

Article

Advancing Waste Electrical and Electronic Equipment (WEEE) Recycling: A Random Forest Approach to Classifying WEEE Plastics for Sustainable Waste Management

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Abstract: The rapid growth of waste electrical and electronic equipment (WEEE) highlights its significance as a critical waste stream, with plastics comprising 30% of its volume. These plastics often contain hazardous brominated flame retardants (BFRs), which are regulated to prevent negative environmental and public health impacts, but are predominantly managed through incineration, challenging circular economy goals. Addressing this issue requires innovation in sorting technologies and predictive methodologies to reduce reliance on incineration and enhance recycling efficiency. Despite progress, existing recycling practices are hindered by overly conservative contamination assumptions and a lack of detailed data on WEEE characteristics, leading to resource inefficiencies and missed opportunities for material recovery. This research aimed to bridge these gaps by developing a Random Forest-based predictive model to classify WEEE plastics as recyclable or non-recyclable, thereby supporting sustainable waste management. Using a dataset of over 15,000 samples analysed for polymer type, bromine concentration as an indicator of recyclability, and five additional variables, the model demonstrated 80–88% accuracy in validation tests. Polymer type appeared as the most significant predictor, followed by manufacturer and year of manufacture. Regional testing highlighted the adaptability of the model but also underscored the need for extended datasets and improved data management to simplify variable retrieval, as the model relies on hard-to-access data. The findings of this study have broad implications, including enhanced sorting efficiency, regulatory compliance, and alignment with circular economy principles. By refining classification accuracy and expanding its application, the model offers a scalable solution to advancing WEEE recycling and optimizing resource recovery, thereby promoting sustainability and reducing the environmental impact.

Keywords: WEEE; Python; modelling



Academic Editor: Cheng Fang

Received: 9 January 2025

Revised: 7 February 2025

Accepted: 15 February 2025

Published: 17 February 2025

Citation: Chaine, C.; Errandonea, M.M.; Vega, B.M. Advancing Waste Electrical and Electronic Equipment (WEEE) Recycling: A Random Forest Approach to Classifying WEEE Plastics for Sustainable Waste Management. *Environments* **2025**, *12*, 68. <https://doi.org/10.3390/environments12020068>

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1. Introduction

Waste electrical and electronic equipment (WEEE) is the fastest growing waste stream globally. A key feature of WEEE is the presence of potentially harmful chemical compounds, classifying it as hazardous. This waste includes a variety of materials, with plastics making up approximately 30% of the total WEEE volume each year, comprising a range of different polymers [1]. From a sorting point of view, this represents a challenge that is increased by the presence of additives such as flame retardants (FRs), particularly brominated flame

retardants (BFRs), some of which are classed as persistent organic pollutants (POPs) under the Stockholm Convention.

The European Union (EU) and the United Kingdom (UK) have introduced regulations concerning the management of POPs waste to prevent the release of these compounds into the environment. For instance, Regulation (EU) 2019/1021 of the European Parliament and of the Council of 20 June 2019 on persistent organic pollutants sets strict limits on the presence of POPs in waste, and materials with concentrations of POPs exceeding specified thresholds must be disposed of or treated in ways that ensure destruction or irreversible transformation of the POPs. Currently, to comply with these requirements, plastics deemed to contain POPs are predominantly managed through incineration rather than sorting and recycling [2,3], as this approach provides a convenient means of meeting the destruction criteria. However, this practice undermines the circular economy principles by diverting potentially recyclable plastics away from material recovery streams.

Additionally, the distribution of POPs in WEEE plastics is uneven, as highlighted in previous studies [4–6]; however, despite this variability, the quantities of waste requiring incineration are often overestimated due to conservative regulatory practices that assume uniform contamination. These conservative assumptions lead to the unnecessary disposal of materials that could otherwise be safely recycled, to the detriment of resource efficiency. Addressing these challenges by refining the assessment methodologies and enhancing sorting technologies could reduce reliance on incineration and align with broader sustainability goals.

Different techniques have been assessed and developed for the characterization of BFRs in WEEE plastics, with the use of X-ray fluorescence (XRF) having become very popular. Through this technique, it is possible to determine the concentration of bromine (Br) present in the material as a tracer of BFRs (including POP-BFRs). The correlation between Br concentration and the presence of BFRs is well-documented, given that most commercial BFRs, including PBDEs, PBBs, TBBP-A, and HBCDD, contain bromine as their primary flame-retardant element. The use of XRF for total Br quantification enables the identification of potentially hazardous plastics without the need for complex chemical analyses. Although XRF cannot distinguish between specific BFR compounds, its capacity to rapidly screen for bromine content provides an effective approach for sorting and managing WEEE plastics, thereby facilitating compliance with environmental regulations such as the RoHS and WEEE directives. By defining a Br concentration limit of 2000 ppm, based on the CENELEC EN-50625 standard [7], WEEE plastics are classified by Category as recyclable and non-recyclable, depending on whether their concentration is less than or greater than this threshold, respectively. The 2000 ppm threshold for bromine in WEEE plastics was established through research and industry practices as a screening level to identify BFR-containing materials, aligning with regulatory limits and ensuring efficient waste sorting in recycling operations [8].

In complying with the regulations, the recycling industry is faced with the difficult task of properly managing these plastics to meet legal requirements and avoid negative environmental and health impacts, while maintaining profitability. In addition to these challenges, recyclers are under increasing pressure to align their operations with circular economy principles, aiming at retaining materials within the production cycle and reducing dependency on virgin resources. This dual condition of compliance and circularity adds complexity to their operations, demanding innovative solutions and technologies to balance environmental responsibility with economic viability.

In recent decades, there has been a growing interest in recycling WEEE for resource recovery. However, predicting the volumes of waste that can be recovered and the volumes of plastics that can be recycled remains challenging. The increasing generation of WEEE

in the UK attracts particular attention from various stakeholders, including regulatory authorities, manufacturers, recyclers, and the general public.

