Smart Solutions for a Cleaner Planet: Artificial Intelligence and Machine Learning in Plastic Waste Reduction

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Dedicatory

To my marvellous wife, the backbone of my success, and to my kids, Salvador and Íris, who inspire me to be my best version every day.

To Fernando Pessoa, who gave me my life motto:

Para ser grande, sê inteiro: nada
Teu exagera ou exclui.
Sê todo em cada coisa. Põe quanto és
No mínimo que fazes.
Assim em cada lago a lua toda
Brilha, porque alta vive.
(14/02/1933)

Sê inteiro. Serei. Sê todo em cada coisa. Serei. Põe quanto tu és no mínimo que fazes. Porei. Nada teu exagera ou exclui. Nada excluirei. A lua toda brilha porque alta vive. Brilhará.

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I want to take a moment to express my gratitude to the people who have supported me during my journey. First and foremost, my wife, Andreia, constantly inspires me with her ideas and serves as my muse. I am forever grateful for her love and encouragement.

I would also like to thank my parents, Maria and Manuel, for their unwavering support and guidance throughout my life. They have given me the tools and knowledge necessary to navigate this complex and beautiful world.

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Finally, I would like to express my gratitude to Xavier, Bruna, Bruno, Jared, Hannah, and Mikael, along with many others who have contributed their valuable input, insights, and enthusiasm towards the subject of waste management. And to you, Diana, I know you will read this one day and be happy to see your name here.

The world is a truly fascinating place.

Abstract

Artificial intelligence and environmental sustainability intersection has become a critical exploration domain in the contemporary era marked by rapid technological advancements and complex global challenges. This work focuses on the application of Machine Learning models, such as Regin-based Neural Networks (R-CNNs), Single Shot MultiBox Detectors (SSDs), and You Only Look Once (YOLO), to address the pressing issue of plastic waste management. By leveraging state-of-the-art computing technologies and Artificial Intelligence (AI), this research aims to enhance the efficiency and effectiveness of Plastic Waste (PW) identification, classification, and recycling processes.

Considering the increasing environmental concerns and information processing potential, this thesis posits that advanced Machine Learning (ML) models can significantly contribute to more sustainable plastic waste management practices. Through systematic analysis of the performance of various ML models in detecting and classifying plastic waste, this study not only benchmarks the current state of the art but also illuminates pathways for future innovations in recycling technologies. Combining AI's analytical prowess with strategic waste management initiatives presents a promising frontier for mitigating environmental impacts, underscoring the thesis's commitment to harnessing technological evolution for the greater good.

Keywords

Artificial Intelligence, Machine Learning and Recycling.

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List of abbreviations and acronyms

AI	Artificial Intelligence
CNN	Convolutional Neural Networks
CSC	Circular Supply Chain
DCNN	Deep Convolutional Neural Networks
IEEEX	Institute of Electrical and Electronics Engineers Xplore
IoT	Internet of Things
ML	Machine Learning
PW	Plastic Waste
QGIS	Quantum Geographic Information Systems
RQ	Research Question
SSD	Single Shot MultiBox Detector
VAE	Variational AutoEncoder
WM	Waste Management
WSCC	Web of Science Core Collection
YOLO	You Only Look Once

1. Introduction

The urgent need for environmental sustainability has brought about remarkable global efforts to promote recycling on a larger scale. Governments, organisations, and individuals worldwide have acknowledged the importance of recycling to reduce PW and conserve resources.

Advancements in technology, infrastructure, and policy frameworks have accompanied the evolution of recycling practices. Today, recycling programs encompass a wide range of materials, and recycling has become a symbol of hope for our planet. Artificial intelligence (AI) will be vital in addressing challenges and increasing recycling rates worldwide [1] [2].

To explore comprehensively the challenges and opportunities presented by integrating Machine Learning (ML) approaches into Plastic Waste (PW) reduction strategies, we must first characterise the context of the problem at hand. This subchapter serves as the canvas upon which we paint a vivid picture of the intricate landscape in which our research is situated.

The global PW problem is a formidable challenge in today's world, casting a long shadow over environmental sustainability, economic efficiency, and social well-being. This multi-faceted issue transcends geographical boundaries, affecting communities, industries, and ecosystems worldwide. This problem is notorious in Figure 1, which describes the cumulative PW generation and disposal over the past years and provides a forecast for the upcoming decades.

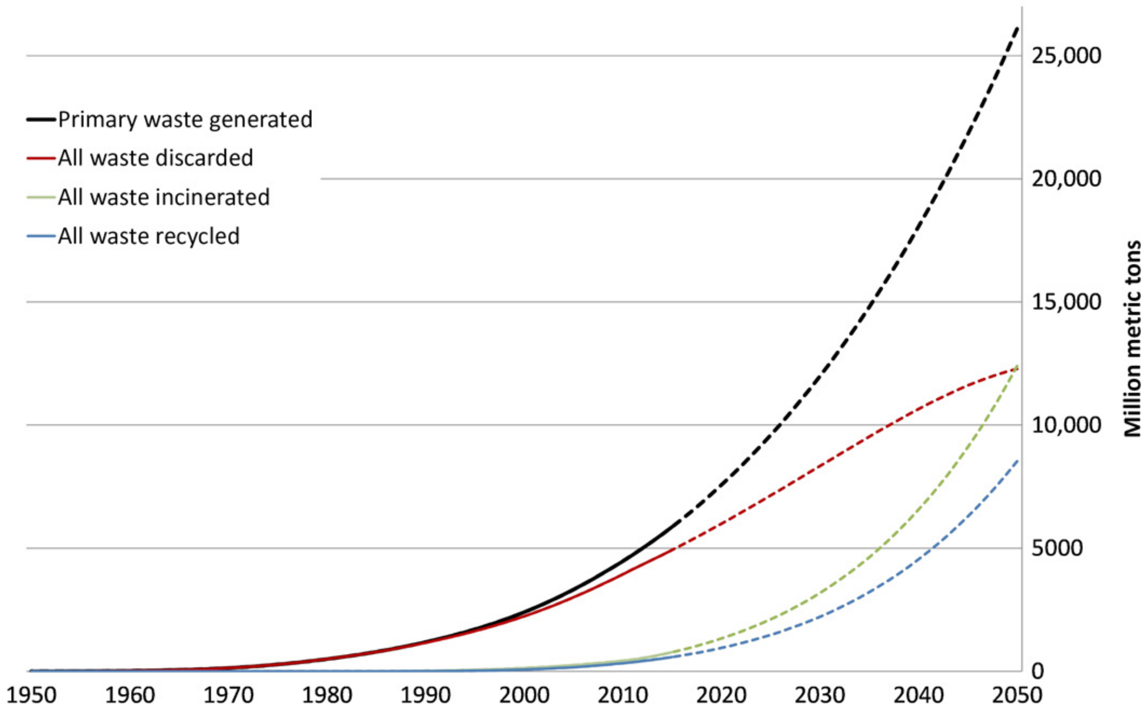

Figure 1 – Cumulative PW generation and disposal (in million metric tons) [3].

Currently, only 9% of global PW finds its way to effective recycling, 12% is incinerated, and 79% is accumulated in landfills or the natural environment. PW, in particular, accounts for a staggering 91% that has yet to be reclaimed [3] [4], [5]. These disheartening statistics portend a dire future, with projections indicating that by 2050, our oceans may be burdened with more plastic than fish by weight [6].

The gravity of this environmental crisis necessitates a concerted and innovative response that harnesses AI and ML's transformative potential. These technologies offer promising avenues for PW reduction and are vital to revolutionising how we approach PW management, recycling, and resource allocation. In this subchapter, we'll explore the complex issue of global trash and investigate ML-driven solutions to address the problem [7].

1.1. Contextualization of the Problem

The problem of global waste is closely related to the widespread use of plastics in our daily lives. Although plastics have brought unprecedented convenience, durability, and versatility to various industries and applications, they have also led to significant environmental problems.

One of the biggest challenges in Waste Management (WM) is the increasing use of non-recyclable plastics. These materials are commonly used for single-use items or packaging and are difficult to recycle using traditional methods. Their persistence in the environment worsens pollution and makes it harder to reduce waste in landfills or through incineration [8]. Figure 2 shows examples of the different types of plastics.

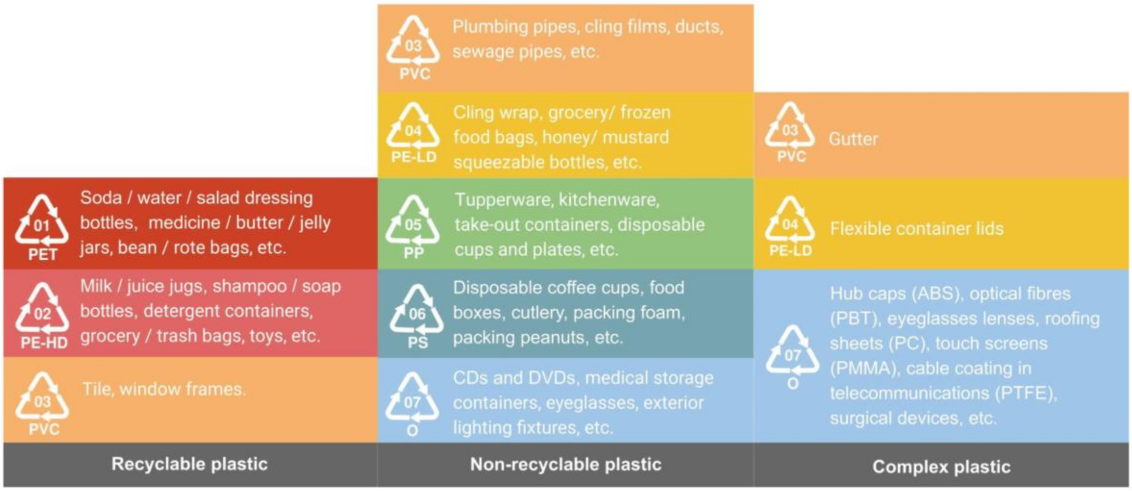

Figure 2 – Different types of recyclables, non-recyclable, and complex plastics [8]

Efficient WM depends on a strong infrastructure that covers the processes of collection, sorting, recycling, and disposal. Unfortunately, many areas worldwide lack the necessary infrastructure to manage the increasing amount of PW. This inadequacy leads to the leakage of plastics into natural ecosystems and oceans, causing long-term environmental damage [9]. As presented in Figure 3, the PW management market is currently focused on landfills, while the recycling market is smaller.

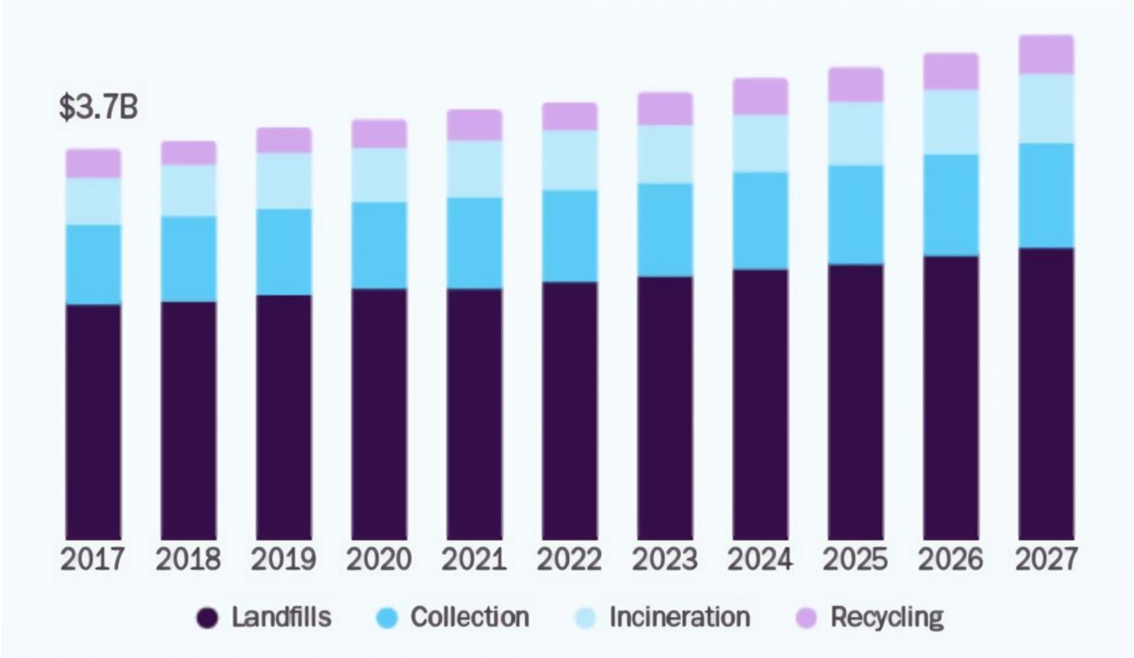

Figure 3 – Plastic WM market size by service, 2017 – 2027 (USD Billion) [9].

Plastics are classified into seven primary categories based on their formulation. Each category has a unique Resin Identification Code (RIC) and specific properties affecting recyclability and disposal methods. For instance, PETE (Polyethylene Terephthalate) is often used in beverage bottles and food containers and is easy to recycle. On the other hand, HDPE (High-Density Polyethylene) is known for its strength and is used in containers and piping. PVC (Polyvinyl Chloride) is commonly used in construction materials, LDPE (Low-Density Polyethylene) is found in plastic bags, PP (Polypropylene) is used in automotive parts and textiles, and PS (Polystyrene) is used in insulation and packaging. Finally, the "Other" category includes various plastics such as polycarbonate and bioplastics. Each category, as depicted in Figure 4, presents distinct challenges in recycling and disposal, which require nuanced understanding and approaches to manage and mitigate their environmental impact. This diversity emphasises the complexity of waste management efforts and highlights the importance of tailored strategies to address each type of plastic's specific needs and challenges [8].

