a broader range of variations, enhancing its ability to generalize well to different scenarios. Table 4.2 below shows the result of the data augmentation process.

Table 4.2 Data Augmentation Process

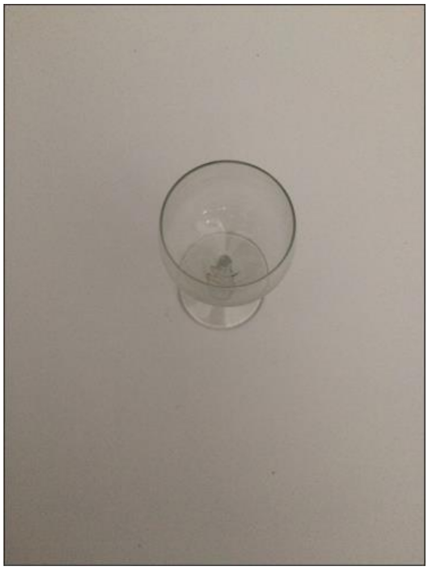
Image Augmentation Process	Image Result
Original image	

Image after pre-processing	
Augmentation detail: Flip: Vertical Rotation: 5° Noise: 4.25% pixels	
Augmentation detail: Flip: Vertical Rotation: 8° Noise: 5.75% pixels	

The total number of training images for both recyclable and non-recyclable solid waste has significantly increased through the augmentation process. The augmentation strategy, generating three outputs per training image, has led to a substantial growth, resulting in a total of 1056 training images. The initial dataset, initially comprising 414 images, has undergone this augmentation, contributing to the overall richness of the training set.

In addition to the expanded training dataset, there are now a combined total of 1118 images designated for training and testing purposes. This integration ensures a comprehensive dataset for both model development and evaluation. The sample images utilized in the model training process are thoughtfully presented in Figure 4.2 below, offering a visual representation of the diverse elements encompassed in the training set.

Figure 4.2 Sample images results after data preparation

4.2 Model Performance Result

Training is a critical aspect of this research, particularly because the efficientdet-d1 model needs to accurately distinguish between recyclable and non-recyclable solid waste. The models must be exposed to a substantial amount of data to effectively learn the distinctions among various types of waste, ensuring the highest level of detection accuracy. following the completion of data pre-processing, the preprocessed waste dataset was delivered into the pre-trained 'efficientdet-d1' model on coco dataset to train the algorithm.

Next, to train the algorithm in this research, various hyperparameters setting was tuned to be compared and create the best model for recognize the recyclable and non-recyclable waste. The training process, conducted on tpu-8, involves fine-tuning from an efficientDet-D1 checkpoint. Loss value identifies how the training is going well. Loss is a number indicating in terms of how bad the prediction of the model over the training samples was. If the model's prediction is perfect, then loss is zero otherwise loss will be greater. The goal of training a model is to find a set of weights and biases that have low loss on average. In subchapters 4.2.1, 4.2.2, 4.2.3, 4.2.4, 4.2.5, and 4.2.6 the comparison for each parameters tuning was discussed.

4.2.1 Batch Size Training Results

The efficiency of training and model convergence significantly relies on the careful selection of an appropriate batch size. The subsequent subsections delve into the influence of varying batch sizes on the training process, assessing the model's performance with a focus on loss values. The model configurations, as depicted in Table 4.3 below, remain consistent across all results, with the only difference being the batch size.

Table 4.3 Model configuration settings for batch size parameter tuning

Configurations	Description
Model	EfficientDet-D1
Model backbone	EfficientNet-b1 + BiFPN
Environment	• TensorFlow 2 • Visual Studio Code with TPU-8
Number of steps	1000
Cosine Decay Learning rate	Base 5e-3, Warmup 0.001, Momentum 0.9
Dataset	1056 images

i) 4 Batch Size

Model 1 used batch size set to 4, this model underwent training to distinguish between recyclable and non-recyclable patterns. This model was trained using the same configurations setting as mentioned in Table 4.3 above. Figure 4.3 below shows different types of loss functions results over the number of steps during the training process. Time taken for the model to complete is 1.737 hours.

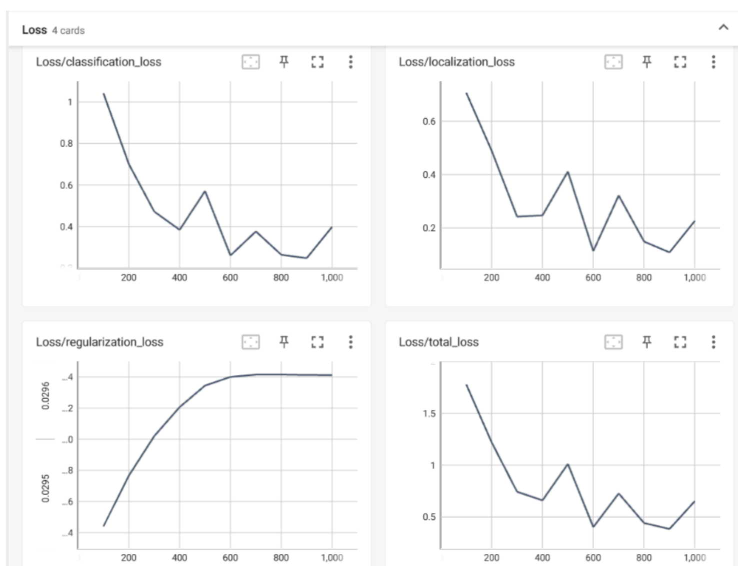


Figure 4.3 Loss functions result graph model 1

The model consistently improved during training, as seen in the decreasing classification, localization, and regularization losses. At the 1000th step, the final losses were 0.4004 for classification, 0.2289 for localization, 0.02964 for regularization, and 0.659 for total. Notably, it seemed a bit harder for the model to correctly classify objects compared to localizing them accurately. On the positive side, the low regularization loss indicates that overfitting is not a big concern for this model.

ii) 6 Batch Size

Model 2 used a slightly larger batch size, set at 6. This adjustment aimed to assess whether a larger batch size could lead to more stable convergence and improved generalization. This model was trained using the same configuration mentioned in Table 4.3. Figure 4.4 below shows different types of loss functions results over the number of steps during the training process. Time taken for the model to complete is 2.498 hours.

