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# Recent Developments in Technology for Sorting Plastic for Recycling: The Emergence of Artificial Intelligence and the Rise of the Robots

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**Abstract:** Plastics recycling is an important component of the circular economy. In mechanical recycling, the recovery of high-quality plastics for subsequent reprocessing requires plastic waste to be first sorted by type, color, and size. In chemical recycling, certain types of plastics should be removed first as they negatively affect the process. Such sortation of plastic objects at Materials Recovery Facilities (MRFs) relies increasingly on automated technology. Critical for any sorting is the proper identification of the plastic type. Spectroscopy is used to this end, increasingly augmented by machine learning (ML) and artificial intelligence (AI). Recent developments in the application of ML/AI in plastics recycling are highlighted here, and the state of the art in the identification and sortation of plastic is presented. Commercial equipment for sorting plastic recyclables is identified from a survey of publicly available information. Automated sorting equipment, ML/AI-based sorters, and robotic sorters currently available on the market are evaluated regarding their sensors, capability to sort certain types of plastics, primary application, throughput, and accuracy. This information reflects the rapid progress achieved in sorting plastics. However, the sortation of film, dark plastics, and plastics comprising multiple types of polymers remains challenging. Improvements and/or new solutions in the automated sorting of plastics are forthcoming.

**Keywords:** polymer; sortation; optical sorter; automation; waste management; recycling; circular economy; sustainability

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## 1. Introduction

The path to resource utilization and circularity passes through the recycling of post-consumer plastics and the reduction in the amounts of plastics landfilled or incinerated. The existing recycling infrastructure cannot manage well the high volume and complexity of the plastic waste generated. Higher throughput and recycling rates of post-consumer plastics can be achieved by increasing the efficiency of sorting. Recycled plastic that is poorly sorted increases reprocessing costs and decreases the value of reprocessed plastics [1].

The recycling of plastics can be achieved via mechanical or chemical processes [2–5]. The mechanical recycling of plastic involves identification, sorting, washing, shredding, and reprocessing of desired types of plastic. All these take place while the solid polymer remains intact. Classification and sortation are key in mechanical recycling, as plastics need to be separated by type and color before reprocessing. Chemical recycling, also called advanced recycling, involves breaking down used plastics into raw materials for fuel, new plastics, or other chemicals [4,6] using chemical processes such as liquefaction, pyrolysis, and gasification [4,7]. Chemical recycling also includes chemolysis, which depolymerizes polymers into monomers, and dissolution/precipitation, which is a solvent-based physical separation of different polymers that does not involve breaking polymer chains [4,8–10]. Pyrolysis is the most common chemical recycling process, but not all plastics are suitable for pyrolysis. For example, the pyrolysis of poly(vinyl chloride) (PVC) is undesirable due to the production of hydrogen chloride (HCl), which causes corrosion to equipment. Similarly, the use of poly(ethylene terephthalate) (PET) in pyrolysis is limited due to the low yield (~50 wt %) and oxygen content, which may lead to combustion. Hence, plastics need to be sorted out for both mechanical and chemical recycling applications [4,11].

Separation of plastic by type is typically performed at Materials Recovery Facilities (MRFs). For recycling purposes, plastics are classified as (1) PET, (2) high-density polyethylene (HDPE), (3) PVC, (4) low-density polyethylene (LDPE), (5) polypropylene (PP), (6) polystyrene (PS), and (7) "other", where the numbers 1, 2, . . ., 7 refer to the Plastic Identification Codes [12]. In principle, all these types of plastics have the potential to be sorted; however, most types of plastic have low or no market value to justify the cost of sorting, the exceptions being PET and HDPE. The "residual" plastic is typically landfilled.

At MRFs, post-consumer plastics are sorted manually by operators and/or mechanically, based on differences in the properties of plastics [13,14]. Separation of plastics by type, color, or shape/size requires specialized equipment such as optical sorters [15–17]. The optimal sorting method depends on the plastic type and product(s) of interest. Sorters of different modality can be combined to improve the sorting efficiency and yield of the desired product [17]. Manual sorting can reduce contamination and improve product quality, but can be relatively costly and slow for high volumes of waste, and potentially dangerous to operators [18,19]. Automated sorting, however, can prove more efficient and cost-effective [18].

Challenges that MRFs face in the sortation of plastic recyclables were identified in a study that our team conducted two years ago [20]. MRFs utilizing manual sorting reported a lower throughput compared to MRFs with automated sorting. For automated MRFs, one of the main challenges are tanglers wrapping around sorting equipment. Films are difficult to sort and typically have high contamination rates. The sortation of black plastics was another challenge identified in this study [20]. The same study compiled and compared information on commercially available automated sorting equipment, thus capturing the progress made in the ten years prior to our study, when similar reports were last published.

The state-of-the-art in technology and equipment for the classification and sortation of plastics is analyzed here. Spectroscopy is primarily used to identify plastics, increasingly augmented by machine learning (ML) and artificial intelligence (AI). The previous report on equipment for sorting plastic [20] dates from over two years ago. In the meantime, the demand for plastics recycling has increased and the recycling technology has advanced. These motivate the present updated inventory of established and emerging sorting equipment and their evaluation regarding their sensors, types of plastics they can sort, primary application, throughput, and accuracy. The information compiled here captures the rapid progress made in recent years that holds promise for positive future developments.

## 2. Spectroscopic Methods for Identification of Plastic Type

Spectroscopy techniques currently used to identify plastic waste in the context of sorting are based on VIS (color analysis), near infrared (NIR), and X-ray fluorescence (XRF) [21–26]. Mid-infrared (MIR) spectroscopy, hyperspectral imaging, and shape recognition show potential for classifying plastics but are not yet deployed in large-scale sorting [27–30]. NIR, XRF, and VIS have different advantages in sorting different types of plastic, as outlined below.

NIR sensors detect variations in the absorption, transmittance, and scattering of light by different materials in infrared wavelengths, which inform on the plastic type [19,31]. NIR intensity can also be influenced by the color, surface texture, and shape of the plastic object [28,32]. Advantages of NIR include high-speed, high penetration depth, and high signal-to-noise ratio [29]. However, NIR is not effective for black plastics, because the black pigment absorbs most light, nor for plastics that incorporate brominated flame retardants (BFRs) [33]. Since the NIR spectra are affected by instrumental noise, baseline drift, and scattered light, preprocessing of spectral data is required for sorting applications [34]. MIR probes the $CH_3$, methylene ($CH_2$), and methine (CH) functional groups and can address some of the drawbacks of NIR, but, at present, standoff measurements are not practical [24,35].

XRF shines primary X-rays onto the plastic object under testing, and measures the fluorescent X-rays emitted at a different wavelengths by the elements present in the plastic [36]. XRF sorters are widely used to classify PVC and plastics containing BFRs [19]. However, their application is typically limited to the removal of PVC contaminant from PET [37,38].

Visible spectrometry works by analyzing the total range of the visible spectrum, thus accurately characterizing all colors. VIS sorts plastics by color [14,39] using a prism-coupled color camera [40] which measures colors (red, green, and blue) based on intensity [40].

Some of the challenges highlighted above can be addressed by combining spectroscopy with machine learning or artificial intelligence [41–43].

## 3. Utilization of Machine Learning or Artificial Intelligence in Plastic Type Identification

To improve the identification accuracy and separation efficiency of plastics, optical detection methods combined with ML/AI are developed and increasingly being deployed [44]. ML is designed to emulate human intelligence by using data to learn from the surrounding environment [45]. Plastics are identified, classified, and sorted based on data captured digitally in real time with sensors or cameras, and then applying algorithms [46]. The classification and detection are done using a combination of sensors and ML algorithms.

ML algorithms can be supervised, unsupervised, semi-supervised, and reinforced [47] (Figure 1). Supervised machine learning algorithms predict an outcome based on previously characterized input data [48,49]. For their learning, supervised models need to be trained with tagged or sorted data [48]. In unsupervised learning, the data input into the model is not presorted or tagged, with no guide to a desired output. Unsupervised models are ideal when used to identify unknown relationships in training data [50,51]. Semi-supervised learning is the combination of supervised and unsupervised learning [51]. The approach employs a limited collection of sorted or tagged training data alongside an extensive compilation of untagged data. The models are used to conduct specific computations to reach the correct outcome. Moreover, the semi-supervised models need to perform the learning and data organization, while they are only given small sets of training data. Semi-supervised models can have better accuracy than supervised and unsupervised models [51]. For waste management applications, supervised learning (classification) and neural network models are often used [48,49], as discussed below.

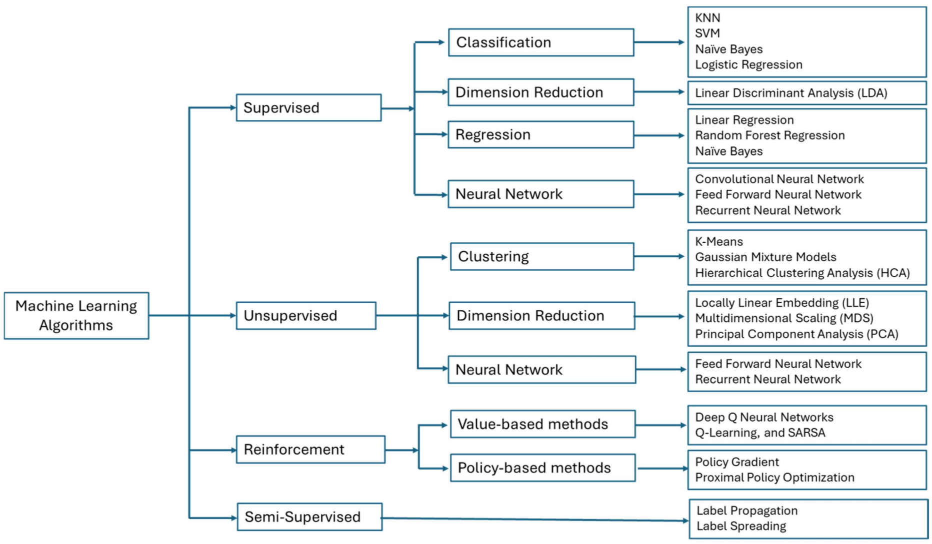


**Figure 1.** Machine learning algorithms used in waste management applications (compiled by the authors from information presented in references [51–58]).

Identification of materials though ML is done in three stages: data processing and feature extraction, selection of machine learning algorithms as classifiers, and testing and performance evaluation [44,59]. The input data are extracted from sensors (e.g., images, spectra), while extraction of features is done through image processing. The spectral data are often pre-processed for baseline corrections and to reduce their dimensionality (e.g., by principal component analysis, PCA), thus helping to reduce the computation time. The classifier transforms the data and, based on these transformations, identifies the optimal boundary between the possible outputs. Performance evaluation selects the best model [59]. Classification models (Classifiers) anticipate or draw conclusions of the input data given for training, and then predicts the class and category for the data. The ML workflow shown in Figure 2 is often utilized for plastic sorting.

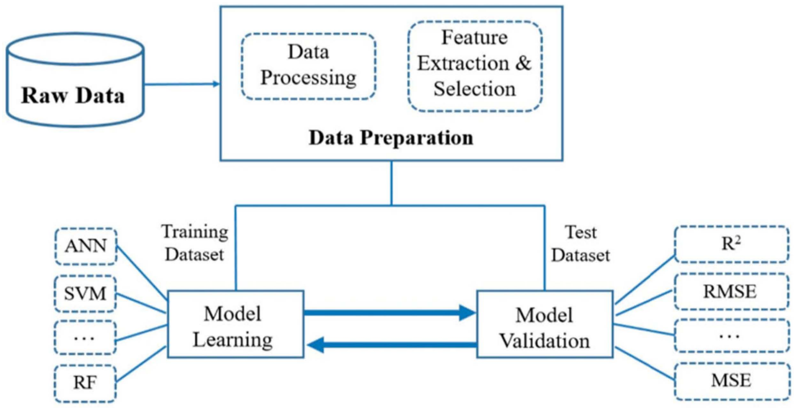


**Figure 2.** Schematic of ML workflow (from [59]; copyright 2022 SAGE Publications, Inc.).

## *3.1. Classifiers*

Several algorithms, such as the adaptive network fuzzy inference system (ANFIS), artificial neural networks (ANNs), decision trees (DTs), support vector machines (SVMs), naive Bayes, k-nearest neighbor (KNN), and random forest (RF) have been used in machine learning and deep learning to classify waste [60]. The classification algorithms (models) that have been utilized in sorting plastic waste are discussed below.