Figure 4 – Potentially recyclable, non-recyclable, and complex plastics based on global annual production data between 2011 and 2018 [8].

The problem of how to recycle these was addressed in multiple initiatives worldwide. Specifically, Operation Green Fences, initiated by Chinese authorities, highlighted the need for stricter quality controls in the recycling industry. The operation exposed the consequences of lax standards in the global trade of recyclables, illustrating the importance of responsible recycling practices [10] [11]. As expected, solving the PW problem requires innovative technology. AI has emerged with promising tools for reducing waste and increasing recycling. These technologies can potentially revolutionise PW sorting, classification, and resource allocation processes, leading to a cleaner and more sustainable planet.

1.2. Objectives

The main objective of this work is to explore the abilities of advanced ML models in developing efficient strategies for managing PW, which is a growing environmental concern. The thesis is based on the idea that cutting-edge ML models can transform the processes of identifying, sorting, and recycling PW. To examine this proposal, two Research Questions (RQ) were formulated:

- RQ 1: Can ML models achieve PW detection and classification accuracy suitable for real-world applications?
- RQ 2: Which ML approach is more suitable for PW detection

Guided by this central aim, the thesis is structured around the following concise goals:

- Goal 1: To identify and examine the leading ML models through a systematic review, highlighting their capabilities in image-based PW detection and classification.
- Goal 2: To gather and analyse existing data to examine the previously identified ML models in PW tasks, establishing a performance benchmark.

By pursuing these goals, this work seeks to provide a detailed and nuanced understanding of the role of ML in environmental sustainability, addressing the proposed RQs. The objective is to create innovative applications of ML that contribute to the global effort to reduce the impact of PW on our planet.

1.3. Structure

The thesis is structured as follows:

- Chapter 2 of this study outlines the search strategy used to identify the initial articles for evaluation. It also covers the eligibility criteria during the screening stage and concludes with the analysis method and the articles included.
- Chapter 3 describes the search results and thoroughly analyses the included articles. It begins by providing a context for the ML models used in this study and then proceeds to discuss the articles that did not utilise ML models and those that did.
- Chapter 4 examined the ML models identified as most suitable by the review analysis. The concept is to benchmark these models on the same data, allowing us to conclude which would be more appropriate for real-world applications in PW.
- Chapter 5 concludes the article by describing the major findings and pointing out future research directions.

2. Materials and Methods

This section offers a detailed understanding of the methods used for retrieving and analysing articles. We have followed the 2020 Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure the reproducibility of our research. Therefore, we have explained the criteria for determining which articles were included or excluded in this review. Moreover, we have clearly outlined the methods employed for data sources, search strategies, data collection, and selection criteria [12].

2.1. Search Strategy

The present study comprehensively searched articles across two databases: Web of Science Core Collection (WSCC) and Institute of Electrical and Electronics Engineers Xplore (IEEEX). WSCC provides a comprehensive and multidisciplinary database that provides access to many indexed journals across various fields of study. The IEEE Xplore Digital Library is a specialised database focusing on electrical engineering, computer science, and electronics. Cumulatively, these databases ensured a rigorous and thorough search due to their extensive coverage of multiple fields and publishers, allowing for a vast and comprehensive examination of the topic under analysis.

The search for articles in these databases was carried out on December 17, 2023, and was filtered to scan only the article's title, abstract, and author-defined keywords published in the 2000–2023 timeframe. The search string "*artificial intelligence AND machine learning AND recycling*" was utilised to filter and narrow down the search results according to the topic of interest.

The keywords were selected to maximise the retrieval of pertinent information while minimising the loss caused by adjectival usage. Specifically, the keyword "recycling" was used to ensure that all search results were related to recycling. In addition, and to ensure the inclusion of standard ML models, the keywords "machine learning" and "artificial intelligence" were used together with the "AND" operator."

2.2. Eligibility Criteria

The systematic article selection process is depicted in the PRISMA diagram shown in Figure 5. A total of 188 articles were found by searching two different databases, and the specifics are presented in Figure 5. The WSCC had the highest number of publications, with 120 articles, while 68 articles were found in IEEEX.

A duplicate records elimination process was conducted before passing the articles to the initial screening phase, where three independent scorers evaluated the relevance of each article. The inclusion criteria were "articles that included ML and AI applied to WM". The exclusion criteria were "articles not focused on WM that did not have either ML or AI mentioned and "articles not written in English".

During this procedure, a voting system was employed. Each scorer evaluated the title and abstract of each article and voted for inclusion, exclusion, or further discussion. Articles receiving two votes for inclusion were automatically included, while those receiving two votes for exclusion were automatically excluded.

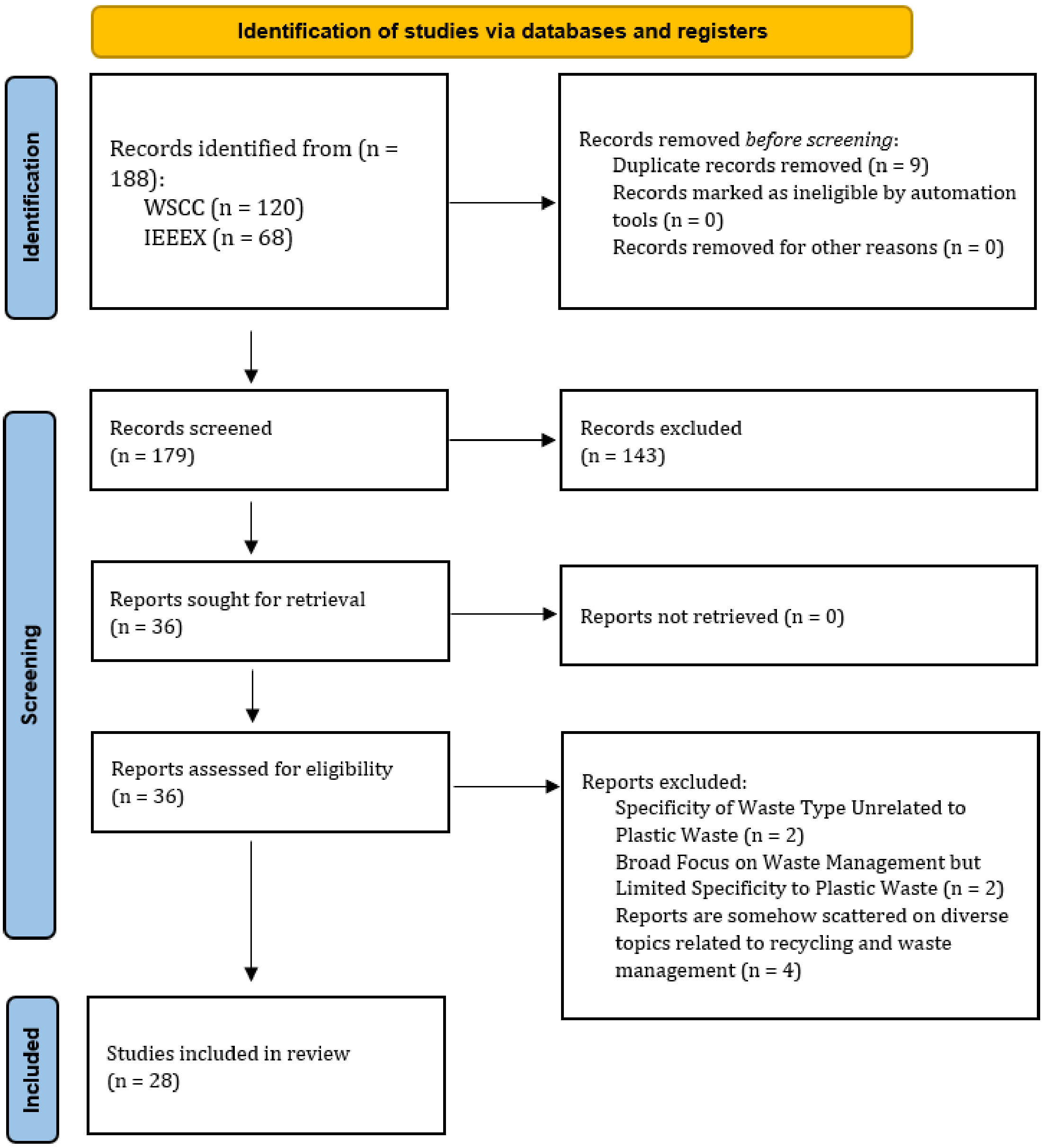

Figure 5 – PRISMA flow diagram of the conducted systematic review

Two articles were excluded during the second screening analysis, which involved the complete article screening process, due to their lack of specificity of waste type unrelated to PW [13] [14]. Another two were excluded because despite having a broad Focus on WM, they had a limited specificity to plastic WM [15] [16]. Finally, four were excluded because the reports were scattered on diverse topics related to recycling and WM [17] [18] [19] [20]. The selection process resulted in a total of twenty-eight articles that were included in the systematic review.

2.3. Method of Analysis

The resulting 28 articles included in this study, as presented in Figure 5, all utilised AI methods to address plastic WM, addressing its reduction and recycling. However, there is a considerable difference among the articles regarding their use of ML models in analysis. Some articles focused on practical and objective analysis, while others adopted a more holistic approach to evaluate the current state of the art. To simplify the analysis and categorise the articles, we decided to group them based on the ML models they used and their accuracy in detecting and classifying waste.

3. Results and Discussion

Based on an analysis of the publication year of the 28 included articles, it was observed that research activity on the studied subject began five years ago. This is shown in Figure 6, which displays the distribution of published articles by year. Article publication started in 2019 (3.57%), and the gradual increase in the number of publications after that year indicates a growing interest in the topic. Five articles (17.86%) were published in 2020, five articles (17.86%) were published in 2021, ten articles (37.71%) were published in 2022, and seven articles (25.00%) were published in 2023. The peak in 2022 suggests that the subject has recently attracted significant attention. At the time of drafting this thesis in January 2024, three articles had already been published, indicating a continuation of the exponential increase in publications. The prevalence of this trend emphasises the contemporary significance of the examined subject matter, stressing the need for this review to consolidate knowledge and point out new directions for future research.

Based on an analysis of the publication year of the 28 included articles, it was observed that research activity on the studied subject began five years ago. This is shown in Figure 6, which displays the distribution of published articles by year. The systematically reviewed articles started in 2019 (3.57%), and the gradual increase in the number of publications after that year indicates a growing interest in the topic. Five articles (17.86%) were published in 2020, five articles (17.86%) were published in 2021, ten articles (37.71%) were published in 2022, and seven articles (25.00%) were published in 2023. The peak in 2022 suggests that the subject has recently attracted significant attention. The prevalence of this trend emphasises the contemporary significance of the examined subject matter, stressing the need for this review to consolidate knowledge and point out new directions for future research.

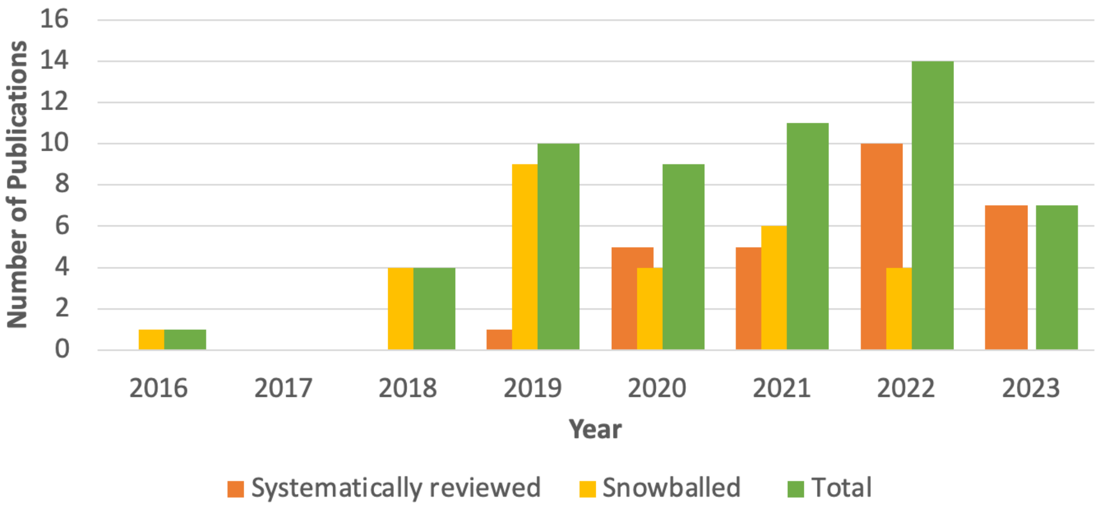

Figure 6 – Published articles by year, indicating the number of systematically reviewed articles, snowballed articles, and the total.

We then checked the cited literature in the articles, snowballing additional literature, especially from previous non-systematic reviews [5] [21]. These reviews pointed out the relevance of deep learning-based models for PW detection and classification. The additional articles were only included if they were published with peer review and if they explicitly mentioned the usage of the method for plastic recycling. This way, it was possible to include 28 additional articles [47-74]. One article was published in 2016, four in 2018, nine in 2019, four in 2020, six in 2021, and four in 2022. These results are presented in Figure 6, showing that the total number of examined articles was 56.

The following subsections analyse the results summarised in Table 1, which provides an overview of these articles, including how many classes/categories were considered. The accuracy is presented more broadly as an initial examination combining different methodologies used in different articles. It was observed that most works use a standard Convolutional Neural Network (CNN) architecture or a model that is based on it, such as Single Shot MultiBox Detector (SSD) and You Only Look Once (YOLO). Therefore, two groups were formed, specifically, the articles that used these ML models and those that used other approaches. When the used architecture was named, it was opted to specify it; otherwise, it is just called CNN.