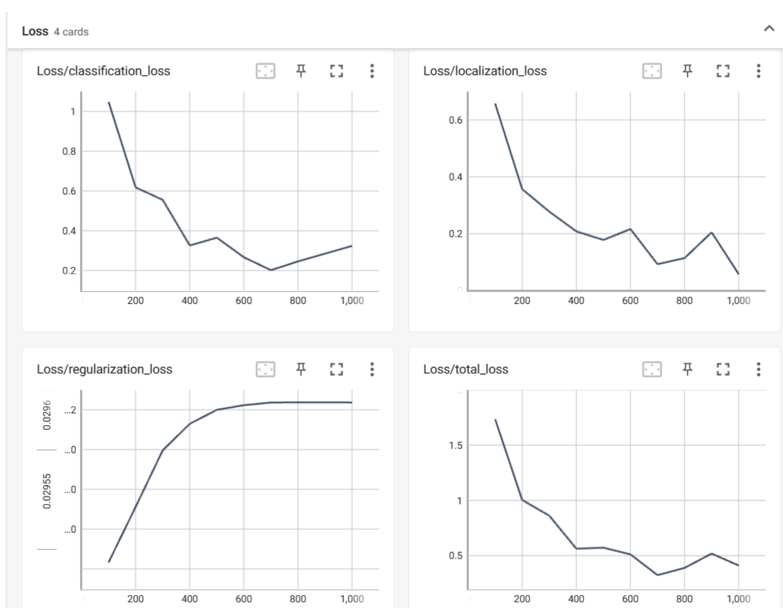


Figure 4.4 Loss function result graph model 2

The model made positive progress during 1000 training steps, with all loss values decreasing, showing successful learning. The balanced losses suggest good control against overfitting, and their convergence indicates potential for further improvement. Notably, object localization accuracy improved significantly, with a lower Localization Loss of 0.05955, and object classification performance also got better, seen in the reduced Classification Loss of 0.327. The model maintained consistent complexity control, as the Regularization Loss stayed stable at 0.02962. Overall, the Total Loss dropped to 0.4162, showing a substantial improvement in the model's overall performance.

iii) 8 Batch Size

In model 3, the batch size was further increased to 8, pushing the boundaries to observe potential improvements in convergence and overall model performance. This model was trained using the same configuration mentioned in Table 4.3. Figure 4.5 below shows different types of loss functions results over the number of steps during the training process. Time taken for the model to complete is 3.29 hours.

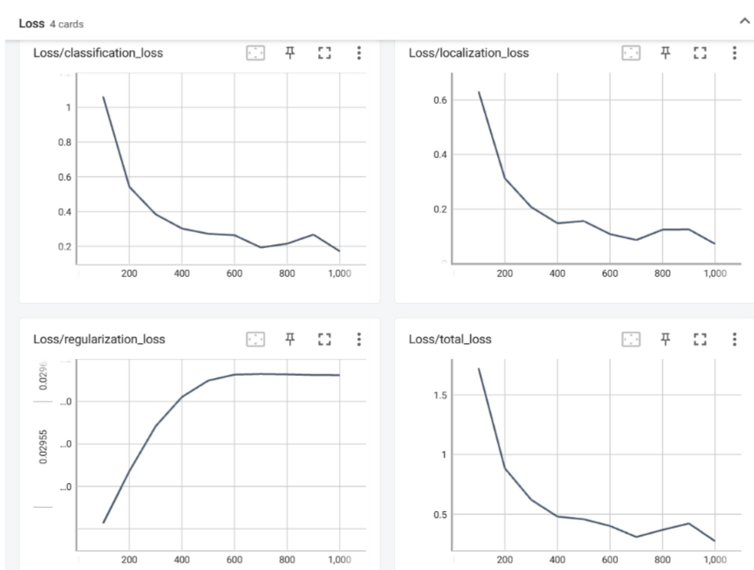
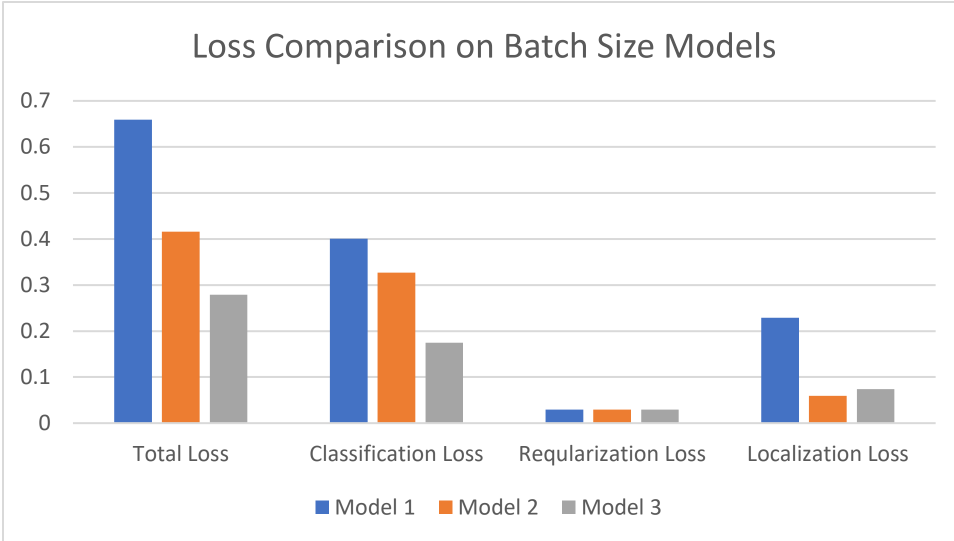


Figure 4.5 Loss function result graph model 3

The model continues its positive trajectory, with ongoing improvement evident in decreasing losses. The converging trend suggests the model is approaching optimal performance, and balanced losses indicate effective learning without overfitting concerns. The persistently low regularization loss reflects the model's stable complexity control and potential for generalization. In specific findings, object localization, though slightly higher than the previous model, which is 0.07403, still shows significant improvement. Object classification accuracy notably increased with a reduced classification loss of 0.175, and the regularization loss remains stable at 0.02961. The overall total loss decreased to 0.2787, marking the best model performance observed to date.