Calculating estimates requires large volumes of high-quality information. Therefore, it is important to understand the intrinsic characteristics of the material, which will, in turn, determine the potential recycling percentages. Generally, the information gathered and reported regarding WEEE generation is recorded by weight without clearly specifying the WEEE category included. In the UK, information is differentiated by stream according to the 14 categories defined in the Waste Electrical and Electronic Equipment Regulation 2013. The lack of granularity in the data affects critical decisions in several ways. For instance, it hinders the ability to design efficient recycling systems tailored to the specific materials and contaminants present in different WEEE categories. Without precise information, policymakers may struggle to set realistic recycling targets or develop incentives for recovery that align with the materials' characteristics. Similarly, waste managers face challenges in allocating resources effectively, such as deciding on the types of sorting technologies or recycling methods to prioritize. This can lead to inefficiencies, such as overinvestment in facilities for less prevalent materials or under-exploitation of high-value recyclables. Moreover, an incomplete understanding of material flows complicates efforts to comply with environmental regulations and to transition towards a circular economy, where the recovery and reuse of materials are maximized. Addressing this gap requires improved data collection practices that provide not only the weight but also the material composition and category-specific details.

For instance, the UK has experienced a significant rise in the market introduction of display equipment due to the transition from CRT (cathode ray tube) equipment to FPD (flat panel display) equipment initially, and later due to the shift from LCD to LED technology [9]. While the FPD manufacturing industry in the UK does not stand out within the sector, the volume of display equipment items placed on the market (POM) has been increasing over the last decade [10], associated with increased consumer demand and programmed obsolescence. In contrast, the corresponding tons of display equipment discarded and collected have been steadily decreasing (see Figure 1). This trend can be attributed to progressive advancements in display technology, which have resulted in lighter, thinner, and more compact devices that reduce the overall material mass per unit. Additionally, extended product lifespans due to improved durability and repairability, as well as increased consumer preference for donating or reselling functional devices instead of discarding them, have further contributed to the reduction in discarded items. These factors collectively highlight the evolving dynamics of the sector, with significant implications for waste management and recycling strategies.

One of the main setbacks of the WEEE and POM recording system used by the UK authorities is evidenced here. As WEEE is recorded by weight, the number of items is unknown. Consequently, the number of items entering the FPD waste stream could be overestimated, since, for example, CRTs are accounted for in the display equipment category and their weight is much higher than that of a FPD of the same screen size. Notwithstanding, CRTs are no longer marketed, so the comparison between POM and waste for this category remain somewhat incongruent when analysing trends. Aiming to bridge this gap, with the information collected from a WEEE manager in the UK, it was determined that the trend in the number of FPD units is markedly increasing, while there is an almost steady decline in CRT disposal. According to these trends, it is expected that the volume of FPDs entering the waste stream will continue to increase in the coming years, along with waste FPD (wFPD) plastics. Nevertheless, processes have not been developed that are effective and efficient enough for the classification of this material, and thus large volumes of WEEE plastics are still not being properly managed. The lack of effective

and efficient classification processes for these materials often results in improper disposal methods, such as incineration or landfilling (depending on the region), which fail to recover valuable resources and may release toxic substances into the environment [11]. Therefore, understanding the future of wFPD plastics' generation and the recycling potential of this stream is very important for sustainable management.

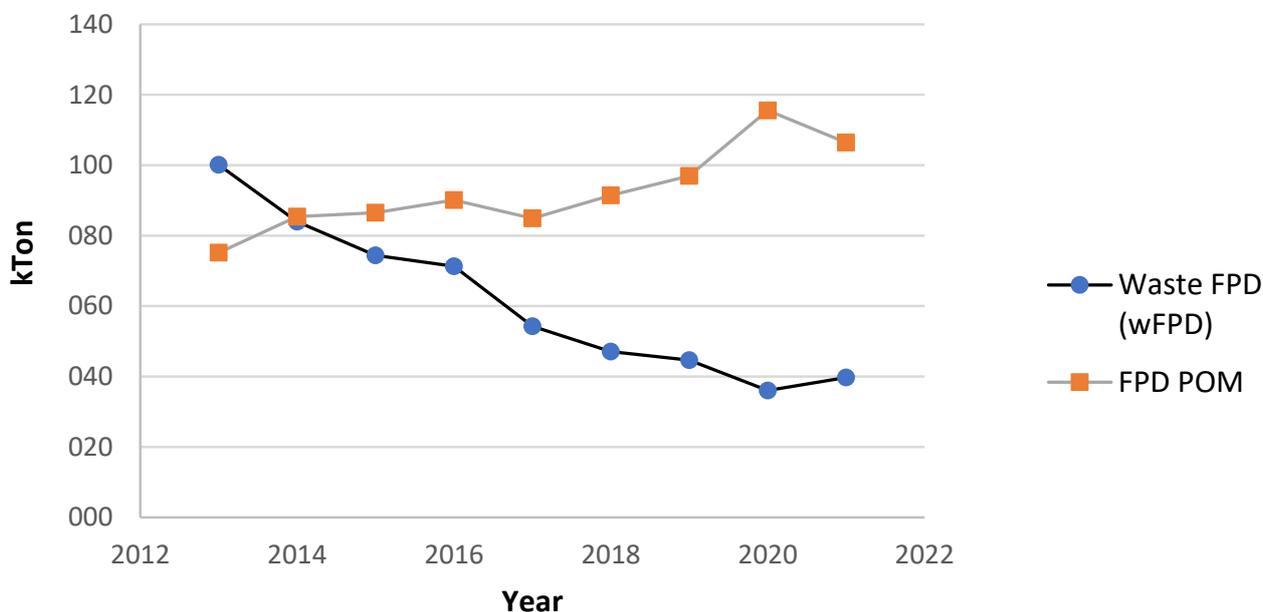


Figure 1. Evolution of waste FPDs and FPDs placed on the market (POM) in the UK. Source: <https://www.gov.uk/guidance/regulations-waste-electrical-and-electronic-equipment> (10 May 2024).