It is important to note that the additional literature included by snowballing was used only to clarify the performance of the considered models. It is not intended to be included in the in-depth subsequent analysis since the articles were not identified systematically. Additionally, the articles identified by snowballing (marked with $ and the reference in front) are included in the same row of the article that was identified by the systematic search to facilitate the replicability of the search. No duplicated snowball-ing-identified articles were included, and the number of classes/categories and year of publication indicated in the row are unrelated to these articles.

Furthermore, three review articles were included but did not specifically examine the considered models. Specifically, [22] studied AI-based systems concerning marine plastics and the circular economy. [23] also reviewed circular economy and WM systems using AI and [24] reviewed enzyme-embedded biodegradable agricultural plastics. Several parameters were extracted from the various articles, and the data from the different articles are presented in Table 1.

A bibliometric analysis was also performed. Of the reviewed 56 articles, 27 were published in international conferences (13 in the systematically reviewed articles) and 29 in journals (15 in the systematically reviewed articles). However, conference articles that were published in a journal paper (for example, the Journal of Physics: Conference Series) were counted as journal articles. The analysis became a balanced mix between international conferences and journal publications. Regarding the number of citations indicated in Google Scholar, for the systematically reviewed articles (on 16 June 2024), it was 1183 for the systematically reviewed articles and 1693 for the snowballed articles, leading to a total of 2876 citations, highlighting the relevance of the reviewed topic. Furthermore, for the systematically reviewed articles, the average number of citations was 36.32 (ranging from 0 to 206), with [25] work having the highest number of citations (published in 2020), while for the snowballed articles, the average number of citations was 68.93 (ranging from 5 to 315), with [26] article reaching the highest number of citations (published in 2019). The average number of citations was 52.63 when considering both systematically reviewed and snowballed articles. The most commonly referenced journal was IEEE Access. However, identifying a predominant author was impossible, indicating that this field may not have dedicated research lines. Instead, the publications appear to be more sporadic.

The five most common general keywords in the examined articles (from most to least common), produced using the pyBibX library (algorithmically generated keywords) on title and abstract, were deep learning, waste management, machine learning, recycling, and artificial intelligence. The frequency of these most common keywords is presented in Figure 7. We can see the top ten general keywords per year of publication in Figure 8, where it is notorious the prevalence of “deep learning” after 2019, and the emergence of keywords “Computers” in 2016, “sociology” in 2020 and “policy-making” in 2023, reflecting the evolving focus and interdisciplinary nature of research over the years. The graph presented in Figure 9 was produced by adjacency analysis of the general keywords. It is highly relevant to note that “deep learning” and “recycling” (the two nodes with more links) are related to “plastics”. Furthermore, “machine learning” is the third node with more links and is associated with “recycling” directly or through “neural networks”, while the link to “deep learning” by “image classification” and “convolutional neural networks”. The ten most prevalent words in the abstract of the examined articles, presented in Figure 10, were (from most to least common) “waste”, “classification”, “image”, “model”, “garbage”, “learning”, “plastic”, “management”, “trash”, and “accuracy”. The most common N-grams with two words were (from most to least common) “deep learning”, “waste management”, “machine learning”, and “artificial intelligence”. From these results, it is possible to conclude that the selected articles align with the review's scope.

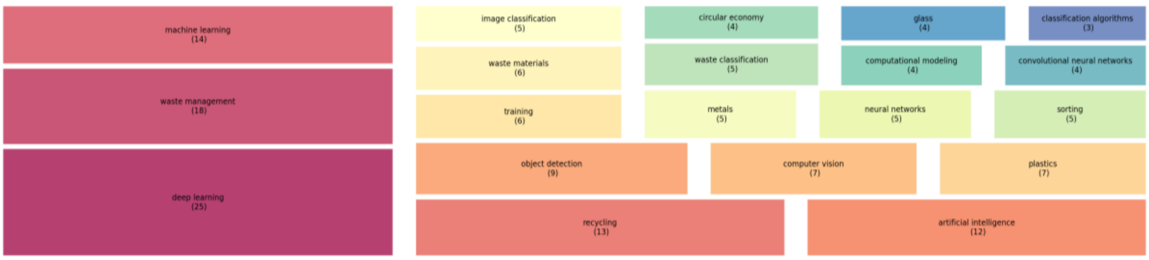

Figure 7 – Frequency of the most common general keywords in the examined articles.

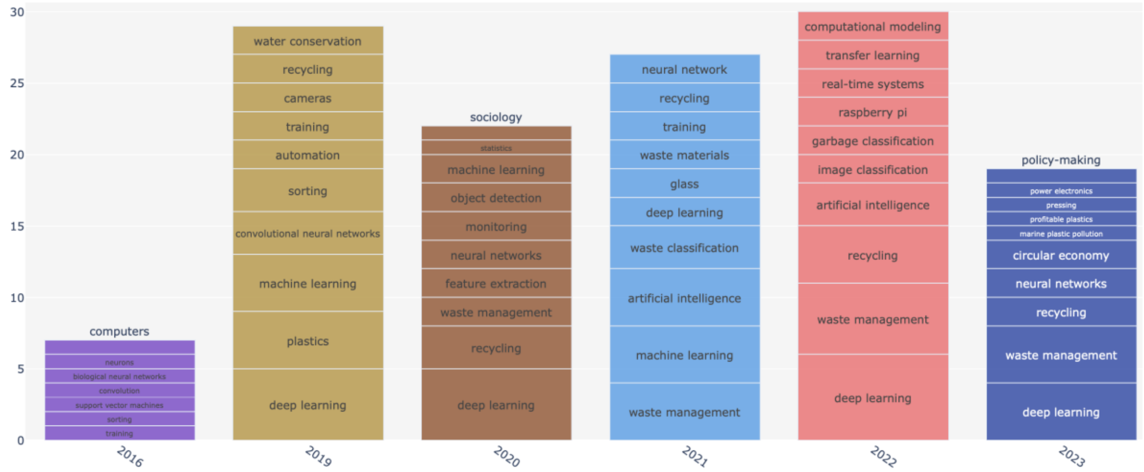

Figure 8 – Frequency of the top ten most common general keywords in the examined articles per publication year (the three keywords on top of the box in 2016, 2020, and 2023 are used to stress them, but they refer to the empty box below). The size of the box indicates the frequency of the keyword.

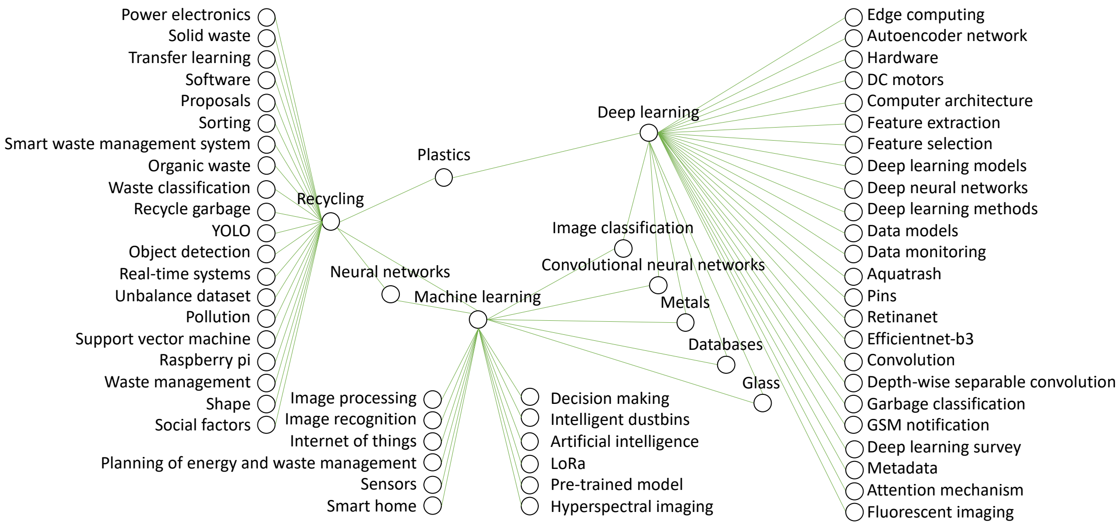

Figure 9 – Graph produced by adjacency analysis of the general keywords in the examined articles.

Figure 10 – Word cloud produced from the reviewed articles abstracts with the most common words.

Figure 11 presents a document projection based on the abstract words. The numbers are the reference of the articles. The projections were performed using the truncated singular value decomposition method. Embeddings were produced using sentence transformers (all-MiniLM-L6-v2). From Figure 7 results, it is noticeable that [69] is the most dissimilar, which is expected since it focuses on circular supply chain hierarchical structures, which is a topic more unrelated to the remaining examined articles. Likewise, we can see the number [24], which examines enzyme-embedded and microbial degradation methods. [22] is about marine plastic, and number [23] also examines the circular economy concept. [35] is also separated as it discusses feature fusion concepts which are still related to the main research line of other articles but is not prevalent. The big cluster of numbers on the right is associated with the works that are more similar and are aligned with the scope of this review.

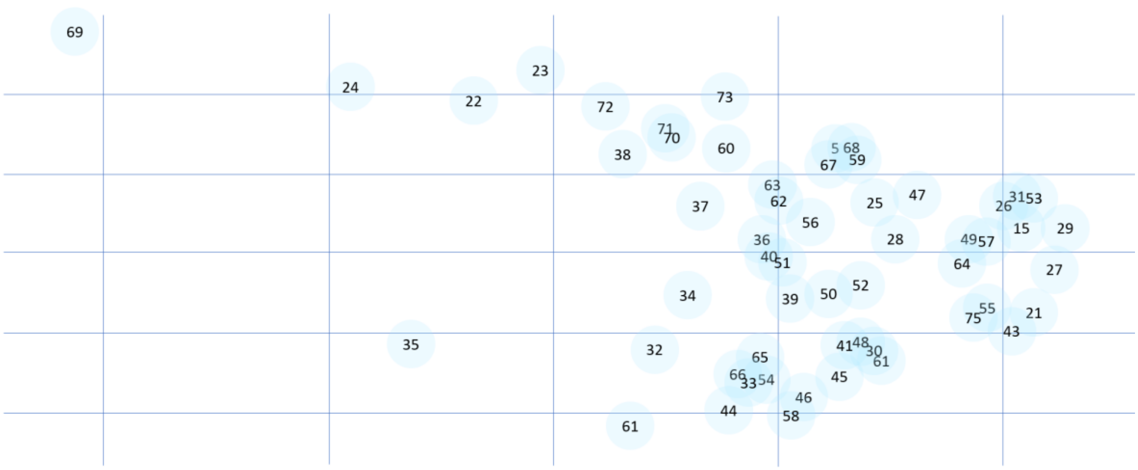

Figure 11 – Document projection of the reviewed articles based on the abstract words. The numbers are the reference of the articles.

Table 1 – Study Analysis

Study	Year of Publication	Study Domain	Purpose	Number of categories/classes	Detection Accuracy (specific method – accuracy in %)	Classification Accuracy (specific method – accuracy in %)
[27]	2022	AI and ML Techniques - Advanced Applications in Deep Learning	Hybrid CNN framework for waste classification with 97% accuracy.	4	-	*CNN – 80.88% [28] $* *VGG16 – 88.42% [29] $* *MLB-DCNN – 92.60% [30] $* *FNN-TH – 97.02%*
[31]	2021	Innovative Approaches - Novel and Innovative Recycling Approaches	CNN (AlexNet, GoogleNet) enhances trash classification accuracy.	6	-	*AlexNet – 75.00%* *InceptionV1 – 82.00%*
[21] †	2022	Reviews and Surveys - Extensive Reviews and Survey Studies	CNN, YOLO, and SSD improve WM efficiency.	-	*Tiny-YOLO – 31.60%* [32] *$* *YOLOv2 – 47.90%* [32] *$* *SSD – 67.40%* [32] *$* *YOLO-Green – 78.04%* [33] *$* *Faster RCNN – 81.00%* [32] *$* *ResNet-50 – 81.48%* [34] *$* *L-SSD – 83.48%* [35] *$* ** Not included in the results: YOLO-Green is not a standard or widely recognised variant within the YOLO family.*	*YOLOv5 – 73.20% [36] $* *CNN – 92.20% [37] $* *EfficientDet – 92.87% [38] $* *InceptionV3 – 93.13% [39] $* *AlphaTrash – 94.00% [40] $* *ThanosNet – 94.70% [41] $* *GCNet – 97.54% [42] $* *DNN-TC – 98.00% [43] $* *DSCAM – 98.90% [44] $*
[45]	2020	AI and ML Techniques - Advanced Applications in Deep Learning	Enhanced ResNet-34 for effective garbage classification.	-	-	*ResNet-34 – 89.96%*
[46]	2020	Innovative Approaches - Novel and Innovative Recycling Approaches	YOLOv3's end-to-end detection boosts recyclable waste sorting.	4	*YOLOv3 – 85.00% +*	-