4.2.2 Discussion of the Training Results for Batch Size

Figure 4.6 depicts a comparison graph illustrating the loss trends of three models with varying batch sizes: Model 1 with a batch size of 4, Model 2 with a batch size of 6, and Model 3 with a batch size of 8. All models exhibited decreasing losses over 1000 training steps, indicating effective learning and improvement. Positive convergence was observed across the models, with losses consistently converging towards lower values. Notably, the experiments reveal that Model 3, utilizing a batch size of 8, yielded the best result with the lowest overall loss value. This outcome suggests that a larger batch size, as employed in Model 3, provides the optimal performance for distinguishing recyclable and non-recyclable waste using the EfficientDet-D1 model algorithms.



Figures 4.6 Loss comparison graph on batch sizes

4.2.3 Number of Steps Training Results

The number of steps selected plays a crucial role in determining the effectiveness of the process and is intricately linked to model convergence. This chapter endeavors to identify the nature and impact of varying step numbers in the training process, with a primary focus on evaluating model performance through loss values. Model configurations, outlined in Table 4.4, remain consistent across all outcomes, differing solely in the number of steps.

Table 4.4 Model configuration settings for number of steps parameter tuning

Configurations	Description
Model	EfficientDet-D1
Model backbone	EfficientNet-b1 + BiFPN
Environment	• TensorFlow 2 • Visual Studio Code with TPU-8
Batch Size	6
Cosine Decay Learning rate	Base 5e-3, Warmup 0.001, Momentum 0.9
Dataset	1056 images

i) 2000 Number of Steps

In the training of model 4, the configuration was established as detailed in Table 4.4, involving a total of 2000 steps. The training process was completed in 5.43 hours. The aim of this model training was to assess effectiveness and achieve the lowest overall loss value, encompassing a greater number of steps compared to model 2, which had 1000 steps. As mentioned in the preceding subchapter, model 2 employed a batch size of 6, consistent with this model but with a distinct number of steps. Figure 4.7 depicted the outcomes of various loss functions over the number of steps during the training process.

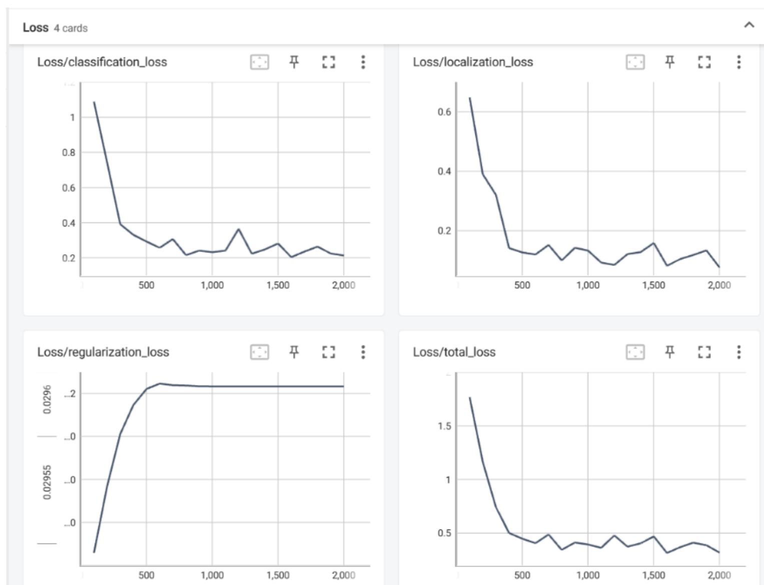


Figure 4.7 Loss function result graph model 4

As the number of training steps for the model 4 increased to 2000th steps, there was a decrease in the loss for the EfficientDet-D1 model in every iteration, which means the learning occurred. A converging trend in the losses is indicative that the model is reaching its optimal performance and, also, the balanced nature of the losses implies control against overfitting. It is important to mention the consistency at which the regularization loss is kept low indicating the ability of the model to manage complexity and generalize well. The mentioned findings of the study successively showed commendable behavior within different objectives used to train the model. Specifically, localization loss at 0.0787 showed a good object localization accuracy. Classification loss was found at 0.2168, showing room for improvement in the model aspect of object classification. And regularization loss was found at 0.02962 - another finding that showed successful control over the model complexity as well. Overall, a total loss of 0.3252 was another valuable step in training the model as a whole.

i) 3000 Number of Steps

In model 5 training, the configuration aligns with that presented in Table 4.4, featuring a total of 3000 steps. The training process was completed in 7.896 hours. The primary aim of this model training is to assess effectiveness and achieve the lowest overall loss value, Figure 4.8 illustrates the various loss functions' outcomes over the number of steps during the training process.

