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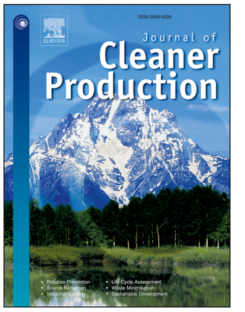

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A waste separation system based on sensor technology and deep learning: A simple approach applied to a case study of plastic packaging waste

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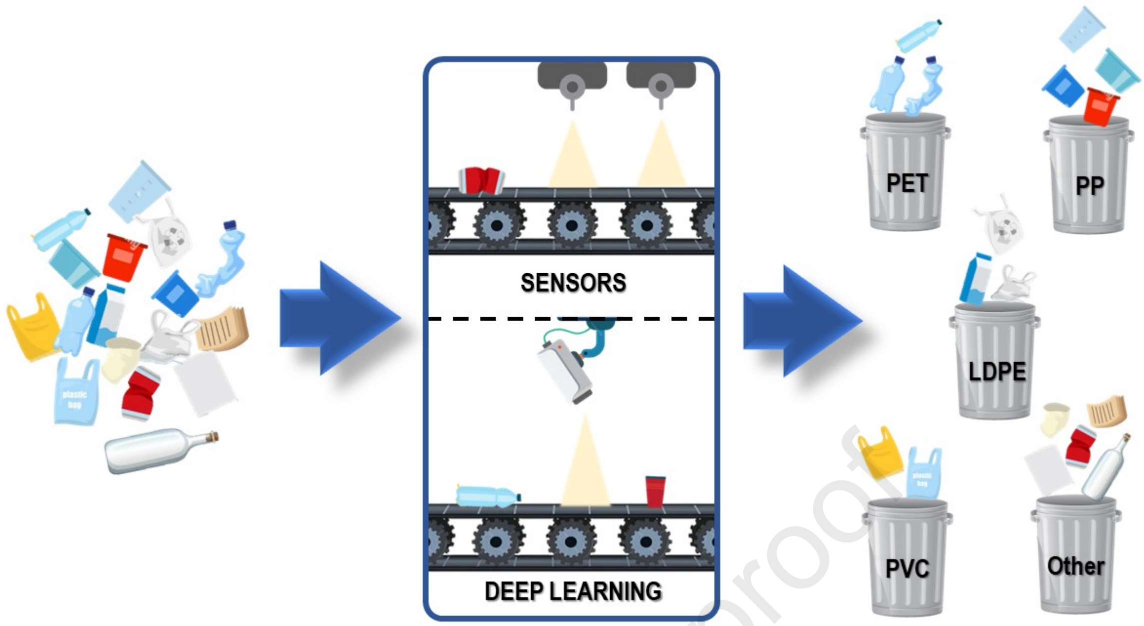
SENSORS
DEEP LEARNING
PET
PP
LDPE
PVC
Other

A waste separation system based on sensor technology and deep learning: A simple approach applied to a case study of plastic packaging waste

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ABSTRACT

Plastic waste pollution is a challenging and complex issue caused mainly by high consumption of single-use plastics and the linear economy of “extract-make-use-throw”. Improvements in recycling efficiency, behaviour changes, circular business models, and a more precise waste management system are essential to reduce the volume of plastic waste. This paper proposes a simplified conceptual model for a smart plastic waste separation system based on sensor technology and deep learning (DL) to facilitate recovery and recycling. The proposed system could be applied either at the source (in a smart waste bins) or in a centralised sorting facility. Two smart separation systems have been investigated: i) the one utilising 6 sensors (near-infrared (NIR), humidity, temperature, CO_2, CH_4, and a laser profile sensor) and ii) the one with an RGB camera to separate packaging materials based on their composition, size, cleanliness, and appearance. Simulations with a case study showed that for a camera-based sorting, Inception-v3, a DL model based on convolution neural networks (CNN), achieved the best overall accuracy (78%) compared to ResNet-50, MobileNet-v2, and DenseNet-201. In addition, the separation resulted in a higher number of misclassified items in bins, as it focused solely on appearance rather than material composition. Sensor-based sorting faced limitations, particularly with dark colouration and organic matter entrapment. Combining the

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information from sensors and cameras could potentially mitigate the limitations of each individual method, thus resulting in higher purity of the separated fractions.

KEYWORDS: Waste management, smart waste bin system, central post-sorting, sensor technology, deep learning, convolutional neural networks

1. Introduction

The global production of waste has reached an all-time high. It is estimated that the annual waste generated will increase from $2.01 \cdot 10^9$ presently to $3.40 \cdot 10^9$ t by 2050 (Kaza et al., 2018), which correlates and is connected tightly with the growing population, rapid urbanisation, and industrial advancements (Kibria et al., 2023). The composition of generated waste depends on the socio-economic state of countries, with high-income ones being the main waste contributors (Kaza et al., 2018). One of the main problems of the accumulated waste is its influence on the environment, as not all post-consumer materials are biodegradable. Furthermore, the most common method of disposal is landfilling, followed by mismanaged waste, and incineration (OECD, 2022).

The total municipal waste presently consists of about 7–12 % of plastics by weight (Babaremu et al., 2022). Plastic materials have a long degradation rate, and they accumulate and disintegrate slowly into microplastics and nanoplastics where they end up in different environment settings (Plohl et al., 2022). Large amounts of plastics in addition to wasting valuable resources contaminate the environment, impact wildlife (Li et al., 2016), result in negative health impacts, and are difficult and costly to clean with limited effectiveness, which is particularly valid for mismanaged plastic (Dijkstra et al., 2020). In 2019, the world generated $353 \cdot 10^6$ t of plastic waste (OECD, 2022), with the main contributors being the packaging and textile industries (Tiseo, 2023). Plastics are often used as packaging materials for food and goods because they are lightweight, have good barrier properties and mechanical performance, are accessible, and with the advanced production technology. The most common packaging polymers are thermoplastics, representing more than 84 % of the plastic market share (Ncube et al., 2021). Polypropylene (PP), polystyrene (PS), polyethylene terephthalate (PET), polyethylene (PE) and polyvinyl chloride (PVC), which are petroleum based materials, are among plastics that have been used extensively in the packaging industry (Ncube et al., 2021). The longevity of those materials can be attributed to different additives, such as antioxidants, heat and light stabilisers, impacts modifiers and plasticisers, that are added in the manufacturing process (Singh et al., 2012).

Various solutions have already been proposed to lower the impact that the disposed plastic materials have on terrestrial and aquatic environments and to increase plastics' circularity. Most of them are based on one or more concepts of 10Rs - refuse and reject, rethink, reduce, re-use, repair, refurbish, remanufacture, repurpose, recycle, and recover (Zorpas, 2020). Due to the chemical and physical differences of plastic waste, effective recycling is a challenging task, especially if the separation step is not conducted well at its earlier stage (e.g., preferably at source). For recycling of plastic, the quality of the waste material (as a raw material) is critical (Eriksen et al., 2019). Various factors hinder the recycling of plastics (Jung et al., 2023), such as difficulty, high cost, and low efficiency associated with the classification and separation of plastics. Especially for mixed plastic, the use of additives and coatings, contamination of plastics, and the use of thermoset plastics, result in hardly recyclable materials (Geueke et al., 2018). The study characterising and assessing the recyclability of plastic waste from recycling centres, found that impurities represent a significant share of the plastic waste (28 %), with most of the sample plastic waste characterised as "Low Quality" (Faraca and Astrup, 2019). A proper separation step has to be included to differentiate the waste with the best recycling potential (Samiha, 2013), thereby maximising circularity and minimising the waste for refuse derived fuel and landfill.

Proper separation of plastic waste coupled with its further treatment would aid in reaching the set recycling targets related to plastics use. Plastics are essential components of a circular economy with ambitious recycling targets (Eriksen et al., 2019). For example, European Union (EU) member states are aiming to achieve recycling targets of 65 % for packaging waste and 50 % for plastic packaging waste in 2025, and, by 2030, both targets will be increased by an additional 5 % (EC, 2023). The New Plastics Economy Global Commitment, which unites more than 500 organisations, sets the target that 100 % of plastic packaging will be reusable, recyclable, or compostable by 2025 (Ellen MacArthur Foundation, 2022). However, the study assessing the quality and circularity potential on an example of household plastic waste (Eriksen et al., 2019) highlighted that less than 42 % of plastic could be recycled with the current technology, due mainly to contamination. This number could be improved to 55 % assuming the best-performing scenario of high source-separation efficiencies, a higher number of target fractions, and high efficiencies in material recovery facilities (MRFs). The study (Eriksen et al., 2019) concluded that *"the presence of impurities in the recovered fractions should be reduced, and more emphasis should be placed on closing the loops for high-quality plastic rather than plastic in general."* To obtain high-quality recycled plastics, the separation of plastic waste by type, colour, shape, and size should be conducted prior to reprocessing (Lubongo and Alexandridis, 2022).