### 3.1.1. Convolutional Neural Networks (CNNs)

Neural networks find many applications in solving a range of problems such as classification and regression [47]. CNN is intended to resemble the human brain. CNN is made up of neurons, which receive input signals and lay out output by measuring the input data with images on many channels. Images go through convolution layers with filters, as indicated in Figure 3 [47,61]. Most calculations are conducted in the convolutional layers. The rectifier function is used by the activation layer to correct the non-linearity of the image, while the pooling layer limits the search of an image on optimal features (e.g., dimension). Afterwards, the assembly is converted into a column by interconnected layers and is transmitted to the neural network for processing. Finally, the activation function sorts the output [61].

CNN is useful in computer vision to extract features in images (e.g., color, size) [27,41,60]. On the basis of differences in the granularity of images, three types of datasets can be identified, resulting in three different approaches: classification, object detection, and segmentation [41]. In classification, the class of an object in an image is determined without providing its location. In object detection, details (categories) and multilabel locations of objects in an image are identified by drawing boundary boxes around them. In segmentation, a pixelwise mask of each object in the image is provided, which facilitates the identification of the shapes of different items [41]. CNN encompasses several variations in architecture (e.g., feed forward networks, deep feed forward). Different CNN architectures are able to extract the features in images layer-by-layer using the information flow from input to output [41].

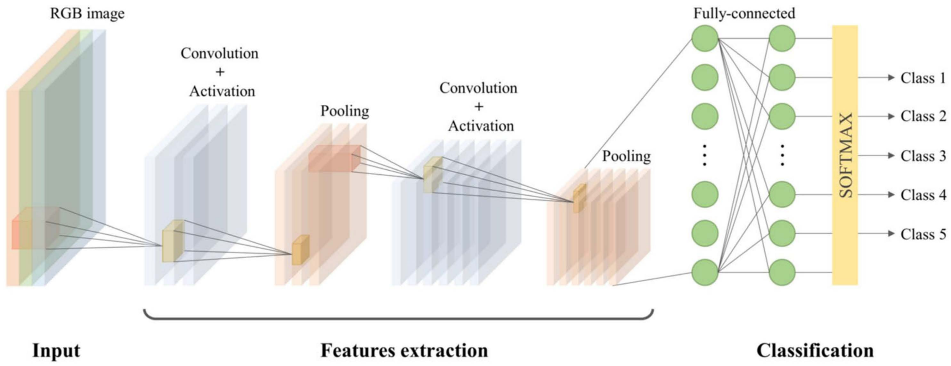


**Figure 3.** Representation of neural networks (from [41]; copyright 2023, Elsevier).

3.1.2. Support Vector Machines (SVMs)

SVMs are non-linear ML algorithms that have been applied to classify the type and shape of plastics [27,62–64]. SVMs construct an ideal boundary within the covariate space (p-dimension) based on the provided samples $(x_1, y_1), \ldots, (x_N, y_N)$ [65]. The input data in SVMs are gathered as points, and these points are classified in a linear manner based on the hyperplane [61]. Furthermore, the algorithm finds or modifies the variables that best fit the hyperplane, and classifies the item being analyzed (e.g., plastic item) into their respective categories. In the SVM classification process, input vectors that are on the hyperplane of the spatial separation belong to one class, and the positions on the other side of the plane belong to a different class [27,61].

3.1.3. Decision Tree Classifier (DTC)

DTC algorithms employ multiple stages to divide data into smaller and less complex sections according to specific criteria [66]. These algorithms are often based on the "if-then-else decision rules", where classifications are conducted in a tree-type structure, with complexity being directly proportional to the depth of the tree. The selection of functions is automatically done with qualitative and quantitative data [61,67]. DTC constructs a hierarchical structure in the form of a tree, where every inner node corresponds to a characteristic or property, while each terminal node represents a classification or group [65]. The algorithm chooses the feature that provides the most useful information at each node [65,68]. When there is an item (e.g., plastic) that requires sorting, it progresses through the decision tree, commencing from the initial node. At each internal node, the algorithm assesses the value of the corresponding characteristic for the plastic input and proceeds along the suitable branch based on the value of that characteristic [65,68]. Once the algorithm arrives at a leaf node, it designates the relevant class or category to the input plastic. The plastic is then assigned the anticipated class or category [65,68]. In decision trees, data points that cannot be separated linearly are mapped to higher dimensional spaces by the DTC algorithm with appropriate kernel functions so that they can be separated into these spaces. Decision tree algorithms have been used to develop prediction models for waste generation [69,70].

3.1.4. Random Forest (RF)

Random forest (RF) classifiers and extra tree classifiers are ensembles of decision trees that are interconnected. In RF classifiers, the input data are subsampled with bootstrap replicas, whereas extra tree classifiers use original data to create subsets of each tree [66]. RF classifiers have been successfully used to classify different plastic materials with accuracies over 98% [66].

3.1.5. k-Nearest Neighbor (KNN)

KNN algorithms use distance measurement methods [53]. When sorting new plastic items, the KNN algorithm measures the disparity (distance) between the plastic being categorized (sorted) and all the plastics data in the training set. These algorithms identify the k nearest samples to the test data and assigns the most prevalent class label from the learning samples [61]. This process employs a method called "majority voting", where the label that garners the highest number of votes is selected as the predicted label for the given plastic input. These classifiers do not make assumptions on how data are distributed, as most data often do not follow a theoretical distribution [53]. KNN algorithms have been used in combination with spectroscopy to classify and sort waste plastics [71,72].

#### 3.1.6. Naive Bayes Classifiers

Naive Bayes classification algorithms utilize the Bayes theorem for probabilistic classification (Equation (1)) [73,74]. The Bayes theorem integrates new evidence (i.e., new data) with previous probabilities of hypotheses to obtain new probabilities for the hypotheses [73]. Through the examination of the input data of a given set parameters or features, denoted as "*B*" in Equation (1), Naive Bayes classifiers can estimate the probability of the input data associated with a particular class, denoted as "*A*" [74].

$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)} \tag{1}$$

Naive Bayes classifiers operate by assuming that classified features are independent of each other, given the class variable [66,73,75]. To perform the classification of input data, an assessment of the probability of it belonging to each of the existing classes is conducted, and the class with the highest probability is then identified as the one to which the input data belongs (Equation (2)).

$$A = argmax_a P(a|b_1,\ \ldots,\ b_n) \tag{2}$$

where $b_1$ is one of the $n$ features or predictors.

The Naive Bayes classifiers have predetermined structures, and during the training phase of the classifier, the class probabilities and conditional probabilities are computed based on the provided training data. Subsequently, the generated probability values are utilized to categorize new observations [76]. This process allows the classifiers to estimate the likelihood of events or outcomes by utilizing conditional probabilities [66,73]. To sort plastic waste, Naive Bayes classifiers can be used by gathering information on different attributes of plastic objects, such as color, shape, size, and composition [77,78]. The collected data are prepared to ensure their reliability, and the classifier is trained on this dataset, acquiring knowledge of conditional probabilities and class probabilities connected to the attributes [78,79]. Subsequently, appropriate attributes are derived from the plastic waste items and utilized as inputs for the trained classifier. The classifier then computes probabilities and decides the most probable class for each item, facilitating the categorization of plastic waste into various groups based on the classification outcomes [73,77–79].

#### 3.1.7. Logistic Regression

Logistic regression algorithms are designed to estimate the likelihood of one of two possible outcomes (classes) and make a definitive prediction based on various input parameters. Test data points are predicted using binary scales that range from zero to one. Points with values exceeding 0.5 are assigned to class 1, while points with values below 0.5 are assigned to class 0 [53,65]. For example, logistic regression can be used to sort clear plastics from colored plastics, given some input parameters. In cases were more than two outcomes or classes are required, multiclass logistic regression can be used [53]. In regression metrics, true targets are compared with their corresponding predictions, where metrics are $R^2$-score, mean absolute error (*MAE*), and root mean square error (*RMSE*) [46]. The closer to 1 $R^2$-score is, the more accurate the model is [46].

#### 3.1.8. You Only Look Once (YOLO)

YOLO integrates image sensors and AI detection algorithms (e.g., Neural networks) to detect and locate objects [80]. YOLO works by applying a neural network to an image, breaks down the image into grid cells, and forecasts the grid cell coordinates into bounding boxes [80,81]. In YOLO, each grid has a corresponding vector in the output that determines if the object is located in that grid cell; if yes, it helps determine the class of the object and the estimated boundary region of the object [81]. Finally, the algorithm generates the final result, which includes the remaining bounding boxes along with their corresponding categories and confidence scores that best fits the items being sorted. The YOLO detection and location of an object is done by looking at the object only once, or a process known as one-stage detection. In a one-stage detector, location and classification of objects are performed at the same time, contrary to a two-stage detector used in algorithms such as a CNN [80]. As a result, a one-stage detector can be computationally efficient compared to a two-stage detector, though less accurate. The YOLO algorithm training allows it to recognize and classify each category, such as plastic bottle, plastic bag, etc. YOLO can be useful in classifying plastics that differ in physical characteristics (e.g., transparency, flexibility) but have similar chemical structure (e.g., PET and PET-G, polyethylene terephthalate glycol) and similar spectra [80]. When sorting plastics with similar chemical compositions, YOLO can reportedly reach an accuracy > 91.7% and mean Average Precision (mAP) much better than traditional optical sorters [80,82].

### *3.2. Performance*

ML classification performance can be measured in terms of accuracy, recall, precision, and *F1-score* [66]. The performance of ML algorithms can be evaluated using these metrics by first splitting the dataset into training and test data, and then comparing the predictions of the trained algorithms for test data to the known target variables of the test dataset [46].

In classification problems, y (true labels or classes of a classification problem) can have two values: "positive" ($P$) and "negative" ($N$). True ($T$) and false ($F$) predictions can be visualized in a $2 \times 2$ confusion matrix as shown in Equation (3) [46].

$$\text{Confusion Matrix} = \begin{bmatrix} TP & FP \\ FN & TN \end{bmatrix} \tag{3}$$

where true positives ($TP$) are the number of samples correctly predicted as "positive", false positives ($FP$) are the number of samples wrongly predicted as "positive", true negatives ($TN$) are the number of samples correctly predicted as "negative", and false negatives ($FN$) are the number of samples wrongly predicted as "negative".

Classification metrics such as accuracy, recall, precision and F1-score can be obtained from $TP$, $FP$, $TN$, and $FN$ as discussed below. Accuracy is a measure of correctly predicted observations among the total observations (Equation (4)). Accuracy computes how many times a model made a correct prediction across the entire dataset. Accuracy is often useful in evaluating model performance in a class-balanced dataset, where each class in the dataset has the same number of samples [83]. Recall is the ratio of correctly predicted observations among all observations for each class (Equation (5)). Precision is the ratio of correct predictions among all predictions assigned to a class (Equation (6)). *F1-score* is the weighted average of precision and recall (Equation (7)) [66]. The observations reported in accuracy, recall, precision, and F-1 score can be translated into purity and yield in the case of plastics.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

$$F1 - Score = \frac{2 \times Recall \times Precision}{Recall + Precision} \tag{7}$$

Accuracy, precision, and recall are often useful in evaluating ML model performance in class-balanced datasets, where each class in the dataset has the same number of samples; however, this can be challenging in unbalanced datasets [83]. Most real-world data are often imbalanced datasets; thus, the F1 score is often used for imbalanced datasets [84]. In imbalanced datasets, for precision and recall, one metric comes at the cost of another. The F1 score combines precision and recall, to better reflect the model's accuracy.

A compilation of performance in accuracy of different algorithms that have been employed to classify and identify waste, extracted from various published studies, is presented in Table 1 and Figure 4. As shown there, different algorithms can attain high levels of classifications of plastic waste. However, direct comparison of different algorisms (e.g., CNN vs. SVM) is currently not possible due to different sizes of databases, items identified, number of layers in the models, training sets, etc.