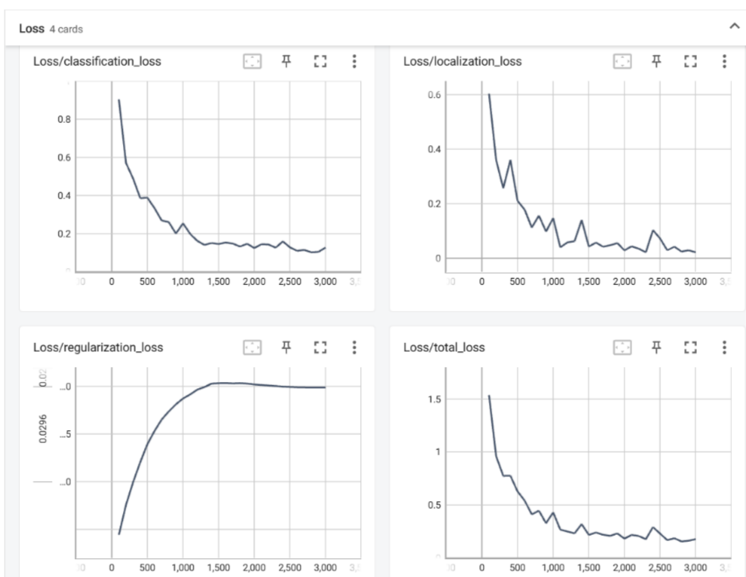


Figure 4.8 Loss functions result graph model 5

In the context of Model 5, which employs the EfficientDet-D1 architecture, with over 3000 number of steps in training, showed notable improvements as decreases in all loss metrics were observed to reiterate its massive learning. The decreases in losses show that the model is getting closer to optimal performance at a slow rate, but also resulting in a not so steep equilibrium that must be handled against overfitting. Persistently low, the regularization loss rests at 0.0297, showing astrometric adeptness of the model in handling complexity and promoting generalization. Specific observations point out that the sensitivity of object localization significantly augments as indicated by dropping the localization loss to 0.02389. Similarly, the progress in classification of objects is depicted by a reduced classification loss of 0.1302. Regularization loss that remains at 0.0297 thus showing that the model is still managing complexity. The total overall loss, which continued to decline to 0.1838, indicated the best performance of the model witnessed so far and certified further improvement in trend regarding the learning of the model.

4.2.4 Discussion of the Training Results for Number of Steps

In Figure 4.9, a comparison graph illustrates the loss trends among three models with different numbers of training steps: 1000 steps in Model 2, 2000 steps in Model 4, and 3000 steps in Model 5. Each model exhibited distinct characteristics in terms of loss trends. Model 2 displayed a relatively steep decrease in loss, indicating rapid learning but suggesting a potential risk of overfitting due to the abrupt decline. On the other hand, Model 4 demonstrated a more gradual and consistent reduction in loss, showcasing continued learning and effective control against overfitting. The extended training steps in Model 4 allowed for nuanced learning and commendable balance in various loss functions. Model 5, with 3000 steps, exhibited a further prolonged decrease in loss, indicating ongoing refinement and improvement. In this discussion, it was shown that a larger number of training steps led to better performance of the model in terms of loss trends.

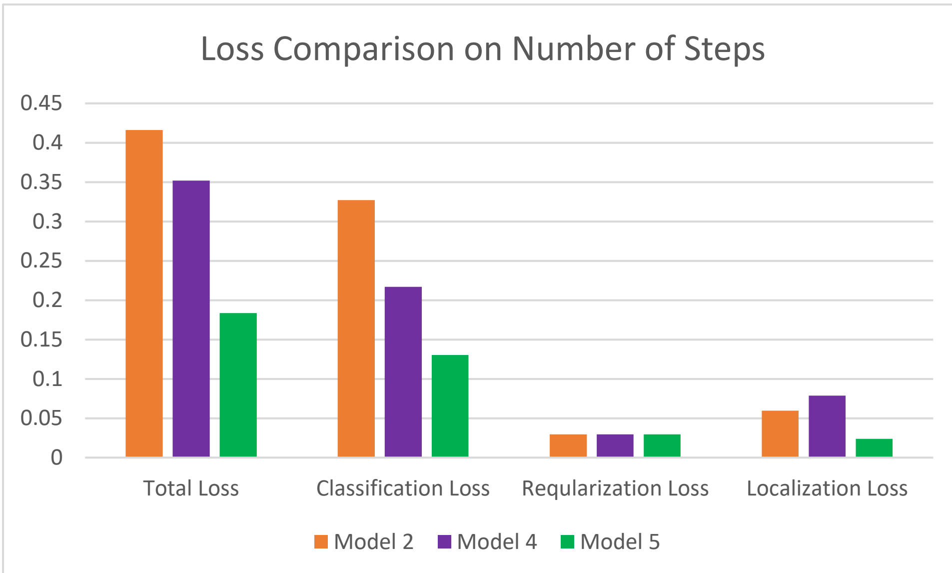


Figure 4.9 Loss comparison graph on number of steps

4.2.5 Base Learning Rate Training Result

After discussions in sub-sections 4.2.3 and 4.2.4, it is evident that a larger number of steps and batch size contribute to improved training results in terms of loss trends. The next experiment takes a different approach, aiming to identify the best result among all models from previous experiment. The parameter configurations for the upcoming models, namely Model 6 and Model 7, are outlined in Table 4.5 below. Notably, these models will have different base learning rate parameters. The base learning rate serves as a fundamental factor influencing the magnitude of weight updates during training. In this section, we delve into the results obtained after training the model with different base learning rates. The analysis includes observations on loss trends, convergence patterns, and the overall performance of the model under varying base learning rates.

Table 4.5 Model configuration settings for Base Learning Rate parameter tuning

Configurations	Description
Model	EfficientDet-D1
Model backbone	EfficientNet-b1 + BiFPN
Environment	• TensorFlow 2 • Visual Studio Code with TPU-8
Batch Size	10
Cosine Decay Learning Rate	Warmup 0.001, Momentum 0.9
Number of Steps	5000
Dataset	1056 images

i) 5e-3 Base Learning Rate

In model 6 training, the configuration aligns with that presented in Table 4.5, with base learning rate set at 5e-3. The training process was completed in 23.86 hours. The primary aim of this model training is to assess effectiveness and achieve the lowest overall loss value, Figure 4.10 illustrates the various loss functions' outcomes over the number of steps during the training process.