WEEE management is complex, highlighting the need for tools to understand and, if possible, predict its generation. Building predictive models in waste management is relevant for a variety of reasons. Firstly, these models aid in resource allocation by predicting future waste generation, enabling waste management authorities to effectively plan and allocate resources such as collection vehicles, recycling facilities, and personnel. Secondly, predictive models provide valuable insights for planning and policymaking in waste management, allowing policymakers to develop strategies to address emerging challenges, set realistic waste reduction targets, and implement appropriate regulations and incentives. Furthermore, these models facilitate environmental impact assessments by forecasting the future environmental consequences associated with waste generation, treatment, and disposal, enabling decisionmakers to develop strategies to minimize the negative impacts on the environment and public health. Historically, predictive models have been employed to forecast municipal waste generation with varying levels of success. For instance, studies have explored machine learning models to predict solid waste generation at the country level using demographic and socio-economic data, offering insights into the impact of these factors on waste trends [12].

Similarly, econometric models have been applied to analyse the influence of socio-economic factors on households' willingness to pay for improved solid waste management services, providing a foundation for understanding waste generation behaviours [13].

While predicting waste remains challenging due to the influence of rapidly changing consumer behaviours, technology advancements, and policy shifts, these approaches have highlighted the potential of combining socio-economic and environmental data to improve models' accuracy. Modern techniques, including machine learning, have begun addressing these complexities by enabling the analysis of large datasets and uncovering patterns previously overlooked. As such, predictive models continue to facilitate environ-

mental impact assessments, optimize recycling efforts, and enhance the sustainability of waste management practices by providing actionable insights into future waste trends and enabling informed decision-making.

Different statistical tools can be applied for data modelling, going from straightforward binary logistic regression to more complex tools like programming languages. Binary logistic regression is particularly effective for modelling dichotomous outcome variables and has been successfully applied in waste management studies [14].

Incorporating programming languages into data modelling has further enhanced analytical capabilities in environmental studies. Python, for example, offers a suite of libraries such as NumPy and scikit-learn which facilitate the analysis and visualization of complex environmental data.

The success of these tools in related fields underscores their potential in waste management applications. Binary logistic regression provides a robust framework for identifying factors influencing waste disposal behaviours, while programming languages like Python offer flexibility and scalability in modelling complex environmental systems. The integration of these tools can lead to more accurate predictions and informed decision-making in waste management practices.

As Category is a binary variable, as defined in this study, a model based on binary logistic regression was initially attempted by the authors. It showed the statistical parameters of the predictive models had substantial limitations. Specifically, the R^2 values were considerably low, reflecting a minimal proportion of variance in the dependent variables that could be explained by the model. This resulted in unsatisfactory probabilities of accuracy, thus compromising the reliability of its predictions.

In response to this challenge, the application of Python and the Random Forest algorithm is presented as a more powerful alternative tool for information processing and production of a predictive model. Python is renowned for its robust data handling capabilities and extensive libraries tailored for machine learning and data analysis. Libraries such as scikit-learn provide powerful, easy-to-use tools for implementing complex algorithms like Random Forest, enabling more sophisticated and flexible modelling approaches [15].

The Random Forest algorithm is well-suited for this task due to its ensemble nature, which combines the prediction of multiple decision trees to improve accuracy and control overfitting. This method is notably helpful for handling datasets with missing or incomplete information, as it can maintain performance by using the strengths of individual trees to compensate for data gaps [16]. Moreover, Random Forest can handle large datasets with higher dimensionality and intricate variable interactions, making it ideal for the complex WEEE plastics dataset.

By exploiting the Random Forest algorithm, this work explores the potential to develop a predictive model focusing on the Category outcome. The capacity of the method to provide information on variable importance is examined to identify the factors that may most influence the results. Such insights could prove valuable for refining the dataset and concentrating on the most predictive variables, potentially enhancing the model's performance. Thus, this study aimed to assess the feasibility and effectiveness of this technique in generating a reliable predictive model, with the intention of evaluating its success and limitations. The Random Forest model was trained using several deep features extracted from 75% of the training dataset to train the trees, while the remaining 25% was set aside as test dataset used to validate the performance of the model. Each decision tree within the forest is independently generated and each node is split based on a randomly selected subset of features. The forest is expanded to a predetermined number of trees, which contributes to high variance and low bias in the model. The final prediction is determined by averaging the class probabilities assigned by all individual trees [17].

Overall, the decision to transition to Python tools and the Random Forest algorithm stemmed from the need to overcome the limitations of the initial models. The low R^2 values and accuracy probabilities highlighted critical shortcomings in the previous approach, primarily due to incomplete data and insufficient variable predictability. By utilizing the advanced capabilities of Python and the robust ensemble nature of the Random Forest algorithm, the aim was to develop more reliable and accurate predictive models for WEEE plastics, ultimately contributing to more effective recycling and resource management strategies.

In addition, the opportunity was seized to evaluate the applicability in another country, in this case, in Spain, of the predictive model developed based on WEEE plastics recovered in Scotland. By testing the model in a different context but under the same regulatory conditions, the impact of other factors such as consumers', manufacturers', or retailers' behaviour can be assessed to determine their influence on the accuracy of the predictive model. This process would aid in determining the robustness and generalizability of the model, ensuring that it is not overly tailored to the specific Scottish conditions. Additionally, such testing highlights the importance of data quality and availability, which can vary significantly between countries, thereby emphasizing the need for comprehensive datasets to improve predictive accuracy.