**Table 1.** Performance of different ML models for waste classification and identification.

| Model | Model Description | Epoch | Layers | Classification Accuracy (%) | Machine Accuracy | Materials Sorted | Reference |
|---|---|---|---|---|---|---|---|
| CNN | CNN | | | 99.74 | | | [41] |
| CNN | ResNet-50 | 24 | 50 | 98.81 | 89.77 | PET plastic, plastic bottles, metal, glass | [85] |
| | CNN | 20 | 15 | 87 | | | [86] |
| | Mask-RCNN | | | 89.6 | 55.6 | Opaque and clear plastic bottle, opaque plastic container, cardboard box, drink can | [87] |
| | Mask R-CNN | | | 71.9 | 66 | Construction waste, i.e., cotton gloves, wood, ferrous items, plastic pipe, bamboo, paper, steel bar | [88] |
| | Faster R-CNN | | | 91 | | Cardboard, plastic, glass, paper, metal, and trash | [89] |
| | Pre-trained Mobile Net | | | 90 | | Garbage (tested only on bottles) | [90] |
| | CNN | | | 95.3 | | Glass, paper, cardboard, plastic, metal, and trash | [91] |
| | CNN | | | 83 | | Plastic, paper and metal | [62] |
| | CNN | | | 76 | | Plastic, paper, cardboard, metals | [48] |
| | Fast R-CNN | | | 88 | | | |

**Table 1.** *Cont.*

| Model | Model Description | Epoch | Layers | Classification Accuracy (%) | Machine Accuracy | Materials Sorted | Reference |
|---|---|---|---|---|---|---|---|
| SVM | SVM | | | 94.8 | | Plastic, paper and metal | |
| | SVM | | | 78.3 | | Paper, plastic, metal, and glass | [92] |
| | SVM | | | 96.5 | | Metal, paper, glass, PET | [93] |
| | SVM | | | 95.5 | | PET, HDPE, LDPE, PVC, PP, and PS | [94] |
| KNN | KNN | | | 98.8 | | PET, HDPE, LDPE, PVC, PP, and PS | [94] |
| Logistic regression | Logistic regression | | | 92.9 | | PET, HDPE, LDPE, PVC, PP, and PS | [94] |
| Random Forest | Random Forest | | | 97.3 | | PET, HDPE, LDPE, PVC, PP, and PS | [94] |
| Naive Bayes | Naive Bayes | | | 90.2 | | PET, HDPE, LDPE, PVC, PP, and PS | [94] |
| YOLO | YOLOv3 | | | 94.99 | | | [95] |
| | YOLOX | | | 94.5 | | | [96] |
| | YOLOv4 | | | 95.16 | | | |

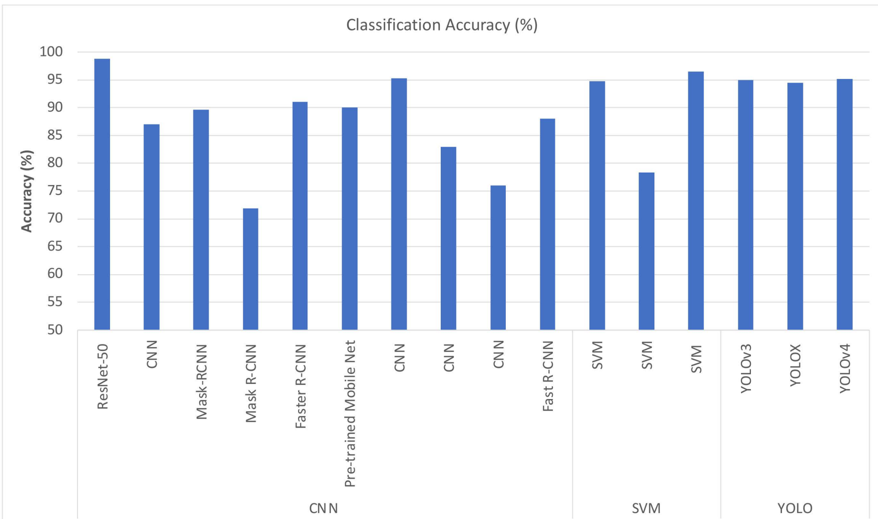


**Figure 4.** Classification accuracy of different ML models in sorting waste (data extracted from various sources [41,62,85–96]).

## 4. ML and AI in Combination with Spectroscopy for Plastic Type Identification

As discussed above, spectroscopy plays a key role in the identification and sorting of plastic waste at MRFs. However, various spectroscopy techniques have their limitations when it comes to sorting plastic. For example, NIR has low resolution and cannot sort black plastics. MIR has slow spectrum acquisition and cannot adequately differentiate between HDPE and LDPE. Raman has low sensitivity and is subject to interference from fluorescence. Laser-induced breakdown spectroscopy (LIBS) does not provide molecular structure information and has difficulty distinguishing polymers with similar chemical formulas [47]. Fluorescence is influenced by the overlap of the molecule's vibrational level with its excited electronic energy level [97].

The fact that no single spectroscopy technique is suitable for all types of plastics motivates the combination of spectroscopy with ML/AI in order to address the limitations [47,98]. The ML models or algorithms discussed in Section 3 have demonstrated the ability to contribute to this end. For example, ML/AI (e.g., CNN) can identify plastics by color, thus correctly sorting black plastics, or sort a plastic based on color (e.g., clear vs. colored PET) [98]. Thus, the combination of AI or ML with spectroscopy-based techniques can increase the sorting accuracy [66]. Carrera et al. [66] used different ML algorithms (SVM, kNN, Naïve Bayes) applied on IR (NIR and MIR) spectra to develop classification models for plastics (PE and PET in the first experiment, PE, PET, PP, and PS in the second experiment, PE, PP, PS, and PVC in the third experiment, and PE, PET, PP, PS, and PVC in the fourth experiment), and reported model accuracy, precision, recall, and *F1-score* rates all over 99% [66]. Neo et al. [47] used CNN, residual networks and inception networks in a decision tree structure with IR and Raman spectra dataset containing over 20 different polymers to classify and identify PE, PP, and PET with an accuracy of 94.9 and 96.7% with the Raman and IR datasets, respectively [47]. The use of a CNN in combination with spectroscopy technologies did not necessarily require pre-processing of spectral data due its feature extraction capabilities [64].

ML can be combined with optical spectroscopy techniques such as NIR or Mid-IR to increase plastic sorting efficiency (Figure 5).

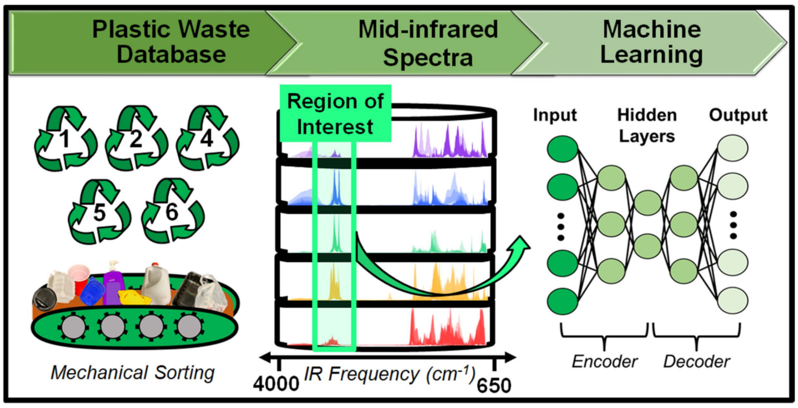


**Figure 5.** Combination of optical spectroscopy and machine learning to sort plastic waste (from [35]; copyright: the authors).

Bonifazi et al. [98] combined ML and data from laser-induced fluorescence (LIF) to identify and sort black plastics (EPS, PS, PP, HDPE) from a plastic waste stream. Long et al. [99] used a combination of CNN ML and MIR (collected at the rate of 100 Hz) for a fast and accurate characterization of mixed plastics (PE, PP, PS, PVC), reaching an overall accuracy close to 100% [99]. Here, MIR was upconverted from the band 2.0–5.0 µm to the near-visible region 695–877 nm, eliminating the thermal noise present in the MIR range for better sortation [99]. The combination of MIR and ML (CNN) enabled the sortation of plastics by type and color (i.e., blue PS, black PE, deep blue PP, and white PVC) [99].

Neo et al. [47] combined ML and Raman or IR for the identification of plastic waste (consisting of PE, PP, and PET) from a dataset containing over 20 polymers [47]. The identification was conducted using Polymer Spectra Decision Net (PSDN) architecture, achieving an accuracy of 94.9% for Raman and 96.7% for FTIR. The developed PSDN had two neural network modules, with the first trained to classify spectral data into recyclable and non-recyclable, and the second neural network classified recyclable polymers into their individual classes (i.e., PET, PE, PP, Other). PSDN [47] reported higher identification and sortation accuracy compared to the end-to-end neural network often used in ML [47].

Various other models such as like Bernoulli NB, Gaussian NB, decision tree, ensemble models, KNN, SVM, linear models, PLS-DA, and a neural network (MLP) have been tested on spectral data, and the results obtained indicated that five classifiers had accuracy, precision, recall, and an *F1-score* over 95%, with the MLP classifier having the best performance with 99.71% accuracy, 99.35% precision, 99.82% recall, and 99.58% *F1-score* [66]. Gaussian NB, Bernoulli, and PLS-DA were reportedly the least effective classifiers, with accuracies of 29.1%, 31.2%, and 75%, respectively [47,66,100].

The following case studies demonstrated the success of AI-based sorting technologies in improving recycling rates. Wilts et al. [17] analyzed the increase in recycling rates and the purity of recovered materials at an MRF in Spain using an AI-based robot (ZenRobotics, Vantaa, Finland) to supplement or replace manual sorting. The waste input of the study comprised 13 different materials, including aluminum, cardboards, HDPE, and textiles. The accuracy or purity of sorted HDPE was approximately 100%, with a recovery rate between 60 to 80% [17]. Manea et al. evaluated the use of smart bins vs. manual sorting or waste segregation by airport passengers, and reported an accuracy of 62% for waste segregation by airport passengers, whereas the smart bin achieved a 90% classification accuracy [100].

## 5. Application of Robotics in Plastic Waste Management

AI-informed robots have the ability to replace manual sorting and can segregate plastic waste by analyzing the captured information (e.g., color, composition) from cameras and sensors [101]. The integration of cyber-physical systems, blockchains, ML, and the IoT can bridge physical and computational infrastructures in waste management, improving the efficiency of identifying and sorting waste (plastics) for recycling [101]. The efficiency of ML models is related to the computational complexities, resources, and requirement (e.g., training time) in learning and performing classification tasks [102]. AI-based robots used in waste management vary based on application, materials to identify or sort, sizes of materials, etc. IT and robotics can be used for prediction of generation waste, roadside waste collection, smart bins, waste monitoring and tracking, and end-of-life treatments such as pyrolysis or mechanical recycling [103–107].

A variety of robots have been reported in the literature, ranging from mobile robots that can be used to collect waste in challenging environments (e.g., beaches) to fixed robots that be employed in MFRs to identify and sort waste [86,87]. Mobile robots can be equipped with tracks, track belts surrounding wheels, a conveyor to move collected waste, robotic arms, grippers, RBG cameras, actuators, proximity sensors, etc. (Figure 6). To enhance the robot capabilities, configurable platforms can be introduced [108]. Such platforms can provide additional degrees of freedom, often used in robotic arms designed for pick-and-place operations (e.g., SCARA robots, Multiple DoFs Robot) [109]. Furthermore, robot capabilities can be enhanced by using grippers with the ability to handle various shapes, or combined grippers that integrate both a suction cup and finger-like appendages, or having grippers specifically for the items to be separated (e.g., plastic films) [109].

With AI-informed robots, the emphasis is on high speed and low power consumption to reduce sorting costs, making parallel structures like Delta robots a preferred choice, and robots with high degrees of freedom more able to handle materials [108].

AI or ML in combination with automated equipment (robots) making the use of computer vision, sensors, arms, grippers, and suction systems are now being extensively investigated for waste management applications [109]. Lu et al. [47] discussed the usage of both deep learning and machine learning algorithms with computer vision to identify and sort municipal solid waste [104,110]. Sundaralingam et al. [110] reported a waste segregation system that could segregate paper, plastic, metal, organic waste, glass, and one more additional empty class into appropriate bins, using a TensorFlow object detection model and a microcontroller. The developed system could predict and segregate waste in the appropriate bin, with a mean Average Precision (mAP) of 86.5% and recall = 88.3% [110].