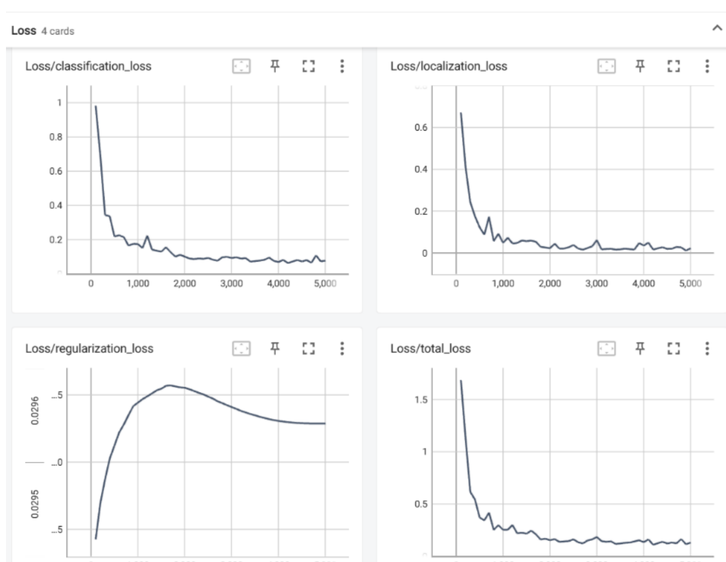


Figure 4.10 Loss function result graph model 6

In this case of model 6, with over 5000 training steps,10 batch size and 5e-3 as base learning rate, the EfficientDet-D1 model consistently reduced all its losses, showing continuous learning in Figure 4.10 above. As the losses leveled off, it indicated the model was getting close to its best performance with the current settings. The balanced losses suggested the model avoided overfitting, and the regular low regularization loss at 0.02963 highlighted the model's ability to manage complexity throughout. Specific loss values demonstrated exceptional object localization accuracy at 0.02513, along with good object classification performance, seen in a reduced classification loss of 0.08119. The stable regularization loss at 0.02963 confirmed the model's consistent control over complexity. The overall total loss, now at 0.136, reflected the model's impressive past performance, showcasing its progress and proficiency during training.

ii) 8e-2 Base Learning Rate

In model 7 training, the configuration aligns with that presented in Table 4.5, with base learning rate set at 8e-2 which is larger than previous model. The training process was completed in 24.12 hours. The primary aim of this model training is to assess effectiveness and achieve the lowest overall loss value, Figure 4.11 illustrates the various loss functions' outcomes over the number of steps during the training process.

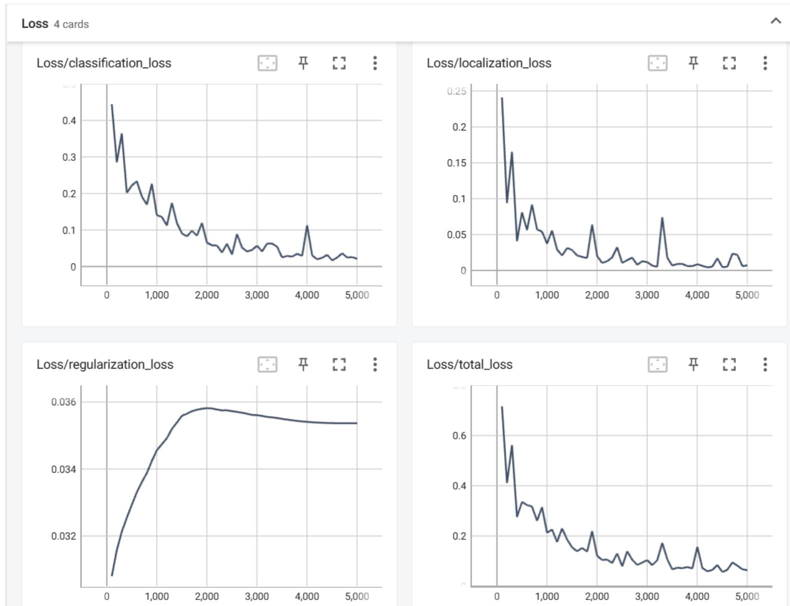


Figure 4.11 Loss function result graph model 7

In the case of Model 7, spanning 5000 steps, a batch size of 10, and a base learning rate of 8e-2, the EfficientDet-D1 model demonstrated substantial learning with marked reductions in all losses in Figure 4.11 above. While the model exhibited exceptional localization accuracy at a loss of 0.00807 and impressive classification performance with a loss of 0.02295, caution was warranted due to a slightly elevated regularization loss of 0.03537. This suggested a potential for overfitting, where the model might have closely fit the training data. Despite this concern, the overall total loss of 0.06639 still indicated excellent past performance. The results, however, indicate a possibility of overfitting, emphasizing the importance of ensuring the model's generalization across diverse data scenarios, which could impact object detection performance negatively.

4.2.6 Discussion of the Training Results for Base Learning Rate

In Figure 4.12, Model 6 with a base learning rate of 5e-3 exhibits a stable and continuous learning trajectory, achieving exceptional object localization accuracy (0.02513) and commendable object classification performance (loss of 0.08119). The consistently low regularization loss (0.02963) signifies effective control over model complexity. In comparison, Model 7, utilizing a higher learning rate of 8e-2, displays substantial learning with exceptional localization accuracy (0.00807) and impressive classification performance (loss of 0.02295). However, a slightly elevated regularization loss (0.03537) raises concerns about potential overfitting. Considering stability and strong performance, Model 6 stands out as the best model for waste detection, with robust results and effective control over model complexity.