2. Materials and Methods

2.1. Sampling: Training and Test Dataset

The data used for training the classification model was generated between 2021 and 2024 from items retrieved from the manual dismantling production line of the recycling plant located in the UK. The database comprising 15,006 samples includes information on different characteristics of the WFPD plastic retrieved directly from individual items' casings.

The following information was recorded for all samples: Type (LED/LCD), Year of manufacture (YoM), Polymer, Size, Origin, and Manufacturer. The date of data collection was also recorded as the Date.

The variable Category was determined by measuring Br, selected as a marker for POP-BFRs. The levels of this element in each sample were measured using the VANTATM X-ray fluorescence analyser—C series (rhodium anode tube) using the RoHS method. Every analysis was conducted three times to ensure consistency, positioning the analyser's window directly on the sample's flat surface without altering its placement between repetitions. A comprehensive account of the methodology and quality control/quality assurance applied for characterizing the plastics is provided in [5].

Items were classed as recyclable or non-recyclable according to the criteria defined in the CENELEC EN-50625 standard [7] (a threshold of 2000 ppm of total Br).

The number of non-null values for each variable is presented in Table 1. As can be observed, the limiting variable was the Polymer. It is important to highlight this extensive database was produced as part of the site's daily operations where information on the polymer was not systematically retrieved.

Table 1. Number of non-null values found in the training dataset.

Variable	Non-Null Values
Date (of sampling)	15,006
Type (LED/LCD)	15,006
Year of manufacture (YoM)	13,505
Polymer	1294
Size	14,995
Origin (country)	9544
Manufacturer (make)	15,006
Category (recyclable/non-recyclable)	15,006

2.2. Sampling: Validation Dataset

To assess the model’s applicability and verify that it does not solely conform to the initial dataset, a validation test was performed using two distinct datasets. The first dataset consisted of 83 items sampled over two weeks at a UK site, while the second included 100 samples collected specifically from wFPD at a Spanish WEEE recycling facility. These datasets were analysed both independently and in combination to validate and fine-tune the hyperparameters of the classification model. In each case, detailed information from the samples was manually gathered and analysed using h-XRF to measure the Br concentrations, serving as an indicator of POP-BFRs, and FTIR (Fourier transform infrared spectroscopy) to identify polymer types.

2.3. FTIR Identification to Determine Polymers

FTIR is a spectroscopic technique that allows the identification of polymer types for qualitative characterization of the samples. The spectra obtained were compared using the equipment’s software for sample identification. Transmission measurements require a short pathlength that, depending on the material and shape of the sample, can be achieved by compressing it into a thin film. In this case, a shaving of less than 1 mm thickness was extracted from each sample.

To verify that the polymer identified on the wFPD casing was correct, a subsample of 100 items was taken from the UK site for the training and test dataset. To calculate the appropriate FTIR sample size, Equation (1) was applied, considering 1000 FPD units (the daily production) as the population (N).

Equation (1). Sample size

$$n = (N \times Z_{\alpha}^2 \times p \times q) / (e^2 \times (N - 1) + Z_{\alpha}^2 \times p \times q) \tag{1}$$

- n: desired sample size;
- N: population size or universe;
- Z_α: Z-score, a statistical parameter depending on the confidence level;
- p: probability of the studied event occurring;
- q: (1 – p) = probability of the studied event not occurring;
- e: maximum accepted estimation error.

As statistical parameters, a confidence level of 99% (Z = 2.579) was considered, and a probability of 50% was assigned since, due to the type of available information, the real probability of the event is unknown. The maximum accepted estimation error was set at 5%.

The samples collected for the validation dataset were all analysed with FTIR to ensure no entry had a null value for the Polymer variable. The instrument used for measurements was the PerkinElmer FTIR spectrometer UATR Spectrum Two. Since all the selected samples were black due to the presence of carbon black (a pigment that gives the material that

shade), the samples could not be analysed in NIR (near-infrared). Therefore, identification was done in MIR (mid-infrared), ranging across 4000–600 cm^{-1} [18].

Before each measurement, the ATR diamond crystal was cleaned with methanol to remove any potential contaminating residue between samples that could affect the results, and a background spectrum was run to eliminate any potential environmental effects.

2.4. Model Development

The development of the wFPD plastics classification algorithm was conducted using the Cognitive Project Management for AI Methodology [19] (Figure 2). The primary stages encompassed the following:

- process understanding;
- data understanding;
- data preprocessing, where variables and entries are modified, created, or eliminated to be more manageable;
- modelling, where the data are used to train machine learning algorithms; and
- model evaluation, where statistical metrics are calculated to assess the performance of the model.

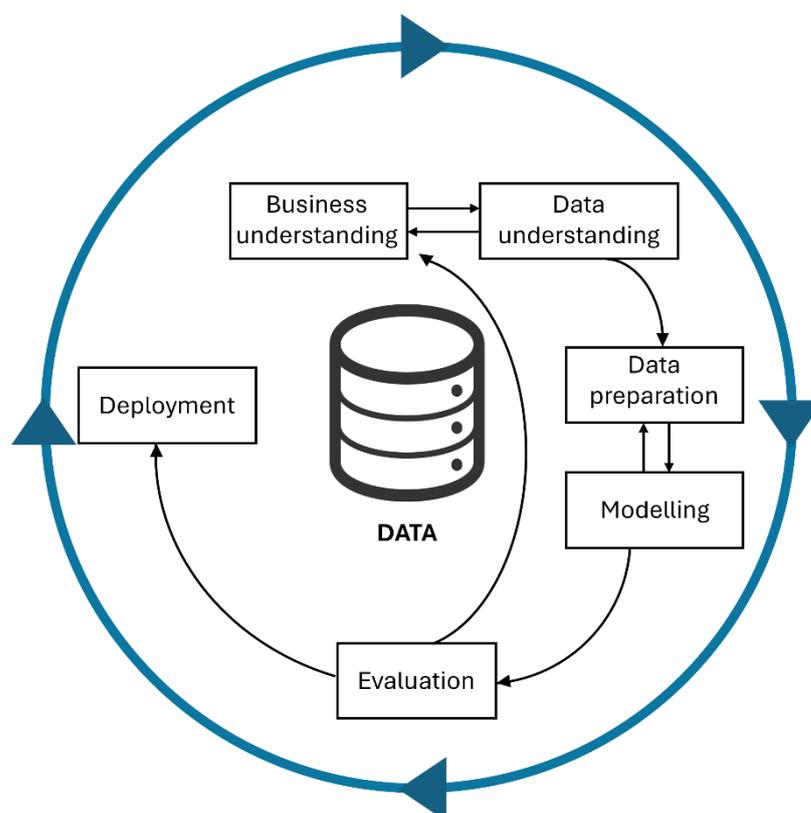


Figure 2. Cognitive Project Management for AI Methodology (source: <https://www.ibm.com>).