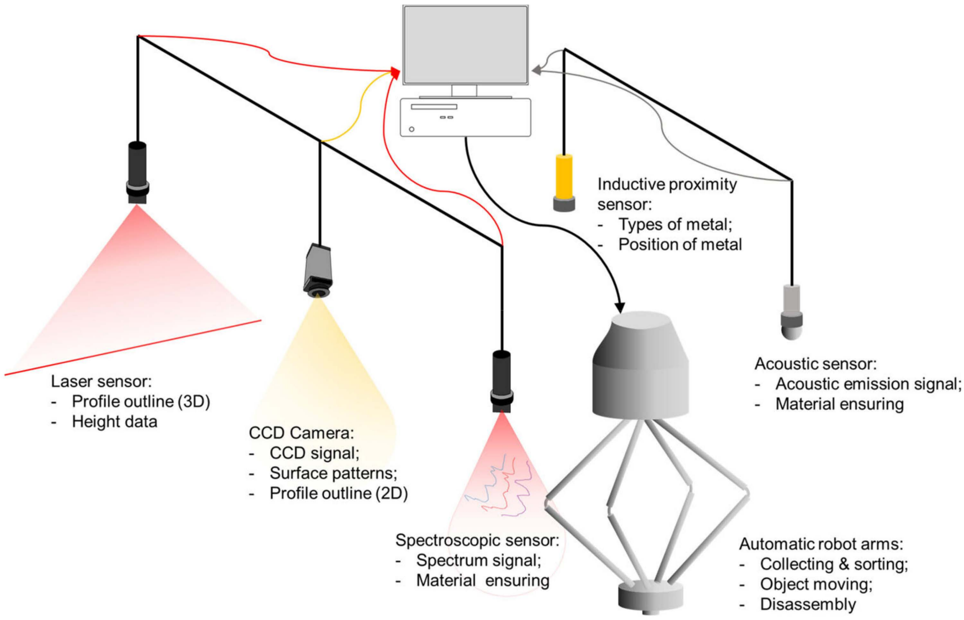


**Figure 6.** Schematic of different types of sensors used in robots to sort plastic waste (from [26]; copyright 2022 American Chemical Society).

Recent studies on robots in plastic waste management often focus on improving the accuracy and efficiency by developing and integrating better sensors and cameras, and better algorithms to accurately classify and sort different types of waste (plastics) [103,111]. Robots can be used to sort plastics based on texture, identifying worn-out plastics and plastics in great physical conditions. With the integration of IT, machine learning, and deep learning into robotics, robots can characterize the shape, size, texture, and colors of different waste materials, and sort them based on adequate categories [109].

Though AI robots have the advantages listed above, they are subject to various limitations, such as not being able to differentiate plastic bottles from glass bottles of the same shape, or to determine between rigid and rubber bottles. Such challenging waste requires better end-effectors and sensors. The end-effector deals with the ability to grasp and sort different waste materials with dirt or deformations, and simultaneously handle both 2D and 3D shaped plastics, while challenges with sensors involve the ability to characterize the shape, color of wet objects, or objects covered with dirt [109]. Examples of AI-informed robots used to sort plastic waste are shown in Figure 7.

*Extracted from everestlabs* *Extracted from Cosmos Magazine* *Extracted from AMP Robotics*

**Figure 7.** Examples of AI based robots used to sort plastic waste (Extracted from everestlabs (https://www.everestlabs.ai/, accessed on 12 July 2024), Cosmos Magazine (https://cosmosmagazine.com/technology/ai/robot-can-sort-soft-plastics-for-recycling/, accessed on 12 July 2024), and AMP Robotics (https://venturebeat.com/ai/amp-robotics-raises-55-million-for-ai-that-picks-and-sorts-recyclables/, accessed on 12 July 2024)).

## 6. Recent Advances in Commercial Equipment That Sort Plastics

### *6.1. Methodology*

In this study, equipment for sorting plastic recyclables was identified using publicly available information obtained from manufacturers' websites and scientific literature. A search for sorting equipment and companies was conducted using Google, Google Scholar, Web of Science, Science Direct, and Engineering Village databases using the keywords "sorting equipment manufacturers or companies", "optical sorters", "plastic sorters", "plastic sorting machines", "sorting equipment", and "plastic recycling".

Sorting devices based on cameras or lasers (e.g., NIR, MIR) to sort whole plastics are classified herein as optical sorters (Table 2). Sorting devices that use ML/AI with cameras or lasers (e.g., NIR, MIR) to sort whole plastics are classified herein as AI-based optical sorters (Table 3). Sorting devices based on cameras or lasers to sort plastic films are classified here as film sorters (Table 4), and sorting devices based on cameras or lasers to sort plastic flakes are classified herein as flake sorters (Table 5). However, sorting devices that use AI in a way to mimic the human brain to make decisions in sorting plastic waste and have a form of robotic arms or SCARA with grippers to sort plastics are classified herein as AI-based sorters or robotic sorters (Table 6).

Contact information of sorting equipment suppliers is reported in Appendix A Table A1 and Appendix B Table A2. The companies listed are based in North America, Europe, and Asia. Our search was conducted in the English language; hence, it may not have captured companies in, e.g., China. The producers (and countries) of optical sorting equipment are summarized in Figure 8.

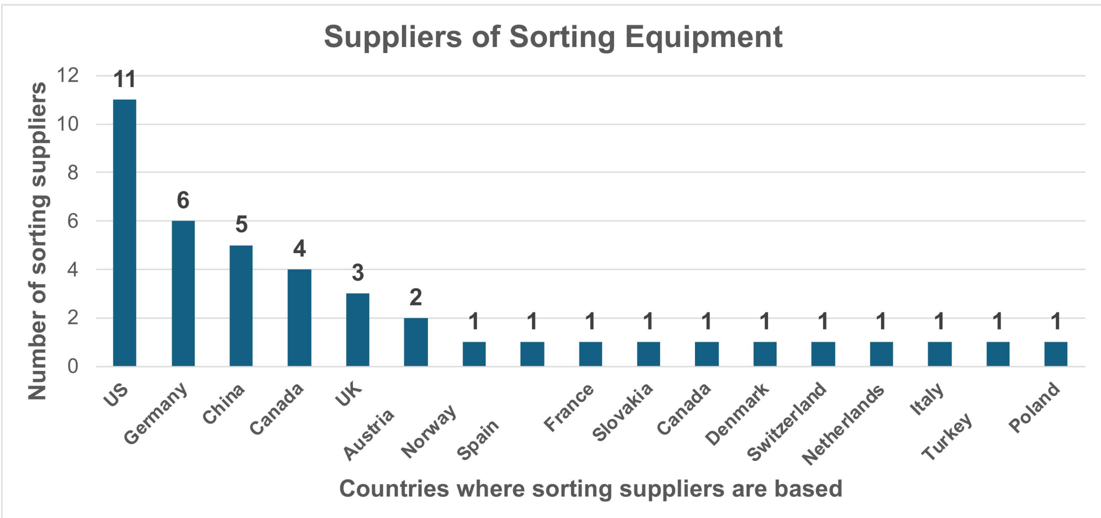


**Figure 8.** Quantities of plastic sorter suppliers per county.

The information collected here reveals the progress made during the two years since our previous report on plastics sorting equipment was published. This information is further used to assess whether the various challenges reported by MRFs in our previous study [20] can be addressed by currently available technologies or emerging technologies.

**Table 2.** Inventory of commercially available sorters for whole (i.e., bottle) plastic. NI: no information reported.

| Manufacturer/ Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|
| Anhui Zhongke Optic-electronic Color Sorter Machinery Co., Ltd. | AMD G-LPI (Uses deep learning) | NIR, deep learning, and visible light technology | Can sort labeled bottles, off-label bottles, plastic bottles with labels, mixed plastic bottles in bale form, loose plastic bottles, plastic food packaging | | | | | | | |
| Binder + Co. | CLARITY belt sorting systems | VIS, NIR, induction and XRT, 3D Scanner | PET, PE, PP, PVC | PET, PE, PP, PVC | Yes | Paper, metals, municipal solid waste, wood, and cardboard | Yes/NI | Up to 30 ton/h for 1000 mm sorting width system and 60 ton/h for 2000 mm sorting width system | Accuracy up to 99.9+% | Metal detection |
| Green Machine LLC | Green Eye Hyperspectral Optical Sorters (Uses AI Tech) | Patented hyperspectral vision systems and AI driven neural net software | Sorts all plastics | 1–7 grades of plastic including difficult-to-sort black plastics, barrier bottles, #5's, PVCs, vinyls, thermal forms; sorts most plastic grades, black plastics, rubber grades, HDPE, LDPE ABS plastics, and more | Yes | Fiber, C&D, E-waste, Textiles, carpeting | Yes/Yes | Up to 12 ton/h (depends on the belt width) | 95% or more | Can be trained to identify and pick out almost any type of polymer by shape and chemical composition |

**Table 2.** *Cont.*

| Manufacturer/ Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|
| Hefei Golden Sorter Co., Ltd. | Plastic Bottle Optical Sorter Gép-T LP (Uses deep learning) | NIR, VIS, deep learning technology | Bottle sorting equipment | non-PET bottle materials, such as PP/PE/PC/ PS/ABS/PVC/ PA, and other non-PET bottles | Yes | Non-plastic bottles | Yes/Yes | Up to 4 ton/h | | |
| Hefei Mayson Machinery Co., Ltd. | MAS-B series bottle separator (Uses deep learning) | Fusion modeling technology, deep learning algorithm, vision system, image processing system, and intelligent self-learning system | Sorts different types of plastic bottles | Non-PET bottle materials, such as PP/PE/PC/ PS/ABS/PVC/ PA and other non-PET bottle sorting | Yes | Non-plastic bottles | No/No | From 1.5–2.0 ton/h to 4–7 ton/h | Up to 99% | Deep learning system helps in improving the sorting quality/efficiency |
| MEYER Europe s.r.o. | KL Sorter (Uses AI Tech) | AI cameras working in the electromagnetic spectrum: full RGB visible light, infrared standard, infrared HD, InGaAs, and UV light | Identify different color PET bottles | Detect and remove non-PET bottles, such as PVC/PS/PC/ PA/PP/PE/ ABS | Yes | Glass, non-ferrous metal, and ore sorting | Yes/Yes | Up to 7 ton/h | | |
| MSW Sorting | Optical Sorter (Uses AI Tech) | VIS, NIR, High resolution camera, and AI | Plastic, paper, glass, and other recyclable materials | PET bottles, HDPE bottles, and plastic bottles | Yes | Cans, glass, and cardboards | Yes/NI | Maximum belt speed can reach 6.5 m/s | Over 95% | |

**Table 2.** *Cont.*

| Manufacturer/Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|
| NRT Optical Sorting | ColorPlus with Max-AI (Uses AI Tech) | RGB line-scan sensor combined with Max-AI | All plastics | Capture form-specific PET (ex. Bottle only, blue/green bottle only.). Capture food-grade-only PET and/or HDPE. Identify black plastics, thermoform trays | Yes | Cardboard, metal cans, and fiber | Yes/Yes | | | |
| | SpydIR-R with Max-AI (Uses AI Tech) | NIR and Multi-layered vision system and neural networks | Plastics, paper, metals | Capture form-specific PET (ex. Bottle only, blue/green bottle only.). Capture food-grade-only PET and/or HDPE, and identify black plastics, thermoform trays | Yes | Paper, metal cans, wood, cardboard, fiber | Yes/Yes | | | PET Boost technology for detection of thin-wall PET, wet PET, and full-sleeve PET |

**Table 2.** *Cont.*

| Manufacturer/ Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|
| Pellenc ST | Compact+ | AI CNS platform | | PET, PE, PP, paper, wood, domestic waste, organic, RDF | | | Yes/Yes | | | Compact+ |
| | Xpert | X-ray along with machine learning | Chlorine or brominated plastic removal | Chlorine or brominated plastic removal | NI | WEE, glass, aluminum | NI/NI | Top Speed ready < 4.5 ms | | |
| PicVisa | Ecopack—Model EP Optical Plastic Sorting Machine | NIR, VIS, deep learning | PET/PE recycling, Plastic film (PEBD, PP, HDPE/LDPE, etc.) | PET, HDPE, PP, PS, PVC, EPS, ABS) HDPE, PET, Mixed LDPE, Sorting film (HDPE/LDPE) | Yes, sorting of films (PE) from bottles of the same material | Paper, and cardboards, wood recycling, metal recycling, textile, RDF, construction and demolition waste | Yes/NI | | | Allows separating the always-present silicone cartridges in HDPE flows. Can add AI technology |
| TOMRA systems ASA | Autosort Sharp Eye | NIR, Sharp Eye technology (Add-on sensors: VIS, Deep Laiser, metal detector, and AI based Cameras) | Sorts all resins | Plastisc, paper | | Wood, RDF, mixed paper, cardboard, metals, and organic waste | Yes/Yes | | | Can add AI deep learning to improve sorting accuracy and can sort glass and black polymers by adding the DEEP LAISER sensor. Remote access |