[25]	2020	Innovative Approaches - Novel and Innovative Recycling Approaches	SSD MobileNetV2 enables efficient waste detection on low-power devices.	3	*MobileNetV2 – 86.23% #*	-
[5] †	2021	Applications in Recycling - Techniques and Processes in Recycling	Review of CNN's role in boosting recycling through advanced waste identification.	-	*CNN – 64.00%* [47] *$* *R-CNN – 74.10%* [48] *$*	*AlexNet – 83.00% [49] $* *VGG16 – 93.00% [50] $* *CNN – 93.50% [51] $* *Capsule-Net – 93.60% [52] $* *Capsule-Net – 95.80% [52] $*
[53]	2023	Innovative Approaches - Novel and Innovative Recycling Approaches	"ConvoWaste" model employs CNN for automated waste segregation.	6	*Resnet50 – 87.00%* [26] *$* *Resnet50 – 88.00%* [54] *$* *VGG19 – 88.00%* [55] *$* *ConvoWaste – 98.30%*	-
[56]	2022	Innovative Approaches - Intelligent Technologies in WM	CNN application in intelligent dustbins for garbage classification.	4	-	*CNN – 95.63%*
[15]	2022	Innovative Approaches - Intelligent Technologies in WM	DCNN models tackle waste segregation challenges.	4	-	*DCNN4 – 37.00%* *DCNN5 – 56.70%*
[57]	2023	AI and ML Techniques - General Methodologies in AI and ML	YOLOv5 and EfficientNet-B3 synergy in waste classification.	8	-	*EfficientNet-B3 – 97.32%* *CNN – 98.50% [58] $*
[59]	2022	Innovative Approaches - Novel and Innovative Recycling Approaches	RVM employs MobileNet to sort PW efficiently.	3	-	*Resnet-50 – 96.50%* *InceptionV3 – 98.60%* *MobileNetV2 – 99.60%*

[60]	2022	Innovative Approaches - Novel and Innovative Recycling Approaches	PLEESE system uses SSD-MobileNet-V1 for plastic reuse.	2	*SSD-MobileNet-V1 – 63.64% #*	-
[61]	2023	Innovative Approaches - Novel and Innovative Recycling Approaches	ResNet addresses class imbalances in domestic garbage classification.	4	-	*InceptionV3 – 36.00%* *ResNeX50 – 45.20%* *VGG-16 – 46.50%* *ResNet50 – 47.85%* *ResNet – 52.44%*
*[62] **	2022	Applications in Recycling - Innovative Systems for Recycling Efficiency	Comparative analysis of deep learning models for waste classification.	4	-	*SqueezeNet – 66.84%* *AlexNet – 68.13%* *InceptionNet – 74.41%* *ResNet – 76.59%* *MobileNet_V2 – 76.77%* *GoogleNet – 76.89%* *VggNet – 77.78%* *EfficientNet – 79.49%* *DenseNet – 80.63%* *CNN – 95.63%*
[63]	2022	Innovative Approaches - Novel and Innovative Recycling Approaches	CNN-based system on Raspberry Pi for waste sorting.	5	*EfficientDet – 67.40%*	-
[64]	2020	Innovative Approaches - Cutting-edge Concepts in Recycling Innovation	CNN and AutoEncoders achieve 99.94% accuracy in waste classification.	2	-	*CNN – 89.00 [65] $* *CNN – 98.20 [66] $* *AlexNet & GoogleNet & ResNet-50 – 99.95*
[67] ~	2022	Applications in Recycling - Recycling Processes and Technique Innovations	YOLOv5's resource-efficient waste classification in IoT.	5	-	*CNN – 95.60%* *YOLOv5 – 98.30%*

* Only the results of the models with pre-training are presented

~ Only the results of the model with the 80%–20% approach are presented, and we are only reporting the CNN-based models

Reporter as Mean Average Precision (mAP)

+ Reported as recognition rate

$ Results of an article identified by snowballing

† Review article

3.1. Articles developed without the use of ML Models

In a research article published [68], an integrated approach that uses AI and ML to plan and manage energy and waste, including recycling processes, has been presented. This aligns with the thesis's aim to develop intelligent solutions for a cleaner planet and specifically addresses the use of AI and ML to reduce PW. The study involves the application of neural networks and ML algorithms to predict waste amounts and improve waste collection efficiency. The proposed framework can significantly reduce waste quantities, landfill use, and transportation needs by applying intelligent WM strategies, demonstrating a significant potential impact on improving recycling efficiency and WM. Integrating neural networks for waste prediction and ML algorithms for optimisation in an energy and WM context represents an innovative and practical approach.

In [69], the article explores the development of a data-driven CSC structure. Such a structure is crucial for effective resource management and promoting recycling, both of which are crucial for a cleaner planet. This study highlights the significance of AI and ML in analysing big data to facilitate better decision-making in CSC. The use of data-driven tools such as the fuzzy Delphi method, fuzzy DEMATEL, and entropy weight method demonstrate the application of AI in enhancing recycling and WM practices. This article provides a comprehensive analysis using advanced methodologies to understand and optimise the circular supply chain. The detailed examination and focus on improving recycling and resource efficiency through intelligent data analysis align with the thesis's objectives of promoting cleaner and smarter WM solutions.

The article in [23] thoroughly examines data-driven technologies and AI applications used in the circular economy and WM systems. The focus is on using intelligent solutions for efficient WM and recycling, which is crucial for reducing PW and promoting a cleaner planet. The study investigates different applications of AI in WM, such as product lifecycle management, waste generation modelling, community engagement, and waste sorting. These areas play an essential role in advancing recycling technologies and strategies, directly addressing the subject of our research. The article analyses the current state of data-driven technologies and AI in WM, identifying gaps and proposing new areas for research and development. The comprehensive analysis and forward-looking proposals provide valuable insights into the latest trends, challenges, and potential solutions in AI-driven WM and recycling, contributing to this research.

The authors of [70] focus on environmental planning with a focus on the principles of Reduce, Reuse, Recycle, and Recover (4R) supported by an AI-based Hybridized Intelligent Framework (AIHIF). The goal is to promote smarter solutions for a cleaner planet by applying AI and ML in WM and reducing PW. The article proposes a novel AIHIF for WM within the 4R concept, aiming to optimise waste collection, promote recycling, and ensure efficient resource recovery. This approach could significantly enhance recycling rates and overall, WM efficiency, contributing to environmental sustainability and cleaner urban management.

[71] presents an economic framework for quality sorting control in plastic recycling classification using ML and spectroscopy technologies. The article incorporates ML algorithms for classifying plastics based on their infrared spectrum, directly addressing the AI and ML aspects. The proposed framework utilises Fourier-transform infrared and near-infrared spectroscopies combined with ML algorithms to classify different types of plastics. The economic analysis of recycling revenue for various polymers and the selection of the most economically advantageous algorithms provide an innovative approach to enhancing the efficiency and profitability of the recycling industry. This could significantly contribute to developing cost-effective recycling strategies crucial for reducing PW and promoting environmental sustainability.

The article [24] comprehensively reviews enzyme-embedded and microbial plastics in agricultural use, focusing on environmentally sustainable solutions. The focus on enzyme-embedded technologies and microbial degradation offers a novel perspective on WM strategies, which could reduce plastic pollution and promote a more sustainable agricultural practice.

In [22], the authors provide a detailed overview of the challenges and solutions related to marine plastics in the context of a circular economy, highlighting the crucial role AI plays in achieving a cleaner planet. The report explores the use of AI-based systems for managing ocean PW, explores AI models for predicting the accumulation of ocean PW, and offers insights into policy-making for effective plastic recycling, all essential for understanding and improving the recycling process. The article covers a wide range of topics, including the effects of PW on marine ecology, computational methodologies utilising AI, and various approaches to manage and reduce marine plastic pollution.

[72] examines the application of AI to manage resources and reduce smart home waste. While it may not specifically mention PW, the broader context of waste reduction aligns well with the thesis theme of cleaner solutions for the planet. The proposal of a smart home resource management system for sustainability is innovative as it integrates AI and ML for practical, real-world application in waste reduction. At the same time, the potential impact is significant in contributing to a cleaner planet by reducing the carbon footprint and managing waste more efficiently.

Finally, the article [73] presents a comprehensive approach to WM using QGIS for descriptive and predictive data analysis. The article details predictive analytics, a subset of ML, to forecast waste amounts and optimise WM operations. It does not explicitly mention AI or recycling, but the principles and methodologies discussed can be applied to these areas, making it tangentially relevant to the search. The use of QGIS for WM is innovative. It reflects a growing trend of incorporating geospatial technologies with ML for environmental solutions, providing a real-world application of predictive analytics in WM and offering insights into how similar methodologies could be applied specifically for PW reduction.

3.2. ML Models Accuracy Analysis

ML is constantly advancing, and the success of models depends on their accuracy and efficiency. This subchapter provides a detailed analysis of various ML methods, including their detection accuracy, classification accuracy, and combined precision. These methods help to improve areas such as object recognition, detection, semantic segmentation, and instance segmentation.

In waste management, the accuracy of ML methods is crucial for waste detection and classification. Waste detection involves identifying waste within a given environment with high precision without false positives. ML models like CNNs and YOLOs are trained to recognise waste objects in complex backgrounds and varying conditions. On the other hand, waste classification categorises identified waste into specific types or materials like plastics, organics, or metals. This task requires a deeper analysis of the detected items, where models like CNNs are further refined to classify the nuanced characteristics of each waste type. The classification accuracy is crucial for effective sorting and recycling processes. Detection accuracy focuses on correctly identifying waste items, whereas classification accuracy measures the precision in assigning the correct category to each detected item. Both accuracies address different challenges in the waste management pipeline, with detection serving as the foundational step and classification as the subsequent detailed analysis required for effective sorting and recycling.

Figure 12 illustrates the function and associated models to clarify the context.

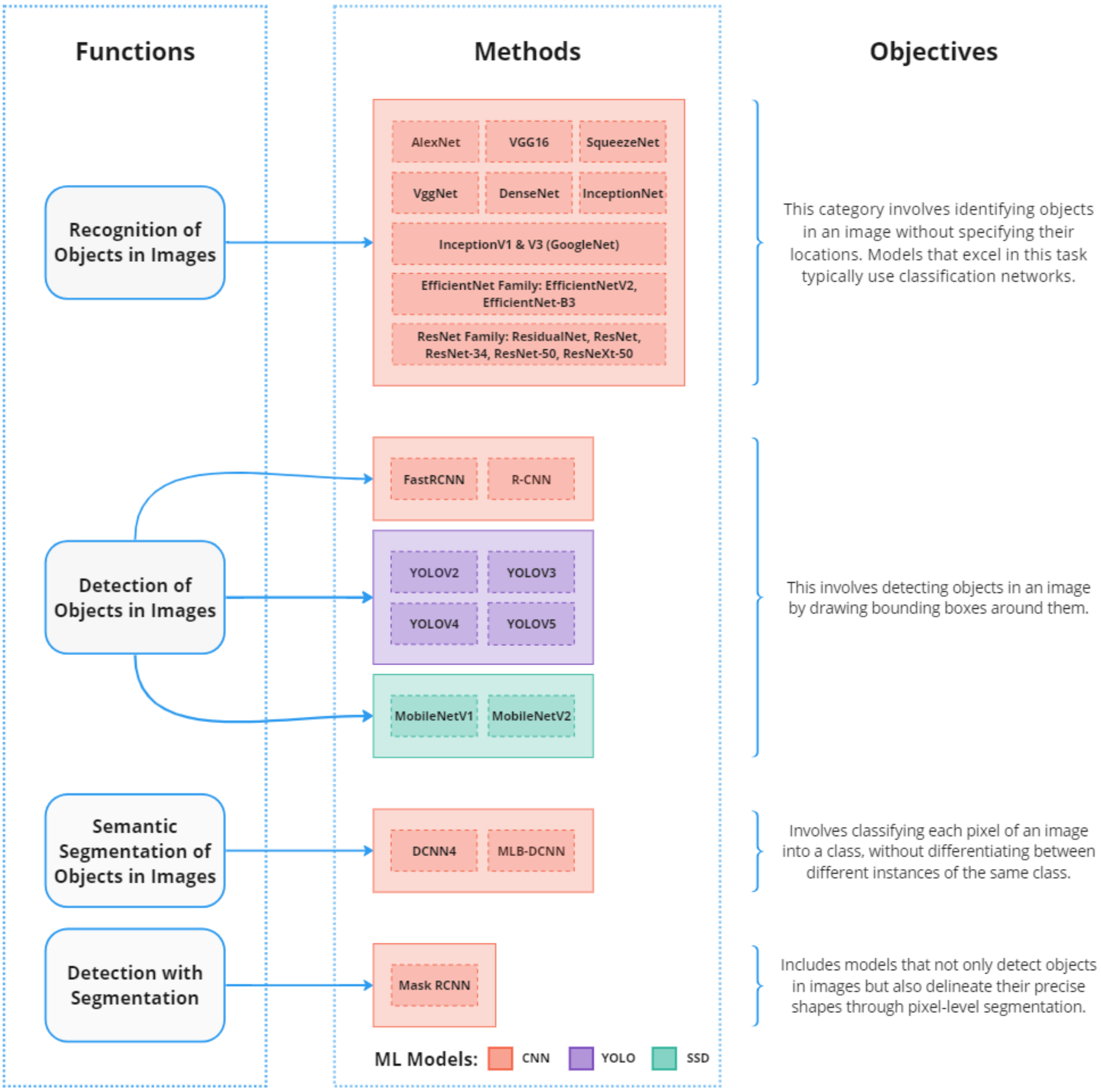

Figure 12 – ML main function, methods, and high-level objectives [74]

[45] highlights the significance of an automatic garbage classification system that employs deep learning techniques. Such systems are vital for effective WM and reduction, which in turn contributes to developing smarter solutions for a cleaner planet, especially for PW recycling. The article explains how deep learning, a complex area of ML, can automatically classify garbage. It emphasises the importance of an automatic garbage classification system with deep learning techniques. Such systems are crucial for effective WM and reduction, contributing to the development of smarter solutions for a cleaner planet, particularly for PW recycling. The article recommends structural and functional improvements in a deep learning model to enhance garbage classification. These improvements include multi-feature fusion, feature reuse, and optimised activation functions. The article reports high classification accuracy and a quick classification cycle, indicating that this system has the potential to improve recycling efficiency and WM significantly.