Each phase in the creation of the classification algorithm is interconnected, with each step both influencing and being influenced by previous and following steps. This iterative approach allows for continuous feedback and refinement of the process. For instance, the initial models for the classification algorithm revealed the significance of specific variables like Polymer, while also identifying that variables such as Date contributed to overfitting without providing additional insights into the process or data. These findings were instrumental in refining the preprocessing and modelling stages, which will be discussed in further detail in subsequent sections.

2.5. Data Preprocessing

The main Python libraries used for data loading, transformation, and extraction were Pandas and NumPy. The initial models constructed with the raw data using Random Forest indicated a significant dependence of Category on the Polymer variable. Consequently, all rows with missing data for these variables were excluded, resulting in a reduction in the dataset to 1294 rows. While this excluded a considerable portion of the data, imputation was not pursued, as imputing more than 10% of the data is generally considered unsuitable due to the potential for introducing statistical inaccuracies [20].

Furthermore, in the preliminary decision tree ensemble models, the variable of Date demonstrated a relevance of up to 20%. Given that this variable merely denotes the date on which each sample was recorded, it logically should not play such a significant role in the model. Additionally, when applied to the validation datasets, this preliminary model exhibited very low accuracy, indicating that the model was overfitting the training dataset. Consequently, the Date variable was excluded from the model training process.

The categorical variables of Manufacturer, Polymer, and Type were converted to integers through the scikit-learn ordinal encoder function (OrdinalEncoder—scikit-learn 1.5.0 documentation). The target classification label was encoded with the label encoder from scikit-learn (LabelEncoder—scikit-learn 1.5.0 documentation) [21], where “non-recyclable” was translated to 0 and “recyclable” to 1.

Missing values were imputed with the K-nearest neighbours (KNN) algorithm using scikit-learn’s KNN imputer (KNNImputer—scikit-learn 1.5.0 documentation). K-nearest neighbours is a non-parametric classifier and predictive tool based on the ‘k’ nearest point in the training dataset. The key characteristics of KNN include its reliance on distance metrics, typically Euclidean, its non-parametric nature, and its learning approach, where KNN bypasses model training and makes predictions directly based on the dataset at hand. In the present study, KNN was configured with 4 neighbours and uniform weights, meaning that regardless of their distance from the target value, each of the ‘k’ nearest neighbours contributed equally to the prediction.

2.6. Model Selection and Evaluation Metrics

The model was built mainly using the scikit-learn library (scikit-learn: machine learning in Python—scikit-learn 1.5.0 documentation) [22]. There are several classification models, from simple, such as Gaussian naïve Bayes, to more complicated models such as ensembles of decision tree algorithms. The best-performing algorithm according to the established metric scores (precision, recall, f1 score, and accuracy) was the Random Forest classifier of scikit-learn [23]. Random Forest is an ensemble learning algorithm that constructs multiple decision trees during training and aggregates their predictions to improve accuracy and robustness. It operates using bootstrap aggregation (bagging), where each tree is trained on a randomly sampled subset of the data with replacement, and at each split, only a random subset of the features is considered to reduce correlation between trees. For classification, the final prediction is determined by majority voting, while for regression, predictions are averaged. This approach reduces overfitting, enhances generalization, and provides feature importance estimation, making Random Forest a widely used and powerful algorithm in various domains [24].

The confusion matrix is a table that allows the performance of the classification algorithm to be evaluated by presenting how the model’s predictions compare with the actual results by showing the number of predicted and true values for each category [25].

For this study, as the model is based on a binary label, the matrix is represented as a table of four quadrants (two rows and two columns). Each row represents the actual instances and each column the predicted ones, allowing an assessment of the accuracy of

the model by showing the counts of true (positive and negative) and false (positive and negative) predictions. True positive cases are those where the model correctly predicted the positive class (recyclable), while true negative cases are those where the model correctly predicted the negative class (non-recyclable). Conversely, false positives are cases where the model predicted a positive class when it was truly negative, and false negatives are cases where it predicted a negative class when it was actually positive. This is represented in Figure 3.

TRUE LABEL	Non-Recyclable (0)	TRUE NEGATIVE	FALSE POSITIVE
	Recyclable (1)	FALSE NEGATIVE	TRUE POSITIVE
		(0) Non-Recyclable	(1) Recyclable

PREDICTED LABEL

Figure 3. Confusion matrix.

From the values of the confusion matrix, the accuracy, precision, recall, and f1 score performance metrics mentioned above can be calculated. The classification evaluation metrics used for individual label performance were the following [26].

Precision is defined as the number of correctly identified members of a class divided by the total instances where the model predicted that class. In the present study, it is defined as follows.

- For non-recyclable (0): $\text{true negative} / (\text{true negative} + \text{false negative})$.
- For recyclable (1): $\text{true positive} / (\text{true positive} + \text{false positive})$.

High precision indicates that the model has a low false rate, meaning that when the model predicts a class, it is often correct. In contrast, low precision indicates a high false rate, suggesting that many of the model's positive predictions are incorrect.