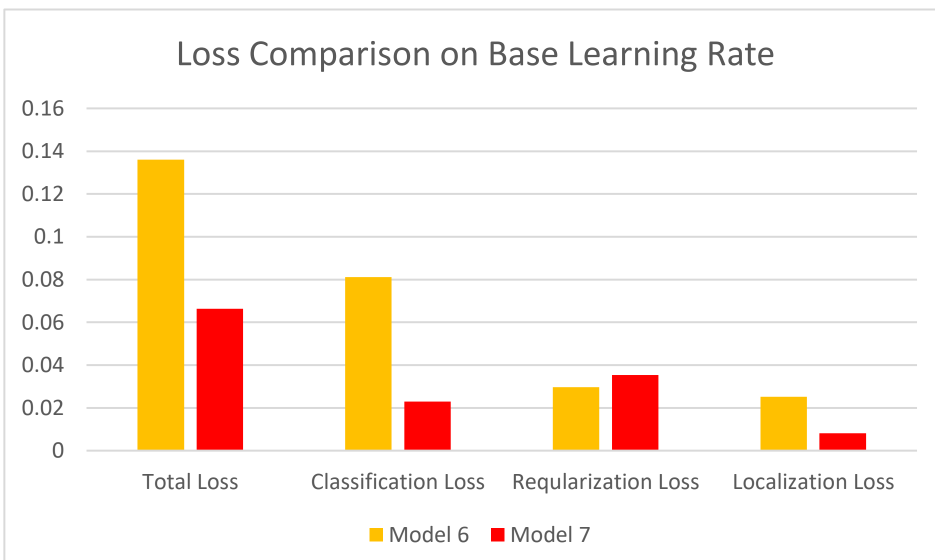


Figure 4.12 Loss comparison graph on base learning rate

Based on all the results gained from training with different hyperparameters, it is shown that the most optimal models for object detection in this research is model 6 with respectively low on overall loss value and balance performance.

4.3 Model Evaluation Result

In this section, an evaluation of all training models with varied hyperparameters is presented, focusing on COCO metrics such as mean average precision (mAP) and average recall (AR). The assessments were carried out using a set of 62 images from the test dataset. The average recall (AR) was split by the max number of detections per image (1, 10, 100).

4.3.1 Evaluation Result Comparison

In the previous section, which was Section 4.2, all the models underwent different parameter settings in the quest to find the optimal model. In this section, all the models are evaluated and compared in terms of achieving the highest mean average precision (mAP), average recall (AR), and the lowest loss value using the 62 images from test dataset.

Table 4.6 Results for mAP of Bounding Boxes for Each Model

Model	**mAP Bounding-Boxes**		
	mAP	**mAP @ 0.50 IoU**	**mAP @ 0.75 IoU**
Model 1	61%	84%	71%
Model 2	62%	89%	70%
Model 3	63%	87%	74%
Model 4	65%	90%	74%
Model 5	68%	90%	76%
Model 6	72%	87%	82%
Model 7	68%	84%	73%

The results from Table 4.6 indicate that the highest mean average precision (mAP) was achieved by Model 6. This suggests that Model 6 consistently outperformed other models, demonstrating superior performance across all Intersection over Union (IoU) thresholds. Its robust and accurate performance remained consistent even with stricter IoU criteria.

Table 4.7 Results for AR max number of detections per image for Each Model

Model	**AR MaxDets**		
	AR maxDets = 1	**AR maxDets = 10**	**AR maxDets = 100**
Model 1	58%	69%	71%
Model 2	62%	71%	72%
Model 3	61%	71%	71%
Model 4	63%	72%	74%
Model 5	65%	74%	75%
Model 6	68%	78%	80%
Model 7	68%	76%	77%

The result from Table 4.7 presents the Average Recall (AR) at various maxDets values for each of the methods presented. MaxDets refers to the maximum number of detections that pertain to every single image. For instance, at AR maxDets = 1, Model 6 achieved a recall of 68% which means correctly placing 68% solid waste objects in each image. As can be seen, Model 6 has the highest recall rate at every value of maxDets, supporting its recognition as the best model for the given data. Model 6 yields recall rates of 78% and 80% at AR maxDets = 10 and AR maxDets = 100 respectively. These results emphasize that Model 6 was very successful in consistently detecting a very large fraction of solid waste items across all maxDets criteria, and thus, seems the best-performing model in our analysis.

4.4 Prototype Interface Overview

In this prototype interface overview, a detailed exposition awaits, delving into the details of the prototype interface titled "RecycleSight". Figure 4.13 shows the interface of the prototype for web-based applications. At the top of the page, the RecycleSight logo and tagline, "Recyclable & Non-Recyclable Solid Waste Detection," immediately convey the tool's purpose. The concise yet informative introduction further clarifies RecycleSight's role: "RecycleSight is your trusted tool to detect whether your waste can be recycled or not." The overall design of the homepage is user-friendly, with an evident emphasis on simplicity and clarity.

Figure 4.13 Prototype Interface for “RecycleSight”

4.5 Prototype Interface Overview

In this section, the prototype's functionality undergoes a meticulous examination, emphasizing user-friendly design principles that prioritize simplicity and functionality. When users interact with the "Detect" button, as depicted in Figure 4.14, the process of detecting recyclable and non-recyclable solid waste commences.

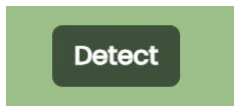


Figure 4.14 Detect button on prototype

The prototype testing utilized the best model obtained from all the completed training, specifically Model 6, which had been selected optimally with 5000 steps, a batch size of 10, and a base learning rate of 5e-3. Combined with the SSD+efficientnet_b1 backbone, the prototype demonstrated its remarkable ability to accurately identify recyclable and non-recyclable solid waste during the testing phase.