In [27], the research introduces a novel hybrid deep-learning framework designed to enhance waste classification, an integral component of effective waste management and recycling processes. By integrating custom-tailored deep learning architectures, including CNNs and EfficientNet models, the study significantly contributes to PW Reduction. It leverages advanced AI techniques to accurately categorise various waste types, particularly plastics, underscoring AI and ML's pivotal role in driving cleaner, more intelligent solutions for environmental sustainability. The proposed methodology aligns with the thesis's thematic core and promises substantial accuracy enhancements over existing classification methods. Such innovations hold the potential to markedly improve recycling efficiency and waste management practices, aligning with the broader thesis objective of fostering a cleaner planet through smarter technological applications.

[31] the study explores a semi-smart adaptive approach to trash classification, blending physical sorting mechanisms with advanced AI techniques, notably CNNs, to enhance waste management and recycling efficacy. The report presents a comprehensive strategy that resonates with the pursuit of intelligent waste management solutions by incorporating methods such as barcode separation, magnetic separators, and hardness tests alongside CNNs for image classification. The innovative integration of physical and digital sorting technologies exemplifies the practical application of AI and ML in addressing environmental challenges and directly contributes to the goal of PW reduction. This adaptive approach, straddling the line between manual sorting methods and cutting-edge AI, heralds a significant leap forward in optimising recycling processes, potentially revolutionising waste management practices to foster a more sustainable and cleaner planet.

[21] survey paper meticulously examines the application of deep learning technologies in waste detection and classification, offering a broad perspective on the role of AI and ML in enhancing waste management systems. By delving into various deep learning methods and their efficacy in identifying and categorising waste materials, the paper aligns closely with the thesis's focus on leveraging intelligent solutions for PW reduction. It reviews critical aspects such as image classification and object detection models, showcasing their relevance to recycling efforts and efficient waste management. Furthermore, the survey's organised exploration of existing methodologies, datasets, and prevailing challenges in the domain provides a rich foundation for understanding the current landscape and identifying avenues for innovation. This comprehensive analysis bolsters the thesis's theoretical framework and underscores the potential impact of advanced AI and ML applications in driving sustainable practices and contributing to environmental conservation efforts.

[46] the study introduces an innovative edge-cloud framework that leverages a deep learning model to enhance the detection of recyclable garbage, a critical component in advancing waste management systems towards sustainability. The framework employs deep CNNs and YOLOv3 to integrate edge computing with cloud-based services for precise image classification and object detection. This approach exemplifies AI and ML's application in identifying recyclable materials, particularly plastics, and aligns with the imperative of refining recycling processes. The proposed

system's capacity to deliver accurate and rapid detection of recyclable waste while addressing computational and latency challenges inherent in deep learning applications presents a scalable solution with significant potential to revolutionise waste management practices. This edge-cloud model underscores a strategic melding of technology and environmental stewardship, promising substantial strides towards achieving a cleaner, more sustainable planet.

[25] study explores a cutting-edge waste management system that synergises IoT technology, LoRa communication, and a TensorFlow-based deep learning model to detect and classify waste items, including plastics. This integration embodies the core objective of employing smart, AI-driven approaches to enhance waste segregation and recycling, aligning seamlessly with the thesis's focus on PW reduction and fostering a cleaner environment. By leveraging TensorFlow for its robust deep learning capabilities in object identification and LoRa for efficient long-range communication, the system presents a comprehensive solution to waste management challenges. This innovative combination ensures precise waste classification and optimises the operational aspects of waste collection and recycling, highlighting a significant potential to revolutionise waste management practices through improved accuracy and efficiency.

[5] the paper explores applying ML techniques to recycling, presenting a direct avenue to enhance waste management practices, particularly for plastics. It aligns with the overarching aim of the thesis to harness AI and ML in crafting more efficient, cleaner waste management solutions by examining a wide array of ML algorithms—including CNNs, support vector machines, decision trees, k-nearest neighbours, and artificial neural networks—the study offers a panoramic view of AI and ML's potential to revolutionise recycling processes. This exploration not only underscores the relevance of these technologies to the thesis's key themes but also highlights the innovative and impactful potential of ML in recycling. The paper's comprehensive review of recent advancements provides valuable insights into various ML applications in recycling, demonstrating how these technologies can significantly improve waste management outcomes.

[75] The study explores deep learning, particularly CNNs, for automated garbage classification, aligning closely with the thesis's objective of utilising AI and ML to advance waste management solutions. By targeting the intelligent segregation of waste materials, including plastics, metals, and paper, the research embodies the thesis's focus on enhancing recycling processes through technological innovation. The employment of CNNs, a cornerstone of AI and ML, showcases a direct application of these disciplines in refining garbage classification systems, thereby contributing to more efficient recycling and waste reduction strategies. The introduction of advanced deep learning techniques to improve sorting accuracy represents a significant leap forward in minimising the inefficiencies associated with manual sorting methods. This innovation holds promise for streamlining waste management operations and

augmenting the effectiveness of recycling efforts, thereby contributing to the development of smarter, cleaner, and more sustainable waste management practices.

[53] the paper introduces ConvoWaste, a novel automatic waste segregation system that harnesses CNNs within a deep learning framework to sort various waste types, including plastics. This aligns closely with the thesis's exploration of AI and ML innovations for enhancing waste management and advancing towards a cleaner environment. ConvoWaste exemplifies the practical application of deep learning in recycling, employing advanced AI to differentiate and accurately classify waste materials such as plastics, metals, glass, organic substances, medical, and e-waste into designated categories. This underscores the relevance of AI and ML in recycling and highlights the system's alignment with the thesis's emphasis on efficient recycling methodologies.

Moreover, ConvoWaste innovative use of Capsule-Net for image classification, combined with a hardware setup involving ultrasonic sensors and servo motors for the physical sorting of waste, showcases a holistic and advanced approach to waste segregation. With a reported classification accuracy of 98% and features designed to notify authorities about waste levels, ConvoWaste presents a significant leap forward in waste management technology. Its potential to streamline recycling processes, reduce manual sorting errors, and enhance overall waste management efficiency resonates with the thesis's objective of leveraging technology for sustainable environmental solutions.

[56] the paper introduces an innovative intelligent dustbin designed to leverage ML for effective garbage classification, directly addressing the challenges of recycling and PW reduction. By employing CNNs for image recognition, the system categorises waste into distinct groups such as recyclable, kitchen waste, and harmful materials, demonstrating a practical application of AI and ML in enhancing waste management processes. Integrating advanced technologies, including intelligent speech recognition, sensor applications, and a visual recognition system, into the dustbin design marks a significant step forward in waste management technology. This multifaceted approach promises to streamline the sorting process and enhance accuracy and efficiency, potentially leading to higher recycling rates and substantially reducing environmental pollution. The system's capability to upload classification data to the cloud further opens avenues for data analysis and system optimisation, underscoring the potential of this intelligent dustbin to contribute to cleaner, more sustainable waste management practices.

[15] the study delves into the application of deep CNNs (DCNNs) for the classification of solid waste, including plastics, highlighting a critical advancement in intelligent waste management systems. By exploring and optimising various DCNN architectures, the paper aligns closely with the thesis's objective to leverage AI and ML to enhance recycling efficiency and reduce PW, thereby contributing to environmental sustainability. The employment of DCNNs, a cornerstone technique in AI and ML, to

accurately identify and categorise different waste types underscores the study's relevance to the core themes of recycling and waste reduction. Despite the challenges posed by the inherent properties of PW, such as transparency and deformation, the paper's innovative approach to tweaking DCNN models to improve waste classification accuracy showcases the potential of AI-driven solutions to overcome obstacles in waste segregation. This research provides valuable insights into optimising DCNNs for waste classification. It underscores the significant impact that enhanced classification accuracy can have on the efficiency of recycling processes, marking a step forward in pursuing more effective and intelligent waste management strategies.

In [57], the paper introduces a novel application of the EfficientNet-B3 CNN, a sophisticated deep learning model, to waste material classification. By harnessing this advanced AI technology, the study makes a significant contribution to intelligent waste management, offering a promising avenue towards more efficient recycling processes and the reduction of PW. The utilisation of EfficientNet-B3, known for its efficiency and high accuracy, exemplifies the practical application of cutting-edge ML technologies in tackling environmental challenges. With an impressive accuracy rate of 97%, the system showcases the potential of deep learning algorithms to revolutionise waste segregation, enhancing the precision and speed of sorting recyclable materials from waste streams. This leap in classification accuracy holds the promise of optimising recycling operations. It paves the way for more sustainable waste management practices, reducing environmental pollution and advancing towards a cleaner planet.

[59] The study introduces an innovative reverse vending machine (RVM) tailored for efficient PW management, leveraging MobileNet, a deep learning model, to classify plastic bottles precisely. Developing a cost-effective and lightweight RVM perfectly aligns with the thesis's overarching goal of integrating smart, AI-driven technologies to foster sustainable waste management practices and mitigate plastic pollution. By focusing on incentivising recycling through an intelligent system, this research directly addresses the urgent need for solutions that promote environmental stewardship.

Employing MobileNet and transfer learning, the study exemplifies the practical implementation of AI and ML in recycling processes, reinforcing the thesis's commitment to exploring the potential of AI and ML in enhancing recycling efficiency. The RVM's design, characterised by its affordability, portability, and high classification accuracy, introduces a novel, user-friendly approach to waste management. The machine's success in a university setting, evidenced by substantial PW collection, underscores its effectiveness and scalability. This pioneering approach, combining technological innovation with user incentivisation, holds significant promise for advancing recycling initiatives and achieving a cleaner, more sustainable environment.

The PLEESE system, introduced in [60], represents a novel intersection of technology and environmental stewardship. It aims to promote the reuse of plastic items by leveraging computer vision and deep learning. This approach aligns with the thesis's objective of employing AI and ML to advance waste management practices, particularly reducing PW by encouraging the repurposing of plastic items. By identifying reusable plastic containers through sophisticated ML algorithms, PLEESE exemplifies the practical application of AI technologies in fostering sustainable behaviours.

While the system's primary focus is on the reuse aspect, it indirectly bolsters recycling efforts by minimising the volume of waste requiring processing, thus aligning with broader waste reduction goals. The innovative nature of PLEESE lies in its strategy to effect behavioural change at the point of disposal, utilising persuasive messaging based on deep learning-driven identification of reusable plastics. This proactive stance on waste management, particularly suited for high-visibility areas like urban centres, has the potential to alter individual behaviours towards plastic use and contributes significantly to the aim of mitigating plastic pollution.

[61] study examines domestic garbage classification through the lens of deep learning, presenting methodologies that, while not exclusively focused on PW, are highly pertinent to the broader objectives of enhancing waste management and recycling processes. The exploration of image classification algorithms, particularly through models like ResNet, showcases the application of advanced AI and ML techniques in identifying and categorising waste materials.

While the paper's primary discourse centres around domestic garbage, the implications for PW management are implicit and significant, suggesting that the methodologies discussed could be seamlessly adapted to target PW specifically. The innovative approach highlighted in the research, leveraging deep learning to classify waste accurately, holds considerable promise for refining recycling systems. This potential to elevate the efficiency and precision of waste sorting processes resonates with the core aim of your thesis, underscoring the viability of AI-driven solutions in fostering more sustainable environmental practices and contributing to the reduction of plastic pollution.

The [62] study introduces a smart household waste classification system that leverages AI to enhance waste sorting and management. While the primary focus is household waste, the AI methodologies employed, including CNNs and transfer learning, hold significant promise for application in PW management. This alignment with the thesis's theme of utilising AI for smarter waste management solutions underscores the relevance of the research to this work.

The application of machine vision technology and neural network algorithms for classifying waste directly addresses the thesis's emphasis on AI and ML, highlighting the potential of these technologies to revolutionise recycling processes. The innovation presented in developing this AI-driven waste classification system paves the way for substantial improvements in the accuracy and efficiency of sorting waste at the household level. Such advancements could profoundly impact recycling practices, contributing to more effective waste management strategies and moving us closer to a cleaner, more sustainable planet.

The "Trash Can!" paper in [63] presents an AI-driven system that automatically classifies waste using advanced computer vision techniques, including plastics. This research is directly pertinent to the objectives outlined in this thesis, which seeks to explore the applications of AI and ML in enhancing waste management practices, with a particular emphasis on PW reduction. The study's approach, employing AI alongside computer vision—a critical area within ML—to accurately segregate waste into recyclable and non-recyclable categories, showcases a direct engagement with the core themes of this thesis, especially the focus on recycling.

Innovatively, the system described in the paper operates on a compact and accessible platform, utilising a Raspberry Pi and a camera module, and employs the EfficientDet-Lite0 model for object detection. This novel methodology demonstrates the feasibility of integrating sophisticated AI models into everyday waste management tools. It highlights the potential for such technologies to significantly improve the precision and efficiency of waste classification locally. The implications of deploying this technology are substantial, promising to elevate the effectiveness of recycling programs and contribute meaningfully to environmental sustainability efforts, resonating with this thesis's vision of leveraging AI for a cleaner and more sustainable planet.

[64] study introduces a sophisticated approach to waste classification by integrating AutoEncoder networks with feature selection techniques in CNN models. While the research does not exclusively focus on PW, the methodologies employed are highly pertinent to the broader goals of enhancing recycling efficiency and waste management through the application of AI and ML. The utilisation of AutoEncoders and CNNs, pivotal elements in deep learning, aligns with the thesis's emphasis on leveraging advanced AI and ML techniques to address recycling challenges.