**Table 3.** Optical Sorters with incorporated AI.

| Manufacturer/ Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|
| Anhui Zhongke Optic-electronic Color Sorter Machinery Co., Ltd. | AMD G-LPI (Uses deep learning) | NIR, deep learning, and visible light technology | Can sort labeled bottles, off-label bottles, plastic bottles with labels, mixed plastic bottles in bale form, loose plastic bottles, plastic food packaging | | | | | 1.5–2.0 ton/h for G-LPI2. 3.0–4.0 ton/h for G-LPI4 model | | |
| Binder + Co. | CLARITY belt sorting systems | VIS, NIR, induction, and XRT, 3D Scanner | PET, PE, PP, PVC | PET, PE, PP, PVC | Yes | Paper, metals, municipal solid waste, wood, and cardboard | Yes/NI | Up to 30 ton/h for 1000 mm sorting width system and 60 ton/h for 2000 mm sorting width system | Accuracy up to 99.9+% | Metal detection |
| Green Machine LLC | Green Eye Hyperspectral Optical Sorters (Uses AI Tech) | Patented hyperspectral vision systems and AI-driven neural net software | Sorts all plastics | 1–7 grades of plastic including difficult-to-sort black plastics, barrier bottles, #5's, PVCs, vinyls, thermal forms; sorts most plastic grades, black plastics, rubber grades, HDPE, LDPE ABS plastics, and more | Yes | Fiber, C&D, E-waste, textiles, carpeting | Yes/Yes | Up to 12 ton/h (depends on the belt width) | 95% or more | Can be trained to identify and pick out almost any type of polymer by shape and chemical composition |

**Table 3.** *Cont.*

| Manufacturer/Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|
| Hefei Golden Sorter Co.Ltd | Plastic Bottle Optical Sorter Gép-T LP (Uses deep learning) | NIR, VIS, deep learning technology | Bottle sorting equipment | non-PET bottle materials, such as PP/PE/PC/PS/ABS/PVC/PA, and other non-PET bottles | Yes | Non-plastic bottles | Yes/Yes | Up to 4 ton/h | | |
| Hefei Mayson Machinery Co., Ltd. | MAS-B series bottle separator (Uses deep learning) | Fusion modeling technology, deep learning algorithm, vision system, image processing system, and intelligent self-learning system | Sorts different types of plastic bottles | Non-PET bottle materials, such as PP/PE/PC/PS/ABS/PVC/PA and other non-PET bottle sorting | Yes | Non-plastic bottles | No/No | From 1.5–2.0 ton/h to 4–7 ton/h | Up to 99% | Deep learning system helps in improving the sorting quality/efficiency |
| MEYER Europe s.r.o. | KL Sorter (Uses AI Tech) | AI cameras working in the electromagnetic spectrum Full RGB visible light, Infrared Standard, Infrared, HD, InGaAs, and UV light | Identify different color PET bottles | Detect and remove non-PET bottles, such as PVC/PS/PC/PA/PP/PE/ABS | Yes | Glass, non-ferrous metal, and ore sorting | Yes/Yes | Up to 7 ton/h | | |
| MSW Sorting | Optical Sorter (Uses AI Tech) | VIS, NIR, High resolution camera, and AI | Plastic, paper, glass, and other recyclable materials | PET bottles, HDPE bottles, and plastic bottles | Yes | Cans, glass, and cardboards | Yes/NI | Maximum belt speed can reach 6.5 m/s | Over 95% | |

**Table 3.** *Cont.*

| Manufacturer/ Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|
| NRT Optical Sorting | ColorPlus with Max-AI (Uses AI Tech) | RGB line-scan sensor combined with Max-AI | All plastics | Capture form-specific PET (ex. Bottle only, blue/green bottle only). Capture food-grade-only PET and/or HDPE. Identify black plastics, thermoform trays | Yes | Cardboard, metal cans, and fiber | Yes/Yes | | | |
| | SpydIR-R with Max-AI (Uses AI Tech) | NIR and Multi-layered vision system and neural networks | Plastics, paper, metals | Capture form-specific PET (ex. Bottle only, blue/green bottle only). Capture food-grade-only PET and/or HDPE, and identify black plastics, thermoform trays | Yes | Paper, metal cans, wood, cardboard, fiber | Yes/Yes | | | PET Boost technology for detection of thin-wall PET, wet PET, and full-sleeve PET |

**Table 3.** *Cont.*

| Manufacturer/ Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|
| Pellenc ST | Compact+ | AI CNS platform | | PET, PE, PP, paper, wood, domestic waste, organic, RDF | | | Yes/Yes | | | Compact+ |
| | Xpert | X-ray along with machine learning | Chlorine or brominated plastic removal | Chlorine or brominated plastic removal | NI | WEE, glass, aluminum | NI/NI | Top Speed ready < 4.5 ms | | |
| PicVisa | Ecopack—Model EP Optical Plastic Sorting Machine | NIR, VIS, deep learning | PET/PE recycling, Plastic film (PEBD, PP, HDPE/LDPE, etc.) | PET, HDPE, PP, PS, PVC, EPS, ABS) HDPE, PET, Mixed LDPE, Sorting film (HDPE/LDPE) | Yes, sorting of films (PE) from bottles of the same material | Paper and cardboards, wood recycling, metal recycling, textile, RDF, construction and demolition waste | Yes/NI | | | Allows separating the always-present silicone cartridges in HDPE flows. Can add AI technology |
| TOMRA systems ASA | Autosort Sharp Eye | NIR, Sharp Eye technology (Add-on sensors: VIS, Deep Laiser, metal detector, and AI based Cameras) | Sorst all resins | Plastisc, paper | | Wood, RDF, mixed paper, cardboard, metals, and organic waste | Yes/Yes | | | Can add AI deep learning to improve sorting accuracy and can sort glass and black polymers by adding the DEEP LAISER sensor. Remote access |

**Table 4.** Inventory of commercially available film sorters.

| Manufacturer/ Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|
| Binder + Co. | Clarity Plastic | NIR, Reflection VIS, Inductive metal detection | Lightweight packaging, film sorting, plastic flakes, plastic granules, and hallow plastic sorting | | | | Yes/NI | 0.5 ton/h for 700 mm sorting width, 0.7 ton/h for 100 mm, and 1 ton/h for 1400 mm | | Metal detection |
| | Clarity Multiway for Light Packaging | NIR, VIS | | PET, PE, PP, PVC | | Paper and cardboard | | Up to 2.1 ton/h for 1000 mmm sorting width and up to 3 ton/h 2000 mmm sorting width | | |
| | CLARITY belt sorting | VIS, NIR, induction and X-ray | Plastics, packaging waste, municipal solid waste, refuse-derived fuels, metals, and wood | PET, PE, PP, PVC | | Municipal solid waste, refuse-derived fuels, metals, and wood | | Up to 30 ton/h for 1000 mm sorting width system and 60 ton/h for 2000 mm sorting width system | Accuracy up to 99.9+% | |
| CP Group (MMS) Sorting Equipment | FilmMax | NIR, color, and metal sensors | Sorts bags, pouches, bags, foil, and other ultra-light products | LDPE/LLDPE, natural/white films, PET, PVC, PS, colored film | No | foil, and other ultra-light products. | Yes/Yes | 0.5–3.0 ton/h | Up to 98% | Metal detector upgrade available |
| | CIRRUS FiberMAX | NIR and color sensors | Flexible plastics packaging (FPP) such as film, bags, pouches | | | All metal detector | | Belt speeds of 1000 ft/min (5 m/s). Capacity 2.0–12.0 ton/h | Up to 98% | |

**Table 4.** *Cont.*

| Manufacturer/Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|
| RTT Steinert GmbH | Unisort Film EVO 5.0 | NIR, VIS, hyperspectral imaging technology | Agricultural film, bio-based film, biodegradable film, conventional PVC film and papers | Identifies and sorts plastics and materials by type. Plastic film, bags, and paper | | Beverage cartons, paper, cardboard, paperboard, and textiles | Yes/NI | | | |
| Pellenc ST | Mistral + Films | NIR | Used to separate films from other plastics | PE film, PP, PVC, metals, fibrous, PS, HDPE | | Papers, cardboards, and metals | Yes/No | Up to 2.5 ton/h | Up to 91% | |
| | Mistral + Connect | NIR/VIS spectrum | provides better detection and sorting of PET bottles versus PET trays or thermoforms, paper versus cardboard in sorting centres | PET, PE, PP, paper, films | | Wood, domestic waste, organic, RDF | NI/Yes | | | |
| | Compact+ | AI CNS platform | | PET, PE, PP, paper, wood, domestic waste, organic, RDF | | | Yes/Yes | | | |

**Table 4.** *Cont.*

| Manufacturer/ Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|
| PicVisa | Ecopack—Model EP Optical Plastic Sorting Machine | NIR, VIS, deep learning | PET/PE recycling, plastic film (PEBD, PP, HDPE/LDPE. . .) | PET, HDPE, PP, PS, PVC, EPS, ABS) LDPE, film (HDPE/LDPE) | Yes, sorting of films (PE) from bottles of the same material | Paper and cardboard, wood recycling, metal recycling | Yes/NI | | | Allows separating the always-present silicone cartridges in HDPE flows |
| | ECOPICK (Uses Robotic, AI, and deep learning) | RGB and/or NIR sensors, 3D, AI based robot, deep learning, and machine vision | PET bottles, HDPE bottles, trays, and film | All types | | Cans, Tetra Pak, paper, cardboard, glass, textile, aluminium | | 1 pick/s | >95% | |
| RTT Steinert GmbH | Unisort Film | NIR, VIS | Agricultural film, bio-based film, biodegradable film, conventional PVC film, and papers | Plastic film | | bags and paper | | | | |
| TOMRA systems ASA | Autosort Speedair | NIR, SHARP EYE™ technology, and can add-on DEEP LAISER | Plastic films and lightweight packaging | Film (LDPE, HDPE), papers, and packaging | | | NI/Yes (with DEEP LAISER) | | | Available as solutions bundle or as an add-on device to an existing AUTOSORT machine setup. |
| Bollegraaf Group | Opti-Sort | Optical sorting and mechanical sorting by pressure | Processing lightweight materials such as flexible plastic packaging or single sheets of paper | | | | | Speed levels to up to 6.5 m/s | | |

**Table 4.** *Cont.*

| Manufacturer/ Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|
| NRT Optical Sorting | SpydIR®-R | NIR, In-Flight Sorting | Film, fiber, PET, HDPE, or mixed plastics | PET container stream with high accuracy including PVC, PS, PETG, PLA, and PC, PE, PP, and other polymer contaminants in any combination | Yes | Cardboard, paper, metals, and other fiber | | throughput rates exceeding 8 ton/h | | |
| | SDi semi-mobile wind shifters | Mechanical sorting based on weight | Plastic, HDPE, film | Plastic, HDPE, film | | Wood, cardboard, paper, rubber | | Capacities up to 15 t/h | | Semi-mobile |

**Table 5.** Inventory of commercially available flake sorters.

| Manufacturer/ Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|
| Best | NIREX | NIR, and vision technology | Sorts e-scrap | | Yes | | Yes/Yes | | Depends on product type | |
| Binder + Co | Clarity Plastic | NIR, reflection VIS, inductive metal detection | Light- weight packaging, film sorting, plastic flakes, plastic granules, and hollow plastic sorting | | | | Yes/NI | 0.5 ton/h for 700 mm sorting width, 0.7 ton/h for 100 mm, and 1 ton/h for 1400 mm | | Metal detection |
| Buhler | Sortex Z + Series | Vision-based and high-resolution IR sensors | Sorts PET, PVC flakes, and nylon | | | | Yes/Yes | 0.675 to 1.16 ton/h depending on model | 99.9% or higher | |
| | Sortex N PolyVision | | Sorts PET flakes | PET, PVC, PP. PE, PS, PA, POM, PMMA, SAN | | | Yes/NI | Up to 6 t/h | | Integrated chute feeding system |
| | Sortex B MultyVision | | Commodities, but sorts plastics as well | plastic | | Pulse, nut, and coffee | No/No | up to 8 t/h | | Remote acess for real-time monitoring |
| | Sortex A GlowVision | | Plastic sorting | | | | | | | |
| | Sortex A | | Plastics, commodities | Plastics | | Nuts, seeds, grains, coffee, pulses | NI/Yes | | | Remote acess for real-time monitoring |