Post-consumer plastic is usually heterogeneous, containing a variety of plastic types of different qualities. Waste sorting is a key step in waste management for the circular economy, since it results in increased recycling efficiencies (Jung et al., 2023) and an increased number of cycles (Lange, 2021). It is estimated that recycling efficiency could be improved by at least 15 % if segregation of recyclable waste is done at source (Suvarnamma and Pradeepkiran, 2021). Successful sorting and separation is also a key to minimising pollution for compostable plastics (Taneepanichskul et al., 2022). The sorting is usually done with a sequence of steps, either manually by operators, automatically by exploiting the differences in material properties, or both (i.e. manual and automated sorting). The study (Lubongo and Alexandridis, 2022) pointed out that many MRFs rely on manual separation to obtain differentiated products with high purities. However, it can be time consuming, contains human errors and affects human health. Smart waste management systems combine different Internet of Things (IoT) technologies with sensors, computer vision, and machine learning (ML) to support automated waste separation. This could lead to a more precise separation of waste materials and could lower occupational risk or health hazards (Bonello et al., 2017). Most cost analyses indicated that, even though automation has higher initial investments, their operating costs are lower in the long term when compared to manual waste sorting (Pandiaraja et al., 2020). In addition, automation is favoured for medium- to high-volume plants (Lubongo and Alexandridis, 2022).

For example, in Hungary (Del-Kom), Slovakia (FCC Slovensko) and Malta (Bonello et al., 2017), some sorting centres employ workers to separate plastic and packaging materials with high recyclability potential manually. These materials are then baled and sent to recycling facilities. Similar packaging handling practices are also observed in certain Slovenian recovery centres (Salomon Group). On the other hand, many Austrian and German MRFs are predominantly automated, relying mainly on sensor-based sorting. However, even these facilities still incorporate some manual sorting, to remove bulk plastic materials that could interfere with machine operations (Neubauer et al., 2020), or to implement quality control at the end of the sorting process (Kusch et al., 2021). Computer vision systems could theoretically automate the process, as machine algorithms can identify such materials solely by their appearance.

The research in the field of automated waste sorting and segregation has two different approaches: sorting using sensor technology or Artificial Intelligence (AI) using ML. Different sorting technologies could be combined to improve product yield or sorting efficiency (Lubongo and Alexandridis, 2022). New sorting technologies are being developed and demonstrated, such as tracer-based sorting, digital watermarks assisted sorting, and others (Lange, 2021). Various studies on waste managements have been performed, including those with the aim of sorting and classifying plastic waste streams into several classes (Esmaeilian et al., 2018) and summarising advances in automated waste sorting (Gundupalli et al., 2017). The literature review regarding sensor and camera-based waste management is presented in the following section. However, more progress in accurate sorting and more versatile sorting technologies are needed, as currently much is left as a mixed plastic waste (Lange, 2021).

Based on records in the Scopus database, most of the academic research studies related to automated waste separation were carried out utilising either sensor or camera technology. However, it should be noted that the simultaneous application of both, visual separation by cameras and sensor-based separation depending on material composition is lacking. Research primarily focuses on the integration of deep learning (DL) models with spectral images from sensors to improve the efficiency of separation. However, the integration of visual classification material using DL together with sensor data is often overlooked. Usually, research studies consider broader classification classes, such as e.g. Plastic, Paper, Metal, while narrower classes, such as e.g. Plastic bags, Plastic bottles, Plastic cups, are not as commonly explored. Consequently, there is still a research gap in the application of a comprehensive approach that integrates visual observations and sensor technologies in the field of plastic packaging waste management.

This paper proposes a simple intelligent waste sorting model, that uses sensor technology and deep learning models to separate plastic packaging materials, with the aim to compare their accuracy of separation. The study tries to complement existing efforts in the development and advancement of efficient sorting technologies that are still needed to maximise the number of affordable closures of material cycles to preserve precious resources and combat pollution. To preserve the high quality of recycled plastic while handling mixed plastics, the key step is reduction of cross-contamination by further optimisation of waste sorting (Rani et al., 2019). In this work, a simple smart sorting system is proposed that can identify and classify single-use plastic waste and separate it into the desired plastic categories for better recycling or recovery processes.

The study contributes new techniques to facilitate the continual improvements in the sorting of plastic packaging waste. It is assumed here that the sorting is conducted by spreading plastic waste on a (small) conveyor belt and identifying and separating the plastic with the help of sensors or camera. Six sensors, such as near-infrared (NIR), humidity, temperature, CO_2, CH_4, and a laser profile sensor are applied together with an RGB camera, to separate packaging materials based on their composition, size, cleanliness, and appearance. Such separation system could be applied either as an on-site smart waste bin system at a smaller (households or community) scale or as a central post-sorting system at a larger scale. A case study of 60 items with six different types of waste items, consisting mainly of single-use plastic packaging materials was conducted, while also considering other non-plastic waste types, and dirty and mixed plastics. For camera-based detection, four convolutional neural network (CNN) models obtained from the Deep Network Designer app on MatLab (MathWorks, 2023) and pre-trained on a custom database, were used and compared: ResNet-50, MobileNet-v2, Inception-v3 and DenseNet-201. The simple optimisation model was developed with the objectives of (1) minimising the number of items ending up in the residual waste and dirty bins, along with (2) minimising the number of placements recognised wrongly by the camera. The model was formulated as a mixed-integer nonlinear (MINLP) model and is solved in the General Algebraic Modelling System (GAMS) (GAMS Development Corporation, 2022).

The paper is structured as follows: Section 2 presents a literature review on sensor- and camera-based waste sorting studies. In Section 3 the problem formulation is presented proposing a smart waste separating system. It is followed by the formulation of the mathematical model presented in Section 4. Section 5 involves the application of the model to a case study of plastic packaging waste. Some strengths and limitations of the study are described and discussed in Section 6. The last section presents the main conclusions and some future recommendations.

2. Literature review

IoT and sensor technologies have been used thoroughly in all the steps of waste management systems, from monitoring and collection, to transportation, processing, disposal/recycling, and analysis of the waste materials (Vishnu et al., 2022). Several studies have been published related to smart waste management systems that use IoT in combination with sensor technology to achieve the desired goal of recovering higher quantities of secondary materials with good quality. Different smart systems have been proposed, that could be used either at the smaller-scale in the primary separation of municipal solid waste in so-called smart waste bins (Wijaya et al., 2017), or at a larger scale in the secondary separation of waste, which occurs in waste treatment plants and MRFs. With the help of sensor technology, smart waste bins have the ability to differentiate dry and wet (Lopes and Machado, 2019), biodegradable and non-biodegradable waste (Raj et al., 2020), different waste classes (Samion et al., 2018), the dimensionality of waste items (Kroell et al., 2021), and others.

Different studies in the literature proposed sorting models, and some studies also smart waste bin prototypes (Suvarnamma and Pradeepkiran, 2021) for separating waste into specific classes, such as metal, plastic and organic waste. For the detection of biodegradable compounds that may be present in the packaging waste, humidity (Das et al., 2021) and different gas sensors are used for detecting gases, such as CO_2, CH_4, H_2S and NH_3 (Misra et al., 2018). To determine the dimensionality of packaging materials (either 3D or 2D), laser sensors could be used to measure the profile of waste items (Kroell et al., 2021). Polymers that comprise different types of plastic packaging materials can be classified and categorised using different optical sensors.

The most commonly used optical sensors for plastic types' classification are NIR reflectance sensors, which measure the intensity of light that is reflected off an object. In the NIR region, which ranges from 750 to 2500 nm (Masoumi et al., 2012), the absorption and reflectance of the light occur due to an overtone or combination of different vibrations of chemical bonds (C-H, O-H and others) (Rani et al., 2019). The different compounds and elements that comprise polymers, lead to different absorption patterns. Utilising different NIR spectral characteristics, the common plastic types, e.g. PET, HDPE, PVC, LDPE, PP, PS and polycarbonate (PC), could be classified successfully (Duan and Li, 2021). Similarly, separation could be conducted for plastic waste from household appliances and electronics containing polymers such as PP, PS, acrylonitrile butadiene styrene (ABS) and ABS/PC (Wu et al., 2020). An IoT system was presented for identification of different types of plastics using economical NIR sensors (Bhati and Bhattacharya, 2020). With the application of different ML algorithms, the system is capable of separating HDPE, PP, PS and PET plastics accurately. The separation of plastics can also occur at source, with the use of a handheld NIR spectrometer (Rani et al., 2019), or in smart waste bins with integrated miniature NIR sensors (Thakker and Rajamanickam, 2015).

In the last decade, the number of publications that implemented AI in waste management systems has increased steadily (Abdallah et al., 2020). Many different models have been proposed and used in waste management systems, like artificial neural networks (ANN), K-nearest neighbour (KNN), decision tree (DT), support vector machine (SVM), adaptive neuro-fuzzy inference system (ANFIS), etc. The study (Xia, W. et al., 2021) highlighted that convolutional neural network (CNN) algorithms, which are part of the DL branch of AI, proved to have very good performance in image classification and recognition. However, training CNN model is challenging (Joshi et al., 2019).