Recall is the proportion of correctly identified members of a class to the total number of actual members in that class. In the present study it is defined as follows.

- For non-recyclable (0): $\text{true negative} / (\text{true negative} + \text{false positive})$.
- For recyclable (1): $\text{true positive} / (\text{true positive} + \text{false negative})$.

High recall indicates that the model can successfully identify the majority of positive instances, minimizing the number of false negatives. Conversely, if the recall is low, it means the model is missing many of the actual positive instances and gives a higher number of false negatives.

F1 score: this metric combines precision and recall, and it is defined as the harmonic mean of these two variables. It measures the model's accuracy, determining how many times the model made a correct prediction across the dataset. It is a quick method to

determine whether the classifier is genuinely effective at identifying members of a class or if it is taking shortcuts, such as labelling everything as a member of a predominant class.

Accuracy: this metric indicates the fraction of correct predictions the model yields. It is defined as (true positive + true negative)/total. This parameter was considered for the combined classification evaluation.

Macro-average is computed by aggregating the individual contributions of each class without weighing them by class prevalence. It treats the problem as a binary classification at the level of individual instances rather than class labels.

Weighted average accounts for the imbalance in class distribution by weighting each class's metric by its support (i.e., the number of true instances for that class). This prevents small classes from having a disproportionate impact on the final score.

2.7. Model Training: Training and Test Dataset Split

The dataset was divided into the training and test subsets using the training–test split function of scikit-learn for model selection. The training–test split in scikit-learn works by dividing a dataset into two separate parts: one for training a machine learning model and the other for evaluating its performance. It randomly shuffles the data to ensure an unbiased distribution, then allocates a specified proportion for training and the rest for testing. The user can control the split ratio, such as assigning 80% of the data for training and 20% for testing. If needed, a random seed can be set to make the split reproducible. This method helps assess how well a model generalizes to unseen data by preventing it from simply memorizing the training examples. A 0.75 training ratio was set in the training–test split, with stratification on the y-axis (target or label, i.e., Category). As the data contained a higher ratio of recyclable samples, a stratification method was used to counteract the imbalance in the dataset. A random seed was also established to ensure the reproducibility of the algorithm. Data rebalancing methods such as the Synthetic Minority Over-sampling Technique (SMOTE) [27] were considered but yielded suboptimal results and issues in overfitting. Once processed, the dataset had a similar ratio of recyclable to non-recyclable samples.

Issues of overfitting emerged in the validation dataset, despite the favourable metrics obtained in the test dataset. This occurred mainly because the dataset did not include a sufficient number of entries to construct a robust rebalancing algorithm that could effectively prevent overfitting problems.

2.8. Hyperparameter Tuning

The parameters of the function that determine how the algorithm is constructed are called hyperparameters, and each dataset and case benefits from different hyperparameter settings. At an initial stage, before acquiring the validation dataset, a grid search, using scikit-learn's GridSearchCV, was used [28]. The resulting hyperparameters were a maximum depth of 10 (number of levels in each decision tree), a minimum samples per leaf of 2 (number of samples that must be present in a leaf node representing a final decision or output in the tree), a minimum samples per split of 2 (number of samples required to split an internal node, controlling the creation of nodes and sub-nodes in the tree), and 150 estimators (the number of trees in the forest, determining how many trees Random Forest uses for this predictive model).

Both validation datasets were used independently and in combination for parameter tuning and model validation. With the validation data and a grid search process, the optimal minimum number of samples per leaf and per split were determined to be 4 and 3, respectively. The values for the number of estimators and maximum depth were kept from the grid search process, as they provided the best classification scores. A higher minimum

samples per leaf value ensures that leaves contain more samples, thereby making the tree more robust and less prone to overfitting. Additionally, a higher minimum samples per split value results in simpler and more interpretable trees.

2.9. Cross-Validation

Cross-validation offers insight on the model's accuracy by building the model on a set number of different training–test splits of the dataset and evaluating each iteration [29]. This aims to determine whether the model is overfitting on a particular training–test split and offer accuracy metrics on the set number of different training–test splits. This outputs accuracy scores for every model constructed with different iterations. A cross-validation was performed with scikit-learn `cross_val_score`, where five rounds of the dataset were established.

3. Results and Discussion

3.1. XRF and FTIR Results

In the initial dataset of 15,006 entries, 28% of items with Br concentrations above 830 mg/kg were identified as non-recyclable. Furthermore, looking at the reduced database determined by the entries with data for the Polymer variable (1294 items), the percentages vary slightly in favour of the non-recyclable material (36% non-recyclable). Table 2 presents details of the percentages by category for each dataset. In no case was the Sb concentration higher than 8300 mg/kg for items with a Br concentration lower than 830 mg/kg, so all items classed as hazardous are themselves POPs and were therefore sorted as non-recyclable.

Table 2. Category distribution by dataset.

	Recyclable (%)	Non-Recyclable (%)
Whole dataset (15,006 items)	72	28
Training–test dataset (1284 items)	64	36
Spanish validation dataset (100 items)	77	23
Scottish validation dataset (84 items)	56	44

Given the nature of wFPD plastics, it was expected to find polymer blends [30], which was verified in the majority of the samples according to the similarity percentages obtained for the polymers identified by FTIR. However, there were, in every case, dominant polymer types masking the characteristic peaks of other polymers present in the blend. Remarkably, in 92% of the cases, the polymer type identified in the sample corresponded precisely to that determined by FTIR analysis.

3.2. Classification Model Results

3.2.1. Importance of Variables

The scikit-learn Random Forest classifier allows the user to easily extract the training weights of each variable for the decision tree [31]. Out of the six variables included in the study, the Polymer is the most important feature. The Manufacturer variable also shows relatively high relevance, with a mean decrease in impurity (MDI) of 24%, followed by YoM with 20%. The most important feature is the Polymer, with an MDI of almost 30%, a measure used in Random Forests to evaluate the importance of a variable based on how much it reduces the impurity (e.g., variance) across all the splits where it is used in the trees of the forest. A higher MDI value indicates that the feature contributes significantly to improving the predictive performance of the model by creating purer splits in the data.