The innovative combination of AutoEncoders for feature extraction with CNNs for waste classification represents a significant leap forward in the domain, achieving an exceptional classification accuracy of 99.95%. This level of precision in distinguishing between various waste types holds immense potential for improving the sorting and recycling of materials, including plastics. The methodology's capability to refine waste classification processes could drastically enhance recycling rates, contributing to more effective waste management strategies and fostering a cleaner, more sustainable environment. This aligns seamlessly with the thesis's objective of exploring intelligent, technology-driven solutions to environmental challenges, highlighting the transformative potential of AI in advancing waste reduction and recycling initiatives.

Finally, the [67] study introduces an Intelligent Municipal Waste Management system that leverages the YOLO network alongside IoT technology, marking a significant stride towards the objectives outlined in this thesis. This system's focus on employing advanced AI techniques for categorising and efficiently managing municipal waste, including recyclables like plastics, aligns with the thesis's aim of utilising AI and ML for waste reduction and smarter recycling solutions.

The paper addresses the core keywords of AI and ML within waste management by incorporating the YOLO network, a cutting-edge deep learning framework. Although the primary focus is not solely on recycling, the system's capacity for precise waste segregation is foundational in enhancing recycling processes, making it highly relevant to the thesis's focus areas.

The innovative fusion of YOLO networks with IoT technology for real-time waste management underscores a novel approach in the domain, offering potential advancements in the efficiency and intelligence of waste handling systems. This approach's impact on improving recycling rates, minimising waste volume, and fostering cleaner urban environments directly corresponds with the thesis's goals. Such a system exemplifies the application of smart, AI-driven solutions to environmental challenges and highlights the transformative potential of integrating AI with IoT for sustainable waste management practices.

- ML Models Functions

It is worth noting that the boundaries between these functions (or categories) can be fluid, as many models are versatile and can be adapted or extended for various tasks beyond their original design. Also, the implementation details (like training datasets, optimisations, etc.) can further tailor these models to specific sub-tasks within these broad categories.

At the heart of image understanding lies the task of object recognition, a domain where CNNs have made significant strides. Some deep learning models, such as AlexNet, VGG16, and the Inception series (including InceptionV1, popularly known as GoogleNet and InceptionV3), are widely used for image classification tasks. ResNet and its variations (such as ResNet-50), have significantly transformed this field by introducing deep residual learning and addressing the vanishing gradient problem. DenseNet and the EfficientNet family, including models like EfficientNet-B3 and EfficientNetV2, have improved image classification algorithms' accuracy and computational efficiency. These advancements have made these models suitable for various applications, ranging from mobile devices to high-performance computing systems—tasks within these broad categories.

Object detection goes beyond recognising objects in an image to identify their location within the image. This is vital for applications that need spatial understanding, like surveillance and autonomous driving. SSD and its variants like MobileNetV1 and MobileNetV2 balance speed and accuracy, enabling real-time object detection on mobile devices. On the other hand, the YOLO family, comprising YOLOv2 to YOLOv5, has revolutionised object detection by proposing a single neural network to predict both class probabilities and bounding box coordinates, thereby accelerating the detection process significantly. Meanwhile, the R-CNN series, especially FastRCNN, has played a pivotal role in achieving high accuracy in object detection tasks, albeit with greater computational demands.

Semantic segmentation models classify each pixel of an image into a category, providing a pixel-wise understanding of the scene. This fine-grained analysis is critical for applications like medical imaging and urban planning. While specific models like DCNN4 and MLB-DCNN are less commonly cited, they represent the broader class of CNNs adapted for segmentation tasks, where the focus shifts from global image classification to local pixel classification.

A task that requires detecting objects and accurately outlining their boundaries is more complex. Mask R-CNN stands out in this category because it builds on the Faster R-CNN framework by adding a parallel branch for predicting segmentation masks. This enables the model to perform both detection and instance segmentation simultaneously. The dual capability of Mask R-CNN is particularly useful for applications that require detailed object contours, such as robotic surgery and high-performance precision industrial inspection.

The development of ML models has progressed towards higher sophistication, efficiency, and adaptability. Different models, including the foundational AlexNet, the EfficientNet variants, and the real-time YOLOv5, have contributed uniquely to the field. There are also adaptations for specific hardware, like implementations on Raspberry Pi, which aim to make advanced ML capabilities more accessible to users across different computational environments.

Evaluating the accuracy of ML models is not just about measuring their performance on standard datasets. It is also about considering the trade-offs between speed, accuracy, and computational requirements in the context of specific applications. This chapter aimed to clarify these complexities and provide insights into how each model's design choices influence its suitability for various tasks. By examining these models, we can gain a deeper appreciation for the creativity and innovation driving progress in ML, paving the way for future advancements that will continue transforming our interaction with technology.

3.3. Performance Analysis

In this subsection, we will analyse the accuracy of various ML models in object detection and classification. Of the systematically reviewed studies, 16 examined the considered CNN-based models, summarising their performance in Table 2. The snowballed additional literature and the combination of both (indicated as global) are also included in the table. It is important to notice that the studies used different databases, training conditions, model structures, and number of classes/categories. Thus, this analysis can only be seen as an initial approximation, highlighting the tendencies regarding accuracy in detection and classification. Therefore, it serves as a global overview of the trends. Thus, the rationale is to provide this overview rather than an in-depth examination, which would have required running all models on the same standard dataset.

Regarding the number of categories/classes used by the systematically reviewed articles, it ranged from 2 to 8, with a median of 4 (average of 4.27). More specifically, for detection problems, the number of used categories ranged from 2 to 6, with a median and average of 4. On the other hand, the classification problems ranged from 2 to 8, with a median of 4 (average of 4.40). These results suggest the trend of using four categories/classes.

Table 2 – Overview of the performance of the considered ML models.

ML Models	Detection Accuracy Data Points	Detection Accuracy Average	Classification Accuracy Data Points	Classification Accuracy Average
Total and weighted average	5	80.11%	28	75.36%
Snowballed total and average	12	71.36%	20	92.05%
Global total and average	**17**	**76.86%**	**48**	**82.62%**

By examining Table 1 and Table 2, it becomes clear that the accuracy in detection problems varies substantially, reflecting the difficulties associated with the need to extract spatial features from images effectively. SSD models are optimised for real-time detection tasks, balancing speed and performance adeptly, and can surpass an accuracy of 84%. YOLO models, which reached a detection accuracy of 85%, are known for their efficiency in processing images in a single evaluation pass, providing rapid and accurate detections. It is relevant to notice the global average accuracy of around 75% for the 17 examined samples.

Shifting to classification accuracy, the data highlights CNN's adaptability and effectiveness in a wide range of image classification tasks, achieving an average global accuracy of around 83%. This reinforces CNNs' position as versatile tools in ML global accuracy.

Although SSD primarily focuses on object detection, it also shows potential for classification tasks, with an accuracy of 76.77% [62]. On the other hand, YOLO stands out in classification with an impressive accuracy of 98.05% [67]. However, further research is necessary to validate the capabilities of these models as the representation is from a single article.

Custom models designed for specific applications perform exceptionally well, with an accuracy surpassing 95% [5] [21], highlighting the effectiveness of tailored solutions in achieving high performance. Additionally, combining multiple models has proved successful in classification tasks, achieving an accuracy that surpasses 99% [64], emphasising the advantage of collaborative approaches in complex ML challenges.

The convergence of the models' performance towards a substantial-high average detection accuracy is an important milestone in the evolution of detection models, as it showcases their refined ability to interpret complex and diverse visual data landscapes. The same is true for classification accuracy, demonstrating the robustness and adaptability of these models in distinguishing and categorising diverse objects within images. These accuracy-based metrics signify a broader trend towards performance and reliability, driven by the contributions from the examined models, from standard CNN architectures to custom and combined methodologies. YOLO's notable performance in classification further enriches this narrative, suggesting an expanding horizon for models traditionally associated with detection tasks.

Figure 13 shows a boxplot summarising the central tendencies and variability of accuracy attained by different ML models. This graphical representation offers a concise yet comprehensive overview of the data, illustrating the distribution and asymmetry of accuracy values and pinpointing any outliers.

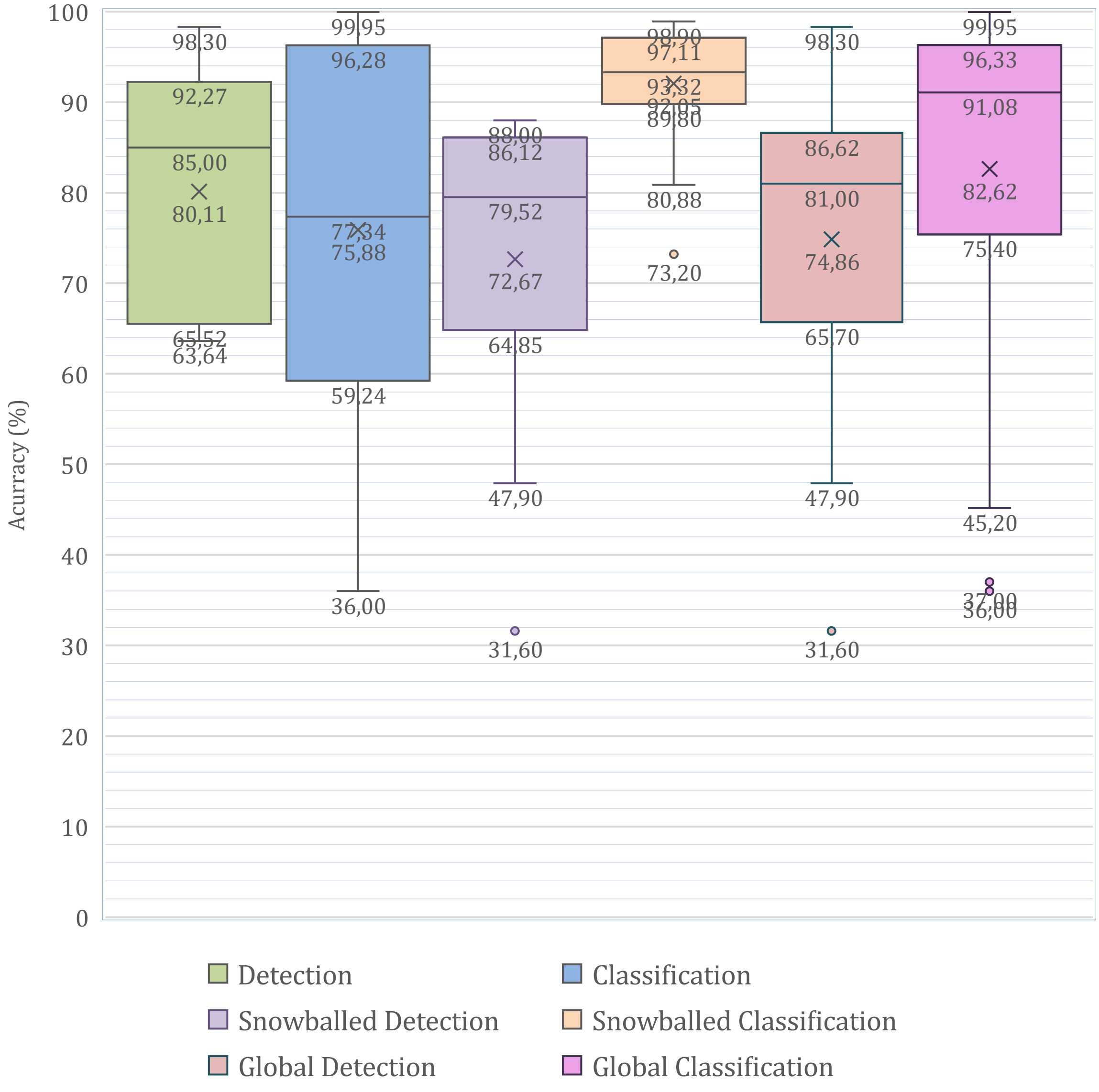

Figure 13 – Box Plot of the performance of the considered ML models.

Considering the classification accuracy of the systematically reviewed article, it is apparent in Figure 13 that the classification accuracy boxplot displays a wide range of model performance, with the lowest accuracy recorded at 36% [61]. This suggests that some models may struggle with complex detection when considering four classes. There are no minimum outliers, which indicates a consistent performance floor across all models studied. The middle 50% of data points are delineated by the first quartile (Q1, 25th percentile) at 59.24% and the third quartile (Q3, 75th percentile) at 96.28%.

This signifies a noteworthy improvement in model performance within this interquartile range, from moderately performing models to those achieving high accuracy. The median accuracy is 77.34%, slightly exceeding the average accuracy (75.36%); thus, the results are reasonably well distributed. The maximum accuracy recorded was 99.60% [59], demonstrating the potential of state-of-the-art models to achieve near-perfect detection in controlled conditions or specific applications. Curiously, the snowballed articles exhibit a much shorter variation, with an outlier at 73.20% [76]. Q1 is 89.80%, and Q3 is 97.11%, with a median of 93.32%. Therefore, in the global classification, [61] performance is now an outlier; Q1 is 75.40%, and Q3 is 96.33%, with a median of 91.08%.

Regarding the detection performance, it is clear from Figure 13 that a lower interquartile range was attained. For the systematically reviewed articles, Q1 was 65.52%, Q3 was 92.27%, and the median was 85%, which is considerably higher than the mean (80.11%). This suggests a slight left skew in the data, where most models cluster around a higher performance band, with fewer models trailing in the lower accuracy regions. This tendency is even more notorious in the examined snowballed articles, where the median and mean are 79.52% and 71.36, respectively, with Q1 and Q3 of 64.85% and 86.12, respectively. The lowest reported performance, comprising an outlier, was 31.60% [32], while the best performance was 98.30% [53]. Regarding the global detection accuracy, Q1, Q3, and median were 65.70%, 86.62%, and 81%, respectively.