To avoid training CNN models from scratch, a concept called Transfer Learning has been introduced, which uses a pre-trained model from another task. Since DL models usually require a lot of data and time for training, Transfer Learning takes the advantage of using a pre-trained model, transferring the knowledge to a new dataset, where it is then retrained for the new target domain (Huang et al., 2020). Many different models, such as ResNet-50, MobileNet, VGG-16, AlexNet and others, were used to differentiate and classify waste into different categories, mainly plastic, metal, paper and organic. For the training of CNN models to be successful, a large image dataset needs to be included and several open sources datasets for waste image sorting have been summarised by Lin et al. (2022). Table 1 represents some of the models used in the classification of waste materials, combined with the size of the datasets and the testing accuracies of the trained models. In addition, the CNN models and the obtained accuracies, data size and classification classes from this study are included in the same table.

Table 1: Overview of CNN models in waste classification.

CNN model	Accuracy	Data size	Classification classes	Reference
Proposed neural network VGG-16 Dense-Net Inception-Net Mobile-Net Res-Net	81.25 % 87.41 % 91.36 % 86.71 % 92.65 % 91.38 %	25,000	Recyclable waste Non-recyclable waste Organic waste	(Thanawala et al., 2020)
ResNet-18	87 %	3102	Plastic Paper Metal Glass	(Gyawali et al., 2020)
WasteNet	97 %	2527*	Paper Glass Metal Plastic Cardboard Other	(White et al., 2020)
Inception-v3	92.5 %	2400	Paper Glass Cardboard Metal Plastic Other	(Azis et al., 2020)
ResNet-50	87 %	4516**	Glass Paper Plastic Metal	(Adedeji and Wang, 2019)
VGG-19 DenseNet-169 NASNetLarge	89.7 % 88.6 % 89.2 %	2527*	Cardboard Paper Glass Metal Plastic Trash	(Huang et al., 2020)
VGG-16 ResNet-50 MobileNet DenseNet-121	67.93 % 91.30 % 83.68 % 77 %	9200	General waste Compostable waste Recyclable waste Hazardous waste	(Srinilta and Kanharattanachai, 2019)
VGGNet-16 ResNet-50	95.6 % 96.6 %	22,010	Organic waste Residual waste	(Wu and Lin, 2022)
MobileNet	87.2 %	2527*	Cardboard Glass Metal Paper Plastic Other	(Rabano et al., 2018)

Table 1 (Cont.): Overview of CNN models in waste classification.

CNN model	Accuracy	Data size	Classification classes	Reference
VGG-16 VGG-19 Inception ResNet Inception-ResNet	76.94 % 79.32 % 87.71 % 88.66 % 88.34 %	2527*	Glass Paper Cardboard Plastic Metal General trash	(Ruiz et al., 2019)
AlexNet	83.0 %	2000	Plastic Paper Metal	(Sakr et al., 2016)
DensNet-201 Inception-v3 MobileNet-v2 ResNet-50	62.61 % 78.34 % 66.72 % 63.59 %	4786	Food packaging Plastic bags Plastic bottles Plastic cups Residual waste Tetra Pak cartons	This study

*TrashNet database **Combination of TrashNet and own database

Even though CNN models have frequently been used in the classification of waste items, it was found that there is scarce academic literature focusing on identifying different plastic types, including the contaminated plastics by using these models. With the help of image recognition technology, it is possible to differentiate plastic packaging items based solely on their appearance. This kind of technology can be implemented at any scale. At the smaller scale, e.g., in smart waste bins, the bin itself could enable separation of single-use plastic materials to specific categories. More commonly, camera detection using DL models is used at the larger scale in MRFs.

Some examples of an image-based classification approach for plastic waste are as follows. A model called the one-shot learning technique has been proposed (Agarwal et al., 2020), which enabled separation of plastic waste into 5 categories, i.e., PET, HDPE, PP, PS and others, with an accuracy of 99.97 %. The authors concluded that their model does not require any image augmentation features, which are used commonly to increase the size of the database, to achieve a higher training accuracy. Another study (Gothai et al., 2022) used the same image database, but segregated the plastic waste into 7 categories (PET, HDPE, LDPE, PVC, PP, PS, and others). A comparison of the performances of their own CNN model with pre-trained models LeNet-5 and AlexNet showed that all the models had a high accuracy rate of separating plastic packaging into their desired categories. A similar CNN 15 layer model (Bobulski and Kubanek, 2021) based on the AlexNet structure to separate plastic waste into HDPE, PET, PP and PS worked best for images of 120x120 pixels, but its classification accuracy was lower compared to other CNN models found in the literature.

Spectroscopic methods have been proven to be effective in classifying waste based on their molecular properties, while computer vision-based methods excel at classifying waste according to visual characteristics. A combination of these two approaches holds promise for achieving optimal separation performance (Zhao and Li, 2022). For instance, a combined approach involving NIR spectroscopy and a CNN model was proposed (Maliks and Kadikis, 2021) to segregate plastics successfully into five polymer classes under various conditions (dry, wet, scratched, and covered in dirt). Similarly, a combined approach was employed to enhance the separation efficiency of weathered polymer samples (Neo et al., 2023). Another study (Xia, J. et al., 2021) used the combined approach to analyse 159 plastic samples, half of which were black in colour. Different spectroscopy techniques, such as NIR in combination with DL (Zinchik et al., 2021), also demonstrated high accuracy in separating plastic components.

In all the aforementioned studies, the spectral data obtained from different infrared (IR) sensors were fed into a CNN model trained on specific spectra. The CNN model then compared the obtained spectra with a database and classified the materials into their respective categories based on similarities. While there is a substantial body of research utilising spectral classification with CNN models, a noteworthy gap exists in the integration of waste image classification with spectroscopy. On an example of the separation of household appliance waste (Tan et al., 2022), the disassembled parts on a conveyor belt system underwent initial classification using a camera in conjunction with an improved YOLO model, separating the items based on visual attributes. Subsequently, some of the fractions underwent a second separation step employing NIR spectroscopy.

3. Problem formulation

Proper waste separation is one of the main factors in reducing the amount of waste that is disposed in landfills and uncontrolled environments. Most of the sorting occurs in waste treatment plants or MRFs, where waste is separated based on its specific characteristics, and, if allowed, reused to make different secondary materials. However, the desired separation of materials is not always achieved, due to the high purity requirements of recycled materials, and similarities of the chemical or physical properties, as in the case of mixed plastics. To avoid such problems, an implementation of additional segregation and/or sorting steps could be beneficial. This could be achieved with using smart waste bins that would be able to separate plastic packaging materials at the source, or as a central post-sorting in MRFs. This fully automated sorting system would help to reduce the amount of waste that still has recycling potential, but could otherwise, due to improper waste segregation, not be identified correctly.

Figure 1 shows a concept of how the proposed intelligent waste management system in this study is an essential part of the overall strategy for sustainable management of plastic waste. The separation process based on the proposed approach is linked to other essential components of the waste management process, to reduce the post-consumption footprint. In addition, key aspects, such as innovation requirements, recycling technologies, and the imperative global engagement, including stakeholder responsibility, policy and regulation, are mentioned, as their integration offers a promising and sustainable path to a cleaner and more responsible plastic waste management system.

The proposed simple conceptual smart waste separation system consists of a chamber where different sensors and a camera are located. Based on the obtained readings, the packaging waste materials are then sent via a (small) conveyor belt, where a mechanical force or air nozzle pushes the waste into the dedicated bins. The smart waste separation system employs a total of 6 sensors: an NIR, humidity, temperature, CO_2, CH_4 and laser profile sensor. The NIR sensor is used to identify and separate different polymer materials, whereas the humidity, temperature and gas sensors are used primarily to determine the presence of unwanted organic matter. Lastly, the laser profile sensor is used to determine the dimensionality of the waste, thus being able to separate 2D materials from 3D. A standard RGB camera is utilised for waste image classification. Figure 2 shows a schematic representation of the proposed smart waste separation system applied to plastic waste.