This is in accordance with the fact that different polymers require different loads of flame retardants to comply with standards, conditioning the material's Category.

The Manufacturer variable ranks as the second most critical factor (MDI: 24%) in the classification of wFPD plastics. Due to legal constrains, the author is not at liberty to disclose the manufacturers according to the recyclability of their products. Nevertheless, it was observed that a number of manufacturers appeared more frequently in the non-recyclable samples.

The YOM emerged as the third most influential feature (MDI: 20%). Recyclable samples were more broadly distributed between 2008 and 2018 and were generally present across a broader time range compared with non-recyclable samples, which were more densely clustered around 2010 and 2016. The fourth most significant feature was the Origin (MDI: 16%). Most recyclable samples originated from Poland, China, and Slovakia, while those with a higher count of non-recyclable samples were predominantly manufactured in the United Kingdom, Turkey, and Poland.

The lowest MDI values were observed for Type and Size, with 3% and 12%, respectively.

3.2.2. Code

The Python code can be found in the Supplementary Materials.

3.2.3. Performance Metrics

The metrics used to validate the model included precision, recall, and f1 scores for individual labels, as well as the accuracy score for the overall classification performance. Cross-validation on the test set produced five accuracy scores: 0.804, 0.809, 0.835, 0.876, and 0.809. This indicates that the model's accuracy ranged from a minimum of 80% to a maximum of 88%. These results for the test set are deemed acceptable, especially within the context of waste classification, being substantial performance, given the inherent complexities and variabilities in waste's characteristics. For instance, the application of Random Forest classifiers was used for waste classification by [32,33], reaching accuracies of 96–98%, emphasizing the algorithm's effectiveness in handling diverse and complex dataset. While these studies report a higher accuracy rate, it is important to note that the performance of predictive models can vary significantly depending on factors such as dataset quality, feature selection, and the specific characteristics of the classification task. In the context of predicting recyclability based on various item characteristics, achieving an accuracy between 80% and 88% reflects a robust model performance, considering the challenges associated with accurately capturing the diverse attributes that determine an item's recyclability.

The classification tests yielded the scores as presented Tables 3 and 4 for the test dataset, the Scottish validation dataset, the Spanish validation dataset, and the validation dataset of both countries combined.

Table 3. Test set classification score.

	Precision	Recall	F1-Score	Units
0 (non-recyclable)	0.79	0.72	0.76	116
1 (Recyclable)	0.85	0.89	0.87	208
Accuracy			0.83	324
Macro avg.	0.82	0.81	0.81	324
Weighted avg.	0.83	0.83	0.83	324

Table 4. Classification report. (A) Validation set (Scotland); (B) validation set (Spain); (C) validation set (combined Scotland and Spain).

	Precision			Recall			F1-Score			Units		
	A	B	C	A	B	C	A	B	C	A	B	C
0 (non-recyclable)	0.79	0.65	0.73	0.64	0.57	0.61	0.71	0.60	0.67	36	23	59
1 (recyclable)	0.76	0.88	0.83	0.87	0.91	0.90	0.81	0.89	0.86	47	77	124
Accuracy	-	-	-	-	-	-	0.77	0.83	0.80	83	100	183
Macro avg.	0.78	0.76	0.78	0.76	0.74	0.75	0.76	0.75	0.76	83	100	183
Weighted avg.	0.77	0.82	0.80	0.77	0.83	0.80	0.77	0.83	0.80	83	100	183

Overall, the model performed well in terms of accuracy in the validation datasets, having the highest in the Spanish dataset, with an accuracy of 83%; the lowest in the Scotland validation dataset, with an accuracy of 77%; and a combined accuracy of 80%.

However, while the model accurately classified recyclable samples, achieving a combined recall score of 90%, its performance was less effective for non-recyclable samples. For instance, in the Spanish validation dataset, the recall score for non-recyclable samples was only 57%, indicating that just over half were correctly classified. This disparity is likely due to the high ratio of recyclable to non-recyclable samples in the training dataset. As discussed in a previous chapter, data rebalancing methods were found to be suboptimal, primarily due to overfitting issues stemming from the low number of samples and variables present in the dataset, resulting in low-quality artificial data.

3.2.4. Confusion Matrix and Misclassification Analysis

The confusion matrices for the test and validation sets were constructed, as displayed in Figure 4.