**Table 5.** *Cont.*

| Manufacturer/Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|
| BT-Wolfgang Binder GmbH (Redwave) | Redwave QXR | XRF | Used for PET and WEEE stream purification | Removes PVC and BFR-containing plastics | | | No/No | 2.5 to 8.0 ton/h | 80% | |
| | Redwave XRF-P | X-ray Fluorescent | Segregation of dark PVC and brominated plastics from an infeed of shredded plastics. | BFR and chloride-containing plastics | | | No/No | | Up to 99%, depending on input material | |
| | Redwave CX | NIR, metal sensor | | | Yes | Glass, metals | Yes/Yes | | | |
| CP Group (MMS) Sorting Equipment | FlakeMax | NIR | Best suited for PET and PE/PP | | Non-metals | | | 3–16 ton/h | Up to 98% | |
| | eMax | NIR, color, and metal always included | Designed for e-scrap recyclers | Sorting of opaque, transparent, and black commodities such as ferrous, non-ferrous, and stainless steel, wires, PCB, as well as durable plastics such as ABS, HIPS, PC, and PMMA | | | | 0.5–3.0 ton/h | Up to 98% | |
| Eagle Vizion | Black Sorter | | Sorts PE and PP Flakes | PE, PP, and others | | | | Up to 0.55 ton/h | | 2–12 mm |

**Table 5.** *Cont.*

| Manufacturer/ Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|
| CP Group (MMS) Sorting Equipment | L-VIS | VIS high-resolution color camera | Color sorting, flakes and pellets. Sorts PET PE, and PP flakes and pellets | Yes, electric scrap | | | Yes/Yes | | 98% | Statistics and quality control report, metal detector, remote modern or ethernet access |
| | E-sort | NIR | Separate different types of plastics (all resin) by composition and color | Useful for flake sorting, shredded plastics (i.e., WEEE) | | | Yes/Yes | Up to 3 ton/h | 92–98% | |
| MEYER Europe s.r.o. | CL-L-Sorter (Uses AI Tech) | AI cameras working in the electromagnetic spectrum: full RGB visible light, infrared standard, infrared HD, InGaAs, and UV light | Detect and remove non-PET materials flakes | PVC/PS/PC/ PA/PP/PE/ABS | | Rubber/aluminum | Yes/Yes | up to 6 ton/h | | |
| Mogensen GmbH/Allgaier Process Technology GmbH | Msort | IR and X-ray | Sorts all resins of size from 0.5 mm up to 250 mm | Sorts all resins (mostly used to sort PET flakes) | | Yes | Yes/Yes | Up to 4.4 tons/h. Detection of up to 25,000 particles/s | Up to 99.9% | |
| | MikroSort AF | CCD Linear Camera | Sorts PET flakes by color | | | | Yes/Yes | 1–3 ton/h | | |
| NRT Optical Sorting | Flakesort | NIR | Mainly used to remove contaminants from PET streams | | | | | Up to 2.5 ton/h | Removal efficiency of flakes up down to 0.1 inch | |

**Table 5.** *Cont.*

| Manufacturer/ Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|
| Pellenc ST | Mistral + Metal Sensor | NIR | Applicable for all resins | Mostly used in shredded e-scrap sorting | | Paper, cardboard, and metals/No | No/Yes | Up to 6.5 tons/h | | |
| Rhewum GmbH | Datasort | CCD camera system, LED | Sorts all resins | | | | Yes/Yes | 4.4 to 8.3 ton/h | Up to 97% accuracy | |
| | RHEWUM DataSort S | | Mostly used for ore sorting, but can be used to sort plastic flakes as well | | | | | | Up to 98% | |
| Satake | Scanmaster IE | High-resolution CCD Camera | Separates plastics by color | PET, PVC | | | Yes/NI | 1–3 ton/h | | Remote monitoring |
| | MikroSort AF | CCD Linear Cameras | Sorts PET flake by color | | | | Yes/Yes | 0.25–5 ton/h | | Remote monitoring |
| | Satake RNEZX | NIR, full-color RGB camera. | Sorts PET flakes by color | | | Yes | Yes/Yes | | | |
| | Beltuza sorter | NIR, full-color RGB | Sorts plastic flakes by color | | | Yes | Yes/Yes | Up to 12.5 ton/h | | |
| | FMSR-IR Sorter | Full-color RGB, infraRed | Sorts plastic flakes by color | | | Beans, seeds, corns, nuts | Yes/Yes | | | |
| | ScanMaster XE | Proprietary inGas/Color camera technology | Removes clear PVC from PET, and other non-contaminants | Sorts all resin | | Yes | No/No | Up to 3 ton/h | | Remote monitoring |
| | RGB Full Color Belt Sorter | NIR, full-color Cameras (RGB) | Separates plastics by color | PET, twisted PVC | | | Yes/Yes | 9 to 19 t/h | Up to 99% | |
| | Pellet Scan | High-resolution CCD Cameras | Separates plastics by color | No | | | | | Up to 99% | Data Scan |

**Table 5.** *Cont.*

| Manufacturer/ Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|
| Sesotec GmbH (S + S Separation and Sorting Technology GmbH) | Flake Purifier N | NIR | Purifies resin streams, also sorts e-plastic | PET, HDPE, PLA, PVC, and more | | | No/No | Up to 10 ton/h depending on how the unit is scaled | 90% to 99.8% depending on input | |
| | Flake Purifier C | CCD linear camera | Color sorting | No | | | Yes/Yes | Up to 10 ton/h depending on how the unit is scaled | 90% to 99.8% depending on input | Dual ejection |
| | Varisort X | X-ray | Identifies BFR-containing plastics | Identifies BFR containing plastics | | | No/No | Up to 2.5 ton/h depending on how the unit is scaled | | Dual ejection |
| TOMRA Systems ASA | Ixus | X-ray | Useful for sorting shredded e-scrap | Useful for sorting BFR- and chloride-containing plastics (i.e., PVC) | | | No/No | 1 ton/h | Depends on product type | |
| | Innosort Flake | NIR, Visible spectra Sensors | Used for purifying PET flakes, purifying transparent and opaque flakes, sorting of mixed color flakes | PVC, PE, PET, PP, PS, and others, including Tetra Pak and film | | | Yes/NI | | | |
| | Autosort Flake | Flying beam, full-color camera | Sorts plastic flakes | PET, PO, PVC flakes | | Yes, metal removal | Yes/NI | 6 ton/h | | Advanced statistics for real-time quality control |
| Unisensor Sensorsysteme GmbH | PowerSort 200 | Ultra-high-speed laser spectroscopy | Useful for bottle-to-bottle recycling | Sorts all resins | | | Yes/Yes | Up to 3 ton/h | 98% or higher | |

**Table 5.** *Cont.*

| Manufacturer/ Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|
| Visys | Spyder | Laser | Separation based on color, structure, shape, and size differences | No | | | Yes/Yes | 1–3 ton/h | Up to 99% depending on input | |
| | Python | Laser and cameras | Separation based on color, structure, shape, and size differences | | | | | | | |
| | Tyrex | X-ray | Separation based on density of materials (i.e., plastic, WEEE, ASR) | Useful for sorting BFR and chloride-containing plastics (i.e., PVC) | | | No/No | | Up to 99% depending on input | |
| Wesort | 6SXZ-680 | AI deep learning | | ABS, PC, PE, PET, PP, PPS, PPU, PVC, bottle plastic, resin, masterbatch, nylon, acrylic | | | Yes/Yes | 1.5–2.5 tonne/h | ≥99% | |
| | 6SXZ-340 | AI deep learning | | ABS, PC, PE, PET, PP, PPS, PPU, PVC, bottle plastic, resin, masterbatch, nylon, acrylic | | | Yes/Yes | 0.75–1.15 tonne/h | ≥99% | |

**Table 5.** *Cont.*

| Manufacturer/ Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|
| | 6SXZ-272 | AI deep learning | | ABS, PC, PE, PET, PP, PPS, PPU, PVC, bottle plastic, resin, masterbatch, nylon, acrylic | | | Yes/Yes | 0.6–1 tonne/h | ≥99% | Multidimentional sorting |
| | 6SXZ-204 | AI deep learning | | ABS, PC, PE, PET, PP, PPS, PPU, PVC, bottle plastic, resin, masterbatch, nylon, acrylic | | | Yes/Yes | 0.45–0.75 tonne/h | ≥99% | Dual camera |
| | 6SXZ-272L | AI deep learning | | ABS, PC, PE, PET, PP, PPS, PPU, PVC, bottle plastic, resin, masterbatch, nylon, acrylic | | | Yes/Yes | 0.6–1 tonne/h | ≥99% | Shape selection |
| | 6SXZ-136L | AI deep learning | | ABS, PC, PE, PET, PP, PPS, PPU, PVC, bottle plastic, resin, masterbatch, nylon, acrylic | | | Yes/Yes | 0.3–0.5 tonne/h | ≥99% | |
| | 6SXZ-68L | AI deep learning | | Same as ebove | | | Yes/Yes | 0.15–0.25 tonne/h | ≥99% | |
| | 6SXZ-68 | AI deep learning | | Same as ebove | | | Yes/Yes | 0.15–0.25 tonne/h | ≥99% | |
| | 6SXZ-90 | AI deep learning | | Same as ebove | | | Yes/Yes | 0.2–0.4 tonne/h | ≥99% | |

**Table 5.** *Cont.*

| Manufacturer/ Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|
| | 6SXZ-136 | AI deep learning | | Same as ebove | | | Yes/Yes | 0.3–0.5 tonne/h | ≥99% | |
| | 6SXZ-136L | AI deep learning | | Same as ebove | | | Yes/Yes | 0.3–0.5 tonne/h | ≥99% | |
| AnySort | VDR Series (6 Series) | | PE, PET, PVC, PP | | | | Yes/Yes | | | Sorts based on shape as well |
| PicVisa | EcoFlake X600 | NIR, RGB cameras | Plastics | PET, PE | Yes, metal (i.e., copper, brass, and aluminum) and seeds | | Yes/Yes | 0.4–1.0 ton/h | 99.5% | |
| | EcoFlake X1200 | NIR, RGB cameras | Plastics | PET, PE | Yes, metal (i.e., copper, brass, and aluminum) and seeds | | Yes/Yes | 0.8–2.0 ton/h | 99.5% | |
| Eagle Vizion | Micro Flake Sorter | | Plastics | PE, PET, PP, and PVC | Wood, glass, paper | | | | | Sorts particles from 5 mm down to 0.5 mm |

**Table 6.** Inventory of AI-based robotic sorters.

| Manufacturer/ Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Plants in the US Using Equipment | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AMP Robotics | Cortex | MSW, e-waste, and construction and demilition waste | | | Yes | Yes | NI/Yes | 60 picks per min | Alpine Waste and Recycling. Denver Co, and Minnesota | 99% | Cortex is continuously learning from experience, becoming better all the time |
| | Cortex C | MSW, e-waste, and construction and demilition waste | | | Yes | Yes | | 65 + picks per min per arm | | 99% | Ideal for smaller spaces |
| Bulk Handling Systems (BHS) | Max-AI | Deep learning technology and the sorting process is based on the evaluation of optical data determined by VIS-sensors | Extract recyclable commodities from a specific stream of material | PET, HDPE | Yes | Yes | NI/Yes | 65 picks per min | Recology, San Francisco | | Continuously learning to improve efficiency |
| Bollegraaf Recycling Solutions | Analyzer | | Used to determine material flow and composition in real time. | | | | | | | | |
| | RoBB-AQC | | Plastics, from PET, HDPE, LDPE, PS and PP to Tetra Pak, OCC, or pa-per/cardboard of various shapes and sizes | Paper, cardboard, plastic, and metal containers, cartons, residue | | | Yes/Yes | Up to 70 picks/min per robot | | | Up to 4 separate sorts per robot Maximum Object Weight: 4.4 lbs. (2 kg) |

**Table 6.** *Cont.*

| Manufacturer/Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Plants in the US Using Equipment | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|---|
| BT-Wolfgang Binder GmbH (Redwave) | RedWave 2i | NIR, RGB cameras and all-metal detectors | Sorts all resins | Sorts all resins | Yes | Paper, metals, e-waste, glass, construction waste | | Up to 7 ton/h | | | 24/7 remote maintenance access for quick service and support |
| Machinex | SamurAI | Delta robot with vacuum gripper | Extract recyclable commodities from a specific stream of material (e.g., plastics from a reject line) | PET, colored, and natural HDPE | Yes | Yes | NI/Yes | Up to 70 picks per min | Lakeshore Recycling Systems. Forest View, IL | Up to 95% | There is ongoing evolution and optimization of AI material recognition. It continually improves and learns from operating experience to assure maximum recognition efficiency. |
| Bulk Handling Systems (BHS) | Max AI AQC | | Removes contaminants, recovers recyclables | | | Yes | Yes | Up to 70 picks per minute<br>Up to 6 separate sorts | | | Maximum object weight: 1 lbs |
| | Max AI Cobot | | Can sort plastics | | | Yes | Yes | | | | Designed to work safely alongside people |