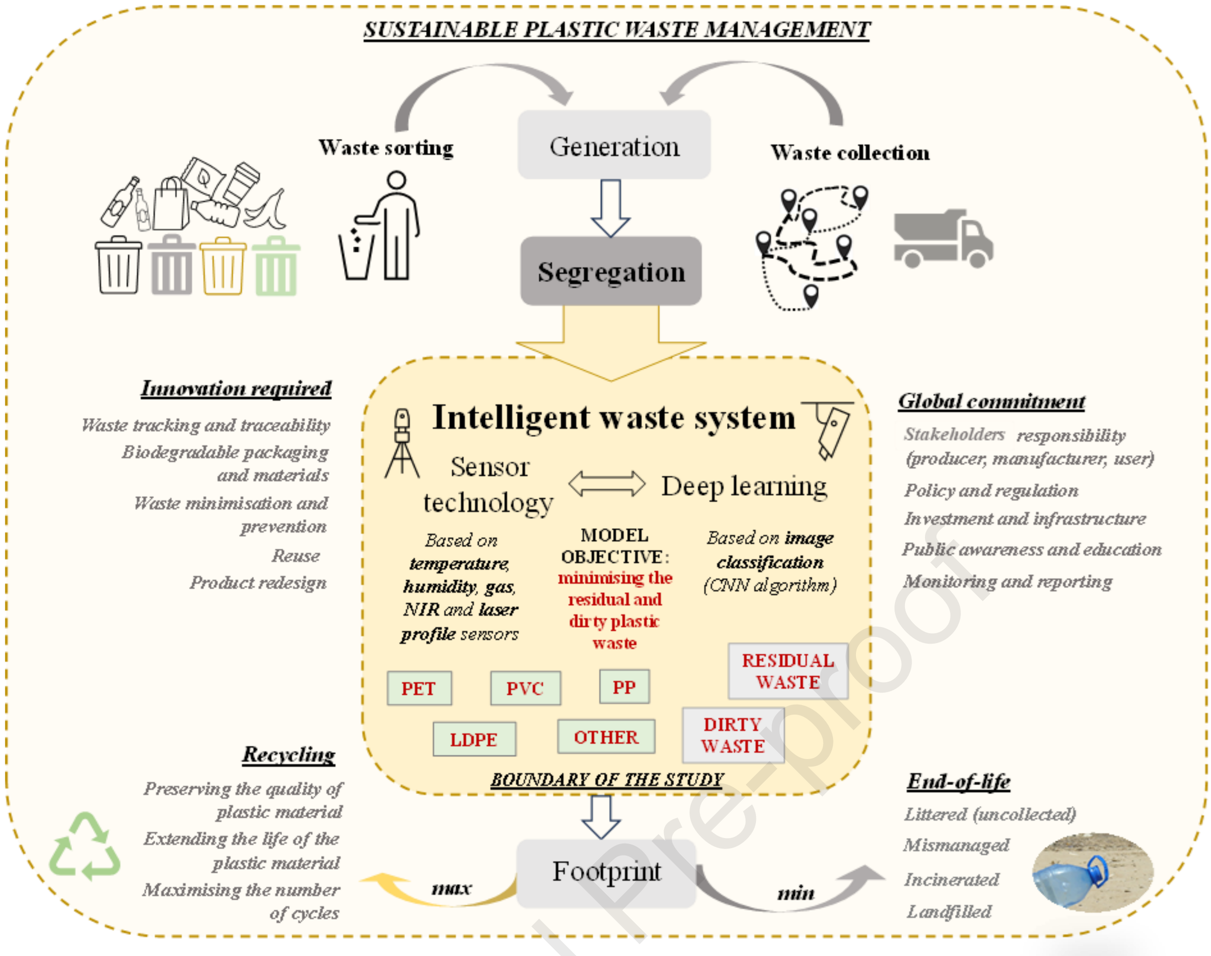

Figure 1: Overall approach focusing on the proposed intelligent plastic waste management system

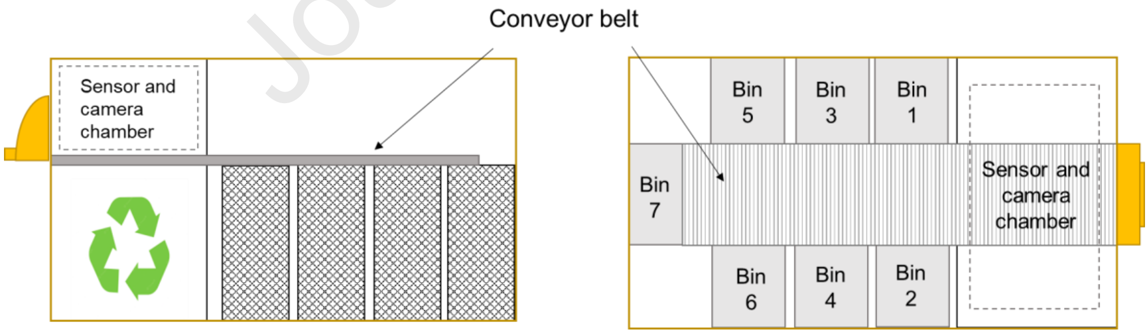

Figure 2: Proposed smart waste separation system

When developing a simple conceptual model, which utilises both the mentioned technologies for waste separation, the following assumptions were made:

- The waste moves on the conveyor belt piece by piece, and there is an absence of waste grouping or cluster formations.

- All the sensors can detect the materials and measure their specific values accurately.
- Waste materials may contain only organic matter and no other dirt (e.g., sand, metals, clay).
- Organic matter is expected to produce CO_2 or CH_4 which can be measured with gas sensors (Wang et al., 2021).
- Organic matter is also presumed to have a higher humidity level compared to clean materials (Das et al., 2021).
- The laser sensor is capable of distinguishing between 2D and 3D materials (Kroell et al., 2021).
- Waste items belonging to the same group are considered to be made of the same material.
- The camera detects the presence of waste material and takes a photo promptly.
- The mechanical force or air nozzle pushes the waste successfully into the designated bin.

Different sensors have already been utilised and implemented in some smart waste bins, but there is limited academic literature combining both sensor and camera technology. For the image classification, a new packaging waste data set was created, which was then used for training image identification models. A multi-sensor approach was applied to increase the recovery rates of materials. As the smart separation system in this study employed different sensors, it could be used for separating not only packaging based on their molecular structure, but also based on dirtiness and dimensions. The camera system works as a visual sorter, which can separate waste materials into dirty waste, clean categories, and residuals. This facilitates that the waste fractions, that are sent to recycling facilities, are of higher purity, with less or no contaminants and unwanted materials, thus resulting in a higher recycling purity.

3.1.1. Waste database

The identification and classification of different waste materials was carried out by using different pre-trained CNN models that were then trained on a custom database. Packaging waste in a demonstrative case study (see also Section 5) was classified into 6 categories: food packaging, plastic bottles, plastic cups, plastic bags, Tetra Pak cartons and residual waste (cardboard, metal, glass and paper materials). The custom image database included images that were obtained from Google Images, some images were obtained from other waste databases like TACO (Proença and Simoes,

2020) and TrashNet (Yang and Thung, 2016) and also some images obtained by the authors of the study.

To broaden the database, an additional image augmentation step was developed in PyCharm using Python. There the images were flipped randomly (vertically or horizontally), rotated and resized. Changes in the image contrast were also made, and some were also augmented using a Gaussian blurriness effect. After the augmentation step, the database consisted of 4,786 images of packaging and other waste materials. 902 of these were plastic bottles images, 750 plastic bags images, 804 plastic cups images, 719 images of different food packaging materials and the Tetra Pak carton class consisted of 847 images. The residual waste category, which included paper, cardboard, metal in glass material, was comprised of 764 images. Figure 3 represents some raw images that were used in the training and validation steps.

3.1.2. Waste detection models

The custom waste database was used in the training of 4 pre-trained models: ResNet-50, MobileNet-v2, Inception-v3 and DenseNet-201. ResNet-50 is a CNN network, that comprises of 48 convolutional layers along with 1 MaxPool and 1 Average Pool layer, making it a 50-layer deep network (Bichri et al., 2023). Residual neural networks work on the mechanism of passing the input of some layers as a shortcut directly to other layers. In hindsight, this method helps tackling the vanishing gradient problem, and produces networks that can be trained easily without increasing the trainer error, even if the depth of the network increases (Amelio et al., 2023).

The MobileNet-v2 model belongs to a family of neural networks that are designed to support classification and detection on mobile devices. MobileNet-v2 uses a bottleneck depth-separable convolution with residuals. The first layer is a fully convolution layer with 32 filters, which are followed by 19 residual bottleneck layers (Sandler and Howard, 2018). It was shown that this model uses less operations, needs a fewer number of parameters and is faster on a Google Pixel phone than its predecessor MobileNet-v1 (Sandler and Howard, 2018).

Figure 3: Image waste database for 6 waste classes: food packaging (a), plastic bottles (b), plastic cups (c), plastic bags (d), residual waste (e) and Tetra Pak (f).

Inception-v3 has a total of 42 layers, with a lower error rate than its predecessors, Inception-v2 and Inception-v1. Factorisation into smaller convolutions, utility of auxiliary classifiers and efficient grid size reduction are some of the main improvements of the third inception instalment (Szegedy et al., 2016). It comprises of 3 main parts: a basic convolutional block, a classifier, and an improved Inception model, in which multi-scale convolutions are conducted in parallel with the convolutional results of each branch being concatenated further. This new model also uses a 1x1 convolutional kernel widely, which reduces the number of feature channels and speeds-up the training process (Lin et al., 2019).

Of the used models, DenseNet-201 comprises of the largest number of layers, 201. Its architecture was proposed to improve the design of the residual neural networks. Here each layer takes input from all the previous layers, and passes its own feature-maps to all subsequent layers. Mitigating the vanishing gradient problems, strengthening feature propagation and reducing the number of parameters are some of its advantages (Djouima et al., 2022).