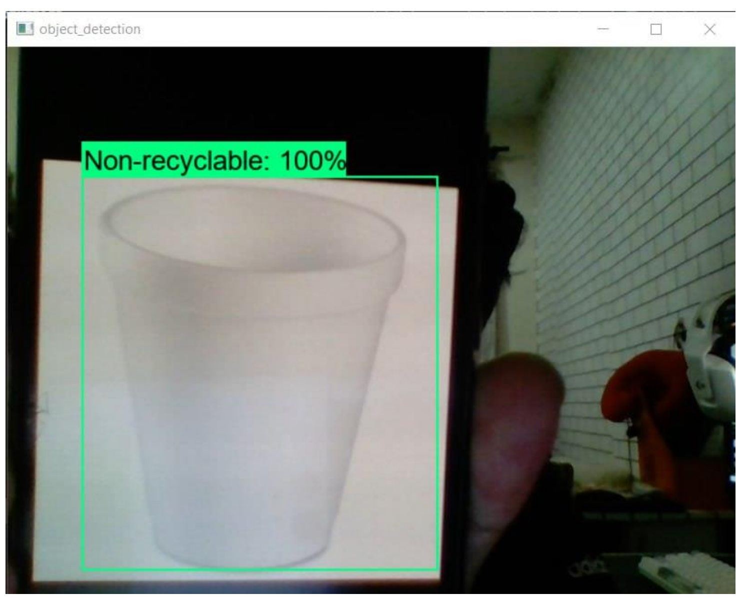


Figure 4.15 Prototype testing result for polystyrene cup

Figure 4.16 Prototype testing result for disposable mask

The proficiency of this prototype was evident in the presented Figure 4.15 and 4.16, illustrating its capability to accurately detect waste within their respective classifications. Specifically, non-recyclable solid waste was identified with notably high confidence levels of 99% and 100%, accompanied by precise bounding boxes for predicting the location of the solid waste.

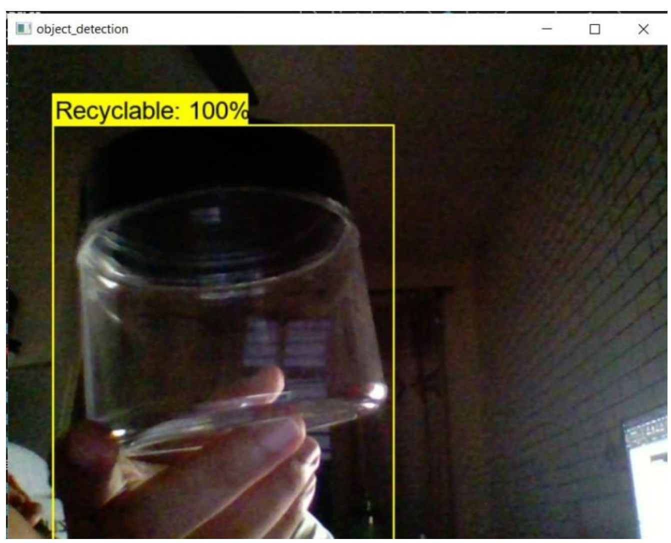


Figure 4.17 Prototype testing result for plastic containers

Figure 4.18 Prototype testing result for paper

The proficiency of this prototype was evident in the presented Figure 4.17 and 4.18, illustrating its capability to accurately detect waste within their respective classifications for solid waste. Specifically, recyclable solid waste was identified with notably high confidence levels of 100%, accompanied by precise bounding boxes for predicting the location of the solid waste.

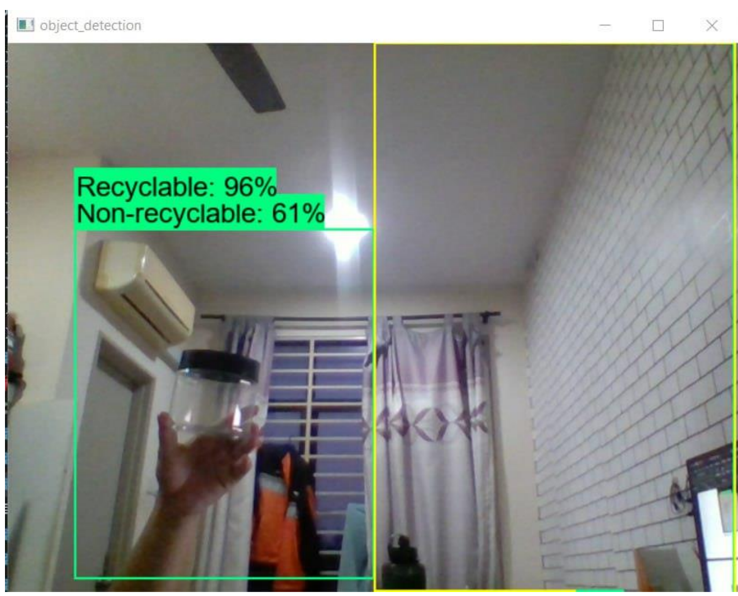


Figure 4.19 Prototype testing result for small waste on plastic container

Figure 4.19 highlighted the limitations faced during this research, where the prototype struggled to accurately detect the class of solid waste if the waste was placed too far from the camera. Additionally, the bounding box did not precisely predict the location of the solid waste.

4.6 Summary

In this chapter, which focused on Results and Findings, the outcomes of different research stages were detailed. The dataset preparation (Section 4.1) outlined the results of data preprocessing and data augmentation. Transitioning to Model Performance (Section 4.2), the training results for various aspects like Batch Size, Number of Steps, and Base Learning Rate were presented, along with corresponding discussions. Model Evaluation Result (Section 4.3) provided insights into the comparison of evaluation results. In summary, the research underscored that Model 6 consistently outperformed other models, achieving the highest mean average precision (mAP), average recall (AR), and the lowest loss value across diverse evaluation criteria. The Prototype Overview (Section 4.4) exemplified the prototype interface view. Lastly, Prototype Testing (Section 4.5) showcased the prediction results and findings from the optimal model choice, Model 6, demonstrating high confidence and accurate detection of recyclable and non-recyclable solid waste.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

This chapter summarized the research's conclusion and recommendations. All the achievements of the research, research strength and limitations, and recommendations for future work. By having this summarize, other researchers can make use of this research as their reference for future work.