**Table 6.** *Cont.*

| Manufacturer/ Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Plants in the US Using Equipment | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Max AI Flex | | Can sort plastics | | Yes | Yes | | Up to 35 picks per minutes per robot arm Up to three separate sorts from a single robot | Mechanical gripper, vacuum gripper | | Ideal for heavy and/or non-uniform objects in a variety of pre- and post-sort applications. Able to grasp objects up to 15 lbs, including non-uniform material |
| OP Teknik | SELMA | Deep learning | | | | Wood, stone, concrete, bricks, metals, cardboard, foam, etc. | | Up to 10,800 picks/h with 6 robots. or 30 picks/min per robot arm | | | |
| TOMRA Systems ASA | AutoSort CyBot | | Packaging, beverage cartons, and all thermoplastics | | | Yes | Yes/Yes | | | | |
| Enerpat | Jet Series | | Plastics | PET | | Yes | Yes/Yes | Up to 8 tons/h | | over 95% | Can quickly identify the color, appearance, shape, size, and even brand characteristics of the waste |

**Table 6.** *Cont.*

| Manufacturer/ Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Plants in the US Using Equipment | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|---|
| PicVisa | EcoPic | NIR, RGB sensors (cameras) | Plastics | PET | | | Yes/Yes | 1 pick per s | | | Maximum payload of 4 kg |
| Sortera Alloys | Sortera's A.I. | | Can sort plastics | Mainly used to sort metals | | | Yes/Yes | | | | Pateneted tech, not commercially available yet |
| Everestlabs | Everestlabs RecycleOS Robotics Cell | | | | | | Yes/Yes | | | 90% + success rate | Six-axis robotic arm |
| | Everestlabs AI | AI (A vision system mounted on top of a conveyor to capture a 3D map of the of objects on the conveyor, and provide the data to the robot platform | | | | Yes | Yes/Yes | | | | Capture high-speed images of the materials in the conveyor using a self-lit, self-contained industrial 3D camera for accurate material characterization that robotics use as input |
| ZenRobotics | ZenRobotics fast picker | | Can sort plastics | | | Yes | Yes/Yes | Up to 80 picks per minute | | up to 99% | |
| | ZenRobotics Heavy picker | | Can sort plastics | | | Yes | Yes/Yes | Up to 2300 picks per hour | | Up to 99% | Max. object weight: 30 kg.<br>Up to 3 robotic arms |

**Table 6.** *Cont.*

| Manufacturer/Brand | Equipment Name | Sorting Method | Primary Application | Plastic Identified | Sorts Non-Bottle Rigids in Addition to Bottles | Non-Plastics Sorted | Colors Sorted/Black Plastic Sorted | Throughput (Average) | Plants in the US Using Equipment | Accuracy | Features |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Waste Robotics | Integrates waste handling processes, computer vision, deep learning and robots to improve sorting efficiency | | Ability to differentiate types of plastic | | | | | Up to 50 effective picks/ min | | | Lift up to 1 kg for fast picker |
| Ishitva Robotic Systems | Suka | Netra machine vision system | Can sort plastics by type, size, and color | PET, PP, HDPE | | | Yes/Yes | 2 to 8 tons per h of Plastic Sorting | | | |
| | YUTA | Netra machine vision system | Can sort plastics by type, size, and color | PET Polymer-based sorting of PET, PP, HDPE | | | Yes/Yes | | | >95% accuracy | |
| Recycleye | Recycleye Robotics | | Plastics | HDPE, PET, paper | | | | | | | |

### *6.2. Sorting Equipment for Post-Consumer Plastics*

This section describes commercial sorting equipment for sorting mixed plastics. The optical sorters considered here utilize NIR, VIS (light- or camera-based), and XRF. Reported technologies are classified here based on criteria such as plastic identification method (e.g., NIR or XRF), primary application, throughput, whether they sort plastics by color and/or by size, accuracy, and additional features (Table 2).

A total of 37 conventional optical sorting machines produced by 16 different companies have been reported. Out of these, 22 sorters possess the ability to classify plastic based on its color, and 18 among them can effectively separate black plastics from other colors through the utilization of both NIR and VIS technologies. Additionally, a total of 13 optical sorting machines integrated with AI, by 11 different companies, have been identified. Among these, 10 machines are capable of sorting plastic by color, and 8 of them have the capability to separate black plastics from other colors by utilizing ML/AI with NIR, and/or VIS technologies. This brings the total number of whole-plastic optical sorters to 50 (conventional optical sorters and optical sorters with integrated AI). Since our 2022 report [20], there has been an 8.7% growth in the number of optical sorters. Moreover, there are now 13 AI-integrated sorters that were not available in our 2022 study (Table 3). The reported accuracy of these sorters in reclaiming materials can reach an impressive 99.99%, contingent upon the input materials being processed. Furthermore, these sorters offer a broad range of throughput capacities, with the capability to handle up to 10 tons per hour.

Although conventional and AI-based optical sorters have high sorting efficiency, they are primarily intended for sorting 3D/rigid plastic items, and are not as efficient when it comes to sorting plastic films and other two-dimensional materials. There is technology available specifically designed for sorting plastic films or 2D plastics. A total of 16 film-sorting machines by 9 different companies have been identified (Table 4). This marks a substantial 60% increase compared to our 2022 report [20]. These film sorters are said to achieve an accuracy rate of 98%, depending on the materials being processed. Out of the total, six of these machines have the capability to sort films based on their color, while the majority of them (81% of sorters) employ a combination of NIR and VIS technologies.

Before plastic is reprocessed, flake sorting is a crucial stage that helps minimize contamination caused by foreign materials or undesired plastics that may have slipped through previous sorting stages. Flake sorters have the capability to segregate plastics based on their size, typically down to 1 mm, although this may vary depending on the specific types of equipment used. Table 5 presents the existing inventory of plastic flake sorters. A total of 55 flake sorters, produced by 21 different companies, are reported. This represents an increase of 57%, compared to the 35 sorters identified in our 2022 publication. The reported accuracy achieved by flake sorters can reach 99%, contingent upon the materials being processed. The identification of plastic types is accomplished through the use of NIR, XRF, and/or VIS technologies. Additionally, out of the 55 flake sorters, 36 possess the capability to sort flakes based on their color.

The variation in the number of all plastic sorters from our 2021 report to this study is presented in Figure 9.

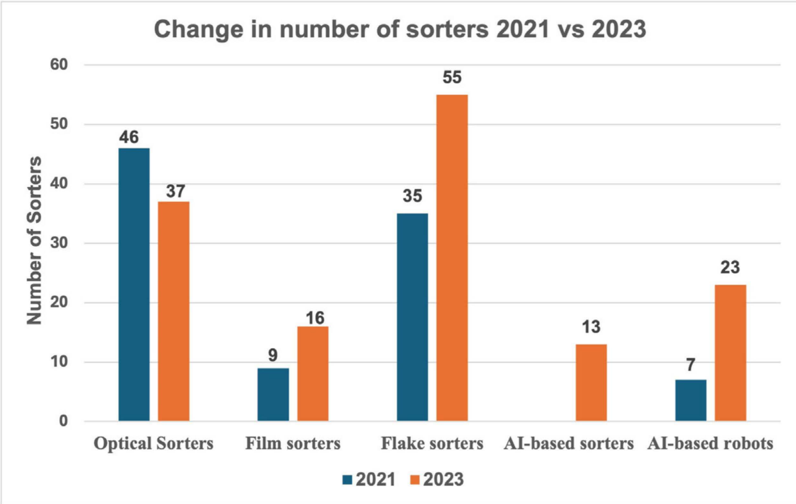


**Figure 9.** Variation in the count of plastic sorters between the years 2021 and 2023.

*6.3. AI-Based Robotic Sorting of Plastics*

In order to tackle challenges encountered in the field of waste management, new approaches are being developed based on the use of computers and robotic technologies [17,112]. Sorting robots, guided by AI, can either operate as an alternative to traditional optical sorters or can supplement optical sorters by purging incorrectly sorted plastics at the end of the sorting process [17]. Moreover, AI sorters have the ability to improve sorting efficiency over time by using available data to mimic a human brain's learning and decision-making processes [85,113,114].

A total of 22 AI-based robotic sorters are reported here from 16 different companies, all with the ability to sort plastic by type and color (Table 6). Some MRFs have already integrated AI-based sorters in their processing line, according to manufacturers of AI-based sorters that report in their publicity materials lists of MRFs that have adopted their technologies. The plastic identification method or sorting method involves deep learning and VIS, and in some cases, combine deep learning, VIS, and NIR. There is an increase of 214% in AI-based sorters compared to the seven AI-sorters identified in our 2022 report.

## 7. Conclusions

The increasingly large amounts of plastic produced and used worldwide necessitate the proper management of plastic waste, which includes various types of recycling processes. Proper classification and sorting of plastic waste are important in recycling, as they increase the quantity and improve the quality and value of the post-consumer plastics that are recovered and sent for reprocessing. Automated sorting promises high throughput and efficient classification of mixed plastic waste. The types and capabilities of commercially available equipment for sorting plastic are reported and analyzed here. To support the content on automated sorting equipment, spectroscopic methods for identification of plastic type are highlighted, and basic principles of ML/AI are presented, with an interest in the combination of spectroscopy and ML/AI, which is at the core of modern equipment employed in plastic type identification.

The inventory of commercial sorting equipment includes 49 optical sorters for whole plastic objects, 55 flake sorters (from 11 companies), 16 film sorters (from 9 companies), and 22 AI-based sorters for mixed plastic recyclables. The recovery accuracy of sorting equipment reported herein can be as high as 99.99%, depending on input materials, with a wide range of throughput capacities (up to 10 ton/h). Growth in available optical sorting technology was about 7%, and a significant shift in incorporating AI in optical sorters was observed, compared to our 2022 study [20]. The observed growth in film sorters, flake sorters, and AI-based sorters signifies the emerging importance of plastics recycling. The potential accuracy of sorting equipment, from past reports and currently available, remains similar when it comes to sorting plastics by chemical composition; however, the introduction of AI has given sorting equipment new capabilities it previously did not have, which is sorting plastics based on physical characteristics such as transparency, morphology, etc., which in turn reduces misclassification of plastics based on physical attributes, thus significantly boosting recycling efficiency. The information presented here can address some of the challenges reported by MFRs in our 2022 article, with an increasing number of available film sorters that can now be integrated in MRFs to sort plastic films for recycling, and an increasing number of sorters for black plastics that could not otherwise be sorted solely by NIR-based optical sorters. Although the available technologies to address those limitations are increasing, economic factors should also be taken into account.

**Author Contributions:** Conceptualization, P.A.; methodology, C.L. and P.A.; formal analysis, C.L. and M.A.A.B.D.; investigation, C.L. and M.A.A.B.D.; resources, P.A.; data curation, C.L. and M.A.A.B.D.; writing—original draft preparation, C.L. and M.A.A.B.D.; writing—review and editing, P.A.; supervision, P.A.; project administration, P.A.; funding acquisition, P.A. All authors have read and agreed to the published version of the manuscript.

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**Data Availability Statement:** Research data are available upon reasonable request.