For waste classification, the Deep Learning Toolbox™ in MatLab was used, which is comprised of all the pre-trained models. All the models were first trained on ImageNet and used the same image input size (224x224), except for the Inception-v3 model which requires images of size 229x229 (Ujawe et al., 2023). The last 3 layers (a fully connected layer, a SoftMax layer, and a classification layer) of the pre-trained CNN models were changed from 1000 to 6, to reflect the different waste classes. After that, all the models were retrained using the developed database, with an 80:20 split for training and validation. This means that 80 % of the images from each category were used for the retraining of the models, while 20 % were used for validation. The training was carried out using a batch size of 64, with 30 epochs and an initial learning rate of 0.01 using the stochastic gradient descent with momentum (sgdm) solver. As the DenseNet-201 model requires lot of memory, the batch size was lowered from 64 to 32. The validation was carried out every 50 iterations. After 9 epochs, the training of all models was stopped manually, due to the fact that the validation accuracy had not increased significantly in the last three epochs. Inception-v3 offered the highest validation accuracy of 97.91 %, followed by ResNet-50 (97.16 %), MobileNet-v2 (94.36 %) and DensNet-201 (91.85 %). As the depth of the latter model is the highest, it required the longest training and learning times. The training time of DensNet-201 was 996 min, Inception-v3 required 759 min for training, while both ResNet-50 and MobileNet-v2 had quicker training times, 471 and 315 min.

4. Mathematical model

As stated previously, the proposed simple conceptual model combines 6 different sensors ($s \in S$), a camera ($c \in C$), and 7 potential bins ($b \in B$). Eq. (1) represents the main objective of the model which considers both sensor and camera separation. Based on the sensor results, the model minimised the number of single-use waste items that would end up in the residual waste bin (bin-7) and dirty bin (bin-3). Additionally, the number of placements recognised by the camera wrongly (NWP) were minimised. Here, both the sensor and camera results have associated weights (a) and ($a - 1$), which are defined as positive variables. In Eq. (2) the variable $y_{p,b}$, represents the connection between the plastic packaging ($p \in P$) and the waste bin, which is described as a weighted sum of connections, obtained from the sensors ($y^s_{p,b}$) and camera ($y^c_{p,b}$), both being defined as binary variables. For sensor sorting, the sensor information of each plastic packaging ($x_{p,s}$) must lie in-between the defined upper ($z^{\mathrm{UB}}_{b,s}$) and lower ($z^{\mathrm{LB}}_{b,s}$) bounds of the sensors for each bin. This is described in Eq. (3) and Eq. (4). Eq. (5) represents the camera sorting, where the camera information ($x_{p,c}$) sends plastic and non-plastic items into specific bins dedicated to the type of plastics, excluding their cleanliness and other data ($z_{p,b}$) and is multiplied by the binary variable $y^c_{p,b}$.

Due to the different factors that will be discussed in the following chapters, the identification and classification of waste using sensors and a camera in combination with deep learning models, is not always correct. This is reflected in Eq. (6), where the number of incorrectly identified placements using the camera data (NWP) is described as the sum of the number of plastic packaging items, that were not recognised correctly by the model, and were therefore placed into the wrong bin. To ensure a proper separation of waste, each item must land into one specific bin. This is described with Eq. (7) for sensor-based sorting and Eq. (8) for camera-based sorting. The $y_{p,b}$ variable in Eq. (9) is a positive variable with an upper bound equal to 1.

$$\min\left(\sum_{p\in P}\left(y_{p,b7} + y_{p,b3}\right)\cdot a + NWP\cdot(1-a)\right), \qquad b7 \in \{\text{bin}-7\} \wedge b3 \in \{\text{bin}-3\} \tag{1}$$

$$y_{p,b} = a\cdot y^s_{p,b} + (1-a)\cdot y^c_{p,b}, \qquad y^s_{p,b} \in \{0,1\}, y^c_{p,b} \in \{0,1\}, \forall p \in P, b \in B \tag{2}$$

$$x_{p,s} \le \sum_{b\in B} z^{\mathrm{UB}}_{b,s}\cdot y^s_{p,b}, \qquad \forall p \in P, s \in S \tag{3}$$

$$x_{p,s} \ge \sum_{b\in B} z^{\mathrm{LB}}_{b,s}\cdot y^s_{p,b}, \qquad \forall p \in P, s \in S \tag{4}$$

$$x_{p,c} = \sum_{b\in B} z_{p,b}\cdot y^c_{p,b}, \qquad \forall p \in P, c \in C \tag{5}$$

$$NWP = \sum_{\forall p\in P, b\in B \wedge z_{p,b}=0} y^c_{p,b} \tag{6}$$

$$\sum_{b\in B} y^s_{p,b} = 1, \qquad \forall p \in P \tag{7}$$

$$\sum_{b\in B} y^c_{p,b} = 1, \qquad \forall p \in P \tag{8}$$

$$\sum_{b\in B} y_{p,b} = 1, \qquad \forall p \in P \tag{9}$$

The CNN models and the described simplified model, that was developed in the GAMS environment, were running on a 64-bit operating system, with an Intel® Xeon I Silver 4212 CPU @ 2.20 GHz and 2.19 GHz processor and 10.2 GB of installed RAM.

Two different scenarios were considered in the study. The first scenario included the separation of single-use packaging materials using solely sensor technology, which was achieved when the weighted variable α was set at 0. The second scenario describes the segregation of packaging materials using only image recognition with the use of a camera. This was achieved when the weighted variable α was set at 1.

5. Case study of plastic packaging waste

In this case study, 60 items of 6 different types of waste items labelled from A to G were separated using the described model. The waste consisted mainly of single-use plastic packaging materials with other waste types, such as glass, metal, paper, and cardboard. Items A and B consisted of plastic bottles, item C of plastic cups, item D of plastic bags, item E of Tetra Pak cartons, and item F of different food packaging. The non-plastic items were categorised as residual waste and labelled as class G. The number of single-use plastic packaging items were the following. Classes A and B contained 5 items each, while the other classes (C, D, E and F) contained 10 items each. The segregation of waste materials into specific waste categories was performed using different sensors and CNN classification models in combination with a camera.

For the sensor-based separation, humidity, temperature, gas, NIR, and laser profile sensors were used to gather information on the disposal of materials. The differentiation of different plastic types that constitute single-use plastic packaging was conducted using an NIR sensor. The identification and separation of plastic by its type was carried out using relative reflectance (RR), by applying a method described in the literature (Masoumi et al., 2012). The RR values were obtained as a calculation at two different wavelengths by dividing the reflectance value at 1656 nm with the values obtained at 1724 nm. For residual waste, the RR values differed greatly, because this category included materials with very different optical properties.

Humidity and gas sensors (carbon dioxide and methane sensors) were used to differentiate the packaging waste that may still contain some organic matter. The results of those sensors represent the deviation of the values obtained in the chamber at the time of the reading. Lastly, a laser profile sensor was used to determine if the waste item that was put in the chamber was 2D or 3D. The readings were represented as binary values, where 1 denotes the presence of a 3D object, whereas 0 denotes the presence of a 2D object.

To ensure more realistic separation of packaging waste, the sensor data were generated randomly using different distribution functions. The RR, humidity, and dimension values used Gaussian distribution, while the carbon dioxide and methane values used the Cauchy distribution. The latter distribution is used in the case of gas values, because it has a narrower peak which spreads out more slowly in comparison to the Gaussian distribution. This offers a greater probability of lower deviation values, as not all organic matter produces those gases. A log-normal distribution was used for the temperature values.

The separation and segregation of waste were carried out using 7 potential bins. Each bin was connected to a certain plastic type, one bin being reserved for mixed plastics (bin-1), several bins for specific plastic types (PP, PVC, LDPE; bin-2, 4, 5), one bin for waste that still contained residual organic materials (bin-3), one bin for Tetra Pak cartons (bin-6), and one was being used for the waste that was not selected by the model to be placed in any other bin (bin-7). The individual characteristics of the bins are also presented in Table 2.

The sensor-based separation is assumed to work based on specified lower and upper bounds of information for each bin as presented in Table 2. If the value lies in between the defined values of a bin, that item will end up in that bin. The sensors bounds are significantly different for bin-3 and bin-7, which are reserved for packaging that still contains food or drinks (dirty packaging) and residual waste. The RR ranges for bins were also different, as they depend on the type of plastics, that correlate to specific bins and were taken from the literature (Masoumi et al., 2012).

Table 2: Bin description and their upper and lower bounds for each sensor.