5.1 Research Achievements

In the realm of waste management, the achievements stemming from this research are significant, touching upon crucial elements such as the comprehensive literature review, meticulous research methodology, and the unveiling of insightful results and findings. The depth of exploration and analysis conducted in these areas has culminated in noteworthy accomplishments, reflecting a substantial advancement in the field. This research has not only contributed to the academic understanding of waste detection but has also provided practical solutions to the challenges associated with identifying solid waste. The development of a system prototype integrating EfficientDet-D1 object detection algorithms within a user-friendly interface stands as a testament to the research's commitment to bridging the gap between theoretical insights and practical applications. These achievements pave the way for enhanced waste management practices, demonstrating the potential of technology-driven solutions in addressing the complex and pressing issues surrounding solid waste detection.

5.1.1 Objective 1: To identify the characteristics of recyclable and non-recyclable solid waste

Identifying the distinguishing features of recyclable versus non-recyclable solid waste was the initial objective achieved through a comprehensive literature examination and interpretation. This study elucidated distinct differences in the qualities of various waste categories into two clear class types - recyclable and non-recyclable solid waste. This thorough analysis established a solid foundation for subsequent research methodology phases. Grasping the qualities of waste that can and cannot be recycled is essential to effective waste management strategies.

5.1.2 Objective 2: To apply object detection algorithm to identify types of solid waste

The successful attainment of the second objective, which involved developing a model for solid waste detection using the EfficientDet-D1 algorithm, is a notable accomplishment. The selected model demonstrates a seamless integration of the EfficientDet algorithm, showcasing its effectiveness in accurately identifying solid waste in real-time scenarios. The EfficientDet-D1 model underwent meticulous training with parameter tuning, resulting in the acquisition of the optimal model. This model exhibits a remarkable ability to distinguish between recyclable and non-recyclable solid waste with high precision and accuracy. The accomplishment not only contributes to the advancement of waste management technologies but also holds promise for the future implementation of efficient and accurate solid waste detection systems across diverse environmental settings, fostering a sustainable approach to waste management practices.

5.1.3 Objective 2: To develop a prototype of a web-based system with implementation of the EfficientDet model

The successful fulfillment of the final objective in this research involved the development of a prototype web-based system for solid waste detection. This prototype, equipped with a user-friendly interface and integrated camera functionality, demonstrated its proficiency in accurately detecting and classifying solid waste. The real-time identification of various types of waste underscored the prototype’s potential for practical application in waste management practices. This accomplishment contributes to the efficient detection of different types of solid waste, distinguishing between recyclable and non-recyclable materials.

5.2 Strengths and Limitations

The research findings highlight notable strengths and some limitations in the development of the solid waste detection prototype using the EfficientDet-D1 model. On the strength side, the prototype showcased remarkable proficiency, particularly through the optimal selection of Model 6, strategically trained with 5000 steps, a batch size of 10, and a base learning rate of 5e-3, coupled with the SSD+efficientnet_b1 backbone. This combination demonstrated an impressive ability to accurately discern recyclable and non-recyclable solid waste during testing. The model exhibited high confidence levels in identifying both recyclable and non-recyclable waste, accompanied by precise bounding boxes for location prediction.

However, the research also identified limitations that merit consideration. A challenge was observed wherein the prototype struggled to accurately detect the class of solid waste when placed too far from the camera. This distance sensitivity poses a constraint on the prototype's effectiveness in certain environmental settings. Additionally, a broader consideration beyond the prototype lies in the computational resource requirements of the EfficientDet-D1 model. While the model excels in object detection, its demand for substantial computational resources may limit scalability, especially in resource-constrained environments. Acknowledging these strengths and limitations provides a nuanced perspective on the prototype's capabilities and areas for potential refinement in future iterations.

5.3 Future Work Recommendations

In the realm of future work recommendations, a primary focus should be directed towards the expansion of the existing dataset. This entails an ongoing effort to collect real-time solid waste data, contributing to the refinement and adaptability of the detection model. By incorporating a more diverse range of waste scenarios, the model can better accommodate the dynamic nature of waste disposal practices, ultimately improving its accuracy and applicability in real-world settings.

Another critical aspect to address in future endeavors involves overcoming device limitations. The research identified constraints related to the computing resources of the employed device. To mitigate this, future work should explore advancements in hardware capabilities or consider the adoption of cloud-based solutions. This strategic shift can enhance accessibility, enabling the deployment of the solid waste detection model on a broader spectrum of devices, thereby increasing its usability and reach.

Future efforts should focus on optimizing the solid waste detection model by fine-tuning hyperparameters, experimenting with architectural adjustments, and exploring advanced optimization techniques. This meticulous exploration aims to yield a more efficient and effective model, contributing to continuous improvement and practical applicability in waste management.

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APPENDICES

APPENDIX A: Literature Review Table

Author	Objectives	Technique	Dataset	Evaluation
W. Lin 2021	The objective of this paper is to propose a newly developed deep learning model called YOLO-Green, which is optimized for waste management.	YOLOv4	The dataset used acquired from Trash X and TrashNet	The result from this paper gets 78.04% of mean average precision(mAP)
Agbehadji et al., 2022	The objective of this paper is to propose a custom waste object detector and waste category classification enabled by a nature-inspired hyper-parameter tuning for	YOLOv3	Custom waste image dataset by collecting waste images obtained online	The results of the experiment indicate that Yolov3 model produces the best performance results (80%) (mAP).

	real-time waste object detection and classification.			
Majchrowska et al., 2022	The objective of this paper is to purpose an efficient and accurate solution for waste detection and classification in natural and urban environments using deep learning techniques.	EfficientDet-D2	The dataset is acquired from unifying and filtering existing open-source datasets of waste observed in different environments.	The test results for detection show that the (mAP) reached 77% with the EfficientDet-D2 model.

APPENDIX B: Literature Review Mind Map