These results highlight a tendency towards good detection and classification performance in the current state-of-the-art. It is especially relevant to the 97.32% classification accuracy attained by [57] using eight classes, and the 98.30% detection accuracy of ConvoWaste, proposed by [53], using six categories. Both articles were published in 2023. They showed increased performance even in the more challenging problems with a higher number of categories/classes.

4. Experimental Examination

The remarkable contributions of CNNs, SSD, and YOLO have significantly improved the field of computer vision. These models have been crucial in developing more efficient, accurate, and faster computer vision models. The foundation for feature extraction and representation learning, which is fundamental to understanding visual data, was established by CNNs. SSD and YOLO, on the other hand, have pushed the limits of real-time object detection, striking a balance between speed and accuracy that was impossible before. These models have opened up a new world of possibilities for applications and have also inspired subsequent innovations, making them essential components of modern ML for vision-based tasks. [74].

CNNs are a type of deep neural network that is primarily used to analyse visual imagery. They are highly effective in various computer vision tasks, such as image and video recognition, image classification, medical image analysis, and more. The key component of CNNs is the convolutional layer, which applies convolutional filters to the input data. This helps the network to capture spatial hierarchies of features. A typical CNN architecture includes a series of convolutional layers interspersed with activation functions (such as rectified linear units), pooling layers to reduce dimensionality, and fully connected layers towards the end.

CNNs have several key features, including local connectivity, shared weights, and depth. Local connectivity means that each neuron in a convolutional layer is only connected to a small input region, which helps detect local features. Shared weights mean that the same filter (weights) is applied across different input parts in convolutional layers, making CNNs efficient in parameter usage and invariant to the location of features in the input image. By stacking multiple convolutional and pooling layers, CNNs can capture complex patterns, with early layers capturing basic features like edges and later layers capturing high-level features.

CNNs are not limited to image classification tasks and have been extended to various tasks like object detection (R-CNN, Fast R-CNN), semantic segmentation (Fully Convolutional Networks), and even in other domains like natural language processing, by treating text data as a one-dimensional image [77].

SSD is an object detection model that uses a single deep neural network to detect objects in images. Due to its speed, it is highly efficient and suitable for real-time applications. The key component of SSD is its ability to divide the image into a grid and predict bounding boxes and class probabilities for these boxes in a single pass. It utilises a base VGG-16 network and several convolutional layers of varying sizes.

SSD has several key features that make it stand out, including Multi-Scale Feature Maps, which allow it to generate predictions from multiple feature maps with different resolutions, enabling it to detect objects of various sizes. It also uses a set of default bounding boxes with multiple aspect ratios at each location in each feature map, which are then adjusted to match the actual object shapes during prediction. The loss function in SSD combines both localisation (bounding box regression) and classification losses, enabling end-to-end training. Due to its balance of speed and accuracy, SSD is widely used in real-time object detection tasks, such as in surveillance, vehicle navigation, and many mobile applications [78].

YOLO is a cutting-edge real-time object detection system. Using a single neural network, it is designed to detect objects in images and videos by predicting bounding box coordinates and class probabilities.

Compared to other models that use image parts to predict bounding boxes, YOLO applies a neural network to the entire image, dividing it into regions and predicting bounding boxes and probabilities for each area simultaneously.

One of YOLO's main benefits is its speed. Its unique architecture allows it to make predictions with just one network evaluation, making it incredibly fast. Additionally, YOLO considers the entire image during prediction, enabling it to capture contextual information about classes and their appearance. This feature also means that YOLO makes fewer background errors than other models because it learns to predict each class's bounding boxes. YOLO is widely used in applications requiring real-time processing. Some of these applications include autonomous vehicles, real-time surveillance, and scenarios where immediate object detection is essential [79].

4.1. Examination of a dataset

To begin analysing our dataset, we had to take a few initial steps. First, we had to choose the appropriate model. Next, we selected the dataset that we wanted to examine. Finally, we accessed a notebook, essentially a repository of information that guides us through training the chosen model and executing any tasks related to the model [80].

The practical examination conducted in this chapter utilised the YOLOv8 model, a state-of-the-art computer vision model developed by Ultralytics, the same team that created YOLOv5. This model was released on January 10th, 2023, and offers built-in capabilities for object detection, classification, and segmentation tasks. It can be accessed through a Python package or command-line interface [81] [82].

The next step was to select a dataset, and for that, we used Roboflow, which provides everything we needed to label, train, and deploy our solution. Roboflow universe search engine has the largest collection of open-source computer vision datasets and APIs, with over 350 million images and 500000 datasets [83] [84].

To ensure that an ML model is accurate and can be generalised, the available data must be divided into distinct subsets for training, testing, and validation.

The training set is the data used to train an ML model. It should include all inputs that the model can handle. For example, if the model classifies plastic, card, and metal pictures, the training set should contain samples of these categories to train an ML model. The test set is unused data used to evaluate the model's performance. It imitates real-world data and helps determine the model's ability to make precise predictions on new data. The validation set, also called the development set, helps adjust an ML model's hyperparameters and assess its performance during training. Unlike the test set, it is used iteratively during model development to make informed decisions about selecting the best-performing model or detecting overfitting/underfitting issues [85].

Our search in Roboflow focused on object detection, allowing us to filter PW images using the YOLOv8 model with over 7,500 object detections. The chosen dataset had 15,301 images, a validation set of 634 images, and a test set of 406 images. This dataset was imported to the project workspace, as shown in Figure 14.

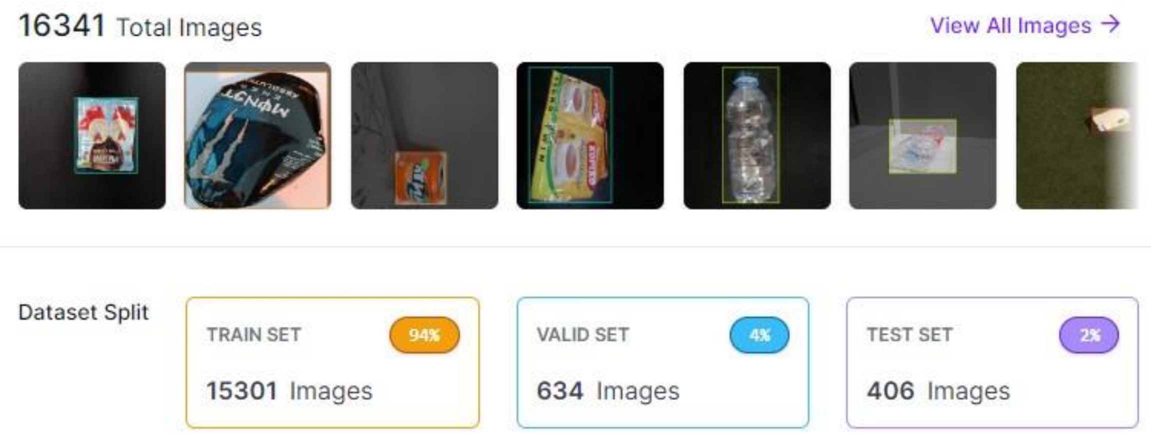

Figure 14 – YOLOv8 10+k images Object Detection Dataset

Finally, we needed a notebook to apply our YOLOv8 model and run our selected dataset. The process is extensive but simple. First, we created a Roboflow account where we created a new project and object detection was chosen as our project type. Then, we uploaded the images to the newly created project. The import was explained before and can be done via the Roboflow search engine. The third step involved labelling our images, which is crucial as it helps the model understand what is in the image. For example, in our case, we labelled the images as plastic, card or metal. Fortunately, the dataset we imported had all the images labelled. The fourth step is optional but could significantly improve the robustness of our model. This step involves generating a version to add preprocessing and augmentations. Once the dataset version is generated, we have a hosted dataset that we can load directly into our notebook for easy training [86].

4.2. YOLOv8 detection performance

Before starting the custom training, a decision was made to evaluate a change in a parameter called epoch. Each time a dataset passes through an algorithm, it is said to have completed an epoch. Therefore, in ML, the epoch refers to the entire passing of training data through the algorithm [87]. The first pass was done using five epochs, and the second run was done using 25 epochs. This change proved relevant because it significantly impacted the final metrics and total execution time, 47 minutes versus 3 hours and 30 minutes, respectively.

The output given by the custom training in the selected notebook (previously mentioned) includes a section that breaks down performance metrics class-wise. This information is useful for evaluating the model's performance for each class, especially in datasets with diverse object categories. For each class, performance details are provided [76] [88]. For the sake of clarity, these are the definitions of each column in

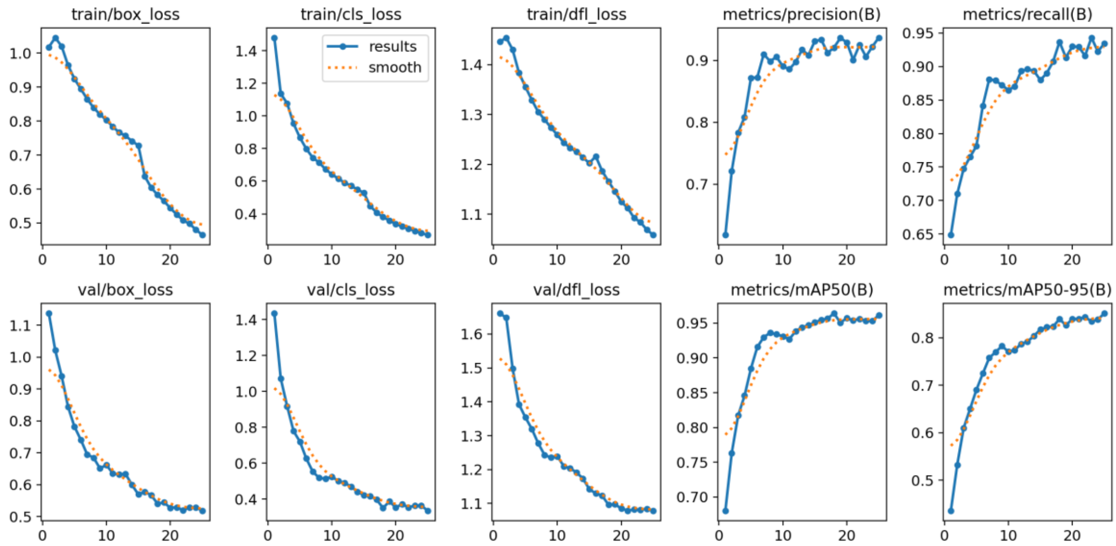

Figure 18 – YOLOv8 key metrics for 25 epochs

These improvements prove the effectiveness of using advanced ML techniques for environmental applications and highlight the potential for deploying such models in real-world scenarios to tackle plastic pollution.

Table 3:

- Class: This denotes the name of the object class
- Images: This metric tells the number of images in the validation set that contain the object class.
- Instances: This counts how often the class appears across all images in the validation set.
- Box (P, R, mAP50, mAP50-95): This metric provides insights into the model's performance in detecting objects:
  - P (Precision): The accuracy of the detected objects, indicating how many detections were correct.
  - R (Recall): The ability of the model to identify all instances of objects in the images.
  - mAP50: Mean average precision calculated at an intersection over a union (IoU) threshold of 0.50. It measures the model's accuracy considering only the "easy" detections.
  - mAP50-95: The average of the mean average precision calculated at varying IoU thresholds, ranging from 0.50 to 0.95. It gives a comprehensive view of the model's performance across different levels of detection difficulty.

The YOLOv8 detection performance with 5 and 25 epochs can be seen in Table 1Table 3.

4.3. YOLOv8 results

The results of our custom training using the YOLOv8 model on a dataset of PW images demonstrate significant improvements in object detection capabilities as the number of training epochs increases from 5 to 25. The metrics used to evaluate the model's performance, including precision, recall, mean average precision at 50% IoU threshold (mAP50) and mean average precision across thresholds from 50% to 95% (mAP50-95), serve as reliable indicators of its efficacy in identifying and accurately classifying instances of PW.

The Precision metric improved from 89.47% at five epochs to 95.57% at 25 epochs, indicating the model's enhanced accuracy in detecting objects as the training progressed. This improvement means fewer false positives, making the model more reliable for practical applications in PW management.

Similarly, the Recall metric increased from 91.73% to 95.70%, indicating the model's improved ability to detect all relevant instances of PW across the dataset. This improvement is crucial for ensuring comprehensive waste identification, which is essential for effective waste management.

The mAP50 metric, which evaluates the model's accuracy in detecting relatively straightforward challenges, increased from 94.73% to 97.73%. This improvement highlights the model's strengthened capability to identify PW objects with a high degree of confidence at an IoU threshold of 0.50.

Most notably, the mAP50-95 metric, which provides a more nuanced understanding of the model's performance across a range of detection difficulties, showed a significant enhancement from 78.43% to 87.66%. This comprehensive metric indicates the model's versatility and reliability in detecting PW under varying conditions and levels of complexity.

Instead of using Table 3 we can see our results using the confusion matrix generated in our custom training as our only reference. To demonstrate this, we only provide the analysis for 25 epochs. Refer to Figure 15. The confusion matrix is the chart showing how our model handles different classes. For example, if we analyse "Plastic Bags", 98.00% of the time, it is detected and classified correctly, whereas 2% is incorrectly detected and classified. For instance, "Plastic Bottles" is detected 90% correctly, while 6% of the time, it is confused as "Background" [80].