	Bounds	**Bin-1**	**Bin-2**	**Bin-3**	**Bin-4**	**Bin-5**	**Bin-6**	**Bin-7**
Bin description		Mixed plastics (mostly PET)	PP plastics	Dirty plastics	PVC plastics	LDPE plastics	Tetra Pak packaging	Residual waste
RR	lower	0	2.60	0	1.20	4.70	4.70	0
	upper	0.80	4.30	l.n**	1.70	6.00	6.00	l.n**
Humidity*	lower	0	0	0	0	0	0	0
	upper	0.15	0.15	1	0.15	0.15	0.15	0.2
Temperature* (°C)	lower	10	10	10	10	10	10	0
	upper	25	25	40	25	25	25	30
CO_2* (ppm)	lower	0	0	0	0	0	0	0
	upper	20	20	l.n**	20	20	20	50
CH_4* (ppm)	lower	0	0	0	0	0	0	0
	upper	20	20	l.n**	20	20	20	50
Dimension	lower	1	0	0	0	1	0	0
	upper	1	1	1	1	1	1	1

*Deviation **l.n.- large number

The camera-based separation works based on the bin location for every waste category, where items A and B could both end up in bin-1, items C and F in bin-2, bin-6 could only contain items E, items from class D could either go into bin-4 or bin-5, and items from class G could only end up in bin-7.

5.1. Sensor-based separation results

In this scenario, plastic packaging materials and other mixed waste items were separated with the help of sensor technology. Table 3 shows the number of waste items obtained for each specific bin. The results show that bin-3, which was reserved for packaging material that may still contain residual food or other organic materials, was the end destination of most of the materials. Because of the defined relatively small intervals between the lower and upper bounds for each sensor and each bin, the randomly generated sensor values could exceed those predefined intervals. This is true mainly for the sensors that are used to detect and separate packaging materials based on their cleanliness, e.g., humidity, CO_2 and CH_4 sensor. As bin-3 and bin-7 were the only bins that did not separate and segregate packaging materials based on the type of plastics, they could be the end destination for all the items (A-G), if the other criteria were not being met.

Table 3: Sensor-based separation results.

Set of random values	**Number of waste items in bins**						
	Bin-1	Bin-2	Bin-3	Bin-4	Bin-5	Bin-6	Bin-7
	Mixed plastics (mostly PET)	PP plastics	Dirty plastics	PVC plastics	LDPE plastics	Tetra Pak packaging	Residual waste
1	5	15	15	1	0	23	1
2	6	14	21	0	0	18	1
3	6	15	24	1	0	14	0
4	2	11	24	0	0	18	5
5	6	12	22	1	0	18	1
6	5	14	24	1	0	16	0
7	3	13	24	1	0	18	1
8	4	12	32	1	0	11	0
9	6	15	24	1	0	14	0
10	6	17	24	0	0	13	0

The next observation that can be obtained from the results is the connection between bin-5 and bin-6, as they differed in just the lower dimension bound. The higher number of items in bin-6 can be explained by the randomisation of items sensors values, as most of them that would otherwise be fitted for bin-5 have either an increased values of temperature, humidity, gas or dimension, which could lead the model to rather choose bin-3, or even bin-6, to be the end destination, rather than bin-5. The maximum number of items that ended in bin-4, was 1, which indicates that only one items contained the necessary values that would allow the model to choose bin-4 as the end destination.

Over the course of 10 sets of random values, the number of items in bin-7 did not exceed 1, with the exception of the 4th set, where the number of items was 5. Even though the model minimised the number of items that ended up in the residual and dirty waste bins, the exactness of the results was not achieved. Plastic packaging waste also includes non-plastic waste materials (items G), which should be placed in bin-7 and not in bin-3, as is indicated in the results. This anomaly can be explained with the randomisation of sensor values related mainly to the humidity and gas sensors.

5.2. Camera-based separation results

In this scenario the prediction accuracies of the CNN models were firstly evaluated, and are presented in Table 4. The models were tested using 94 different images that contained items of the 6 defined classes. The CNN networks were evaluated and compared by their probability of correct classification. The average accuracy of the models was lower, as it is presented and advised in various literature sources, also those classifying plastic waste (Agarwal et al., 2020). The highest average probability for correct classification of waste items was 78.34 %, which was achieved with Inception-v3. The second-best probability result was obtained using MobileNet-v2, which had already resulted in a probability lower than 70 %. The models ResNet-50 and DensNet-201 achieved probability values slightly higher than 60 %. A comparison between the probability result of the Inception-v3 model with others resulted in an overall higher accuracy for all waste classes, with the exception for residual waste. The latter value was the lowest recorded value in this category.

Table 4: CNN model classification results

Model	**Classes**						**Average**
	Food packaging	Plastic bag	Plastic bottle	Plastic cup	Residual waste	Tetra Pak cartons	
DensNet-201	41.67 %	66.67 %	81.82 %	60 %	66.69 %	58.82 %	62.61 %
Inception-v3	80 %	83.33 %	72.73 %	93.33 %	52.38 %	88.24 %	78.34 %
MobileNet-v2	42.86 %	72.22 %	81.82 %	93.33 %	57.14 %	52.94 %	66.72 %
ResNet-50	46.15 %	66.67 %	72.73 %	80 %	57.14 %	58.82 %	63.59 %

From the results in Table 4 the class of plastic bottles and plastic cups has the highest probabilities of correct classification overall. This indicates that the retrained models are suited for identification of those waste types. On the other hand, Tetra Pak cartons and food packaging are the classes for which the models had the most difficulties in determining correct classification, except for the model Inception-v3. With this exception, the average correct classification of food packaging materials was 43.56 %, and 56.86 % for Tetra Pak cartons. The low probability values for the food packaging class might be due to its data size, as this class contains the lowest number of images. Also, there is no uniformity with the packaging materials, as they differed in size, shapes and colours. As Inception-v3 yielded the overall best classification results, this model was used in the camera-based separation model.

After choosing the best performing CNN model, its predictions were then used for the camera-based sorting. The model was run with 10 sets of random values. The number of items landed in specific bins and the number of incorrectly placed items were obtained for each set. Table 5 shows the results for the camera-based sorting.

Table 5: Camera-based separation results.

Set of random values	**Number of items in bins**							**NWP**
	Bin-1	Bin-2	Bin-3	Bin-4	Bin-5	Bin-6	Bin-7	
	Mixed plastics (mostly PET)	PP plastics	Dirty plastics	PVC plastics	LDPE plastic s	Tetra Pak packaging	Residual waste	
1	19	19	0	8	0	10	4	11
2	15	22	0	8	0	8	7	9
3	16	20	0	9	0	10	5	6
4	17	20	0	6	3	8	6	12
5	18	18	0	10	0	9	5	10
6	16	18	0	9	0	10	7	6
7	25	14	0	7	0	9	5	17
8	19	18	0	6	3	9	5	12
9	17	19	0	0	10	9	5	12
10	18	19	0	8	0	10	5	12

For the majority of runs with sets of random values, the number of items in bin-2 are high, with a median value of 19 items. This could be explained, as two categories of single-use packaging items could land into this bin (items C and F). Category C (plastic cups) had a high probability for correct identification using the CNN model. Thus, all the items were identified correctly and put in the dedicated bin. However, this does not true for item F (food packaging), as the prediction accuracies were lower. This resulted in incorrect identification of items F, where some items landed in the wrong bin.

The number of items that ended up in bin-6 (Tetra Pak packaging) was relatively consistent with every set of random values. This is because bin-6 was reserved for Tetra Pak cartons (items E), which have a high probability for being identified correctly. The results for the number of items for the mixed plastics (mostly PET, bin-1) indicate that this bin also contained non-PET plastic items. Only 10 items in the case study were defined as being mainly from PET plastics. The higher number of items which landed in bin-1 is due to other items being identified incorrectly. Significant differences occurred in the number of items which landed in bin-4 and bin-5 between the runs, as the camera was not able to recognise different plastic types well.

In residual waste bin (bin-7) the number of waste items was similar for all sets of random values, with an average value of 5 items. Overall, the model placed up to 17 items incorrectly, depending on the randomised values. The biggest limitation of plastic waste separation using solely DL and a camera in this study was that there was a connection missing between waste items and bin-3 (dirty items). Thus, the model did not choose bin-3 to be a specific end destination.

6. Strengths and limitations of the study

Even though the simple model proposed in the study separated some of the plastic packaging items successfully, the separation was not accurate, and the results are not fully reliable. This chapter firstly presents and discusses the strengths of the study, and, further, some of the identified limitations related to the sorting system and the developed model.

6.1. Strengths of proposed smart waste separation system

The proposed smart waste design exhibits several potential positive aspects for people, the economy and the environment. The primary objective of the proposed smart waste separation system is to increase the amount of plastic packaging that is recycled, thereby generating higher-quality secondary raw materials, instead of resorting plastic waste to incineration or disposal. To achieve the highest quality of recyclables, quality requirements should be considered for the input materials throughout the entire recycling process. This is essential, as contamination usually limits the functionality and usability of the recycled materials. Additionally, the presence of impurities can impact both the costs associated with investments and the revenues obtained from selling the recycled materials (Roosen et al., 2022). The more diverse the feedstock is, the more challenging it becomes for MRFs to achieve higher levels of purity in the sorted fractions.