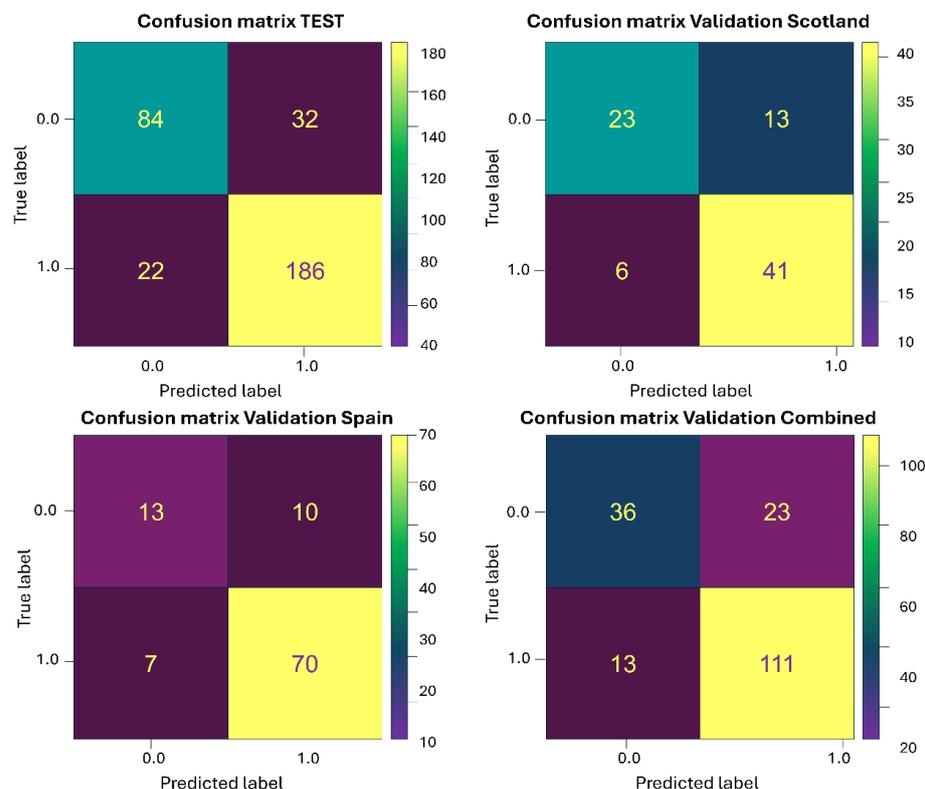


Figure 4. Confusion matrices (results).

While the test dataset misclassification is relatively low (22 out of 324 false negatives and 32 out of 324 false positives), the validation datasets present a higher number of misclassifications, mainly for non-recyclable samples, as the training dataset presents a higher ratio in favour of recyclable items. As mentioned previously, data rebalancing methods were tried, although—probably due to the relatively low number of entries and variables—the imbalance resulted in overfitting on the training dataset, which was evidenced by the generally lower precision of the validation sets compared with that of the test data.

4. Conclusions

This study demonstrates the effectiveness of Python and Random Forest algorithms in developing predictive classification models, achieving a notable 80% overall accuracy on the validation dataset. The model remarkably identified recyclable samples, with over 80% classification precision and 90% recall, highlighting its potential for practical application in waste management, particularly for classifying flat panel display plastic casings. These results underscore the promise of this approach in enhancing recycling efforts and supporting sustainable waste management practices. However, the classification of non-recyclable materials proved less accurate, attributed to dataset imbalances and limited training data. Addressing these limitations through the inclusion of more balanced and comprehensive datasets could further improve the model's performance, particularly in distinguishing non-recyclable materials effectively.

The insights from this study can inform practical applications in the recycling industry. Specifically, the model could be integrated into sorting and preprocessing systems to estimate the proportions of recyclable and non-recyclable plastics within WEEE streams. By identifying these proportions, waste managers can gain a clearer understanding of the material composition entering their facilities. This information is essential for several reasons: it helps forecast potential revenues from recyclable materials, informs the design and scaling of recycling infrastructure, and enables tracking of the trends and variability in material recovery over time.

Estimating these proportions is particularly relevant, given the growing complexity of WEEE streams, which often contain a wide range of plastic types with varying levels of contamination and thus recyclability. Accurate predictions can support operational decisions by optimizing sorting processes, reducing contamination in recycling outputs, and improving the allocation of resources such as labour, machinery, and storage. Moreover, having detailed data on material composition can assist in demonstrating compliance with environmental regulations, such as recycling rate targets and hazardous material handling standards. Ultimately, these applications not only enhance the efficiency and profitability of recycling operations but also contribute to advancing the circular economy principles by maximizing resource recovery and minimizing waste. To fully exploit this potential, several conditions must be met. First, a significantly larger dataset—approximately 25,000 entries—would be necessary to refine the model and improve its performance to meet industry sorting standards. Second, data management practices must evolve to facilitate the retrieval of key predictive variables. Currently, the model relies on more than five variables, many of which are challenging to obtain from labels or sample identifiers, such as the case of the polymer type. Simplifying the data requirements and improving variable accessibility would be crucial for practical deployment.

Furthermore, the observed differences in the hyperparameters between the Scottish and Spanish validation datasets highlight unaccounted factors, such as consumer behaviour, retailer practices, and manufacturing trends, which influence the composition of materials entering the waste stream. Accounting for these regional and market-specific variations

would enhance the model's predictive accuracy and adaptability across different waste management contexts.

In conclusion, the model was achieved, showcasing significant potential as a foundation for advancing plastic recycling processes and promoting sustainable waste management strategies. By addressing key areas such as expanding the data volume, enhancing variable accessibility, and accounting for regional variations, this methodology can be further refined to achieve practical applicability. With these improvements, the model holds promise as a transformative tool for optimizing recycling operations, improving resource efficiency, and supporting regulatory compliance in waste management systems.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/environments12020068/s1>.

Author Contributions: C.C.: Conceptualization, supervision, writing—original draft, writing—review and editing, data curation, investigation, methodology, validation, project administration. M.M.E.: Writing—original draft, writing—review and editing, investigation, software, methodology. B.M.V.: Writing—review and editing, software, methodology. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by European Union's Horizon Europe research and innovation programme under grant agreement No. 101091668, project REDOL.

Data Availability Statement: The authors confirm that the data supporting the findings of this study are available within the article and its Supplementary Materials.

Acknowledgments: The authors would like to acknowledge both WEEE recycling companies that generously provided the samples required for this research. Their contributions were invaluable to the progress and success of this study. We also extend our gratitude to the University of the West of Scotland for granting us access to their specialized equipment, which was crucial in conducting the experimental work presented in this paper.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

WEEE	Waste electrical and electronic equipment
POP	Persistent organic pollutant
BFR	Brominated flame retardant
XRF	X-ray fluorescence
FR	Flame retardant
FTIR	Fourier transform infrared spectroscopy
CRT	Cathode ray tube equipment
FPD	Flat panel display equipment
POM	Placed on market
wFPD	Waste FPD
YoM	Year of manufacture
MDI	Mean decrease in impurity

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