**Conflicts of Interest:** The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

## Appendix A

**Table A1.** Contact information of optical sorter suppliers.

| | |
|---|---|
| Amut Ecotech<br>Via San Marco 11/a<br>31052 Candelù—Maserada sul Piave (TV)—Italy<br>Phone: +39-0422-877-688<br>Fax +39-0422-877-690<br>E-mail: info@amutecotech.it<br>Website: www.amut.it/amutecotech<br>(Last accessed 30 January 2024) | Anhui Zhongke Optic-electronic Color Sorter Machinery Co., Ltd.<br>No. 43, Yulan Avenue, Baiyan Science Park, Hefei high tech Industrial Development Zone, China<br>Email: export@cn-amd.com<br>Phone: +8613655516956<br>Fax: 0551-66396866<br>Website: http://english.cn-amd.com<br>(Last accessed 30 January 2024) |
| Anysort<br>ANYSORT, Schnackenburgallee 179, 22525 Hamburg<br>Phone: +49-40-819768-0<br>Email: info@anysort-usa.com<br>Website: https://www.anysort-usa.com<br>(Last accessed 30 January 2024) | Binder + Co.<br>Grazer Straße 19-25<br>A-8200 Gleisdorf, Austria<br>Phone: +43-3112-800-0<br>Fax: +43-3112-800-300<br>Email: office@binder-co.at<br>www.binder-co.com<br>(Last accessed 30 January 2024) |
| Bollegraaf Group<br>Tweede Industrieweg 1<br>9902AM Appingedam<br>The Netherlands<br>Email: info@bollegraaf.com<br>Phone: +31-(0)596-65-43-33<br>Website: https://www.bollegraaf.com<br>(Last accessed 30 January 2024) | Buhler<br>Gupfenstrasse 5<br>Uzwil<br>9240 Switzerland<br>Phone: +41-71-955-19-00<br>Website: https://www.buhlergroup.com<br>(Last accessed 30 January 2024) |

**Table A1.** *Cont.*

| | |
|---|---|
| Cimbria<br>Faartoftvej 22<br>7700, Thisted, Denmark<br>Phone: +45-96-17-90-00<br>E-mail: cimbria.holding@agcocorp.com<br>https://www.cimbria.com<br>(Last accessed 30 January 2024) | CP Group (MSS) Sorting Equipment<br>6795 Calle de Linea<br>San Diego, CA 92154, USA<br>Phone: +1 619-477-3175<br>Fax: 619-477-3426<br>https://www.cpgrp.com<br>(Last accessed 30 January 2024) |
| Eagle Vizion<br>www.eaglevizion.com<br>(Last accessed 30 January 2024) | Green Machine LLC<br>8300 State Route 79<br>Whitney Point, NY 13862, USA<br>Phone: +1 800-639-6306<br>Email: sales@greenmachine.com<br>Website: www.greenmachine.com<br>(Last accessed 30 January 2024) |
| Hefei Mayson Machinery Co., Ltd.<br>Block A, Zhongrui Tech-research Building,<br>No. 9 Hongfeng Road, Hefei City, China<br>Email: info@hfm-sorter.com<br>Phone: +86-199-5659-5855<br>Website: https://hfm-sorter.com<br>(Last accessed 30 January 2024) | Hefei Golden Sorter Co., Ltd.<br>No.230, Jinxiu Road, Economic and Technological Zone, Luan,<br>Anhui province, China.<br>Email: goldensorter@gmail.com<br>Phone: +86-19965476623<br>Website: https://goldensorter.com<br>(Last accessed 30 January 2024) |
| IMRO<br>Landwehrstrasse 2,<br>D-97215 Uffenheim, Germany<br>Phone: +49-(0)-9848-9797-0<br>Fax: +49-(0)-9848-9797-97<br>Website: https://www.imro-maschinenbau.de/en/<br>(Last accessed 30 January 2024) | MachineX<br>2121, rue Olivier, Plessisville<br>QC, G6L 3G9, Canada<br>Phone: +1-877-362-3281<br>Website: https://www.machinexrecycling.com<br>(Last accessed 30 January 2024) |
| MEYER Europe s.r.o.<br>Nam. L. Novomeskeho 1<br>040 01 Kosice, Slovakia<br>Email: sales@meyer-corp.eu<br>Phone: +421 948 209 976<br>Website: https://meyer-corp.eu<br>(Last accessed 30 January 2024) | Mogensen GmbH/Allgaier Process Technology GmbH<br>Ulmer Straße 75<br>73066 Uhingen<br>Germany<br>Phone: +49-7161-301-175<br>E-mail: process-technology@allgaier-group.com<br>https://www.allgaier-process-technology.com/en<br>(Last accessed 30 January 2024) |
| MSS, Inc. [A division of CP Group]<br>300 Oceanside Drive<br>Nashville, TN 37204, USA<br>Phone: +1 615-781-2669<br>Email: info@mssoptical.com<br>https://www.mssoptical.com<br>(Last accessed 30 January 2024) | MSWsorting<br>Zhengzhou high-tech zone, China<br>Email: info@MSWsorting.com<br>Website: https://www.mswsorting.com/index.html<br>(Last accessed 30 January 2024) |
| NRT Optical Sorting<br>1508 Elm Hill Pike<br>Nashville, TN 37210, USA<br>Phone: +1-615-734-6400<br>Email: service@nrtsorters.com<br>www.nrtsorters.com<br>(Last accessed 30 January 2024) | Pellenc ST<br>125 rue François Gernelle BP124<br>84 124 Pertuis Cedex 4<br>Phone: +33-4-90-09-47-90<br>Email: contact@pellencst.com<br>www.pellencst.com<br>(Last accessed 30 January 2024) |

**Table A1.** *Cont.*

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| PicVisa<br>Isaac Newton, 2<br>Barcelona, Spain<br>Email: info@picvisa.com<br>Phone: +34-938-268-822<br>Website: www.picvisa.com<br>(Last accessed 30 January 2024) | Redwave (a division of BT-Wolfgang Binder GmbH)<br>Wolfgang Binder Str. 4<br>8200 Eggersdorf bei Graz, Austria<br>Phone: +43-3117-25152-2200<br>Fax: +43-3117-25152-2204<br>Email: office@redwave.com<br>https://redwave.com/en/<br>(Last accessed 30 January 2024) |
| Rhewum GmbH<br>Rosentalstrasse 24<br>42899 Remscheid, Germany<br>Phone: +1-(888)-474-3986<br>Email: info@rhewum.de<br>Website: https://www.rhewum.com/en<br>(Last accessed 30 January 2024) | RTT Steinert GmbH<br>1234 Hardt Circle<br>Bartlett, IL 60103, USA<br>Phone: +49-221-49840<br>Email: sales@steinert.de<br>Website: https://steinertglobal.com<br>(Last accessed 30 January 2024) |
| Satake<br>10900 Cash Road<br>Stafford, Texas 77477<br>USA<br>Phone: +1-281-276-3600<br>Website: https://satake-usa.com<br>(Last accessed 30 January 2024) | Sesotec GmbH (S + S Separation and Sorting Technology GmbH)<br>Regener Strabe 130<br>D-94513 Schonberg, Germany<br>Phone: +1-224-208-1900<br>Fax: +1-224-208-1909<br>Email: info.us@sesotec.com<br>www.sesotec.com<br>(Last accessed 30 January 2024) |
| Steiner US<br>285 Shorland Drive<br>KY 41094 Walton<br>Phone: +1-(859)-962-2648<br>Website: https://steinertglobal.com/us/<br>(Last accessed 30 January 2024) | TOMRA Systems ASA<br>Drengsrudhagen 2<br>Asker 1385<br>Norway<br>Phone: +47-66-79-91-00<br>https://www.tomra.com/en<br>(Last accessed 30 January 2024) |
| Unisensor Sensorsysteme GmbH<br>Am Sandfeld 11<br>76149 Karlsruhe, Germany<br>Phone: +49-(721)-97884-0<br>Email: info@unisensor.de<br>Website: www.unisensor.de/en/<br>(Last accessed 30 January 2024) | Visys<br>Birlik Sanayi Sitesi 2. Cadde No:97<br>PK:34520 Beylikdüzü—İstanbul—Turkey<br>Phone: +90-212-876-90-36<br>Fax: +90-212-876-90-37<br>E-mail: info@visystr.com<br>Website: www.visys.com.tr<br>(Last accessed 30 January 2024) |
| Wesort<br>Building 29 LongWangMiao industrial area,<br>BaiShiXia Community, FuYong Street, Shenzhen, China<br>Phone: +86-13226817096<br>Email: wesort.info@gmail.com<br>Website: https://www.wesortcolorsorters.com<br>(Last accessed 30 January 2024) | |

## Appendix B

**Table A2.** Contact information of suppliers of AI-based robots and sorters.

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|---|---|
| AMP Robotics<br>1500 Cherry Street, Suite A<br>Louisville, CO 80027, USA<br>Phone: +1 (888)-402-1686<br>Website: www.amprobotics.com<br>(Last accessed 30 January 2024) | Back Handling Systems (BHS)<br>3592 West 5th Avenue<br>Eugene, OR 97402, USA<br>Phone: +1 541-485-0999<br>Email: sales@bhsequip.com<br>Website: https://www.bulkhandlingsystems.com<br>(Last accessed 30 January 2024) |
| BIN-e<br>Pasjonatów 9<br>62-069 Dąbrowa, Poland<br>Email: contact@bine.world<br>Website: https://www.bine.world<br>(Last accessed 30 January 2024) | Bollegraaf Recycling Solutions<br>Tweede Industrieweg 1, 9902 AM<br>Appingedam, The Netherlands<br>Phone: +31-596-654-333<br>Email: info@bollegraaf.com<br>Website: https://www.bollegraaf.com<br>(Last accessed 30 January 2024) |
| CleanRobotics<br>Email: zak.wehman@cleanrobotics.com<br>Website: https://cleanrobotics.com<br>(Last accessed 30 January 2024) | Enerpat<br>Enerpat Group Uk Ltd.<br>55 Crown St, Brentwood,<br>Essex CM14 4BD, UK<br>Email: info@enerpatgroup.com<br>Phone: +86-15051237913<br>Fax: +86-513-8778-2755<br>Website: https://www.enerpatrecycling.com<br>(Last accessed 30 January 2024) |
| Everestlabs<br>48820 Kato Rd Suite 500B, Fremont, CA 94538, USA<br>Email: hello@everestlabs.ai<br>Website: https://www.everestlabs.ai<br>(Last accessed 30 January 2024) | Greyparrot<br>Greyparrot AI Ltd.<br>100 Drummond Road<br>A401<br>London, SE16 4DG, UK<br>Email: contact@greyparrot.ai<br>Website: https://www.greyparrot.ai<br>(Last accessed 30 January 2024) |
| Intuitive AI<br>1200-555 W Hastings St, Vancouver, BC V6B4N6, Canada<br>Email: hello@intuitiveai.ca<br>Website: https://intuitiveai.ca<br>(Last accessed 30 January 2024) | Ishitva Robotic Systems<br>Website: https://ishitva.in<br>(Last accessed 30 January 2024) |
| Machinex<br>2121, rue Olivier, Plessisville<br>QC G6L 3G9, Canada<br>Phone: +1-(819)-362-3281<br>Website: www.machinexrecycling.com<br>(Last accessed 30 January 2024) | OP teknik<br>Lastbilsvägen 2<br>298 32 Tollarp<br>Sweden<br>Phone: +46-(0)-10-456-82-70<br>Email: info@opteknik.se<br>Website: https://www.opteknik.se/sorteringssida?lang=en<br>(Last accessed 30 January 2024) |
| PicVisa<br>Isaac Newton, 2<br>Barcelona, Spain<br>Email: info@picvisa.com<br>Phone: +34-938-268-822<br>Website: www.picvisa.com<br>(Last accessed 30 January 2024) | Recycleye<br>179 Hercules Road,<br>London<br>SE1 7LD, UK<br>Email: hello@recycleye.com<br>Website: https://recycleye.com<br>(Last accessed 30 January 2024) |

**Table A2.** *Cont.*

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|---|---|
| Redwave (a division of BT-Wolfgang Binder GmbH)<br>Wolfgang Binder Str. 4<br>8200 Eggersdorf bei Graz, Austria<br>Phone: +43-3117-25152-2200<br>Fax: +43-3117-25152 2204<br>Email: office@redwave.com<br>https://redwave.com/en/<br>http://www.btw-binder.com/en/<br>(Last accessed 30 January 2024) | Sortera Alloys<br>49 S 500 E<br>Markle, IN 46770, USA<br>Phone: +1 260-330-7100<br>Website: https://www.sorteratechnologies.com<br>(Last accessed 30 January 2024) |
| TOMRA Systems ASA<br>Drengsrudhagen 2<br>Asker 1385<br>Norway<br>Phone: +47-66-79-91-00<br>https://www.tomra.com/en<br>(Last accessed 30 January 2024) | Waste Robotics<br>3055, rue Tebbutt<br>Trois-Rivières, QC G9A 5E1<br>Canada<br>Phone: +1-819-201-2525<br>Website: https://wasterobotic.com<br>(Last accessed 30 January 2024) |
| ZenRobotics<br>Perintötie 8 C 1<br>01510 VANTAA<br>Finland<br>Email: info@zenrobotics.com<br>Phone: +358-50-4363803<br>Website: https://www.terex.com/zenrobotics/<br>(Last accessed 30 January 2024) | |

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