According to the findings of the study (Lase et al., 2022), incorporating an additional sorting step before the recycling process can affect the quality of output materials significantly. The recycling rate of packaging materials may remain constant, however, the purity of the materials is improved (Lase et al., 2022). This is a crucial observation, as the quality of the recycled materials determines their potential future applications. Contaminants can hinder their use, while, if impurities are not present, recycled material could also be employed in, e.g. food grade plastic packaging, thus adapting a closed-loop recycling scheme (Gerassimidou et al., 2022). The high quality recyclates can thus reduce the amount of virgin plastic in the material blends (Radhakrishnan et al., 2020) and its related environmental footprint. For example 1.2 t CO_2 are saved per t of mechanically-recycled plastics as compared to the use of virgin plastics (Fellner and Brunner, 2022).

A study by (Roosen et al., 2022) demonstrated that implementing additional collection policies, such as the separate P+MD (all post-consumer plastic packaging, metallic packaging and drinking cartons) collection system used in Belgium, led to an increase in the average net recovery rate of plastic packaging from 29.2 % to 49.7 %. Specifically, the system resulted in a recovery rate of up to 41.8 % for PP material, while the recovery rate for PET bottles remained almost unchanged. By implementing the approach proposed in this study for the separation of plastic packaging materials (however, improved further to enable more precise separation), better quality of plastic recyclates could, potentially, also be achieved.

Another potential advantageous aspect of this model is the reduced water requirements in the recycling process. A typical recycling procedure involves sorting, shredding, washing, drying and material extrusion. However, in certain cases where post-consumer waste is shredded, certain regrinds or agglomerates can be processed without washing (Shen and Worrell, 2014). However, washing could not be eliminated completely, as many waste materials still contain some impurities. Surface dirt, bottle labels, caps, or residual content can affect the end quality of materials adversely (Feil and Pretz, 2020). Nevertheless, the amount of water required to operate the recycling plant can be reduced by reducing water-intensive separation techniques like sink-and-float separation (Larrain et al., 2021). Since the smart waste system in this study can also separate materials based on their physical and chemical properties, theoretically, it allows for a reduction in the use of wet separation processes, thereby saving water and the energy required for wastewater treatment.

Additionally, the separation process in this study has the capability to distinguish materials based on their dimensions. For instance, it can separate 2D materials like plastic bags or plastic films effectively from 3D materials. Previous surveys on various mechanical recycling facilities (Lubongo and Alexandridis, 2022) revealed that the separation of lightweight plastic foils was challenging, as they often interfere with the sorting equipment. The separation system in this study may handle such materials, thus, it could potentially lead to enhanced recyclability of other fractions.

6.2. Limitations of sensor-based sorting

Some of the major parameters that could affect the sensor readings and the obtained separation results are the colour and reshaping of the plastic packaging materials, mixing of different plastic types embedded in a single packaging, the presence of less volatile waste, etc. In the sensor-based separation, the segregation of different single-use plastic packaging types works primarily based on the chemical differences of the mentioned plastic types. These differences are determined based on their characteristic spectra, which are obtained by the light that is reflected from the object when using an NIR laser sensor. This method is useful for clear and light plastic materials, but is not suitable for black or dark coloured plastics, as those types absorb the projected light (Wu et al., 2020). Correlating this to the case study, more dark-coloured clean plastic items would end up either in the residual waste bin (bin-7) or in the bin for mixed plastic (bin-1) because of their defined bounds of RR values. Bin-7 has a wide RR range, but the RR range for bin-1 is smaller, with comparably lower RR values. Because of the small reflectance intensity of black and dark plastics, the calculated RR value would be smaller, and the materials could end up in bin-1.

Another problem that could occur is that the single-use packaging could contain different types of plastics. For example, PET bottles could still contain the PP label and/or HDPE cap, which might affect the obtained readings. This problem was investigated previously (Masoumi et al., 2012) where different plastic types (PET, HDPE, soft and hard PP, PVC and PS) were separated using NIR spectra. In their research, the influence of labels and caps on plastic bottles has also been investigated, mainly regarding the obtained RR readings. The results depicted that, if the label covers more than 35 % and the cap more than 50 % of the PET bottle surface, invalid results would be obtained. The coverage of labels and caps are, in real-life situations, lower, and the authors concluded that those items would not interfere with the final readings of the PET bottles. In this study, these observations were considered, which resulted in most bottles with or without caps/labels ending up in bin-1, which is reserved for (mainly) PET materials. Because it is hard to separate different plastic types that form single-use packaging (e.g., bottles with caps, Tetra Paks with caps, plastic bags with stickers), they should go through different processes in waste treatment plants to reach the desired separation (Zawadiak et al., 2017).

A further concern with the proposed method is the separation of clean plastic packaging from the ones that still contain organic waste. The simple conceptual model proposed in this study separates these materials based on the differences in the humidity and concentration of the present gases. However, this separation assumes that organic matter produces CO_2 and/or CH_4 gases. If the waste is still fresh or comparatively dry, the gas concentration is lower than the threshold level for the organic waste bin (bin-3), which means that the plastic item would end up in the bins for clean plastics. The residual food or drink could also be trapped in the packaging, e.g., a closed juice bottle or closed plastic bag, where the sensors could not detect the gases which are present. This leads to improper waste separation and could impact the recycling process. If the disposed packaging contains dry food (e.g., spices), the humidity reading would not be a suitable indicator. In these cases, only a temperature reading remains to be used to separate packaging that may still contain food or drink from clean ones. This will not suffice, as even clean items could have lower or higher temperature readings. The lower temperature reading could be due to the food (packaging) being frozen or refrigerated before being disposed of, while the degradation of organic material may not increase its temperature.

Another concern that the model may not address properly is the entanglement of different waste packaging together. If, for example, a PET bottle is placed into a PVC plastic bag, the NIR sensor might detect the plastic waste items improperly. The sensors would separate the bottle-bag combination based on the NIR reading of the PVC bag, thus combined waste might land into bin-4 (reserved for PVC plastics). However, this separation would not be appropriate, as those two plastic materials cannot be recycled together. This means that an additional separation step will need to be introduced in the recycling process, which, if not successful, would lead to a decrease in the purity of the recycled material.

The detection and identification of waste is also determined by the shape of the item that is put into the chamber of the proposed smart waste separation system. If a 2D object is reformed to a 3D object, or vice versa, if a 3D object is flattened into a 2D object, the profile sensor would identify the object wrongly. For example, a flattened milk carton would be considered a 2D object, which would cause the model to select bin-5 instead of bin-6. This would lead to improper packaging segregation, as the recycling process of Tetra Pak materials is different from that of LDPE materials. A single sensor is thus insufficient to achieve a high accuracy separation for circular plastic utilisation.

6.3. Limitations of camera-based sorting

For the camera-based separation the main challenges lie with the training and accuracy of the CNN models that are used for classifying the waste into the desired categories. The median accuracy of all the used models was only 67.82 %, with only one model (Inception-v3) having an accuracy greater than 70 %. This relatively low accuracy, compared to the accuracy of other DL models in the waste management field, could be due to many factors, one of them being the size of the image database. Other factors that can affect the accuracy of the CNN model are some of the parameters that are related to the retraining of the image identification models. While training the models, caution must be implemented not to achieve underfitting or overfitting. The latter could occur in the case of a smaller database, as images repeat more frequently as compared to a larger database. This means that the model can memorise some of the training examples instead of learning, thus resulting in high training accuracy. When a new image is then introduced, the model has difficulties in the classification, which can result in an improper categorisation and waste segregation (Joshi et al., 2019).

Another problem with the camera-based separation is the difficulty of separating plastic packaging waste based on the type of polymer. Plastic packaging items of the same category, e.g. food packaging or plastic bottles, can be constructed from different plastics, depending on their use. Plastic cups, for example, are usually made from PP (Szaky, 2014) and PS (Siddiqui et al., 2008) but can also be made from PET, polylactic acid (PLA) (Flow Mold, 2022) and others. This means that those plastic cups cannot be recycled together, thus resulting in additional segregation steps. The initial assumptions in the development of the model was that the camera captures individual waste items that are not clustered together. Thus, the used CNN models were not trained to identify the single-use plastic categories in clustered and grouped materials.

The camera-based separation system separated plastic waste only into 6 categories, and not 7 as in the case of sensor-based segregation. The camera-based separation of plastic packaging materials was not based on purity. This was due mainly to the difficulties of obtaining enough data that could compete and be compared to other waste classes. Therefore, one of the main limitations of the camera-based separation lies in the separation and segregation of plastic packaging materials based on their cleanliness.

6.4. Model limitations

As mentioned above, both sensor- and camera-based separations work based on capturing packaging waste on a one-by-one basis rather than identifying and classifying a cluster or a group of waste items. This presents a limitation, as most packaging waste when disposed of is somehow intertwined into a cluster. This means that an additional separation step would need to be included to separate those grouped items further into single ones. Another challenge lies in the entrapment of wastes into one another, such as different packaging items in plastic bags. To achieve correct and reliable sensor readings and CNN outputs, the waste should not be trapped. This would result in an additional separating step, similar as for separating clustered items.