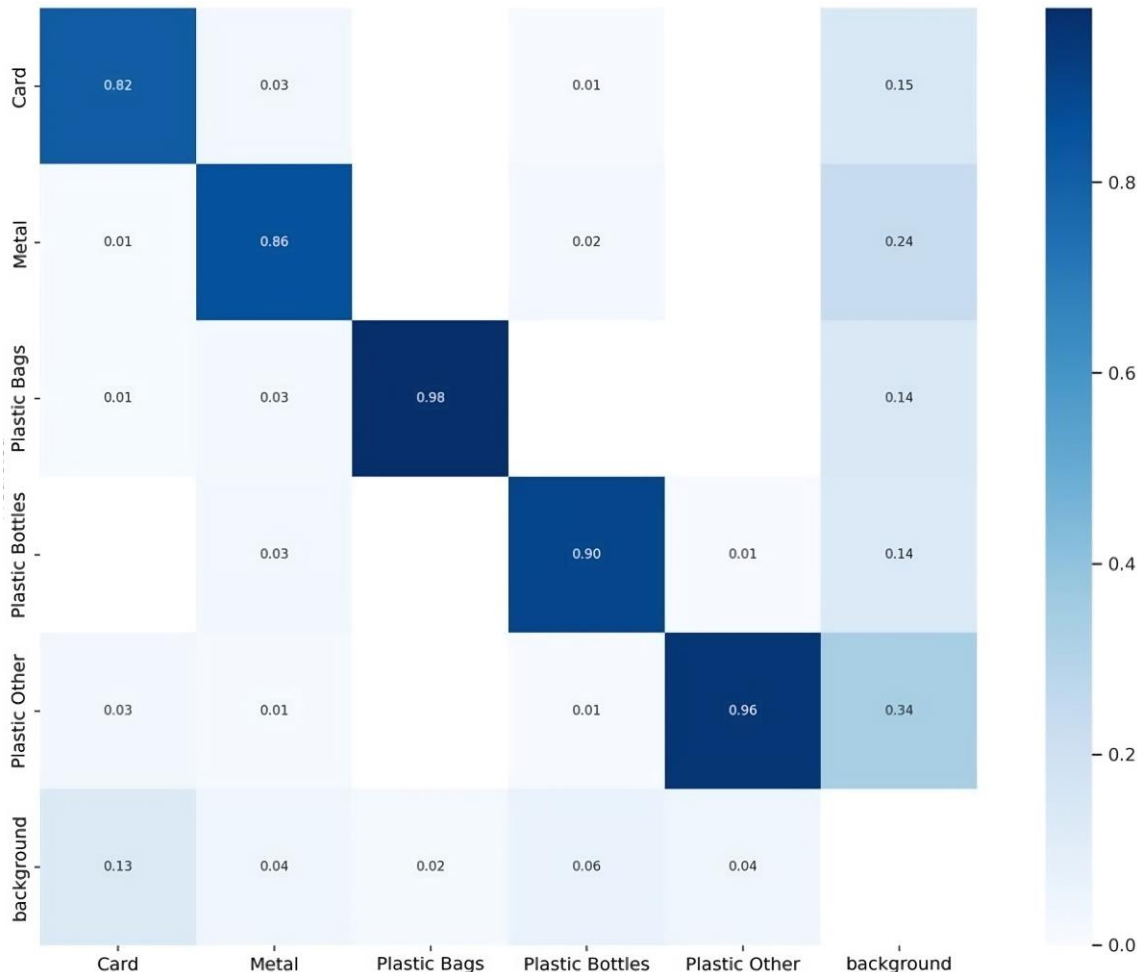

Figure 15 – Confusion Matrix for 25 epochs

To confirm the correct image classification, we can also use a specific visualisation of a small extract from the dataset. We can see this in Figure 16.

Figure 16 – Visual confirmation of the Dataset

To summarise, the results show that training the model adequately for PW identification is essential. The improvements in all metrics with increasing training epochs demonstrate this importance. This fact is also evident when comparing Figure 17 – YOLOv8 key metrics for five epochs and Figure 18 – YOLOv8 key metrics for 25 epochs. The more epochs the model undergoes, the more precise its results become over time. It also means that if we had chosen to do 50 or 100 epochs, the blue line, the chart, would have stabilised, meaning that more accurate results would have occurred.

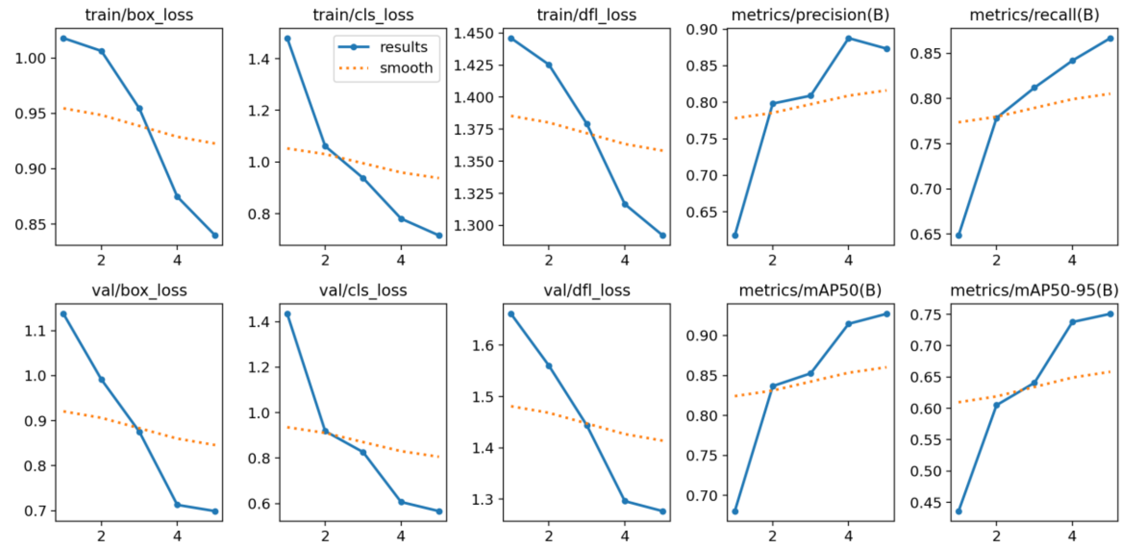

Figure 17 – YOLOv8 key metrics for five epochs

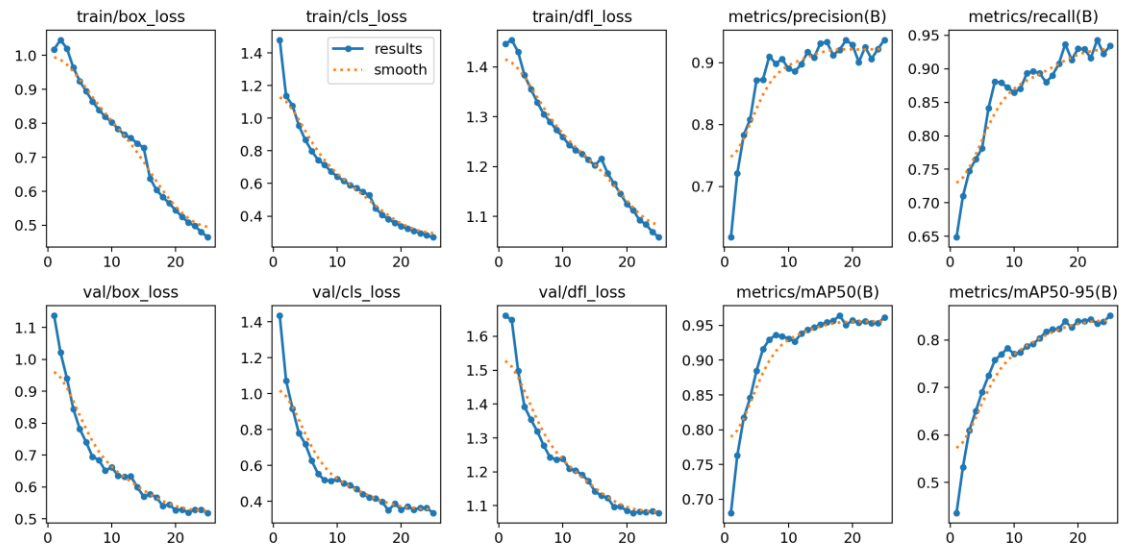

Figure 18 – YOLOv8 key metrics for 25 epochs

These improvements prove the effectiveness of using advanced ML techniques for environmental applications and highlight the potential for deploying such models in real-world scenarios to tackle plastic pollution.

Table 3 – Overview of YOLOv8 detection performance with 5 and 25 epochs

Class	Images	Instances	Box(P		R		mAP50		mAP50-95)	
			5 epochs	25 epochs	5 epochs	25 epochs	5 epochs	25 epochs	5 epochs	25 epochs
all	634	748	87.50%	93.60%	86.60%	93.40%	92.70%	96.10%	75.00%	85.10%
Card	634	98	86.10%	85.10%	75.60%	89.80%	87.60%	92.10%	69.10%	81.00%
Metal	634	119	83.10%	95.90%	82.40%	89.90%	91.70%	96.30%	70.60%	80.08%
Plastic Bags	634	234	94.80%	**99.20%**	94.90%	**99.60%**	98.50%	**99.50%**	81.30%	**90.08%**
Plastic Bottles	634	151	94.50%	**98.50%**	90.80%	**93.70%**	94.90%	**97.40%**	80.70%	**91.60%**
Plastic Other	634	156	79.10%	**89.00%**	89.50%	**93.80%**	90.80%	**95.40%**	73.30%	**81.30%**
Plastic Only	634	541	89.47%	**95.57%**	91.73%	**95.70%**	94.73%	**97.73%**	78.43%	**87.66%**

5. Conclusion

This thesis has comprehensively examined the application of ML techniques in PW detection and classification, revealing relevant advancements in the field over the past five years. Furthermore, a bibliometric analysis was executed to examine relevant keywords, to asses which articles are more similar to each other, and the citations of the reviewed articles, which is a standard examination that was previously conducted on wastewater treatment with AI [89].

5.1. Addressing Research Questions

Our analysis demonstrates that CNN-based models, particularly YOLO and SSD architectures, have emerged as highly effective tools in this domain, consistently achieving detection accuracies exceeding 80% and classification accuracies surpassing 83% across diverse studies. Thus, addressing the research questions, it was concluded that:

- RQ 1: Can ML models achieve PW detection and classification accuracy suitable for real-world applications?

It was concluded that ML models achieve a detection accuracy that meets but often exceeds the 80% detection accuracy benchmark. It is also important to notice that the accuracy surpassed the 95% threshold in many instances. These results support a positive answer to the first research question.

Moreover, the experimental examination done in the previous chapter demonstrates that YOLOv8 can have a precision above 95%.

- RQ2: Which ML approach is more suitable for PW detection?

It is more challenging to provide a more direct answer; however, Table 1's results suggest that YOLO is likely the best model.

The field has witnessed rapid progress, with recent studies in 2023 reporting classification accuracies of 97.32% for eight waste categories and detection accuracies of 98.30% for six categories, indicating the growing capability of these systems to handle complex, multi-class waste management scenarios. This progress suggests that ML technologies are approaching the threshold of practical applicability in real-world waste management contexts.

However, significant challenges remain. The variability in methodologies, datasets, and performance metrics across studies hampers direct comparisons and standardised benchmarking. Furthermore, laboratory results are promising, but there is a notable gap between controlled experimental performance and the robustness required for real-world waste management applications.

These findings have important implications for environmental sustainability efforts and waste management policies. The high accuracies suggested that ML could significantly enhance the efficiency and effectiveness of PW sorting and recycling processes, potentially revolutionising waste management practices. However, successful implementation will require close collaboration between specialised technicians, waste management professionals, and policymakers to address practical deployment challenges. It is essential to consider the hardware requirements and the need for interpretability [90].

5.2. Future Directions: Plastic Recycling through AI and ML

The knowledge presented in this master's thesis offers a promising path towards achieving environmental sustainability. It highlights the potential of AI and ML in addressing one of the biggest ecological challenges of our time - plastic pollution.

The recommendation is first to develop a benchmark dataset that allows the examination of all models in the same condition, facilitating direct comparisons between different approaches. Furthermore, it is essential that the used datasets are made publicly available to allow independent validation of the models and results. Lastly, validating the performance and scalability of the proposed solutions in real-world pilot studies is also needed.

Future research lines could examine multimodal approaches combining image data with other sensor types to improve robustness in varied environmental conditions, explore federated learning techniques to enable collaborative model training and examine the potential of unsupervised and self-supervised learning methods to reduce reliance on large labelled datasets. It is also advisable to further refine the used transfer learning and few-shot learning methods to address the challenge of limited labelled data in specific waste management contexts.

The research set the stage for a subsequent PhD program, which will focus on developing advanced ML models tailored to the complex task of identifying, classifying, and refining PW. The aim is to use AI to revolutionise recycling methodologies and create sustainable solutions. This forthcoming scholarly endeavour seeks to lay a solid foundation for eco-friendly innovations and redefine sustainability standards by introducing cutting-edge efficiency and precision to recycling processes. The ultimate goal is to create a future where technological advancements and environmental stewardship work together.

5.3. Concluding Remarks

This thesis is not just the culmination of an academic pursuit but marks the beginning of a visionary journey towards a sustainable future. Through the exploration of CNN, SSD, and YOLO models, as well as the innovative strides in custom and combined ML solutions, we have illuminated the way forward. The aim is to create a future where technology and sustainability go hand in hand, and this thesis should serve as a call to action for the next generation of researchers and innovators. With the insights and inspirations from this study, we can surpass boundaries, turn challenges into opportunities, and create a greener tomorrow.

This Master's Thesis already had its results validated by the publication of an Article in the MDPI Open Access Journal [91].

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