As described above, both models have some limitations that hinders the efficient separation of packaging waste. Colour plays a major role in the sensor-based separation, as black plastics present a challenge for correct sorting (Becker et al., 2017). Accurate sorting of plastic waste materials based on their cleanliness represents another challenge, especially for camera-based sorting. As both models (and sorting approaches) have strengths and limitations, it would be desirable to integrate them, to produce a model that enables efficient and accurate segregation of plastic packaging waste materials using both technologies simultaneously.

7. Conclusions

To combat the increased waste accumulation that arises from the overconsumption of products, an efficient and cautious waste sorting system would be desired. Its goals are to reduce the amounts of waste, conserve resources, and to provide high-quality recycled materials suitable for use in various product applications, thereby enabling a more circular economy. As high-quality recyclable materials require precise separation of waste, automated systems based on sensors and/or cameras have been proposed, to be used either at source as smart waste bins or as a central post-sorting in MRFs. The proposed model considers different sensor technologies and a camera for separation of single-use plastic packaging items based on plastic types (PET, PVC, LDPE, PP, and Tetra Pak) and their cleanliness.

Improved technologies for collection, sorting, and recycling the plastics will be needed to enhance the circularity of plastic materials. For post-consumer plastic packaging waste, collection and recycling systems are still less developed compared to paper, glass or metal packaging (Brouwer et al., 2019). Sorting technologies usually do not handle great variability in plastic materials accurately, and, with the impurities present, it may cause pre- and post-use contamination. Landing of plastic waste items in the wrong bin can be attributed to different factors, such as the presence of dark or black coloured materials, the reshaping of the packaging material before the disposal, mixing of different plastic types that may constitute single-use packaging, the presence of residual non-volatile organic matter in the disposed of plastic packaging, and others. The misclassification of packaging materials may result in contamination within containers dedicated to specific polymer types (PET, PP, PVC, HDPE). In these cases, contaminants (misclassified plastics, additives, etc.) affect the quality of the recyclates adversely by reducing their purity. Consequently, the secondary raw materials derived from recycling centres might be transformed into items that are unsuitable for certain applications, such as food contact materials.

The results of the study show that perfect separation was still not achieved. The investigation of the smart separation system based on sensors showed that it has a superior sorting efficiency based on waste composition, whereas the separation system based on camera could outperform sensors in certain areas, such as in determining colours and entanglement. To account for different problems that may occur during the separation, the proposed conceptual model should be upgraded and developed further, to ensure more precise separation. The proposed waste sorting system can be improved further by adding different sensors, providing the real sensor readings, testing the method by conducting experimental research and improving the accuracy of CNN models, which may identify and separate the single-use plastics more precisely. To improve classification accuracy for camera-based separation from the current 78.3 % and less, the two main areas of improvement are: i) Increasing the number of images in the database to enhance the training process, and ii) Narrowing down some of the categories to make them more homogeneous, especially the residual waste category. The upgrading of the smart separation system at source could also occur with the addition of motion and fullness sensors to automate the disposal of waste fully and to prevent the overflowing of trash bins.

As both sensor and camera sorting have some advantages and drawbacks as discussed, a combined approach using both methods could lead to a more precise waste segregation of plastic packaging items. Thus, the investigation of a combined smart separation system is under way, and it is expected that it would lower the amount of packaging materials that would be disposed of in the environment, as it would be collected and transformed to form a new product. Improved plastic waste separation is, thus, expected to lead to reduced demand for virgin plastic materials and the related environmental footprints, but at a price. It is expected that some fractions would require more frequent collection, potentially leading to an increase in transport emissions and cost. A trade-off analysis could define the most sustainable fractions of recycled plastic materials and their shares, to minimise the net environmental footprint.

In addition to segregation, sustainable waste management chains require ongoing research and innovations to develop workable and effective solutions for waste collection systems, waste prevention and end-of-life of products. Modelling of potential improvements in waste collection could be incorporated, such as a waste collection tariff structure and transport of waste involving routing, network flow or facility location approach (Adeleke and Olukanni, 2020). An important research field is also the development of projections identifying future trends in material use and waste production offering valuable tools for forecasting trends in used/produced material quantities.

Ongoing research might be widened beyond these model extensions to include other sustainable solutions, such as product redesign opportunities for easier recycling and advanced treatment, various valorisation processes of waste streams and production of renewable products (bioplastics, e-fuels, etc.). Other than enhancing the relatively mature technologies (anaerobic digestion, incineration, mechanical recycling) for waste handling, advanced solutions could be explored such as hydrothermal treatment (Čolnik et al., 2021) and waste to hydrogen (Hren et al., 2023). A key to more sustainable waste management and transition to a circular and low-carbon economy is also to make products that are sustainable by design, prioritising renewable inputs, maximising product use and recovery of products from waste (Ghisellini et al., 2016). One such example to consider is sound management of solar panels' end-of-life, which is gradually becoming an important environmental issue (Chowdhury et al., 2020). Finally, an evaluation of the economic, environmental and social footprint of the advanced waste management system is required, to address trade-offs potentially leading to circular economy rebound and raw material scarcity (Xie et al., 2023).

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Nomenclature

Abbreviations

ABS	Acrylonitrile butadiene styrene
ABS/PC	Acrylonitrile butadiene styrene/polycarbonate
AI	Artificial Intelligence
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial neural networks
CNN	Convolutional neural network
D	Dimensionality (2D or 3D)

DL	Deep learning
DT	Decision tree
EC	European Commission
EU	European Union
GAMS	General Algebraic Modelling System
HDPE	High-density polyethylene
IoT	Internet of Things
KNN	K-nearest neighbor
LDPE	Low-density polyethylene
MINLP	Mixed integer nonlinear programming
ML	Machine learning
MRF	Material Recovery Facility
NIR	Near-infrared
OECD	Organisation for Economic Co-operation and Development
P+MD	All post-consumer plastic packaging, metallic packaging and drinking cartons
PC	Polycarbonate
PE	Polyethylene
PET	Polyethylene terephthalate
PLA	Polylactic acid
PP	Polypropylene
PS	Polystyrene
PVC	Polyvinyl chloride
RGB	Red, green and blue
RR	Relative reflectance
SVM	Support vector machine

Sets

P Plastic packaging waste with elements $p \in P$

B Waste bin with elements $b \in B$

C Camera with elements $c \in C$

S Sensor with elements $s \in S$

Subsets

$PA(P)$ Plastic bottles (smaller) as waste classes with items $pa \in PA \subseteq P$

$PB(P)$ Plastic bottles (larger) as waste classes with items $pb \in PB \subseteq P$

$PC(P)$ Plastic cups as waste classes with items $pc \in PC \subseteq P$

$PD(P)$ Plastic bags as waste classes with items $pd \in PD \subseteq P$

$PE(P)$ Tetra Pak cartons as waste classes with items $pe \in PE \subseteq P$

$PF(P)$ Different food packaging as waste classes with items $pf \in PF \subseteq P$

$PG(P)$ Non-plastic items as waste classes with items $pg \in PG \subseteq P$

$b1(B)$ Mixed plastics (mostly PET) with items $b \in \{\text{bin} - 1\} \subseteq B$

$b2(B)$ PP plastics with items $b \in \{\text{bin} - 2\} \subseteq B$

$b3(B)$ Dirty plastics with items $b \in \{\text{bin} - 3\} \subseteq B$

$b4(B)$ PVC plastics with items $b \in \{\text{bin} - 4\} \subseteq B$

$b5(B)$ LDPE plastics with items $b \in \{\text{bin} - 5\} \subseteq B$

$b6(B)$ Tetra Pak packaging with items $b \in \{\text{bin} - 6\} \subseteq B$

$b7(B)$ Residual waste with items $b \in \{\text{bin} - 7\} \subseteq B$

Parameters

$x_{p,c}$ Camera information for each plastic packaging

$x_{p,s}$ Sensor information for each plastic packaging

$z_{b,s}^{\mathrm{UB}}$ Upper bounds of sensor values for each bin

$z_{b,s}^{\mathrm{LB}}$ Lower bounds of sensor values for each bin

$z_{p,b}$ Bin locations for specific plastic packaging types identified by the camera

Variables

a Weight associated with the sensors, $0 \leq a \leq 1$

$1 - a$ Weight associated with the camera, $0 \leq a \leq 1$

NPW Number of placements recognised wrongly by the camera

$y_{p,b}$ Connection between the plastic packaging and the waste bin, $0 \leq y_{p,b} \leq 1$

Binary variables

$y_{p,b}^{s}$ Binary variable used for selection of waste bins based on sensor information

$y_{p,b}^{c}$ Binary variable used for selection of waste bins based on camera information

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- Plastic packaging waste is separated using sensors and deep learning algorithms
- The Separation is based on plastic type and cleanliness
- Inseption-V3 yielded the best classification results (78.34 %)
- Sensors resulted in a better identification of dirty packaging items then camera
- Both methods minimized the number of items in the mixed waste bin

Declaration of interests

☐ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☒ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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